A Dynamic Structural Model of User Learning in Mobile-Media Content on the Internet

Anindya Ghose
Stern School of Business, New York University, New York, New York 10012, aghose@stern.nyu.edu

Sang Pil Han
Stern School of Business, New York University, New York, New York 10012, shan2@stern.nyu.edu

Consumer adoption and usage of mobile-based multimedia content services has been growing steadily over the past few years in many countries around the world. In this paper, we develop and estimate a structural model of users' dynamic learning in mobile digital media environments with regard to multimedia content generation and usage activities on the Internet. Users learn about two different categories of mobile content usage – content from regular Internet social networking websites and that from mobile portal sites and then choose to engage in the creation (uploading) and consumption (downloading) of these two categories of content. In our model, users have two sources of learning about mobile content quality– (i) direct experience through their own content creation and usage activities on the Internet, and (ii) indirect experience through word-of-mouth such as the content creation and usage behavior of their social network neighbors. Our model seeks to explicitly explain how direct usage experience and indirect experience from social interactions influence the content creation and usage behavior of users over time. We estimate this model using a unique dataset of several hundred users' mobile media usage over a 13 week time period. Our estimates suggest that when it comes to users' learning from direct experience, the content that is downloaded from mobile portal websites exhibits the highest level of consistency in quality. In contrast to this, content that is uploaded by users to regular websites on the Internet exhibits the least amount of consistency in quality. We use our estimates to assess the importance of learning in generating the content upload and download sequences observed in the data through different counterfactual experiments. Our policy simulations involving changes in the accuracy of prior beliefs suggest the existence of complementarity between activities involving content upload to mobile portal sites and upload to off-portal, regular Internet websites, and a weak substitution between activities involving content download from mobile portal sites and download from regular Internet websites. Further, policy simulations involving changes in the accuracy of direct and indirect experience signals suggest that these two kinds of signals act as complements for activities involving uploading content to the mobile portal site and for activities involving downloading content from regular social networking sites. On the other hand, they act as substitutes for activities involving uploading content to regular Internet and downloading content from the mobile portal sites. Potential implications for mobile operators and internet advertisers are discussed.

Key words: structural modeling, mobile media, complements, substitutes, mobile portal websites, Internet social networking websites, uploading content, downloading content, dynamic programming, simulated maximum likelihood estimation.

1. Introduction

Taking cues from electronic commerce, different kinds of user-generated content (hereinafter UGC) are becoming available in mobile media environment as well, spurred by rapid advances in the cellular telephony market. Besides regular Internet websites and social networking sites that can be browsed through mobile phones, other examples of content created and accessed through mobile digital media settings include photos, graphics, ring tones, videos, podcasts, and other kinds of multi-media content on mobile portals. As of today, several content management systems and social media platforms have created lightweight versions of their hosted sites automatically for users that come in via a mobile phones or WAP (Wireless Application Protocol) browsers. These websites work in much the same way as the regular Internet. However, rather than viewing web pages designed for PC's/Mac's, mobile sites are especially designed to be viewed on the small screens of a phone, are quick to load and simple to use. This process has facilitated user adoption of mobile commerce and is gradually paving the way for mobile advertising to become even more widespread in the coming years. Increasingly, we see more and more companies and mainstream brands launching a mobile web presence so they can engage directly with their consumers.

A unique aspect of the mobile digital media is that users need to explicitly incur expenses (for example, by paying data transmission charges) during their mobile content generation and usage endeavors based on the number of bytes uploaded or downloaded. This is in contrast to the online digital media in electronic commerce where content usage and generation on blogs and opinion forums through a PC or laptop using a fixed Internet connection (broadband or DSL) can be done without incurring any additional variable costs over and above the fixed monthly fees. With mobile becoming an increasingly significant medium for Internet access, mobile operators' portals offer an innovative and differentiated route for advertisers to reach users. So understanding what kinds of websites (and content) users access using their mobile phones is a key issue towards examining its potential as an advertising medium and other forms of monetization.

We are fortunate in that our data has explicit information on the two broad categories of websites that users can access through their cell phones – mobile portal sites and regular Internet and social networking websites (more information on these two categories is provided in the 'Data' section). This distinction is important because of the fundamental differences in the operation of mobile portal sites from regular websites. Mobile portal sites are owned and hosted by mobile phone companies. Examples include Vodafone live, T-Mobile's Web'n'Walk, Planet3, Orange World and O2 Active. A substantial part of the original content on these sites comes from third-party content creators who have entered into contracts with mobile phone operators. As a result, mobile operators have control on the kinds and quality of content that is available on these websites. This is as opposed to off-portal, regular Internet websites where these mobile phone operators can exercise less control on the content that is available to be shared, for obvious reasons. Hence, an understanding of differences in user behavior (both upload and download) between mobile portal sites and off-portal, regular Internet sites can be useful from the point of view of monetization and mobile advertising.

In this paper, we develop and estimate a dynamic model of users' content generation and usage activities in a mobile media setting. The context of our empirical analysis is akin to that of user dynamics and learning in experience goods. We model how users learn about two different categories of content usage – content from regular Internet websites and that from mobile portal sites and then choose to engage in the creation (uploading) and consumption (downloading) of these two categories of content. We do so in a structural model setting, and there are a couple of reasons why we choose to adopt such an approach. First, incorporating user and firm dynamics into structural econometric models can enhance our understanding of user behavior. A dynamic structural approach takes into account the fact that when current choices influence future pay-offs, and hence the behavior of a rational decision-maker must be forward-looking. Second, dynamic structural models may be able to explain certain empirical patterns that are not captured by static models especially when it comes to situation involving uncertainty and learning. Hence, ignoring the dynamics could potentially "throw away" valuable information and in the worst case could generate misleading conclusions about behavior.

In our context, there are several reasons why user choice behavior might exhibit dynamics. First, as is known in the prior literature on state dependencies, choices made in previous periods might causally affect a user's current period utility and behavior. Second, as is known from the work on habit persistence there are temporal dependences in the random component of utility users derive from products (Heckman 1981). Third, users can exhibit forward-looking behavior in which they maximize the stream of expected utilities over a planning horizon rather than their immediate utility. As an example, current choices might depend on their information value and their impact on future utilities like in strategic consumer trial or sampling behavior (Eckstein et al. 1988). If this were so, then decision makers need to take into account the impact of their current actions on the future stream of utilities. We do find evidence of dynamics from the descriptive statistics of our data. Specifically, there is positive state dependence in the content generation and content usage behavior of the users in our sample. However, these descriptive statistics cannot explicitly explain how and why users' current choices depend on past choices. In addition, we have seen a positive association between the behavior of social network neighbors and the content generation and content usage behavior of a user in our descriptive statistics. However, we cannot explicitly explain how and why one's choices depend on the choices of the friends' or family members' of that user.

Furthermore, there are reasons why there might be user uncertainty due to imperfect information about product characteristics in our context. Under uncertainty, past experience with brands (products) as well as marketing mix elements may affect a consumer's information set, which in turn affects his/her current choices (Erdem and Keane 1996). The environment is typically characterized by fast-changing and new product characteristics. It is easy to see how there can be uncertainty and learning incentives in our setting. Users can be uncertain about the benefit from content generation and content use in the mobile digital media setting. Further, they can learn the benefit from content generation and usage at the content type level. For example, downloading audio files can provide information about the direct benefit from audio content while provide little information about the benefit from other types of content use (such as video games or ringtones). Furthermore, there are additional quality-signaling mechanisms in our context which could facilitate learning from social network neighbors such as friends or colleagues.

Our paper builds and estimates a structural model of users' dynamic learning in which forward-looking users learn about mobile media content quality through direct signals such as their own content creation and usage activities as well as through indirect word-of-mouth (WOM) signals such as the content creation and usage behavior of their social network neighbors. Our model seeks to explicitly explain how direct usage experience and indirect experience from social interactions influence the content creation and usage behavior of users over time.

A number of recent papers have developed dynamic demand models. The main focus of prior work has been on modeling direct learning and too in the context of durable goods or other storable goods. For example, Hendel and Nevo (2006) focus on sales and consumer inventory behavior in a product category (e.g., detergent). They show that if there is consumer's stock-piling behavior, the own-price elasticity driven by temporary price cut would be smaller static estimates suggest because of the inter-temporal substitution. Gowrisankaran and Rysman (2007) examine demand for new durable goods (e.g., digital camcorders) and claim that people could obtain biased welfare estimates if they ignore consumer's dynamic behavior. In their empirical analysis, they show that the static demand estimation model produces unreasonable coefficients (e.g., a positive price coefficient) because within a time period, the cheapest models were often not the most popular. Erdem and Keane (1996) look at usage experience and advertising exposure as a means to enable user learning also in a product category (e.g., detergent).

To our knowledge, little work exists in the domain of services, especially wherein expenses incurred by users are frequent, as in the case of mobile content creation and consumption. For example, Ackerberg (2001) examines advertisements in nondurable experience-goods markets (e.g., yogurt) and empirically measure the existence and extent of informative effects and prestige effects separately. Crawford and Shum (2005) look at user learning from direct experience such as symptomatic signals and curative signals in the pharmaceutical industry. Similarly, Israel (2005) looks an automobile insurance service market and examines consumer learning about the service quality from experience. Erdem et al. (2008) incorporate user experience, advertising content, advertising intensity, and price as signals of product quality in a learning model in a product category like ketchup. None of these papers consider the possibility of any kind of indirect learning through WOM. Erdem et al. (2005) look at consumers' active learning in a fast-changing market (e.g., computers) and develop a structural model of consumers' decisions about how much information to gather prior to making a purchase. However, they employed survey data where they asked subjects about the source of information without using the actual communication history between consumers or the strength of the WOM communications. Iyengar et al. (2007) look at a wireless service industry and model the dual learning process of service provider's quality and consumer's consumption quantity within a Bayesian learning framework but do not include learning in content creation and usage behaviors in the mobile media setting nor the WOM effect.

In summary, there are three aspects we address in our paper: a structural model of user uncertainty about and learning of content quality, users' dynamic learning about content quality from their own content generation and usage behavior as well as indirect WOM experience as a source of learning based on actual communication data between network neighbors. Whereas previous work has examined some of these issues separately, we address these aspects together. Moreover, our study is in the context of mobile digital media which has not been explored in prior work.

The rest of this paper is organized as follows. Section 2 describes the data that we employ. In Section 3, we provide the theoretical framework for the structural model. This includes information on user decision-making process, description of the utility specification with posterior mean and variance, the formulation of the dynamic optimization problem and econometric estimation. We describe the key results in Section 4. Section 5 presents results from various counterfactuals and policy simulations. Section 6 discusses implications and concludes.

2. Data Description

Our data is drawn from 3G mobile users in Korea who used the services of the company between March 15, 2008 and June 15, 2008. 3G mobile services enable users to upload their content faster than conventional mobile services. Further, these services are more commonly available in the large screen handsets that facilitate more user-friendly content generation and usage compared to the small-screen devices. The dataset that we employ in our analysis consists of 20,000 mobile data transaction records encompassing several hundred users' content uploading and downloading behaviors. We also have data on voice calls made by the same users that enables us to construct their social networks.

As briefly outlined in the introduction, there are two broad categories of websites users can access through their mobile phone, either for uploading content or for downloading content. The first category is one consisting of regular websites that any user can browse through a PC or laptop. By forcing these off-portal sites to comply with mobile web standards, mobile operators try to ensure visitors a consistent and optimized experience on their mobile device. The second category of websites includes portal sites specifically created by the mobile phone company. The content on these sites can be accessed through a mobile phone by a user who subscribes to the service of the mobile operator. These mobile portals are community-oriented sites that allow users to download and upload (in order to share with others) ringtones, wallpapers, videos, screen savers, video games, etc. Users pay transmission charges for every upload and download, just as they would have to do when accessing the regular Internet sites. The transmission charges are in general the same, irrespective of whether users upload or download content.

We have precise transmission data and time stamp information from individual-specific transactions that involve either an upload or download of content. Table 1 shows summary statistics of our data. The first interesting observation is that users are more actively engaged in content usage instead of content creation. This suggests that most users' content creation activities are still in a nascent stage. Further, their content usage activities primarily focus on content download from mobile portals. Hence, users may engage in experimentation through content creation in order to learn about its benefits. This helps us capture users' dynamic learning behavior in the mobile media setting.

As noted before, there are two kinds of learning in our setting. First, users can learn through their own usage over time. We refer to this as direct experience. Second, users can learn from the behavior of their social networks (i.e., some kind of a word of mouth from their network neighbors). We refer to this as word-of-mouth (WOM) or indirect experience. In our model and data, the extent of such indirect learning can be adjusted by communication strength (i.e., call frequency or call duration).

Table 1: Summary Statistics

Variable	Mean	Standard deviation	Minimum	Maximum
Direct Experience				
Frequency of Upload to the Internet	0.002	0.039	0	1
Frequency of Upload to the Mobile Portal	0.003	0.055	0	1
Frequency of Download from the Internet	0.001	0.032	0	1
Frequency of Download from the Mobile Portal	0.494	0.500	0	1
Indirect Experience				
Frequency of Upload to the Internet	0.003	0.066	0	1.771
Frequency of Upload to the Mobile Portal	0.009	0.143	0	10.543
Frequency of Download from the Internet	0.003	0.066	0	1.771
Frequency of Download from the Mobile Portal	2.150	15.831	0	464.857

Notes*: The frequency of indirect WOM experience is a weighted average of the number of times the network neighbors of a given user have engaged in a given activity in a given time period. Hence, it may exceed 1. Note that we use call frequency as a weight (proxy) for the strength of social interactions between users.*

We find that users may receive a higher number of quality signals from their indirect experiences compared to their own experiences. This is not surprising given that the average number of calls made by users in our sample is 6.1 times a day and the average number of unique call-recipients is 3.3 users a day. Based on our sample statistics, we compute that a user may receive indirect signals as many as 1.65 times a day on an average. Also, since we do not observe when users actually began their first downloading or uploading activity since the inception of the service, there could be potential initial condition or left-censoring problems. To avoid such issues, we include only those users in our sample whose activities we first observe after the first month.

We next present some suggestive evidence of learning through users' switching propensities across the five options available to them in Table 2. First, these probabilities suggest that some activities tend to elicit a relatively higher probability of switching (activities 1, 2 and 3) while other activities tend to elicit a relatively lower probability of switching (activities 4 and 5). For any given activity, this phenomenon is evident from comparing the off-diagonal elements with the diagonal elements. For the first 3 activities, the off-diagonal values are higher than the diagonal ones. For activities 4 and 5, it's the opposite. More interestingly, we find that for activity 4 there are non-zero probabilities of users switching to three different activities - 1, 2 and 3. Recall that activities 1 through 3 denote content upload to both regular Internet websites and mobile portal sites, and content download from the Internet, all of which are relatively recent service features in the mobile setting, as opposed to the content download from the mobile portal sites. This indicates that to some extent users try to engage in new types of content service, which further suggests the experimental nature of users' service usage behaviors. Similarly, for activity 1, there are non-zero probabilities of users switching to two different activities – 3 and 4. These descriptive statistics motivate further examination of exactly how the learning process works in this setting.

Table 2: Matrix Highlighting Switching Between Activities

Switching Probability (%)		Time t+1				
		Activity 1	**Activity 2**	**Activity 3**	**Activity 4**	**Activity 5**
Time t	**Activity 1**	0.17	0.00	0.01	0.16	0.02
	Activity 2	0.00	0.07	0.00	0.17	0.09
	Activity 3	0.01	0.00	0.01	0.03	0.01
	Activity 4	0.15	0.16	0.03	57.91	3.13
	Activity 5	0.02	0.10	0.01	3.16	34.19

Notes: *Activity 1-5 denote upload content to the Internet, upload content to the mobile portal, download content from the Internet, download content from the mobile portal, and doing nothing, respectively.*

3. Structural Model

We model user behavior in an environment where users have uncertainty about the quality level of content that is being consumed or the content being generated through mobile phones, and may be risk averse with respect to quality variation. This is reasonable to assume in a context where usage is costly and users need to pay transmission charges based on the amount of traffic that is being downloaded or uploaded.

We adopt a single agent problem framework. The user's objective is to find an optimal sequence of content generation and usage choices. They update their expectations in a Bayesian manner as they receive additional signals of quality. We set our time period of analysis to be a 'day.' Posterior beliefs are updated once at the end of each day. So within a given day, users have the same posterior belief regardless of their uploading/downloading experiences for that day. This helps us to synchronize the incidence timing of two sources of learning – direct experience and indirect experience.

We model users' information set and choice timings as follows. Based on users' own experiences and the information they have received from their social networks, they start with a pair of prior beliefs in time *t*. Users then evaluate their choices amongst the various alternatives. For each choice they calculate the choice-specific value using their value functions, and choose the one with highest value. Thereafter, users learn the quality from their own experience in creation or usage and update the posterior at the end of time *t*. In our paper, we focus on distinguishing between the two broad classes of websites as described before. Hence, in order to model user choices/alternatives set, we model users as having five distinct options: (i) upload content to the Internet, (ii) upload content to mobile portal sites, (iii) download content from the Internet, (iv) download content from mobile portal sites, and (v) doing nothing.

In order to incorporate decisions from network neighbors and the associated communication strength, we fix network neighbors for each user to as many as five users based on the call frequencies between them. Note that the qualitative nature of our results is likely to be robust to the use of other numbers as well. We set the communication strength between them as being fixed throughout the sampling window. The types of upload and download behavior of the network neighbors is the source of uncertainty in indirect experience of quality.

3.1. User Decision and Product Quality Uncertainty

Since users are forward-looking in our model, their current choices could influence their preferences during future periods. They select the sequence of content choices that maximizes their expected utility. We specify user *i*'s expected utility as follows:

$$\max_{D=\left\{\left\{\left\{d_{ijt}^{s}\right\}_{j=1}^{J}\right\}_{s=1}^{s_t}\right\}_{t=1}^{\infty}} E_D\left(\sum_{t=1}^{\infty}\beta^t\sum_{s=1}^{s_t}d_{ijt}^{s}U_{ijt}^{s}\right) \tag{1}$$

where $j\in\{1$ = upload to the Internet, 2 = upload to mobile portal sites, 3 = download from the Internet, 4 = download from mobile portal sites and 5 = doing nothing}, s_t is the number of times user *i* is involved in content choices in time *t*, β is a discount factor, d_{ijt}^{s} denotes 1 if user *i* chose activity *j* at *s*th choice in time *t* and 0 otherwise, and U_{ijt}^{s} denotes the associated utility.

We model user uncertainty as follows. Users are imperfectly informed and hence uncertain about each content's mean attribute levels as in prior work (Erdem and Keane 1996). User experiences vary. There could be a number of reasons why user experiences may vary. First, in our setting, user's experience of content quality is very likely to be context dependent (Erdem et al. 2008). In our mobile context, since users may access mobile services from very diverse locations (e.g., on the road in a bus, car or train, at home, at work, etc.), there could be substantial variation in the perceived quality of the content that is consumed as well content that is created. We denote the direct experience quality signal as Q_{Eijt}^{s}. We assume that each direct experience of content use or generation provides a noisy but unbiased signal of quality for all activities except "doing nothing" as follows:

$$Q_{Eijt}^{s} = Q_j + \xi_{ijt}^{s} \qquad \text{where} \quad \xi_{ijt}^{s} \sim N\left(0,\sigma_{\xi j}^{2}\right). \tag{2}$$

That is, $Q_{Eijt}^{s} \sim N\left(Q_j,\sigma_{\xi j}^{2}\right)$,. Here, Q_j and $\sigma_{\xi j}^{2}$ are the latent quality index and the "choice-specific direct experience variability," respectively, like in Erdem et al. (2008).

In addition to variation in the direct experiences of users, there can be variation in the indirect experiences of users. This can happen because the network neighbors of a user, like users themselves, receive a noisy but unbiased signal of perceived content quality from both upload and download activities. Moreover, when the information regarding content quality is transferred via (say) word-of-mouth, there could be additional sources of noises; they are incorrect delivery of the information by a sender, misunderstanding by a recipient, etc. Hence the information from network neighbors provides a noisy but unbiased signal. We assume that each indirect experience of content use/generation comes only from network neighbors who have experienced the content usage or generation in that period. We denote user *i*'s indirectly experienced quality signal about activity *j* from a network neighbor *k* who has participated in activity *j* at the same time *t* as follows:

$$Q_{WOMkjt} = Q_j + \delta_{kjt} \qquad \text{where} \quad \delta_{kjt} \sim N(0, \sigma_{\delta j}^2). \qquad (3).$$

That is, $Q_{WOMkjt} \sim N(Q_j, \sigma_{\delta j}^2)$. We refer to $\sigma_{\delta j}^2$ as the "choice-specific indirect experience variability." We expect that $\sigma_{\delta j}^2 \geq \sigma_{\xi j}^2$ for each activity *j*. One can also interpret $1/\sigma_{\delta j}^2$ as an indicator of the precision of the information (signal) delivered/transferred via WOM.

Note that *k* is *k*th network neighbor of user *i* and *k* = 1,..., $n(i)$, where $n(i)$ is the total number of network neighbors of user *i*. That is, user *i* can receive signals about the quality from as many as $n(i)$ network neighbors. The information set I_{it} includes all quality signals that user *i* received through time *t*. For example, for user *i* at time *t*, it includes Q_{Eijt}^s and Q_{WOMkjt} where $k \in n(i)$ through time *t*. Given this information set, a user forms an expectation of the experienced quality given by Q_{Eijt}. Let $Q_{ijt} \equiv E[Q_j | I_{it}]$ denote user *i*'s expectation of activity *j*'s true quality level at time *t*. Assume that all signals are unbiased. Hence, $E[Q_{Eijt}^s | I_{it}] = E[Q_j | I_{it}] = Q_{ijt}$.

3.2. User Utility Specification

Let U_{ijt}^s denote user *i*'s single-period utility from activity *j* for the *s*th choice in time *t*. Let Q_{Eijt}^s denote user *i*'s quality signal from directly experiencing activity *j* at *s*th choice in time *t*. This follows from the fact that utility is a function of experienced attribute levels and not the mean attribute levels (Erdem and Keane 1996). p_j is the average price of activity *j*. We assume that users are risk averse with a concave sub-utility function of the quality and a linear term in price. Consistent with Erdem et al. (2008), we assume users have a utility function of the form, for activity *j* = 1,..., 4:

$$U_{ijt}^s = w_g * Q_{Eijt}^s + w_g * r_g * (Q_{Eijt}^s)^2 - a_g * p_j + \varepsilon_{ijt}^s. \qquad (4)$$

We consider the discrete latent segments by denoting subscript *g*. Note that *w* is user *i*'s utility weight on quality/benefit, *r* captures the extent of the risk aversion towards variation in quality (*r* < 0: utility is concave, so the user is risk averse), *a* is the price coefficient, and ε^{s}_{ijt} captures a taste shock known to user *i* but not by the econometricians. We re-write as follows:

$$Q^{s}_{Eijt} = Q_{ijt} + \left(Q_{j} - Q_{ijt}\right) + \xi^{s}_{ijt}. \tag{5}$$

Then the expected utility to user *i* from doing activity *j* in time *t* is

$$E\left[U^{s}_{ijt}|I_{it}\right] = w_{g} * Q^{s}_{Eijt} + w_{g} * r_{g} * E\left[\left(Q_{j} - Q_{ijt}\right)^{2}|I_{it}\right] + w_{g} * r_{g} * \sigma^{2}_{\xi} - a_{g} * p_{j} + \varepsilon^{s}_{ijt}. \tag{6}$$

There are two sources of expected variability of experienced quality Q_{Eijt} about true quality. First is the experience variability, σ^{2}_{ξ}. Second is the variability of true quality around perceived quality, $E\Big[\big(Q_{j} -$ Qijt2|Iit. Note that this is similar to a "risk term". That is, if a user has little information about the product/service/activity, then true quality will tend to depart somewhat from expected quality, and thus the risk term is large (Erdem et al. 2008). We simply assume that the expected utility associated with "doing nothing" to be a constant plus a stochastic error component.

$$E\left[U_{i5t}\right] = U_{i5t} = \Phi_{0} + \varepsilon_{i5t}. \tag{7}$$

3.3. User Learning

Users have prior beliefs about the "mean" quality levels for each activity *j*. We model them as follows:

$$Q_{j} \sim N\left(Q_{0}, \sigma^{2}_{Q_{0}}\right). \tag{8}$$

That is, all activities have a quality level of Q_{0} but the true quality of activity *j* has variance $\sigma^{2}_{Q_{0}}$. Following Erdem et al. (2008), we restrict the prior mean Q_{0} to be equal to the mean of the all activity-specific quality levels Q_{j} for *j* = 1,..., 4.

User *i* does not know the true quality of any of the four possible options, but receives signals which allow that user to update his/her perceived quality belief from engaging in as well as indirectly learning via WOM about activity *j*. Note that user *i* may receive multiple quality signals in time *t*. That is, *k* = 1,..., $n(i)$, and this is assumed to be independent and distributed normally across periods.

Note that $E\left[Q^{s}_{Eijt}|I_{i}(t-1)\right] = E\left[Q_{WOMkjt}|I_{i}(t-1)\right]$ where $k \in n(i)$. This implies that the expected level of the direct experience signals and the expected level of indirect experience signals, given the information available to user *i* in time *t*-1, are equal. In terms of the learning process, we assume that users use information (i.e., either the direct experience signal or the indirect experience signal, or both) that they receive over time. To be specific, they learn about the mean and variance of quality levels in a Bayesian fashion (DeGroot 1970) according to the process described below in (a) and (b).

(a) Posterior Mean of Perceived Content Quality

Unlike cases where there is only one signal per a source at a given time (e.g., Crawford and Shum 2005, Erdem et al. 2008), users receive varying numbers of multiple signals of direct experience as well indirect experience at a given time (e.g., day) in the mobile media context. It is not only because in a mobile digital media context, users create and consume content far more frequently compared to durable goods or less frequently purchased products (e.g., computers and drugs), but also because they are in general frequently involved in communication activities with friends and colleagues so that opinions or ideas about one's service or product experience is easily shared to each other. To address the modeling complication arising from this, we posit that although users can receive multiple quality signals within a day, they update their posterior beliefs once at the end of a day. Also we posit that multiple quality signals from network neighbors of a user at a given time can be aggregated into one representative signal, which carries an average of all quality signals received from network neighbors of that user. In doing so, we only need to consider two variables - the representative quality level of and the number of quality signals from indirect experience. We explain below how these help us formulate the posterior mean and variance of perceived content quality.

We compute the posterior mean of perceived quality about activity *j* in time *t*+1 denoted as μ_{ij}^{t+1}, according to the following expression. If user *i* engages in his/her first activity *j* in time *t*+1 (i.e. $d_{ijt+1}^{1} = 1$), then the posterior mean can be written as the sum of three separate components - (i) prior mean, (ii) difference between the realized quality from direct experience and the prior mean, and (iii) difference between the realized quality from indirect experience and the prior mean. This is written as follows:

$$\mu_{ij}^{t+1} = E[Q_j|I_i(t+1)] = E[Q_j|I_i(t)] + \beta_{1ij}(t) * \{Q_{Eijt+1}^{s} - E[Q_{Eijt}|I_i(t)]\} \\ +\beta_{2ij}(t) * \{Q_{WOMkjt+1} - E[Q_{WOMkjt}|I_i(t)]\} \quad (9)$$

where

$$\beta_{1ij}(t) = \frac{\frac{1}{\sigma_{\xi j}^2}}{\frac{1}{\sigma_{vij}^2(t)} + \frac{1}{\sigma_{\xi j}^2}} \quad \text{and} \quad \beta_{2ij}(t) = \frac{\frac{\sum_{k\in n(i)} \eta_{ij}\left(w_{ik}d_{kjt}\right)}{\sigma_{\delta j}^2}}{\frac{1}{\sigma_{vij}^2(t)} + \frac{\sum_{k\in n(i)} \eta_{ij}\left(w_{ik}d_{kjt}\right)}{\sigma_{\delta j}^2}}. \tag{10}$$

The intuition behind the above updating Equation (9) is that the posterior mean of perceived quality at the end of time *t*+1 is a weighted average of the three components described above. This implies that we update the posterior mean by incorporating a (prior) mean-differenced realized quality signal from direct experience, weighed by the relative accuracy of the signal. Moreover it is important to note that as shown in Equation (10) we use the inverse of variance of each source such that the less diverse a signal generated from a source, the more accurately it represents the true quality. For example, the second component denoted as $\beta_{1ij}(t)$ represents the ratio of accuracy of the direct experience signal to the sum of the accuracy of the prior belief and the direct experience signals. We could interpret the third component denoted as $\beta_{2ij}(t)$ in a similar manner.

However, complication arises from the fact that users can have multiple indirect experience signals at a given time. We simplify the updating process for indirect experience-based learning as mentioned above. First, we compute the weighted count of frequency of engaging in each activity by network neighbors of a given user. We use voice call frequency as a weight because it is conceivable that the more the number of voice calls between a caller and a receiver, the higher the probability of occurrence of indirect experience. Hence, we can denote that user *i* has $\sum_{k\in n(i)} w_{ik}d_{kjt}$ times of indirect experience signals in time *t* where w_{ik} is call frequency between user *i* and user *k* who is a network neighbor of user *i* and d_{kjt} is an indicator variable indicating whether or not user *k* engaged in activity *j* in time *t*. Moreover, to control the varying extent of the activity-specific influence from network neighbors, in the count of number of indirect experience, we normalize it by using the individual-specific, activity-specific denominator denoted as η_{ij}, $\eta_{ij} = \max_k\left(w_{ik}d_{kjt}\right)$ for each activity *j*. Hence, we can interpret the third component,

$\beta_{2ij}(t)$ as the ratio of accuracy of the multiple signals from indirect experiences compared to the combined accuracy of the prior belief and the indirect experiences.[1]

On the other hand, if user *i* does not engage in activity *j* in time *t+1*, then the posterior mean can be written as the sum of only two separate components - (i) prior mean and (ii) difference between the realized quality from indirect experience and the prior mean. This is written as follows:

$$\mu_{ij}^{t+1} = E\left[Q_j | I_i(t+1)\right] = E\left[Q_j | I_i(t)\right] + \beta_{2ij}(t) * \left\{Q_{WOMkjt+1} - E\left[Q_{WOMkjt} | I_i(t)\right]\right\} \tag{11}$$

For simplicity, note that the network neighbors and the communication strength between them remains fixed throughout our sampling period. This knowledge is public in the sense that the econometrician can treat this information as exogenously given. $\sigma_{vij}^2(t)$ is the variance of user *i*'s belief of activity *j*'s mean quality in time *t*. We explain this in the next section.

(b) Posterior Variance of Perceived Content Quality

Similarly, we compute the posterior variance of perceived quality about activity *j* in time *t*+1 denoted as $\sigma_{vij}^2(t+1)$, according to the following expression. There are three components of relevance here - (i) the inverse of variance of prior belief about the quality, (ii) summation of the inverse of the variance of the direct experience signals and (iii) summation of the inverse of the variance of the indirect experience signals. The higher the value of (ii) or (iii), the lower the posterior variance implying higher the posterior accuracy. This can be written as follows, if user *i* engages in activity *j* in time *t*+1, then

$$\sigma_{vij}^2(t+1) = \frac{1}{\frac{1}{\sigma_{Q_0}^2} + \frac{\sum_{t=1}^{t+1}\sum_{s=1}^{s_t} d_{ijt}^s}{\sigma_{\xi j}^2} + \frac{\sum_{t=1}^{t+1}\sum_{k\in n(i)}\left(w_{ik}d_{kjt}\right)}{\sigma_{\delta j}^2}}. \tag{12}$$

On the other hand, if the user *i* does not engage in activity *j* in time *t*+1, then

$$\sigma_{vij}^2(t+1) = \frac{1}{\frac{1}{\sigma_{Q_0}^2} + \frac{\sum_{t=1}^{t}\sum_{s=1}^{s_t} d_{ijt}^s}{\sigma_{\xi j}^2} + \frac{\sum_{t=1}^{t+1}\sum_{k\in n(i)}\left(w_{ik}d_{kjt}\right)}{\sigma_{\delta j}^2}}. \tag{13}$$

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[1] Note that $\beta_{2ij}(t)$ can be re-written as $\frac{\frac{\sum_{k\in n_t(i)}\eta_{ij}\left(w_{ik}d_{kjt}\right)}{\sigma_{\delta j}^2}}{\frac{1}{\sigma_{vij}^2(t)}+\frac{\sum_{k\in n_t(i)}\eta_{ij}\left(w_{ik}d_{kjt}\right)}{\sigma_{\delta j}^2}} = \frac{\frac{\eta_j\left(w_{i1}d_{1jt}\right)}{\sigma_{\delta j}^2}+\dots+\frac{\eta_j\left(w_{in}d_{njt}\right)}{\sigma_{\delta j}^2}}{\frac{1}{\sigma_{vij}^2(t)}+\frac{\eta_j\left(w_{i1}d_{1jt}\right)}{\sigma_{\delta j}^2}+\dots+\frac{\eta_j\left(w_{in}d_{njt}\right)}{\sigma_{\delta j}^2}}$ meaning that it captures the relative accuracy of all WOM signals from network neighbors of user *i*. n denotes the last network neighbor of user *i*.

3.4. Users' Dynamic Optimization Problem

(a) State Variables

In our dynamic learning model, there are four kinds of state variables, S_{it}. The first is user *i*'s posterior mean of perceived quality from doing activity *j* in time *t*, denoted as μ_{ij}^{t}. The second is the count of number of times that user *i* has done activity *j* up to and through time *t* which is given by:

$$l_{ij}^{t} = \sum_{t=0}^{t} \sum_{s=1}^{s_t} d_{ijt}^{s}. \tag{14}$$

The third is the count of number of times that network neighbors of user *i* have engaged in activity *j* up to and through time *t*, weighted by a communication frequency therein, given by:

$$m_{ij}^{t} = \sum\nolimits_{t=0}^{t} \sum_{k \in n(i)} \eta_j \left(w_{ik} d_{kjt} \right). \tag{15}$$

And finally, we have the idiosyncratic errors denoted as ε_{ijt}^{s}.

(b) Dynamic Decision-Making

The user's optimal decision rule is to choose the option that maximizes the expected present value of utility over the planning horizon. This leads to a dynamic programming problem, and one can apply the Bellman's principle to solve this problem by recursively finding value functions corresponding to each alternative choice. Based on the Bellman's equation, the value function in the infinite-horizon problem is given as follows:

$$V_{it}(S_{it}) = \max_{j} E\left[U_{ijt} + \beta * E\left[V_{it}(S_{it+1}) | d_{ijt}, Q_{Eijt}, Q_{WOMkjt}, w_{ik} d_{kjt}\right] | S_{it}\right] \tag{16}$$

where β is a discount factor and *k* denotes network neighbors of user *i*. Hence, the optimal decision rule is $\mathrm{argmax}_j\{V_{ijt}^{s}(S_{it})\}$ where, for every *j*,

$$V_{ijt}(S_{it}) = U_{ijt} + \beta * E\left[V_{it}(S_{it+1}) | d_{ijt}, Q_{Eijt}, Q_{WOMkjt}, w_{ik} d_{kjt}\right] \tag{17}$$

is the choice-specific value function.

Recall that signals received by users are random variables and these are only observable to the users but unobservable to researchers. In order to derive the value function, we need to eliminate the random component of these signals. The way to do this is to generate a sequence of signals for the current period own experience and for both the direct and indirect experience in the next period. Note that in the above equation we have two components: one outer "expectation" term and the other inner "expectation" term. Hence, towards computing this value function, we take the outer expectation over Q^{s}_{Eijt} and the inner expectation over both Q_{Eijt+1} and $Q_{WOMkjt+1}$. We employ a variant of the Keane and Wolpin (1994) approximation method for computing the value function.

(c) Integrated Value Function

The integrated value function is the expectation of the value function over the distribution of unobservable state variables (e.g., ε_{ijt}), conditional on the observable state variables: (for simplicity, we drop out subscripts *it* for $\overline{V}$ and *i* for S_t)

$$\overline{V}(S_t) = \int V(S_t, \varepsilon_{ijt}) dG_{\varepsilon}(\varepsilon_{ijt}). \tag{18}$$

This function is the unique solution to the integrated Bellman's equation:

$$\overline{V}(S_t) = \int \max_j E\{U_{ijt} + \beta * E[\overline{V}(S_{t+1}|d_{ijt}, Q_{Eijt}, Q_{WOMkjt}, w_{ik}d_{kjt})]|S_t\} dG_{\varepsilon}(\varepsilon_{ijt}). \tag{19}$$

Hence, the choice-specific value function becomes:

$$V_{ijt} = U_{ijt} + \beta * E[\overline{V}_{it}(S_{it+1})|d_{ijt}, Q_{Eijt}, Q_{WOMkjt}, d_{kjt}]. \tag{20}$$

We use this choice-specific value function with the integrated value function to compute the choice probability. We will explain this in the estimation section. Note that if ε_{ijt} are i.i.d. type-1 extreme value random variables, this becomes the dynamic problem conditional on logit model with Bellman's equation:

$$\begin{aligned}\overline{V}(S_t) = \log\Bigg(\sum_{j=1}^{4} \exp\Big\{ & w_g * Q^{s}_{Eijt} + w_g * r_g * \left(Q^{s}_{Eijt}\right)^2 - \alpha_g \\ & * p_j + \beta * E[\overline{V}(S_{t+1})|d_{ijt}, Q_{Eijt}, Q_{WOMkjt}, w_{ik}d_{kjt}]\,|S_t\Big\} \\ & + \exp\{\Phi_0 + \beta * E[\overline{V}(S_{t+1})|d_{ijt}, Q_{Eijt}, Q_{WOMkjt}, w_{ik}d_{kjt}]\,|S_t\}\Bigg).\end{aligned} \tag{21}$$

Note that the idiosyncratic error term is integrated out. We can also interpret the value from the integrated value function as "inclusive value" for deciding which activity to engage in conditional on a set of state variables. Also note that the last additive term represents the utility from the fifth option, "doing nothing" and we integrate out the indirect experience signals.

3.4. Econometric Estimation

We start by outlining the choice probabilities and the likelihood function. Then we discuss the estimation procedure followed by a discussion of our main identification restriction.

(a) Choice Probability

Let Ξ denote the complete set of model parameters for a user. We define the deterministic part of the choice-specific value function as

$$V^*_{ijt}(S_{it}|\Xi_g) = V_{ijt}(S_{it}|\Xi_g) - \varepsilon_{ijt}. \tag{22}$$

If ε^s_{ijt} are i.i.d. type-1 extreme value random variables, the probability of user *i* doing activity *j* during time *t* is given by: (for simplicity, we drop out the superscript *s* denoting *s*th experience)

$$\text{Prob}(d_{ijt} = 1|S_{it}, \Xi_g) = \frac{\exp\{V^*_{ijt}(S_{it}|\Xi_g)\}}{\sum_{m=1,5} \exp\{V^*_{imt}(S_{it}|\Xi_g)\}}. \tag{23}$$

(b) Likelihood Functions

Let $H_i = \left\{\left\{\{d^s_{ijt}\}_{j=1}^{5}\right\}_{s=1}^{s_t}\right\}_{t=1}^{T}$ denote user *i*'s choice history, where *T* is the last observation period. Recall that we have five options ranging from 1 (upload to the Internet) to 5 (doing nothing). Then,

$$\text{Prob}(H_i|\Xi_g) = \prod_{t=1}^{T}\prod_{s=1}^{s_t}\prod_{j=1}^{5} \text{Prob}(d^s_{ijt} = 1|S_{it}, \Xi_g)^{d^S_{ijt}}. \tag{24}$$

Also, let $\tilde{\xi}_{ijt} = \left\{\left\{\{d^s_{ijt}\xi^s_{ijt}\}_{j=1}^{4}\right\}_{s=1}^{s_t}\right\}_{t=1}^{t}$ and $\tilde{\delta}_{kjt} = \left\{\left\{\{d_{kjt}\delta_{kjt}\}_{k\in n(i)}\right\}_{j=1}^{4}\right\}_{t=1}^{t}$ denote the sets of direct experience signals and indirect WOM signals, respectively, received by user *i* up to and through time *t*, such that $S_{it} = S_{it}(\tilde{\xi}_{ijt}, \tilde{\delta}_{kjt})$. Then we can write the probability of observed history of user *i* as follows:

$$\int_{\tilde{\xi}_{ijt}}\int_{\tilde{\delta}_{kjt}} \prod_{t=1}^{T}\prod_{s=1}^{s_t}\prod_{j=1}^{5} \text{Prob}(d^s_{ijt} = 1|S_{it}(\tilde{\xi}_{ijt}, \tilde{\delta}_{kjt}), \Xi_g)^{d^S_{ijt}} dF(\tilde{\xi}_{ijt}, \tilde{\delta}_{kjt}). \tag{25}$$

(c) Simulation Estimation

We adopt the simulated maximum likelihood estimation (see Stern 2000). Let $\left(\tilde{\xi}_{ijt}^{m}, \tilde{\delta}_{kjt}^{m}\right)$ denote the *m*th draw for user *i*, where *m* = 1,..., *M*, we have an unbiased and consistent simulator:

$$\widehat{\mathrm{Prob}}\left(\mathrm{H_i}|\Xi_g\right) = \frac{1}{M}\sum_{m=1}^{M}\prod_{t=1}^{T}\prod_{s=1}^{s_t}\prod_{j=1}^{5}\mathrm{Prob}\left(d_{ijt}^{s} = 1|S_{it}\left(\tilde{\xi}_{ijt}^{m}, \tilde{\delta}_{kjt}^{m}\right), \Xi_g\right)^{d_{ijt}^{s}}. \tag{26}$$

Then the simulated likelihood for the sample is:

$$\prod_{i=1}^{N}\sum_{g}\pi_g * \widehat{\mathrm{Prob}}\left(\mathrm{H_i}|\Xi_g\right). \tag{27}$$

In finding the maximums of the simulated likelihood for the sample, we adopt the quasi-Newton methods. To be specific, we use the BHHH numerical maximization, which makes use of the outer product of the gradients (see Berndt et al. 1974). Also, we obtain consistent estimates of the variance of $\widehat{\Xi}_g$ using the outer product of gradients variance estimator.

In sum, we solve the dynamic optimization problem and estimate the simulated likelihood function recursively.[2] To be specific, we start with an arbitrary values of parameters and initial values to the value function, thereafter, we implement the value function iteration until convergence. Then, given converged value function, we construct choice probabilities and develop the sample likelihood using the simulated maximum likelihood estimation. Finally, we update the parameters using the BHHH method and given updated parameter values, repeat to the value function iteration.

(d) Identification

We briefly discuss the restrictions we impose on parameters and the variation in the data that helps to identify our structural model parameters. First we impose a restriction that $Q_1 = 1$ for the quality of upload to the Internet. This is because the utility scale normalization is required in the discrete choice setting (Erdem et al. 2008). Other activities' qualities are measured relative to the upload to the Internet. Another identification issue is to separate the impact of direct experience from the impact of indirect experience on a user's learning process with respect to content quality. The main identification restriction in our model

[2] We adopt our overall estimation strategy from the nested fixed point algorithm (NFXP) to obtain the maximum likelihood estimator of the structural parameters (see Aguirregabiria and Mira 2009 for detail).

is that the direct experience from own usage and generation behaviors impacts a user's utility whereas indirect experience from the usage and generation behaviors of network neighbors influence the kinds of quality signals received but not the utility. This is consistent with the approach of Crawford and Shum (2005). In this sense, we are fortunate in that our data includes cases where either there is no or little direct experience or there is no or little indirect WOM experience from a given user's social network. Each of these unique attributes of our data help in identification because variation in the mix of direct experience via own behavior and indirect experience via WOM from network neighbors is important for identifying the parameters related to the perceived quality from each signaling source.

4. Empirical Results

The results of the parameter estimates are shown in Table 3. First, we discuss the estimates on the belief structure. We find that there is substantial heterogeneity in both the mean values and the standard deviation of the prior beliefs about content quality not only across different content types (based on the mean values) but also across different users (based on the standard deviations). The mean estimate of the users' prior belief about content quality is positive with respect to the quality of upload to regular Internet sites and about the quality of download from the mobile portal site. In contrast, the mean estimate of the users' prior belief is negative with respect to the quality of upload from mobile portal sites and about the quality of download from regular Internet sites. However, the estimate of the standard deviation of the users' prior belief about content quality is generally smaller than the mean estimates except in the case of upload to the mobile portal. This implies that the extent of quality heterogeneity across content types is larger than heterogeneity across users except in the case of content upload to mobile portals.

Second, in terms of signal accuracy, we find that for direct experience, signals about the quality of download from mobile portals are the most accurate while signals about the quality of upload to the regular Internet sites are the least accurate. These are in contrast to the results from indirect experience wherein we find that signals about the quality of upload to the Internet are the most accurate while signals about the quality of upload to the mobile portals are the least accurate. Furthermore, we note that for direct experience signals about the quality of upload are less accurate than signals about quality of download. However, for indirect experience signals there is no clear trend.

Table 3: Parameter Estimates

Parameter	Description	Estimates	Standard Error
Utility function			
w	Quality coefficient	750.83	0.000
r	Risk-aversion coefficient	30.59	0.000
α	Price coefficient	10.69	0.000
Φ_0	Constant utility from doing nothing	50.56	0.350
Prior beliefs			
Q_{01}	Mean of prior quality belief of activity 1	9318.71	2.028
Q_{02}	Mean of prior quality belief of activity 2	-2306.50	0.112
Q_{03}	Mean of prior quality belief of activity 3	-2759.34	112.885
Q_{04}	Mean of prior quality belief of activity 4	450.83	0.874
$\sigma^2_{Q_01}$	Std. dev. of prior quality belief of activity 1	4885.09	0.053
$\sigma^2_{Q_02}$	Std. dev. of prior quality belief of activity 2	4357.72	84.121
$\sigma^2_{Q_03}$	Std. dev. of prior quality belief of activity 3	639.08	6.714
$\sigma^2_{Q_04}$	Std. dev. of prior quality belief of activity 4	1.08	0.000
Signals			
$\sigma^2_{\xi1}$	Std. dev. of direct experience signal of activity 1	2915.75	0.088
$\sigma^2_{\xi2}$	Std. dev. of direct experience signal of activity 2	2293.36	116.000
$\sigma^2_{\xi3}$	Std. dev. of direct experience signal of activity 3	990.91	4.337
$\sigma^2_{\xi4}$	Std. dev. of direct experience signal of activity 4	1.06	0.000
$\sigma^2_{\delta1}$	Std. dev. of WOM experience signal of activity 1	0.98	0.000
$\sigma^2_{\delta2}$	Std. dev. of WOM experience signal of activity 2	824.37	0.002
$\sigma^2_{\delta3}$	Std. dev. of WOM experience signal of activity 3	40.98	0.000
$\sigma^2_{\delta4}$	Std. dev. of WOM experience signal of activity 4	117.51	0.024

Notes: *Activity 1-4 denote content upload to the Internet, content upload to the mobile portal, content download from the Internet, and content download from the mobile portal, respectively. These estimates are based on g=1.*

5. Policy Simulations

We next use our estimates to assess the importance of uncertainty, learning, and experimentation in generating the content upload and download sequences observed in the data. To assess the extent of learning, we simulate upload and download sequences for 2,000 randomly generated users under different counterfactual assumptions, where the accuracy of prior belief about the quality of content and the accuracy of direct and indirect signals are modified.

One of key decisions for mobile phone operators is to select the third-party mobile content providers who are responsible for aggregating and providing various kinds of multi-media content on the mobile portal sites. As in any business situation, higher the quality of content provided in mobile portal sites, higher the costs incurred by mobile content providers. The benefits from high quality content provision include increased content usage by the users of the mobile service. Content is often dynamically tailored to subscribers according to factors such as demographics, device capabilities and subscriber profile. These practices can lead to higher customer satisfaction in the short term and has long term implications for revenue generation and content monetization by targeted advertising. So operators need to invest time and effort in the selection of mobile content providers.[3] In addition, they also spend resources in changing user perception of their mobile content by advertising in other, more traditional media. Hence, mobile phone companies are interested in understanding the effect of changes in user perceptions about the quality of their content as well as the actual quality signals (from both direct and indirect sources) on user upload and download behavior. Accordingly, we conduct several counterfactuals to tease out these insights.

The counterfactuals we conduct can be broadly classified into two different scenarios. In the first scenario, we examine the effect of an increase in the accuracy of prior mean belief about quality. In the second scenario, we conduct three different counterfactuals by altering the extent of accuracy of the direct and indirect experience signals, separately and simultaneously. To be precise, in the second scenario of counterfactuals, we separately study the effect of an increase in the accuracy of direct experience and an increase in the accuracy of indirect experience (WOM) signal qualities, respectively. In addition, we study the effect of a simultaneous increase in the accuracies of direct and indirect experience (WOM) signal qualities. This helps us examine whether direct and indirect signal have a complementary or substitutive effect on each other. For each of these counterfactuals, we increase signal accuracy by 50% although our results are not sensitive to this particular value.

5.1. Changes in the Accuracy of the Prior Mean Belief

The first panel of Table 4 presents baseline estimates of average propensity to upload to the Internet, upload to the mobile portal, download from the Internet, download from the mobile portal and doing nothing implied by the model at the estimated parameter values. The 2nd through 5th panels in this table represent the cases when we change the accuracy of the prior mean belief about the quality of each of the options available to the user. When we increase the accuracy of the prior mean belief about quality of

[3] The content usage fee is fairly divided 9:1 between content providers and mobile carriers in Korean mobile industry.

upload content to the Internet by 50%, we find that there is a significant increase in the propensity to upload to both, portal sites and the Internet. At the same time there is a significant decrease in users' propensity to download content. Although the download probability from mobile portal increases, it is more than compensated by a decrease in download probability from regular Internet sites.

When we increase the accuracy of the prior mean belief about quality of mobile portal upload by 50%, we find a similar result with respect to increases in the upload probabilities and a decrease in over all download probabilities. The difference is that although download probability from regular Internet sites increases, it is more than compensated by a decrease in download probability from the portal sites. With respect to download, when we increase the accuracy of the prior mean belief about quality of Internet download by 50%, we find that there is a significant increase in the propensity to download from the Internet but a significant decrease in users' propensity to download content from portal sites. The overall impact on upload propensities is positive, led primarily by the increase in probability of portal upload which compensates the decrease in probability of Internet upload.

Table 4: Changes in Activity Levels from a 50% Increase in Accuracy of Prior Beliefs

	Benchmark Case	Impact on activity 1	Impact on activity 2	Impact on activity 3	Impact on activity 4
1. Upload to the Internet	3.04%	5.68%	4.81%	2.62%	3.33%
2. Upload to Mobile Portal	5.31%	9.59%	7.94%	7.42%	4.79%
3. Download from Internet	59.39%	41.91%	67.91%	63.42%	59.74%
4. Download from Mobile Portal	22.60%	33.44%	6.78%	19.88%	22.47%
5. Doing nothing	9.66%	9.37%	12.55%	6.67%	9.66%
Total	100.00%	100.00%	100.00%	100.00%	100.00%

5.2. Changes in the Accuracy of the Direct and Indirect Signals

As before, the first panel of Table 5 presents baseline estimates of average propensity to upload to the Internet, upload to the mobile portal, download from the Internet, download from the mobile portal and doing nothing implied by the model at the estimated parameter values. The 2nd through 5th panels in this table represent the cases when we change the accuracy of signal quality of each of the options available to the user coming from direct experience only. The 6th through 9th panels in this table represent the cases when we change the accuracy of signal quality of each of the options available to the user coming from indirect experience only. The final four panels in this table represent the cases when we simultaneously change the accuracy of signal quality of each of the options available to the users coming from both direct and indirect experience.

Table 5: Changes in Activity Levels from a 50% Increase in Signal Accuracy

Activity	Bench-mark Case (%)	Increase in direct signal accuracy (%)				Increase in indirect signal accuracy (%)				Increase in both direct and indirect signal accuracy (%)			
		Impact on activity 1	Impact on activity 2	Impact on activity 3	Impact on activity 4	Impact on activity 1	Impact on activity 2	Impact on activity 3	Impact on activity 4	Impact on activity 1	Impact on activity 2	Impact on activity 3	Impact on activity 4
1	3.04	3.24	3.02	3.14	3.05	3.11	2.68	3.05	3.04	3.04	2.67	3.14	3.05
2	5.31	5.13	2.49	4.91	5.40	5.31	3.39	5.20	5.31	5.40	1.65	4.87	5.40
3	59.39	59.39	60.56	56.13	59.24	59.39	59.96	58.77	59.39	59.40	60.93	55.54	59.24
4	22.60	22.58	24.18	22.60	22.66	22.63	24.79	23.23	22.60	22.60	25.46	23.23	22.66
5	9.66	9.66	9.75	13.22	9.66	9.57	9.19	9.75	9.66	9.57	9.28	13.22	9.66
Total	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00

***Notes**: Activity 1-5 denote upload content to the Internet, upload content to the mobile portal, download content from the Internet, download content from the mobile portal, and doing nothing, respectively.*

We discuss the impact of changes in signal quality of the direct experience first. An increase in the accuracy of Internet upload signal quality does not change the overall download or upload propensities by much. However, it leads to a reallocation of resources within the content upload behavior. Users substitute mobile portal uploads for Internet uploads. Note that given the positive prior belief on Internet upload this is intuitive. Furthermore, we note that an increase in the accuracy of mobile portal upload signal quality leads to a significant decrease in the mobile portal upload but an increase in mobile portal download behavior. Note that the given the negative prior belief on portal upload and the positive prior belief on portal download, this is intuitive.

We next discuss the impact of changes in signal quality of the indirect experience. An increase in the accuracy of Internet upload signal quality does not change the overall download or upload propensities much but leads to users engaging in more Internet uploads. Furthermore, we note that an increase in the accuracy of mobile portal upload signal quality leads to a significant decrease in the mobile portal upload as well as a decrease in Internet upload. In addition, there is an increase in mobile portal download behavior. Note that the given the negative prior belief on portal upload and the positive prior belief on portal download, this is intuitive.

We next examine the relationship between signals of direct experience and indirect experience to discuss whether these are complements or substitutes. This is done by comparing the cases where we change the quality of direct and indirect experience separately with the case when we change both signal qualities simultaneously. Based on the comparisons, it appears that the direct and indirect experience signals act as complements for the user options involving uploading content to the mobile portal. On the other hand, they act as substitutes for the options involving uploading content to the Internet and downloading content from the Internet.

6. Discussion and Implications

We have proposed a dynamic content choice model in which users learn about content quality through two distinct channels: (i) direct experience from own content creation and usage behavior, and (ii) indirect experience from the content creation and usage behavior of social network neighbors. The model was estimated on a mobile media dataset where we have information on the content upload and download behavior of users from two different categories of websites - regular Internet sites and mobile portal sites.

Our estimates suggest that when it comes to user learning from direct experience, the content that is downloaded from mobile portals exhibits the highest level of consistency in quality as seen by the highest levels of perceived accuracy in the quality signals received by users. In contrast to this, content that is uploaded by users to regular websites on the Internet exhibits the least amount of consistency in quality. This is consistent with the anecdotal fact that content provision via mobile portals (owned and hosted by mobile operators) preceded content provision via access to regular Internet websites. In the early stages after the launch of their mobile services, most mobile phone operators implemented "closed" content management systems to exercise control on the kinds and quality of content that is available to users on their mobile devices. Subsequently, users had access to WAP-enabled regular Internet websites. Hence, content access via mobile portal sites preceded content access via regular Internet sites.

We are seeing mobile sites that combine social networking, UGC and messaging applications are establishing large user bases across a number of regions and monetizing services via a combination of advertising, revenue-share (with operators) and subscription models (Chard 2008). Our results can provide some insights for online advertising, given that advertisers are increasingly using the mobile Web as platform to reach users. The total value of advertising on mobile was 2.5 billion dollars in 2008. A recent study reports that about one-in-ten mobile Web users said they have made a purchase based on a mobile Web ad, while 23% said they have visited a Web site, 13% said they have requested more information about a product or service (OPA News 2007). Our result suggests that when it comes to embedding advertisements within multi-media content like audio or video files, advertisers would find it more profitable to insert their ads (such as intromercials or rich media ads) within multi-media content that is available on mobile portal sites compared to content that is available regular Internet sites.

Our policy simulations involving changes in the accuracy of prior beliefs suggest the existence of complementarity between activities involving content upload to mobile portal sites and upload to off-portal, regular Internet websites, and a weak substitution between activities involving content download from mobile portal sites and download from regular Internet websites. An implication of this is that if mobile phone operators are able to incentivize increases in user generated uploads to one category of websites, they are likely to see an increase in user content creation and uploads to the other category of websites. There may be opportunities for firms to monetize their content in the process. For example, this could lead to more frequent and high quality user-generated content updates on online social networking sites. Indeed, anecdotal evidence also suggests that there is a growing trend of cell phone users creating and sharing video and photo content on mobile portals as well as regular websites, pushed by the popularity of video-camera embedded phones, and content-sharing mobile applications. And there are incentives for users to engage in content creation and uploading to mobile portals. Even in the U.S., mobile operators like Cingular offer a “Messaging Awards” program, where customers vote on the best user-generated video, photo and text submissions. From the firms’ perspective, mobile carriers are looking to take advantage of user-generated mobile content, given it doesn’t cost the carrier anything to create, and motivates the consumer to transmit content over the pipes that is more profitable than the transmission of low-margin voice services.

Our policy simulations involving changes in the accuracy of direct and indirect signals also suggest the existence of complementarity between learning from direct and indirect experiences for each of the two different user actions: content upload to mobile portals and content download from Internet sites. This implies some kind of reinforcement in the consumer learning process with regard to the quality of these kinds of content usage and consumption. On the other hand, they act as substitutes for the options involving uploading content to the Internet and downloading content from the mobile portal. These results suggest that firms looking to influence users’ behavior by influencing their social network neighbors might benefit from recognizing that behavior depends not only on the kind of content (portal site or website) but also on the kind of user activity (upload or download).

Our paper has several limitations. For example, we do not consider the actual amount of content generation and usage activities, focusing only on frequency of these activities. In addition, we do not consider the initial condition problem since our data is not collected from the inception of the mobile content service. Notwithstanding these limitations, we hope our study paves the way for future research in the area of mobile media usage and commerce.

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