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EFFECT OF MOBILE APPS ON ENVIRONMENTAL IMPACT OF SMARTPHONES

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Abstract. *Mobile applications (mobile apps) are major ways of using a smartphone. They can greatly affect environmental performance of a smartphone. To better understand potential implications of mobile apps on environmental impact of smartphones, this empirical study performed three analyses: (1) mobile apps usage behavior survey, (2) energy and data consumption test of mobile apps, and (3) simulation of environmental implications of mobile apps. A summary of results is given along with discussion on how mobile apps can affect the degree and variability of environmental impact during usage stage of smartphones.*
Keywords: Life cycle assessment (LCA), Smartphone, Mobile application (App), Energy consumption, Data consumption, Environment

1. Introduction.

A smartphone has a life cycle, including production, usage, and end-of-life disposal and recycling. During its life cycle, it has environmental impact, including greenhouse gas emissions, waste, and natural resource depletion. Although the environmental impact of each smartphone is low compared to other electronics, their total impact could be very high considering the total number of smartphone users worldwide [1].

According to life cycle assessment (LCA) results reported by major smartphone manufacturers (Table 1) [2,3], the usage stage of smartphone is known as the secondary source of environmental impact, which accounts for approximately 20% of its total environmental impact. However, most of these results did not fully take the effect of various mobile web and applications (*hereinafter* mobile apps) into account.

Most previous smartphone LCA has been conducted based on a single usage scenario. However, diversity exists regarding how people use their phones (e.g., what apps are used and how much time is spent on each app). Such diversity in app usage should be reflected in LCA. Another issue is that previous studies have focused solely on energy consumption (i.e., battery charging) of the device while impacts of data consumption have been generally neglected, although such impacts can be significant. According to Suckling and Lee [4], environmental impact of smartphone during usage stage will increase by almost 400% if servers and networks are considered in LCA. If app usage is properly reflected, a significant change in the environmental impact of smartphone is anticipated.

To better understand how mobile apps would affect the degree and variability of environmental impact during the usage stage of smartphones, this paper presents results from an empirical study consisting of the following three components:

- Surveys on mobile apps usage behavior
- Energy and data consumption tests of mobile apps
- Simulation of environmental implications of mobile apps

TABLE 1. Summary of life cycle assessment studies reported by two major manufacturers

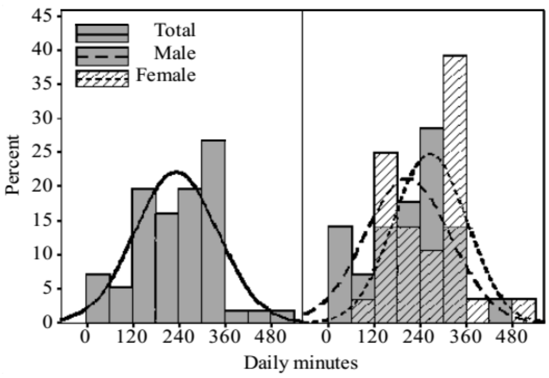
Brand	Share by life-cycle stage (%)			Average total environmental impact (kg CO_2 eq.)
	Production	Usage	End-of-life	
Apple	73.5	25.4	1.2	60.5
Samsung	82.7	16.7	0.6	22.5
Total	76.5	22.6	0.9	–

Usage behavior surveys were conducted to confirm diversity in people's app usage. Energy and data consumption tests were performed to demonstrate differences in individual apps' energy and data efficiency. Finally, simulation of environmental implications of mobile apps was performed to show that diverse usage behaviors and mobile apps' characteristics could lead to significant variability in a smartphone's environmental impact. Thus, smartphone LCAs should change their scope of analysis and consider various usage behaviors as well as data consumption during the usage stage. Although many studies have reported mobile apps usage (e.g., [5-7]) and apps' energy and data consumption (e.g., [8-10]), this study is distinguished from them in that it considers these two perspectives simultaneously. This study also clarifies the link between mobile apps and the environmental impact of smartphones.

The remainder of this paper is organized as follows. Section 2 describes results of usage behavior surveys. Section 3 presents test results of energy and data consumption of mobile apps. Section 4 performs a simulation regarding environmental implications of mobile apps. Section 5 then concludes the paper.

2. **Surveys on Mobile Apps Usage Behavior.** To better characterize diverse app usage behaviors of smartphone users, a survey was conducted in September 2015. A total of 56 university students (28 male and 28 female Korean students) participated in the survey. They were asked to download an application called 'UBhind' (i.e., an app that captures how much time the user spends with each and every application in his/her smartphone [11]) and use it for seven days. Total minutes spent with the smartphone and minutes spent on individual mobile app were surveyed after the 7-day period. Results are shown in Figures 1 and 2, respectively.

Figure 1 shows a histogram of daily minutes spent on mobile apps. As shown in Figure 1, the variable (daily minutes) followed a normal distribution. Survey participants spent approximately 236 minutes on average on mobile apps. Average daily minutes were slightly different between male and female students. Female students tended to use their phones for about an hour longer than male students.



	Mean (minute)	StDev.	Goodness of fit test* (Normal distribution)
Total	236.49	108.10	0.381,0.391
Male	206.71	112.65	0.277,0.626
Female	266.26	96.30	0.549,0.143
*Anderson-Darling test statistics, p-values			

FIGURE 1. Histogram of daily minutes spent on mobile apps and the difference by gender

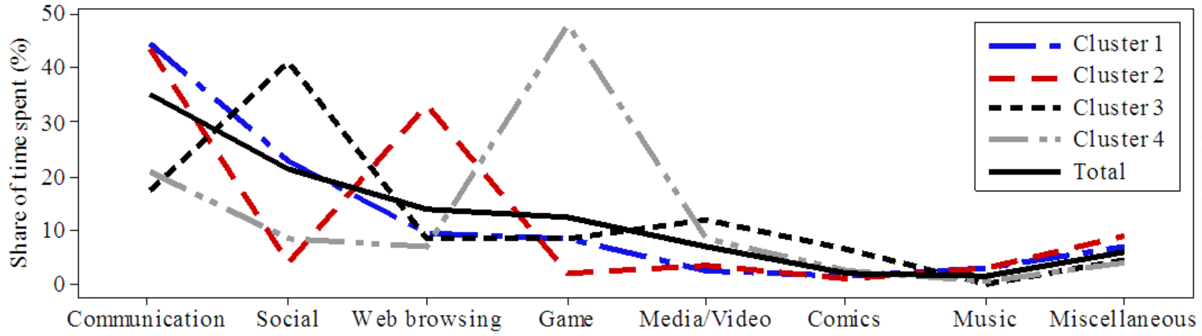


Figure 2. Share (%) of daily minutes spent on mobile apps by category and cluster

Table 2. Share (%) of daily minutes spent on mobile apps by category and cluster

	App category	Total (56 students)	Cluster 1 (21 students)	Cluster 2 (14 students)	Cluster 3 (13 students)	Cluster 4 (8 students)
1	Communication	35.3	**44.8**	**44.0**	17.3	21.1
2	Social (SNS)	21.4	**22.9**	3.9	**41.5**	8.4
3	Web browsing	14.2	9.7	**33.3**	8.7	7.1
4	Game	12.6	8.3	2.0	8.7	**48.1**
5	Media & Video	6.9	2.5	3.6	12.1	8.5
6	Comics	2.2	1.7	1.2	6.6	2.4
7	Music & Audio	1.6	2.9	3.2	0.2	0.4
8	Miscellaneous	5.8	7.2	8.8	4.7	4.0

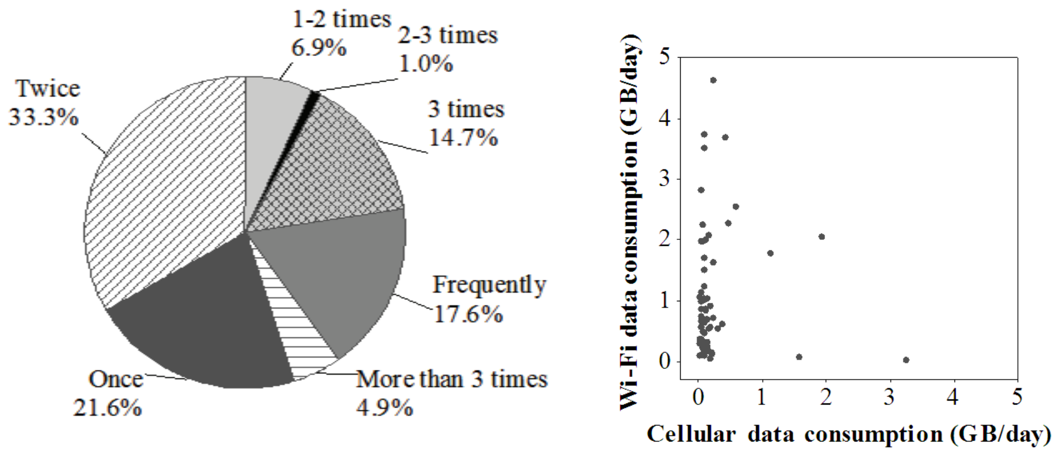
Figure 2 illustrates types of mobile apps mostly used by participants. There were seven most popular app categories: communication (e.g., Kakao Talk), social (e.g., Facebook), web browsing (e.g., Google), game (e.g., Candy Crush Saga), media and video (e.g., Youtube), comics (e.g., Naver Webtoon), and music and audio (e.g., Melon).

As shown in Figure 2, participants can be clustered into four groups depending on daily minutes spent on each app category. Detailed clustering results are shown in Table 2. Cluster 1, the biggest group of participants, mainly used communication and social apps. Cluster 2 participants mainly used apps for communication and web browsing. Clusters 3 and 4 participants used social and game apps, respectively. To determine whether there was any difference by cluster in terms of total minutes spent on these apps, ANOVA was conducted. Results showed that there was no significant (p-value = 0.14) difference in mean total minutes among these clusters.

In December 2016, an additional survey was conducted among 102 university students to investigate their daily charging frequency and data connection type (i.e., cellular or Wi-Fi connection). Survey results are shown in Figure 3. Most (over 88%) participants responded that they charged their devices more than once a day (Figure 3(a)) and used Wi-Fi connection more intensively than cellular connection (Figure 3(b)).

3. **Energy and Data Consumption Tests of Mobile Apps.** In order to clarify how app usage affects environmental impact of smartphones, it is essential to understand characteristics of individual apps in terms of energy and data consumption. Therefore, energy and data consumption tests were performed in this study. For energy consumption, this study focused on energy consumed by the screen and app itself without including energy consumed for Wi-Fi connection, Bluetooth, phone radio, or others.

To encompass the seven most popular app categories identified earlier (Table 2), a representative app was selected for each category based on the number of downloads in



(a) Daily charging frequency (b) Data connection type

Figure 3. Average daily charging frequency and data consumption by connection type

Google Play Store. For each app, tasks for test were defined as shown in Table 3. During tests, each task was performed 12 times. At each time, task duration (in minutes) and total energy and data consumption were measured to calculate consumption per minute. Among 12 results, two extreme values (i.e., the largest and the smallest values) were removed to reduce the effect of outliers. The remaining 10 results were used to identify the minimum, median, and maximum consumption per minute. As for test device, Samsung Galaxy S5 equipped with a new battery was used. Device settings such as brightness and volume were controlled. To see the effect of data connection type, Wi-Fi and cellular environments were tested separately. Test results are shown in Table 3, Figure 4 and Figure 5. They implied the following points.

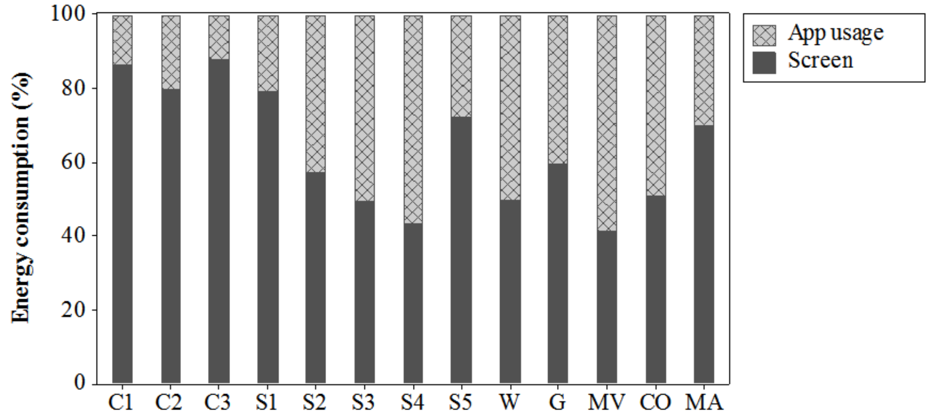
- Data connection type (Wi-Fi vs. cellular) did not seem to have much influence on energy or data consumption (Table 3). Nonparametric sign tests for median differences were conducted between Wi-Fi and cellular environments. p-values for energy and data consumption were 0.391 and 0.099, respectively.
- As shown in Figure 4, both app usage and screen caused energy consumption. However, the proportion was different by task. Similarly, each task had its own characteristics in terms of sources of data consumption.
- Mobile apps and their tasks had distinctive characteristics in terms of energy and data consumption per minute. Depending on app and task, energy and data consumption greatly differed (Table 3). While some tasks (e.g., MV, S3) consumed relatively more data but less energy, some tasks (e.g., C2, S2) showed the opposite trend, i.e., relatively more energy but less data (Figure 5).

4. **Simulation: Environmental Implications of Mobile Apps.** Based on results from Sections 2 and 3, a simulation was conducted to demonstrate the effect of mobile apps on degree and variability of smartphone impact. For the simulation, assumptions were made as follows:

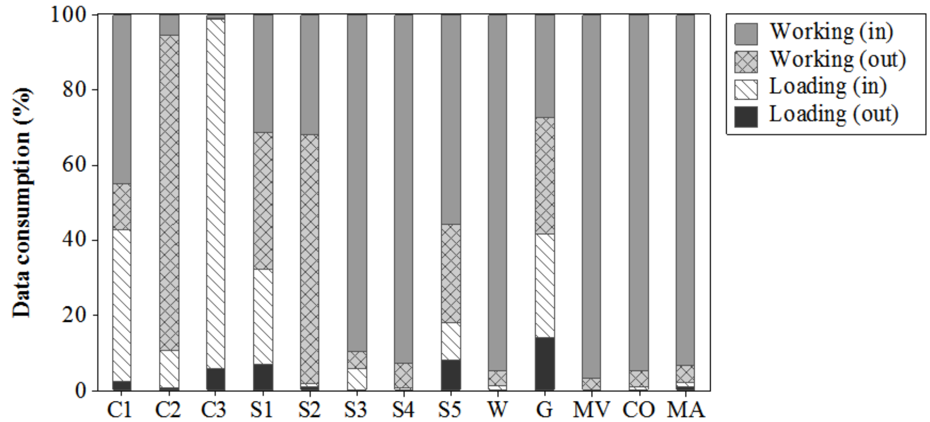
- Wi-Fi connection
- Normal distribution for total daily minutes spent for apps
- Triangular distribution for energy and data consumption of apps
- Communication app usage proportions were 60% for task C1, 15% for C2, and 25% for C3. Social app usage proportions were 15% for S1, 15% for S2, 30% for S3, 20% for S4, and 20% for S5.

Table 3. Energy and data consumption per minute by app category and task

App category	Task for test		Energy consumption (Wh)						Data consumption (MB)					
			Wi-Fi			Cellular			Wi-Fi			Cellular		
	ID	Description	Min	Median	Max	Min	Median	Max	Min	Median	Max	Min	Median	Max
Communication	C1	Chat (text messages)	0.019	0.021	0.022	0.023	0.034	0.047	0.672	0.944	1.285	0.471	0.703	0.929
	C2	Send selected photos	0.024	0.051	0.075	0.007	0.012	0.042	0.930	1.486	2.156	0.809	1.017	1.771
	C3	View selected photos	0.022	0.033	0.058	0.018	0.031	0.060	0.546	1.137	1.203	0.599	1.078	1.190
Social	S1	Upload specific sentences	0.019	0.021	0.030	0.018	0.028	0.038	0.233	0.605	4.012	0.226	0.886	4.135
	S2	Upload selected photos	0.022	0.039	0.055	0.025	0.041	0.051	0.537	1.196	1.739	0.730	1.311	1.781
	S3	Read news feeds	0.010	0.023	0.060	0.023	0.032	0.040	2.937	7.930	11.302	1.267	4.082	8.044
	S4	Watch selected videos	0.011	0.019	0.022	0.018	0.019	0.021	0.334	2.075	8.113	0.787	8.872	14.508
	S5	View selected photos	0.020	0.029	0.055	0.025	0.031	0.047	0.160	0.362	0.818	0.320	1.120	2.020
Web browsing	W	Browse specific websites	0.016	0.020	0.032	0.020	0.033	0.039	4.090	5.180	6.684	4.491	5.801	7.350
Game	G	Play a specific game	0.021	0.033	0.046	0.019	0.025	0.063	0.111	0.149	0.167	0.113	0.140	5.486
Media & Video	MV	Watch selected videos	0.018	0.021	0.023	0.023	0.024	0.025	7.464	9.683	13.815	10.544	12.180	13.321
Comics	CO	Read specific comics	0.031	0.038	0.053	0.019	0.029	0.043	5.457	8.194	11.580	4.155	5.507	7.784
Music & Audio	MA	Listen to selected songs	0.025	0.028	0.030	0.009	0.020	0.028	1.104	2.018	2.926	0.867	1.784	2.902



(a) Energy consumption



(b) Data consumption

FIGURE 4. Comparison of mobile apps in terms of sources of energy and data consumption (Wi-Fi connection)

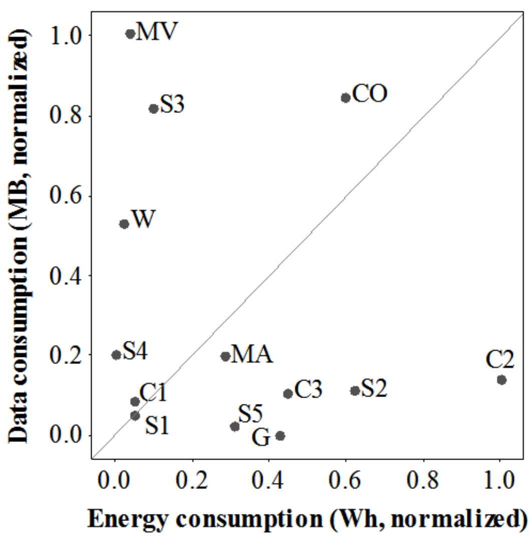
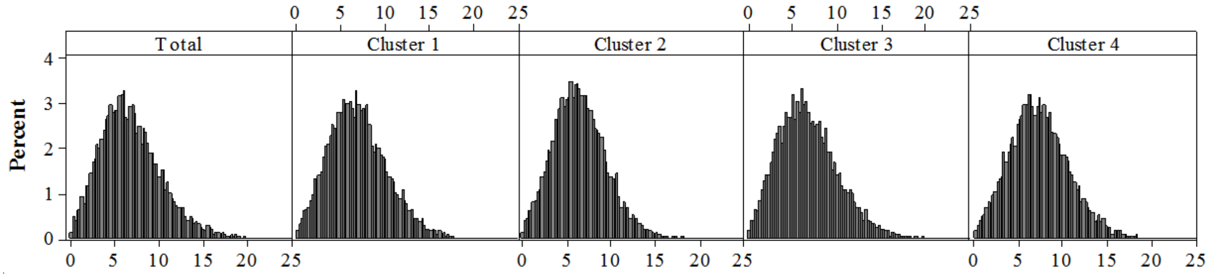
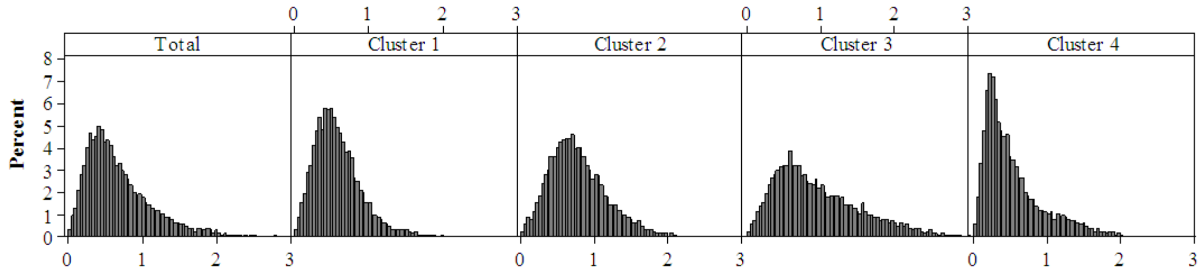


FIGURE 5. Comparison of median energy and data consumption (Wi-Fi connection)



(a) Daily energy consumption (Wh)



(b) Daily data consumption (GB)

FIGURE 6. Histogram of daily consumption of energy and data

TABLE 4. Daily energy and data consumption and their differences among clusters

		Mean	StDev.	Q1	Median	Q3	Statistical test on median difference among clusters
Daily energy consumption (Wh)	Total	6.86	3.55	4.34	6.43	8.92	Mood median test: p-value $= 0.000$ Kruskal-Wallis test: p-value $= 0.000$
	Cluster 1	6.94	3.33	4.52	6.68	9.04	
	Cluster 2	6.52	3.04	4.37	6.31	8.41	
	Cluster 3	6.73	3.41	4.24	6.37	8.81	
	Cluster 4	7.24	3.34	4.90	7.01	9.34	
Daily data consumption (GB)	Total	0.70	0.49	0.35	0.57	0.92	Mood median test: p-value $= 0.000$ Kruskal-Wallis test: p-value $= 0.000$
	Cluster 1	0.58	0.35	0.34	0.52	0.75	
	Cluster 2	0.77	0.40	0.48	0.71	1.00	
	Cluster 3	0.97	0.62	0.50	0.82	1.33	
	Cluster 4	0.54	0.43	0.22	0.40	0.72	

Simulation results are shown in Figure 6 and Table 4. Results showed that diverse usage behaviors and mobile apps' own characteristics could lead to significant variability in environmental impact of a smartphone. Results also revealed that data consumption had greater variability than energy consumption.

5. **Conclusion.** To investigate how mobile apps might affect the degree and variability of environmental impact of smartphones, this paper presented an empirical study that consisted of three parts: (1) mobile apps usage behavior survey, (2) energy and data consumption test of mobile apps, and (3) a simulation of environmental implications of mobile apps. This study demonstrated that diversity in people's app usage behaviors and differences in individual mobile apps' energy and data efficiency could significantly increase the variability in smartphone's environmental impact. Considering that survey respondents used in this study are a very homogeneous group (i.e., students at the same

university of similar age) and the app test environment was controlled, the actual variability of smartphones' impact is expected to be much greater in reality.

Results of this study point out that current smartphone LCAs that provide only a single impact number are not appropriate. They are highly likely to mislead the public. To facilitate proper evaluation of products, more studies on app usage behaviors should be conducted so that representative usage patterns can be identified in the future. This study also highlights the importance of app efficiency. To reduce smartphone's environmental impact, it is essential to increase energy and data efficiency of mobile apps.

One limitation of this study was that environmental impact values were not calculated. In the future, an LCA reflecting mobile app usage should be conducted. To do so, more research is needed to determine not only the impact of devices, but also the impact of servers and networks [12]. Another issue was that increasing use of video was not taken into account in this study. As uploading and sharing videos are becoming more popular, data consumption is expected to be much greater in the future. Such a trend should also be considered in the future.

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