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Understanding Economic Attitude Elasticity toMHealth Services among the Underprivileged in Rural India: A Piecewise Latent Growth Modeling Approach

Xixi Li
Tsinghua University, ciciattsinghua@gmail.com

Arun Rai
Georgia State University, arunrai@gsu.edu

Ganapathy Krishnan
Apollo Hospitals Educational and Research Foundation, drganapathy@apollohospitals.com

Understanding Economic Attitude Elasticity to MHealth Services among the Underprivileged in Rural India: A Piecewise Latent Growth Modeling Approach

Completed Research Paper

Xixi Li
Department of Management Science and Engineering
School of Economics and Management
Tsinghua University
ciciattsinghua@gmail.com

Arun Rai
Center for Process Innovation & CIS Department
Robinson College of Business
Georgia State University
arunrai@gsu.edu

Krishnan Ganapathy
Apollo Hospitals Educational and Research Foundation
drganapathy@apollohospitals.com

Abstract

We examine the changes in economic attitudes toward mHealth services at four different levels of pricing, i.e., economic attitude elasticity (EAE), among 2129 Indian villagers who participated in two free health camps. We employed an innovative contingent valuation survey instrument for data collection and a piecewise latent growth modeling method for data analysis. Three key findings emerged from the study. First, we found that when mHealth services are free, three groups of villagers who (a) did not have mobile phones, (b) who shared mobile phones, or (c) who owned dedicated personal mobile phones showed different economic attitudes at one health camp, while the latter two groups showed similar attitudes at the other camp. Second, when the price for mHealth services changed from free to less than 100 Indian rupees (INR), the two groups who shared and who owned mobile phones had an identical EAE, while the group who had no mobile phones displayed a different EAE from the other two groups who had access to phones at both camps. Third, when the price changed from less than 100 INR to between 100 and 200 INR and to greater than 200 INR, similar cross-group EAE patterns were found at both camps. Our findings provide insights for policy makers in developing countries to promote the use of mHealth services among the socio-economically disadvantaged.

Keywords: economic attitude elasticity, mHealth services, piecewise latent growth modeling, multi-group analysis

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1. Motivation

In their 2011 best seller, *Poor Economics*, Banerjee and Duflo describe the societal problem of diarrhea: 1.5 million children die of diarrhea every year, almost all of whom belong to the world's 2.4 billion underprivileged population with an average daily living expense of less than $2 US (World Bank statistics 2013). Diarrhea is a disease that can often be avoided in the first place through purified tap water. Water purification is now commonplace in developed countries. However, in developing countries, tap water can be unavailable and the purification process of adding chlorine bleach into drinking water is often done at the household level – city or district, which not only means additional monetary costs for a family but also extra effort calculating and adding the appropriate amount of bleach into a particular volume of drinking water.

Oral rehydration solution (ORS) is a practical and cost-effective solution for diarrhea, given by nurses to the mothers of afflicted children, but which is seldom used because mothers do not believe simple packs of salt and sugar can save their children. Both researchers and policy makers have wondered why the underprivileged are not motivated to utilize cost-effective solutions that can protect their health but rather spend much more time and money on curation after the disease has be diagnosed (Banerjee and Duflo 2011).

The development of the technological infrastructure in rural areas of developing countries seems to create a more favorable climate for mobile-based solutions. For example, 3G mobile coverage in India reaches 75% of the population and 2G 87%. The mobile subscriber base hit 451 million by the end of 2014, with an equal penetration rate of 35% (Hatt et al. 2015). Comparatively speaking, mobile devices and the telecommunication infrastructure are more cost-effective, and thus more accessible, to the underprivileged as compared to traditional personal computers and Internet infrastructure. At the same time this infrastructure better serves the distribution of urgent data and management of critical information in the healthcare industry (Prahalad 2006).

Taking the above facts into consideration, imagine what would happen in the diarrhea case if reminder messages of using solution packets or purifying water could be sent via mobile phones for free or at nominal prices? Or if parents could ask physicians or nurses for advice via mobile phones? Or, if standard answers for frequently asked questions could be automatically sent to parents upon request via mobile phones? We refer to these services as mHealth services and define it as individuals' receiving healthcare-related advice, reminders, and information via mobile phones or other mobile devices. This information can be either device-generated or device-mediated with physicians rendering the advice (Froehle and Roth 2004; Froehle 2006). MHealth services are obviously a promising solution that can help nudge the underprivileged to pick such "low-hanging fruits" as using ORS for diarrhea children and adding chlorine bleach to unpurified drinking water in order to counter their unequal access to healthcare services, i.e., the health divide (Banerjee and Duflo 2011).

To this end, our study aims to understand the adoption potential of mHealth services among the underprivileged in rural India. Since the underprivileged usually have low incomes and therefore almost a flat demand elasticity to commercial services, we approach the adoption potential issue by understanding their economic attitude elasticity (EAE) to mHealth services. This is different from either the traditional measures of intention to use or use frequency in the technology adoption literature (Davis et al. 1989, Venkatesh et al. 2003), or monetary transaction prices archived in sales systems in the econometric domain (Granados et al. 2012; Shankar and Bayus 2003). Specifically, we adopt a contingent valuation format question (Luzar and Cosse 1999; Olsen and Smith 2001) to assess economic attitudes toward mHealth services at different levels of pricing among the underprivileged, apply a piecewise latent growth modeling (LGM) method to model their EAE to mHealth services, and perform multi-group comparisons on the EAE differences across three mobile phone ownership groups in rural India, i.e., those who have no mobile phones, those who share mobile phones with family members or friends, and those who own dedicated personal mobile phones. In the remainder of the paper, we (a) introduce our empirical sites, sample, and data collection procedures, (b) perform the piecewise LGM method and multi-group analysis, (c) summarize our key findings, and (d) discuss the implications for policy makers and future research.

2. Site, Sample, and Measures

In collaboration with Apollo Hospitals (one of the largest hospital groups in India), we conducted surveys at two free health camps[1] that were held in two different villages in rural South India (Bodinayak and Srirangam). Both camps were co-presented by the local Indian government, not-for-profit non-governmental organizations, and Apollo Hospitals.

The survey instrument we developed was translated and back translated between English and Tamil by professionals hired by the hospital (Brislin et al. 1973). We recruited and trained interviewers who orally administered the survey to attendees of the health camps. Our survey instrument included questions to capture: (a) economic attitudes toward mHealth services, (b) mobile phone ownership types—i.e., do not have, share, or own, and (c) demographic variables (Table 1). In particular, we utilized the contingent valuation format of questions (Luzar and Cosse 1999; Olsen and Smith 2001) to ask individuals about their economic attitudes toward mHealth services for free and at three different nominal price intervals, i.e., less than 100 Indian Rupees (INR) (approximately $1.50 US), between 100 and 200 INR ($ 1.50-3.00 US), and greater than 200 INR ($3.00 US)[2] (Mataria et al. 2007; Mazumdar and Guruswamy 2009). We adopted a five-point Likert scale, ranging from 1 for "very unlikely" to 5 for "very likely". We observed that respondents in our sample could be segmented into three groups based on mobile phone ownership: those who have no mobile phones, those who share mobile phones with family members or friends, and those who own dedicated personal mobile phones.

The demographic statistics in Table 1, based on our attendees from both villages, reveal that our sample has a large underprivileged population: (a) less than 10% of our sample received a college education or above, and less than 20% possessed an occupational certification; (b) 40 to 50% of the sample were farmers, and 15% were unemployed; and (c) over 95% of the sample had individual monthly incomes lower than 7500 INR (i.e., approximately $120 US/month) and 90% had household monthly incomes lower than 7500 INR. Nevertheless, as we still identified significant statistical differences among the sample from the two rural Indian villages in terms of age, education, possession of occupational certification, and individual and household monthly incomes in ANOVA tests, we later performed data analysis and reported findings for the samples from each of the two villages.

Table 1. Sample Demographics

Category		Bodinayak Camp		Sriramgam Camp	
		Frequency	Percentage (%)	Frequency	Percentage (%)
Age (yrs)	<20	36	3.21	75	7.46
	21-30	71	6.32	100	9.94
	31-40	160	14.25	178	17.69

[1] Well-known *free health camps* are Aravind Hospital's Eye Camps (aravind.org), Dr. Mohan's Diabetes Camps (drmohansdiabetes.com), and Narayana Hrudayalaya's Cardiac Diagnostic Camps (narayanahealth.org). The sponsoring hospitals usually operate with a "hybrid revenue model" and segment customers into free and paying groups (Esposito et al. 2012, p. 532). Hospitals bring medical equipment and healthcare personnel to the communities or places where special interest groups could be easily reached, e.g., schools, nursing homes, rural villages, etc. The camps often last for 1-2 days, during which preliminary diagnosis or screening tests are provided and the patients diagnosed with a certain disease are then taken to specialized clinics or hospitals in remote cities for further treatment or surgeries.

[2] We select the price ranges based on the poverty line latest set by World Bank and a reasonable estimation of daily living cost per person according to Apollo Hospitals' preliminary interviews with the rural population.

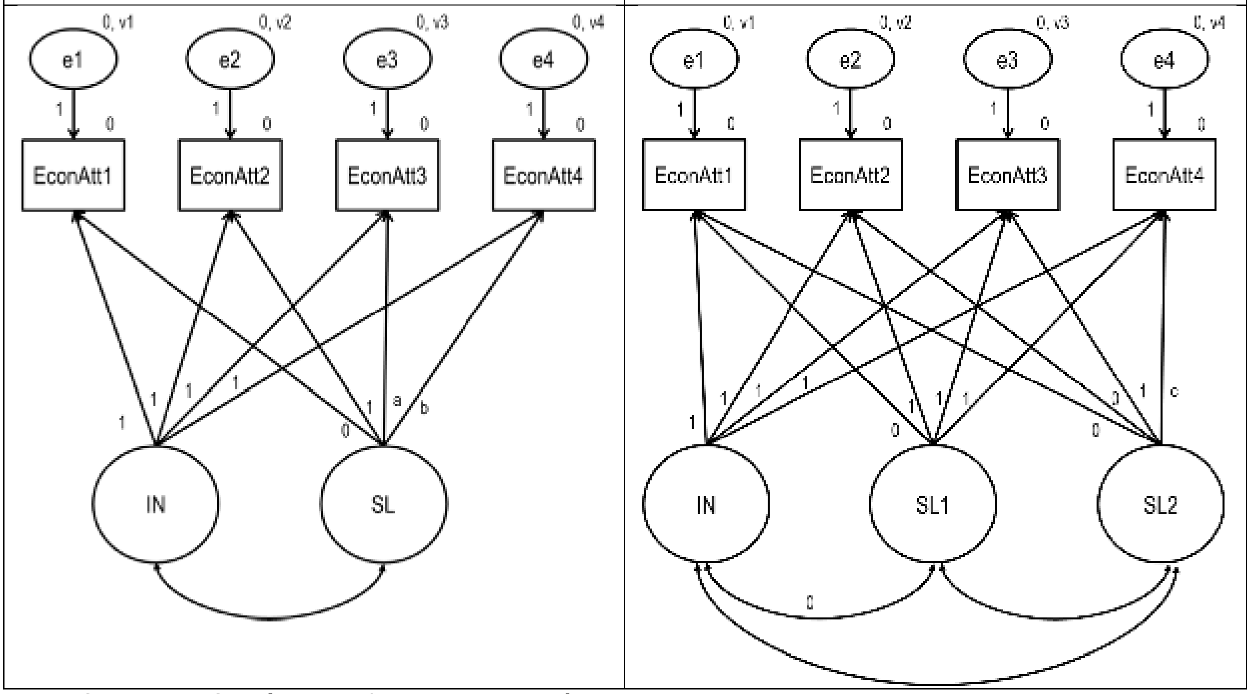
Table 1. Sample Demographics					
Category		Bodinayak Camp		Sriramgam Camp	
		Frequency	Percentage (%)	Frequency	Percentage (%)
	41-50	236	21.02	230	22.86
	51-60	276	24.58	202	20.08
	61-70	271	24.13	173	17.20
	>70	73	6.50	48	4.77
Gender	Male	475	42.30	456	45.33
	Female	648	57.70	550	54.67
Education	None	109	9.71	69	6.86
	1-4 Standard	522	46.48	303	30.12
	5-8 Standard	320	28.50	296	29.42
	Higher secondary	138	12.29	265	26.34
	Graduate	30	2.67	56	5.57
	Post-graduate	4	0.36	17	1.69
Occupational Certification	No	937	83.44	911	90.56
	Yes	186	16.56	95	9.44
Occupation	Unemployed	213	18.97	153	15.21
	Farmer	615	54.76	383	38.07
	Vegetable/ fruit seller	24	2.14	20	1.99
	Retired	76	6.77	31	3.08
	Others	195	17.36	419	41.65
Individual Monthly Income	No	117	10.42	75	7.46
	<7500 INR	990	88.16	888	88.27
	7501-15000 INR	11	0.98	32	3.18
	15001-25000 INR	4	0.36	8	0.80
	25001-50000 INR	1	0.09	3	0.30
Household Monthly Income	No	2	0.18	8	0.80
	<7500 INR	1075	95.73	931	92.54
	7501-15000 INR	29	2.58	37	3.68
	15001-25000 INR	15	1.34	21	2.09
	25001-50000 INR	2	0.18	9	0.89
Mobile Ownership	No	479	42.65	349	34.69
	Share	354	31.52	397	39.46
	Own	290	25.82	260	25.84
Total		1123	100	1006	100

3. The Piecewise Latent Growth Modeling Method

A general latent growth modeling (LGM) method has recently been introduced in the IS field to understand change trajectories constituted in longitudinal data, e.g., employees' perceived job demand and job control during the IS implementation process (Bala and Venatesh 2013), and books' review volumes and sales rankings over time at Amazon.com (Zheng et al. forthcoming). In our study, the survey instrument assessing individuals' economic attitudes toward mHealth services was repeated at the individual level across different levels of pricing, though not necessarily longitudinal in nature. As described earlier, individuals were asked to share their economic attitudes toward mHealth services at four pricing levels: free and nominal price intervals of less than 100 INR, between 100 and 200 INR, and greater than 200 INR. Therefore, we consider general LGM as an appropriate approach to understand how economic attitudes change across different levels of pricing among the underprivileged in rural India, i.e., the economic attitude elasticity (EAE) to mHealth services.

We further differentiate between general LGM and piecewise LGM methods in Figures 1a and 1b. Essentially, the piecewise LGM is derived from the general LGM method, breaking a single change trajectory into two separate segments (Wang and Wang 2012). In Figure 1a, the general LGM has two reflective latent factors derived from a set of repeated measures: intercept and slope. In Figure 1b, the piecewise LGM has three reflective latent factors: intercept, slope 1, and slope 2. We assessed individuals' economic attitudes toward mHealth services at the four different pricing levels. With the general LGM method in Figure 1a, the intercept captures individuals' economic attitudes toward free mHealth services; the slope signifies the EAE to mHealth services across the four different levels of pricing. With the piecewise LGM method in Figure 1b, the intercept still represents individuals' economic attitudes toward free mHealth services. Slope 1, in particular, refers to their EAE to mHealth services from free to less than 100 INR. Slope 2 stands for the EAE to mHealth services across the latter three nominal price intervals. While it is reasonable to approximate the EAEs to mHealth services across the latter three nominal price intervals (i.e., from less than 100 INR to between 100 and 200 INR and to greater than 200 INR) as functionally consistent, the EAE to mHealth services from free to less than 100 INR could be differentiated in terms of functional forms from the EAEs across the three nominal price intervals. In this vein, the piecewise LGM method fits even better with the nature of our data since it allows us to estimate two separate slopes among a set of repeated measures, which possibly require different functional forms for different change segments.

Figure 1a. General Latent Growth Modeling | **Figure 1b. Piecewise Latent Growth Modeling**



Note: IS – Intercept, SL – slope, EconAtt – economic attitude
In Figure 1b, the covariance between IN and SL1 is set to zero for identification purposes.

4. Results

We performed LGM analysis using AMOS 22.0. We first present the findings for the baseline model validating the functional forms in the EAEs to mHealth services across different levels of pricing and then the results for multi-group analysis comparing the EAEs across the three mobile phone ownership groups at the two camps.

4.1. The Baseline Model

Table 2 presents the baseline model results. The baseline model first determines if the modeling approach on EAE trajectories should follow a general or piecewise LGM approach, or in other words, a single slope factor or two slope factors separating the EAE to mHealth services from free to less than 100 INR and the EAE to mHealth services across the three different nominal price intervals—from less than 100 INR to between 100 and 200 INR and to greater than 200 INR. Second, it determines if the slope factor (or the second slope factor in the piecewise LGM model) should be linear or not (i.e., fixing the change factors loadings at 0.0, 1.0, 2.0, and 3.0/free for the slope factor in general LGM, at 0.0, 0.0, 1.0, and 2.0/free for the second slope factor in piecewise LGM) (Bentein et al. 2005; Chan and Schmitt 2000). The results consistently show that the piecewise LGM approach with a free change trajectory is preferred over the other model specifications (Models 1c and 2c displayed the best fit indices in Table 2). Therefore, we adopted the piecewise LGM approach and the free growth function for estimating EAEs to mHealth services in further analysis.

Table 2. Baseline Model Test Results

		X^2	d.f.	CFI	TLI	RMSEA	SRMR
Bodinayak Camp	Model 1a – General, Free	211.760	3	0.949	0.899	0.249	--
	Model 1b – General, Linear	378.588	5	0.909	0.891	0.258	0.0308
	Model 1c – Piecewise, Free	**0.560**	**1**	**1.000**	**1.001**	**0.000**	**0.0012**
	Model 1d – Piecewise, Linear	187.858	2	0.955	0.865	0.288	0.0291
Srirangam Camp	Model 2a – General, Free	538.156	3	0.741	0.481	0.421	--
	Model 2b – General, Linear	578.741	5	0.722	0.666	0.338	0.0312
	Model 2c – Piecewise, Free	**0.188**	**1**	**1.000**	**1.002**	**0.000**	**0.0013**
	Model 2d – Piecewise, Linear	86.212	2	0.959	0.878	0.205	0.0260

Note: Model 1a – General, Free: a, b set as free in Figure 1a; Model 1b – General, Linear: a = 2, b = 3 in Figure 1a;
Model 1c – Piecewise, Free: c set as free in Figure 1b; Model 1d – Piecewise, Linear: c = 2 in Figure 1b.

Table 3 summarizes the means and variances of the growth parameter estimates in the established piecewise LGM models. The underprivileged participants at both camps displayed a significant intercept as their economic attitudes toward free mHealth services (2.284** in Model 1c and 2.835** in Model 2c), a significant EAE to mHealth services from free to a nominal price of less than 100 INR (-0.537** in Model 1c and -1.196** in Model 2c), and a significant EAE to mHealth services from less than 100 INR to between 100 and 200 INR and to greater than 200 INR (-0.280** in Model 1c and -0.286** in Model 2c).

Table 3. Growth Parameter Estimates in Baseline Models

		Mean		Variance	
		Estimate	S.E.	Estimate	S.E.
Model 1c Bodinayak Camp	Intercept	2.284**	0.049	1.316**	0.072
	Slope 1	-0.537**	0.037	0.272**	0.089
	Slope 2	-0.280**	0.021	0.523**	0.074
Model 2c Srirangam Camp	Intercept	2.835**	0.051	0.679**	0.059
	Slope 1	-1.196**	0.049	0.427**	0.093
	Slope 2	-0.286**	0.024	0.455**	0.073

Note: ** $p < 0.01$, * $p < 0.05$, two-tailed test.

4.2. Multi-Group Analysis Based on Mobile Phone Ownership

As prerequisites for multi-group analysis, we performed measurement invariance tests across the three groups who have no mobile phones, who share mobile phones, and who own mobile phones: configural invariance, metric invariance, and error variance invariance (Bentein et al. 2005; Steenkamp and Baumgartner 1998). Configural invariance describes when the item loading patterns of the four economic attitude measures are invariant across the three mobile phone ownership types in our study context; metric invariance describes when the relationships between economic attitude measures and their corresponding intercept or slope factors are unchanged across the three mobile phone ownership groups. Because we already verified in the previous section that the piecewise LGM approach is preferred over the general LGM approach and the second slope factor in the piecewise LGM approach is better to set as free, we executed the configural invariance test by fixing all item loading patterns as established in Models 1c and 2c and examining the model fit indices, and performed the metric invariance test only for the economic attitude measure at the fourth price interval (i.e., loading c from SL2 to EconAtt4 in Figure 1b). Error variance invariance describes when the measurement errors are invariant for the same economic attitude measure across the three mobile phone ownership groups.

Table 4 shows that (a) the piecewise LGM models with the second slope factor set as free displayed good configural invariance across the three mobile phone ownership groups (Models 3a and 4a displayed good fit indices); (b) the economic attitude measures at the fourth price interval (i.e., loading c from SL2 to EconAtt4 in Figure 1b) were consistent across the three mobile phone ownership groups (Models 3a and 4a were not preferred over Models 3b and 4b, respectively), and (c) error variances need to be set as freely estimated rather than equal for the same economic attitude measure across the three mobile phone ownership groups (Models 3c and 4c showed much worse fit indices than Models 3b and 4b, respectively).

Table 4. Measurement Invariance Test Results

		X^2	d.f.	CFI	TLI	RMSEA	SRMR
Bodinayak Camp	Model 3a Unconstrained	0.892	3	1.000	1.003	0.000	0.0010
	Model 3b Loading – EconAtt4	**5.654 (p = 0.056 vs. Model 5a)**	**5**	**1.000**	**0.999**	**0.017**	**0.0014**
	Model 3c Error variance	116.275 (p = 0.000** vs. Model 5b)	13	0.976	0.967	0.084	0.0090
Srirangam Camp	Model 4a Unconstrained	0.368	3	1.000	1.009	0.000	0.0030
	Model 4b Loading – EconAtt4	**0.541 (p = 0.917 vs. Model 6a)**	**5**	**1.000**	**1.009**	**0.000**	**0.0024**
	Model 4c Error variance	96.976 (p = 0.000** vs. Model 6b)	13	0.953	0.935	0.080	0.0502

Note: ** p < 0.01, * p < 0.05, two-tailed test.

Table 5 reports the multi-group analysis results, including the mean and variance values of the intercept and two slopes for the three mobile phone ownership groups at the two health camps, and the chi-square changes and the corresponding significance levels when any intercept or slope was fixed to be equal among any two of the three mobile phone ownership groups. Specifically, the intercepts differed across the three mobile phone ownership groups for the Bodinayak Camp sample, but were the same between the group that shared mobile phones with others and the group that owned mobile phones for the Sriramgam Camp sample. The two slopes were significantly different between the group that did not own mobile phones and the group that either shared or owned mobile phones; the two slopes were similar between the two groups who shared and who owned mobile phones at both camps.

Table 5. Multi-Group Analysis Results in AMOS

			Mean	Variance	Gp 1 vs. 2	Gp 1 vs. 3	Gp 2 vs. 3
Bodinayak Camp	Group 1 – No Phone	Intercept	1.777**	1.356**	*Δx² (d.f.=1)* Intercept: 38.920 (p = 0.000**) Slope1: 49.207 (p = 0.000**) Slope2: 3.408 (p = 0.035*)	*Δx² (d.f.=1)* Intercept: 83.786 (p = 0.000**) Slope1: 52.213 (p = 0.000**) Slope2: 10.317 (p = 0.000**)	*Δx² (d.f.=1)* Intercept: 11.248 (p = 0.000**) Slope1: 0.538 (p = 0.232) Slope2: 1.477 (p = 0.106)
		Slope 1	-0.174**	0.127^{+}			
		Slope 2	-0.207**	0.481**			
	Group 2 – Shared	Intercept	2.463**	0.999**			
		Slope 1	-0.779**	0.221*			
		Slope 2	-0.296**	0.457**			
	Group 3 – Own	Intercept	2.903**	1.325**			
		Slope 1	-0.862**	0.888**			
		Slope 2	-0.377**	0.808**			

Table 5. Multi-Group Analysis Results in AMOS

			Mean	Variance	Gp 1 vs. 2	Gp 1 vs. 3	Gp 2 vs. 3
Srirangam Camp	Group 1 – No Phone	Intercept	1.874**	0.254**	*Δx² (d.f.=1)* Intercept: 168.552 (p = 0.000**) Slope1: 47.471 (p = 0.000**) Slope2: 46.314 (p = 0.000**)	*Δx² (d.f.=1)* Intercept: 139.713 (p = 0.000**) Slope1: 32.572 (p = 0.000**) Slope2: 41.259 (p = 0.000**)	*Δx² (d.f.=1)* Intercept: 0.004 (p = 0.475) Slope1: 0.427 (p = 0.257) Slope2: 0.369 (p = 0.272)
		Slope 1	-0.715**	0.064			
		Slope 2	-0.066**	0.141**			
	Group 2 – Shared	Intercept	3.343**	0.482**			
		Slope 1	-1.485**	0.827**			
		Slope 2	-0.388**	0.578**			
	Group 3 – Own	Intercept	3.350**	0.604**			
		Slope 1	-1.403**	0.778**			
		Slope 2	-0.427*	0.593**			

Note: ** p < 0.01, * p < 0.05, one-tailed tests were performed as the directional comparison were hypothesized.

Table 6 presents the ANOVA test results where we simply compared economic attitude values at different levels of pricing across the three mobile phone ownership groups but cannot generalize any specific conclusions. For the Bodinayak Camp sample, the economic attitude values were similar for the group that did not own mobile phones and the group that shared mobile phones at the latter three nominal price intervals. For the Srirangam Camp sample, economic attitude values were identical for the two groups that shared and that owned mobile phones across all four levels of pricing.

Table 6. ANOVA Test Results in SPSS

			Mean	S.D.	Gp 1 vs. 2	Gp 1 vs. 3	Gp 2 vs. 3
Bodinayak Camp	Group 1 – No Phone	EconAtt1	1.777	1.441	*p-value* EAttM1: 0.000** EAttM2: 0.150 (n.s.) EAttM3: 0.223 (n.s.) EAttM4: 0.227 (n.s.)	*p-value* EAttM1: 0.000** EAttM2: 0.000** EAttM3: 0.000** EAttM4: 0.000**	*p-value* EAttM1: 0.000** EAttM2: 0.000** EAttM3: 0.000** EAttM4: 0.000**
		EconAtt2	1.605	1.143			
		EconAtt3	1.403	0.874			
		EconAtt4	1.359	0.819			
	Group 2 – Shared	EconAtt1	2.463	1.623			
		EconAtt2	1.689	1.180			
		EconAtt3	1.373	0.860			
		EconAtt4	1.333	0.808			
	Group 3 – Own	EconAtt1	2.903	1.671			
		EconAtt2	2.055	1.391			
		EconAtt3	1.710	1.100			
		EconAtt4	1.600	1.001			
Srirangam Camp	Group 1 – No	EconAtt1	1.874	1.419	*p-value* EAttM1: 0.000** EAttM2: 0.000** EAttM3: 0.000** EAttM4: 0.000**	*p-value* EAttM1: 0.000** EAttM2: 0.000** EAttM3: 0.000** EAttM4: 0.000**	*p-value* EAttM1: 0.250 (n.s.) EAttM2: 0.134 (n.s.) EAttM3: 0.133 (n.s.) EAttM4: 0.193 (n.s.)
		EconAtt2	1.161	0.614			
		EconAtt3	1.089	0.423			
		EconAtt4	1.075	0.387			
	Group 2 – Shared	EconAtt1	3.343	1.494			
		EconAtt2	1.859	1.183			
		EconAtt3	1.464	0.851			
		EconAtt4	1.355	0.783			
	Group 3 – Own	EconAtt1	3.350	1.432			
		EconAtt2	1.946	1.197			
		EconAtt3	1.527	0.876			
		EconAtt4	1.392	0.796			

Note: ** p < 0.01, * p < 0.05, one-tailed tests were performed as the directional comparison were hypothesized.

Figures 2a and 2b plot the EAE trajectories for the Bodinayak Camp sample and the Srirangam Camp sample, respectively. We can clearly observe that the groups who shared and owned mobile phones follow similar EAE trajectories to mHealth services for free and across the three different nominal price intervals. While the piecewise LGM method did help us statistically confirm such interesting patterns (Table 5), the traditional ANOVA test did not (Table 6).

Figure 2a. The Economic Attitude Elasticity Trajectory (Bodinayak Camp)

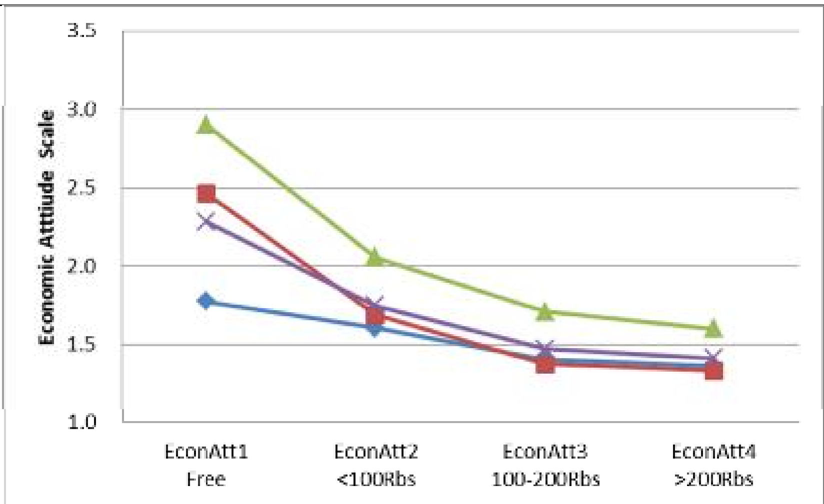
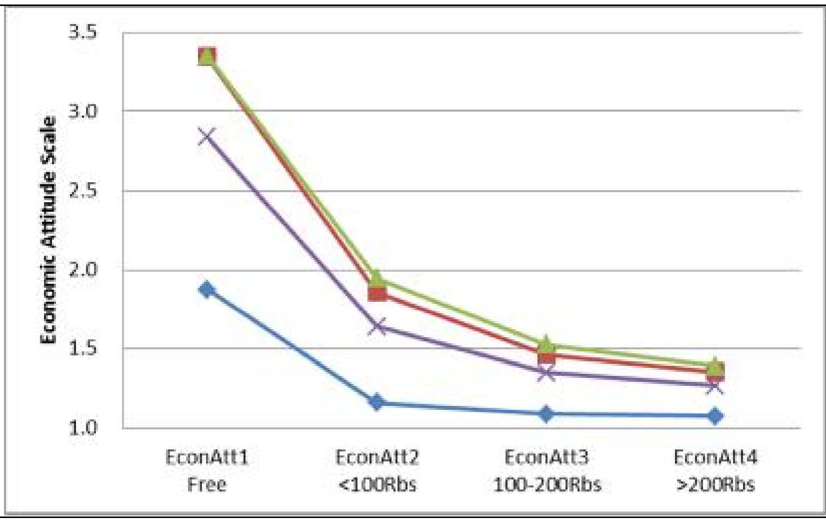


Figure 2b. The Economic Attitude Elasticity Trajectory (Srirangam Camp)



Note: EconAtt: economic attitude toward mHealth
5-point Likert scale, 1 – very unlikely, 2 – unlikely, 3 – neutural, 4 – likely, 5 – very likely;

5. Discussion

Our study aims to understand the adoption potential of mHealth services among the underprivileged in developing countries. We utilized the contingent valuation format question to assess individuals' economic attitudes toward mHealth services for free and at three different nominal price intervals and innovatively applied the piecewise latent growth modeling method to understand ***the economic attitude elasticity (EAE) to mHealth services*** among the underprivileged in rural India. We performed multi-group comparisons to examine EAE differences across three groups who have no mobile phones, share mobile phones, and own dedicated personal mobile phones. Our findings reveal that those who share mobile phones with others displayed similar EAEs to mHealth services as their counterparts who own dedicated mobile phones, though the economic attitudes toward free mHealth services may or may not differ among the three mobile phone ownership groups. Table 7 summarizes our objectives, methods, findings and implications.

Table 7. Summary of Study Objectives, Methods, Findings, and Implications

Research questions	Ÿ What is the adoption potential of mHealth services among the underprivileged in rural areas of developing countries, i.e., their economic attitudes toward mHealth services for free and at three different nominal price intervals? Ÿ How does the economic attitude elasticity (EAE) differ across different mobile phone ownership groups?
Methods	Ÿ Piecewise latent growth modeling Ÿ Multi-group comparison
Findings	Ÿ When mHealth services are free, the three groups who have no mobile phones, share mobile phones, and own mobile phones showed different economic attitudes at one health camp, but the latter two groups showed similar attitudes at the other camp Ÿ When the price of mHealth services changes from free to less than 100 INR, the two groups who share and who own mobile phones had an identical EAE, while the group who had no mobile phones displayed a different EAE from the groups who either share or own mobile phones at both camps. Ÿ When the price of mHealth services changes from less than 100 INR to between 100 and 200 INR and to greater than 200 INR, similar cross-group EAE patterns were found at both camps
Implications for policy makers	Ÿ Insights on how the adoption of mHealth services can be managed as a quasi-public good for the underprivileged in rural areas of developing countries
Implications for research	Ÿ Applied the contingent valuation format question to assess economic attitudes toward quasi-public goods like mHealth services among the underprivileged population in rural areas of developing countries Ÿ Introduced the piecewise latent growth modeling method to investigate repeated measures that are not necessarily longitudinal in nature

5.1. Implications for Policy Makers

Our findings offer insights for policy makers to devise cost-sharing policies for public or quasi-public goods that cannot be garnered through traditional economic experiments or objective archive data (Mataria et al. 2007; Mazumdar and Guruswamy 2009). We suggest policy makers collaborate with hospital systems, healthcare information technology companies, or even telecommunication companies to leverage our findings to help broaden healthcare service access among the underprivileged in developing countries. For example, mobile devices could be distributed across rural neighborhoods in developing countries, countering not only the digital divide, but also the health divide (Srivastava and Shainesh 2015; Venkatesh and Sykes 2013). In addition, mobile devices could be offered for free to the underprivileged, while charging nominal prices for mHealth services such as advice giving on particular health questions. Since our findings have shown that the people who share and own mobile phones display similar EAEs in adopting mHealth services, we suggest that mobile devices can be shared among people based on household units or other ownership sharing policies but not necessarily limited to individual ownership.

5.2. Implications for Research

Our research design and data analysis methods also shed lights for research. We do not consider mHealth targeted at underprivileged citizens at the bottom of the pyramid as typical commercial services. As we have mentioned, the underprivileged population usually has very low or even unstable incomes, and their demand elasticity and income elasticity to mHealth services will not be sensitive to small or even some subtle changes in pricing (Banerjee and Duflo 2011). Furthermore, mHealth services, as an emerging effective solution to counter the health divide among the underprivileged in developing countries, are likely to receive subsidies and be treated as quasi-public goods (Mazumdar and Guruswamy 2009). Therefore, we adapt the contingent valuation question format and assess the economic attitudes toward mHealth services for free and at three different nominal price intervals among the underprivileged (Luzar and Cosse 1999; Olsen and Smith 2001). This measurement approach enabled us to reveal nuanced information regarding the adoption potential of mHealth services among the underprivileged population at nominal pricing schemes.

In addition, since the contingent valuation questions repeatedly ask individuals' economic attitudes toward mHealth services at different levels of pricing, we utilize the piecewise latent growth modeling method to investigate the EAE to mHealth services among the underprivileged in developing countries. While the general latent growth modeling method has recently been introduced to the IS field to understand longitudinal phenomenon (e.g., Bala and Venkatesh 2015; Zheng et al. forthcoming), our study is among the first to introduce and apply the piecewise latent growth modeling method to understand (a) repeated measures that are not longitudinal in nature, and (b) evolving trajectories that are composed of two separate growth segments. Our study also provides an illustration of how piecewise latent growth modeling can be applied to understand changes in economic attitudes toward digital products and services at different levels of pricing.

5.3 Limitations and Future Research

Since our research is still at a preliminary stage, we will next pinpoint its limitations that offer opportunities for future study. First, our paper so far focuses more on introduction of the piecewise latent growth modeling method and presentation of the preliminary findings. The next version of our manuscript will be providing more comprehensive literature review on adoption potential of mHealth services in developing countries and how our study makes unique contributions to related knowledge domains. Correspondingly, we will also be able to articulate in detail of our practical implications for policy makers.

Second, our study approaches the EAE to mHealth services solely through the mobile phone ownership lens. While mobile phone ownership could be a great opportunity for policy makers to broaden access to healthcare among the underprivileged, researchers can also investigate the EAE to other healthcare related behaviors such as health checkups, in-person advice seeking from trained medical professionals, and in-person interaction with village kiosks that disseminate authenticated health-related information. In addition, we assume that the EAE to mHealth services across different levels of pricing remain homogeneous across groups with different mobile phone ownership types. We plan to relax this assumption and allow for heterogeneity in the EAE to mHealth services among the underprivileged groups and also examine factors contributing to such embedded heterogeneity in EAE.

Third, although the group that shared mobile phones and that owned mobile phones displayed similar EAE to mHealth services, their economic attitude values at a particular price interval still possibly differ. Therefore, we plan to examine what factors contribute to different economic attitude values among the underprivileged population. The ultimate goal is to help policy makers implement effective pricing mechanisms across the heterogeneous underprivileged population to broaden their access to modern healthcare.

6. Conclusion

Based on survey data collected from 2129 villagers who participated in free health camps in two rural South Indian villages, we generated insights on how to promote the adoption of mHealth services among the underprivileged in developing countries through effective nominal pricing mechanisms. We used the contingent valuation technique to develop hypothetical questions in the survey and applied piecewise latent growth modeling and multi-group comparison methods to investigate the economic attitude elasticity (EAE) to mHealth services across three groups who have no mobile phones, who share mobile phones with others, and who own dedicated mobile phones. Our findings revealed that the economic attitudes toward free mHealth services were different across the three mobile phone ownership groups for one camp, but were similar between the groups who share and who own mobile phones for the other camp. Besides, when mHealth services change in price from free to a nominal price of less than 100 INR and from less than 100 INR to between 100 and 200 INR and to greater than 200 INR, the EAEs to mHealth services for the samples from both camps were identical between the two groups who share and who own mobile phones.

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