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A Systemic Smartphone Usage Pattern Analysis: Focusing on Smartphone Addiction Issue

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Abstract

Despite the recent massive popularity of smartphones and their impact on our lifestyles, only few objective studies have been conducted on smartphone usage patterns. In this paper, using a comprehensive smartphone usage logging system (a client app and a server), various statistical analysis results from more than 800 man-days usage logs are presented. The analysis shows 1) significant difference in usage frequency and time statistics among the applications, 2) different application category preferences between addicts and non-addicts, and 3) little usage variation between weekdays and weekends, but higher usage in night time for addicts.

Keywords: *Smartphones, Usage Pattern, Behavior Addiction, Data Mining*

1. Introduction

During the last decade, smartphones have gained popularity all over the world. In July of 2013, over 50% of mobile subscribers in the US and over 65% of mobile subscribers in South Korea are using smartphones, and these percentages keep increasing [1]. The key differences between smartphones and previous mobile phones are full-featured Internet access and easy installation of new applications through modern OS platforms and app stores. Hence, smartphones are now considered handheld computers rather than traditional phones [2].

Understanding the application and service usage of users is the first important step for designing applications and systems on which the applications run. Because of the short existence of smartphones, only a few previous works has been done yet. Roehlich *et al.* developed 'MyExperience' [3], a logging system for cellphones. Falaki *et al.* [4] studied the usage pattern of cellular phones in the perspective of energy efficient scheduling algorithm design for mobile systems. Kang *et al.* [5] also studied the usage pattern of smartphones for network traffic management study. Our smartphone addiction management system (SAMS) is presented in the previous work [6] and general usages pattern from Korean smartphone users is studied in [8]. This paper focused in smartphone usages pattern comparison between smartphone addicts and non-addicts peoples.

The rest of this paper is organized as follows. First, this paper briefly describes the SAMS system and data gathering methods that are used for archiving and analyzing usage patterns. Then, the usage pattern analysis results, popularity analysis of applications, usage pattern analysis of weekly and hourly patterns, and usage pattern- based categorization methods are presented.

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2. Data Collection System and Procedure

Figure 1 illustrates the overall system architecture and workflow of the SAMS (Smartphone Addiction Management System) framework. On the client side, the SAMS application continuously monitors the applications in use and stores the usage records in its local storage. The stored records can be displayed locally to users for self-recognition and control. Periodically, the new records are transmitted to the SAMS server via the Internet. The SAMS server stores the usage records in its database for later processing. Data analysis and visualization are performed on the records to help the clinicians' diagnosis and treatment. Clinicians can determine feedback actions, such as requesting current condition check survey or updating the usage limit time table for a specific application.

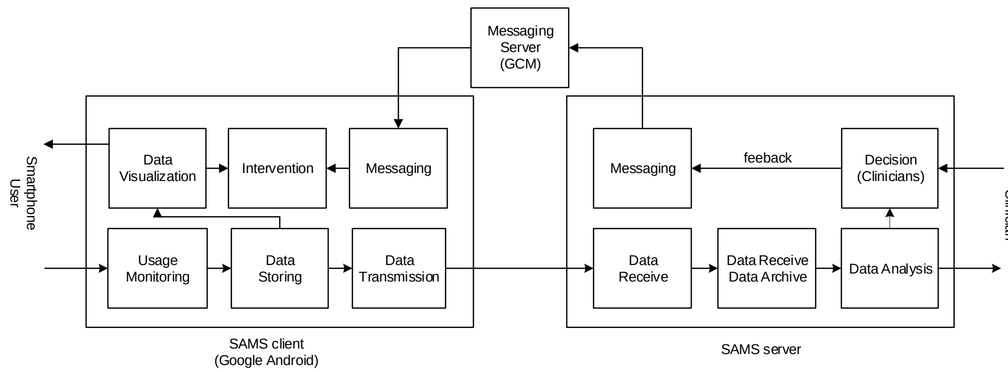


Figure 1. System Architecture and Workflow of Smartphone Usage Monitoring System (SAMS)

The SAMS client application is developed on Google Android-based smartphones. The monitoring service periodically checks the changes in the foreground application and records its start time, end time, GPS location, and URL (if the application is a browser). Taking into account the LCD display device's status, note that the system does not include the duration of time the LCD display is off. Then, the usage data is first stored in local SQLite database, and then transmitted to the server whenever network access is available. The server receives and stores the data (user profile and client system information) from SAMS clients, performs data analysis/mining, and finally, provides graphical and numerical information for the clinicians for analysis, diagnosis and treatment. For basic treatment strategies, the SAMS client is requested through GCM messaging to update the limitation time table or prompt the current survey status of the user.

3. Usage Pattern Analysis

Various usage pattern analyses such as popularity analysis of applications, usage pattern-based categorization method, and usage pattern analysis of weekly and hourly patterns, were performed in order to understand user behavior. Whenever possible, we performed the contrast group analysis between addicts and non-addicts. The grouping of users into addicts and non-addicts is done though K-SAS survey questions [7]. The SAMS client application is distributed to about 60 anonymous users who were from 4 persons' phone number lists. Among 60 targets, about 30 installed the SAMS application. The number of males and females are same and, and the age ranges from 18 to 51 (average of 26.57, standard deviation of 8.25).

3.1 Popularity Analysis

Google Play app store provides application ranks, such as the number of downloads, paid, top-grossing, and customers' rate average. However, these rankings do not have correlation with the user's usage, especially on which application is most often used or used in longer duration.

We analyzed the log records, and the observations from the graph are as follows. First, less than 10 applications contribute to more than 50% of total usage in time duration. Also, there are less than 50 applications which contribute to more than 80% of total usage time in frequency (Figure 2). Second, there is a significant difference in the rank of applications between usage time and frequency. Table 1 lists the top 10 applications in usage time and frequency. Except for the top 2 applications, KakaoTalk and browser, the rankings of top applications differ in usage time and usage frequency.

Table 1. Top 10 Applications Ranked by Average Daily Use Times and Counts

Rank	App name by usage duration			App name by usage frequency		
	App name	Freq. (%)	Duration (%)	App name	Freq. (%)	Duration (%)
1	KakaoTalk	18.86	17.48	KakaoTalk	18.86	17.48
2	Android Browser	10.02	8.69	Android Browser	10.02	8.69
3	African TV for LGU +	0.28	5.52	Facebook	7.06	4.97
4	Facebook	7.06	4.97	Address	5.22	1.19
5	You + HDTV	0.48	4.48	Phone	5.07	1.27
6	NAVER	3.28	4.34	Vintage Red Story	3.45	2.09
7	YouTube	1.03	3.92	NAVER	3.28	4.34
8	Aenipang	0.76	3.71	Line	3.12	1.48
9	Naver Real Madrid	1.27	3.00	GO Locker	3.04	0.37
10	Vintage Red Story	3.45	2.09	Messaging	2.89	0.87

3.2 Category Analysis

The contrast between usage time and usage frequency for each application is related with the category of that application. Based on figure 3, it can be concluded that some application categories may have high usage frequencies but lower usage durations. In this case, the application in communication category, KakaoTalk, has a higher tendency to be used more frequently, but in shorter duration. Other categories are less frequently used, but once the user uses these applications, the usage duration gets longer. M. Salehan *et al.* also [9] reported the positive correlation between SNS application usage and smartphone addiction scale.

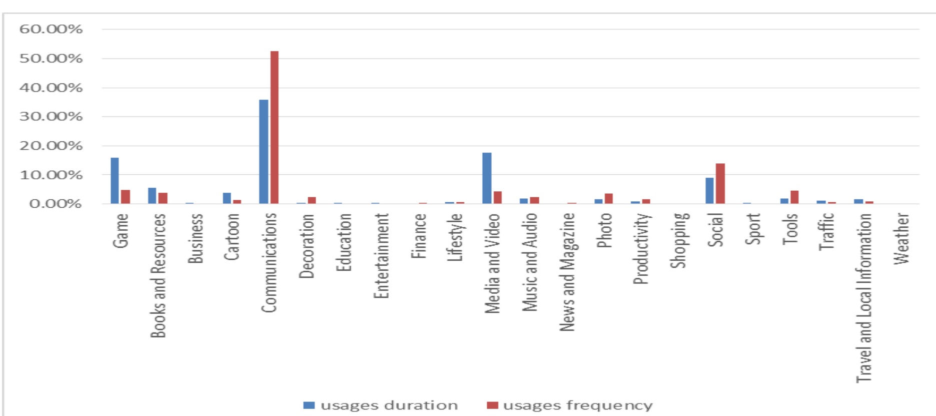


Figure 2. Application Usage Frequency and Duration Ratios in Each Category

We examined if the apps in the same category show similar pattern of usage count and usage time. Because the Google categories are too many for our analysis, we merged and rearranged the Google Play categories as shown in Table 2. Moreover, considering the application style, we changed the categories for some applications, *e.g.* KakaoTalk from Communication to Social category. Table 3 shows the difference in application preferences between addicts and non-addicts. As expected in the previous work [6], [9], compared to non-addicts, addicts have more usage frequency and duration in social network service.

Table 2. Category Grouping from Google's Detailed Categories

Grouped Category	Google Detailed Category
Social Network	Communication and social
Game	Arcade game, Puzzle game, card game, casual game, and sport game
Entertainment	Comic, media and video, and music and audio
Browsing	Finance, lifestyle, health, medical, news, weather, books and reference, education, shopping, traffic and travel
Others	Photo, personalization, productivity, decoration, and business tools

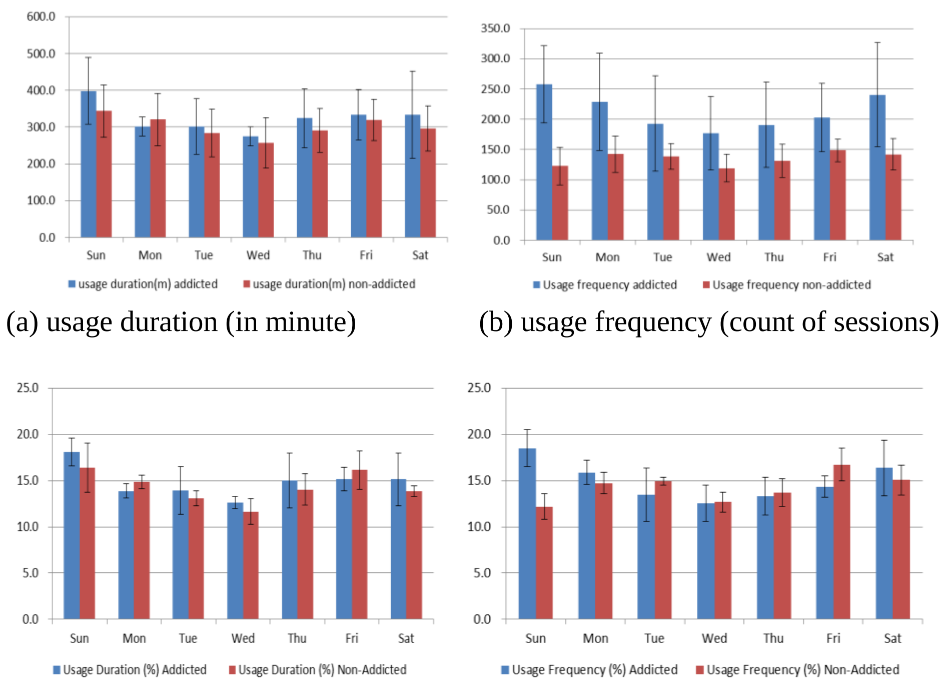
Table 3. Category and Usage Difference Between Addicts (A) and Non-addicts (N)

Category	App name	Rank by Usage Frequency		Rank by Usage Duration		Daily Usage Frequency		Daily Usage Duration (min)		Original Google category
		A	N	A	N	A	N	A	N	
Social Network	KakaoTalk	1	1	1	1	54.6	25.16	75.12	50.37	Coms.
	Facebook	3	3	4	3	27.34	8.75	29.05	10.26	Social
	Vintage Red Story	23	10	23	10	0.94	2.50	1.20	3.09	Social
	Subtotal					**98.2**	**62.1**	**111.8**	**86.0**	
Game	Marble of All	29	50	29	50	0.71	0.32	7.50	3.92	Casual Game
	Cookie Run	67	167	62	167	0.07	0.01	0.19	0.02	Casual Game
	Gray City	74	158	69	158	0.03	0.02	0.08	0.16	Puzzle
	Subtotal					**3.7**	**7.2**	**22.6**	**46.3**	
Entertainment	YouTube	42	15	42	15	0.33	1.80	5.38	15.15	Media and Video
	African TV for LGU +	65	34	65	34	0.05	0.65	0.16	31.41	Media and Video
	Genie Music	32	140	32	140	0.62	0.04	0.59	0.80	Music and Audio
	Subtotal					**21.0**	**12.0**	**88.2**	**89.3**	
Browsing	Android Browser	4	2	4	2	20.05	13.59	43.03	22.54	Comms
	Seoul Bus	33	71	33	71	0.61	0.19	0.19	0.14	Travel
	NAVER	9	6	9	6	5.71	6.42	13.67	14.84	Books and Reference
	Subtotal					**37.8**	**33.7**	**77.5**	**61.9**	
Others	Go Locker	2	174	2	174	29.05	0.01	5.88	0.01	Decoration
	Camera	15	33	15	33	1.55	0.69	0.76	0.27	Photo
	Gallery 3D	10	13	10	13	3.74	0.30	3.13	0.14	Photo
	Subtotal					**44.0**	**15.4**	**17.9**	**15.7**	

3.3 Time Domain Usage Pattern

Figures 4 and 5 show the patterns of daily and hourly usages. In contrast to our prediction of significant difference in weekday and weekend, day by day usage differences are small. The standard deviation from each day is quite high. It can be explained that every user has a different daily usage pattern. The decrease in usage by 11 p.m. until 5 a.m. is due to this period being the rest time for common users.

For the hourly pattern, usage from non-addicted users get slightly higher than addicted users by 9 a.m. until 5 p.m., but usage from addicted-users get higher by 11 p.m. until 3 a.m. Usually, usage is decreasing at night, but in this time, usage from addicted users is increasing.



(a) usage duration (in minute) (b) usage frequency (count of sessions)

(c) ratio of usage duration (%) (d) ratio of usage frequency (%)

Figure 4. Weekly Pattern Comparison Between Non-addicts and Addicts

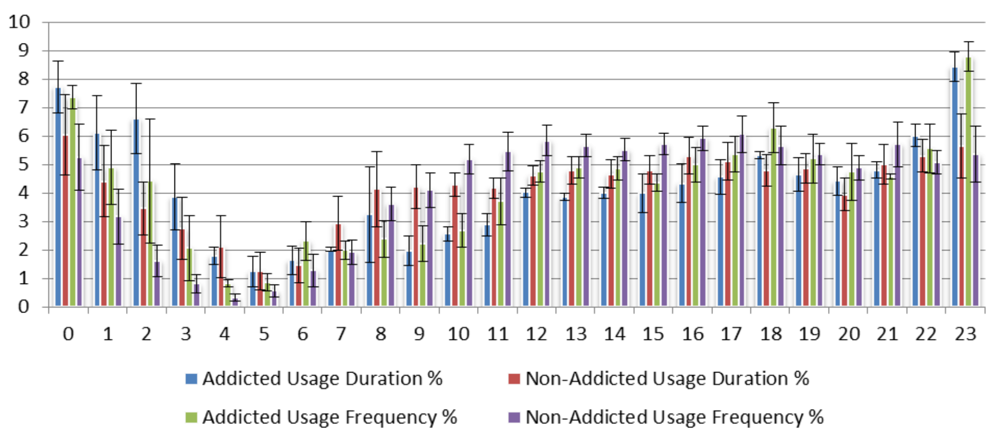


Figure 5. Hourly Usage Time and Usage Frequency

4. Conclusion

The conclusions from our experimental study are as follows: 1) social and communication applications have shorter usage time and higher daily usage frequency than game applications,

2) users' daily usage time has slight differences and hourly usage time is mostly high at night and decreasing after midnight, 3) comparison between addicted and non-addicted usage patterns, in daily or hourly, shows that in daily usage, it is only during Sundays wherein the difference is high. However, day to day comparison between addicts and non-addicts usage also shows slight differences. In hourly analysis, addicted users' usage is mostly at night and non-addicted users' usage is mostly in the afternoon. For the future work, we will extend the number of subjects and performs comprehensive data mining analyses, such as geographic pattern.

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