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Automated Time Manager: Effectiveness of Self-Regulation on Time Management through a Smartphone Application

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ABSTRACT We investigated the effectiveness of a self-regulation strategy on time management leveraged by smartphone capabilities using a theoretical framework of self-regulation that consists of four elements: (a) goal setting, (b) task strategy utilization, (c) self-monitoring and reflection, and (d) self-efficacy and intrinsic motivation. We determined goals and strategies adopted during college life by surveying 295 college students and identified time management as a fundamental element for achieving such goals and strategies. To improve students' time management, we developed a smartphone application, Automated Time Manager (*ATM*), designed to provide users with visualizations of their physical activities and phone usage reports and also to acquire smartphone sensor and usage data. From a field study of 46 college students, we highlighted three primary user experiences – *awareness of unawareness*, *preferred feedback*, *contextual but obvious use* – and an overall positive time management outcome with *ATM*. We present an empirical study that transforms self-regulation, a well-known approach in social sciences, into computing, and discuss the salient design implications for supporting time management in a more effective manner with a smartphone application.

INDEX TERMS Mobile application, Positive computing, Self-regulation, Smartphone use, Time management.

I. INTRODUCTION

Smartphones have brought massive changes to people's lives, allowing easy information access, diverse social communications, flexible task management, more options for entertainment, etc. [1]. While such a technology brings several positive influences (e.g., convenience, efficiency, diversity) [2]–[4], side effects exist, including smartphone addiction. According to statistics in 2017 [5], 30.3% of teens and 23.6% of twenties in Korea are in a smartphone addiction risk group. Especially for student populations, such smartphone addiction has an adverse impact on their academics, including failure to focus during classes or assignments. In addition, students' achievement level on the day of excessive smartphone usages was found to be the lowest at 58.5% [5].

Studies in social sciences have reported that students are actually "aware" that excessive smartphone use is detrimental to various aspects of their daily lives, such as academic performance, physical and mental health, and social relationships, but they often encounter difficulty regulating their usages of the smartphones [6], [7]. Studies have report that the lower their self-regulation, the more easily they become addicted to their smartphones [8]–[11]. Improvement of self-regulation skills is therefore effective in resolving smartphone addiction [12].

Drawing on the findings of previous research, we investigate the manner in which students' self-regulation skills can be improved by leveraging certain technical features of the smartphone, such as the ability to track users' digital traces, and create real-time visualization feedback. Our research is motivated by positive computing [13], which refers to the design and development of technology to support psychological well-being and human potential. As a part of positive computing, we introduce a smartphone application – Automated Time Manager (*ATM*) – to improve self-regulation skills (in our work, on time management) efficiently.

In particular, we incorporate a theoretical framework of social cognition on self-regulation [14], [15] to time management strategy and adapt this framework to fit the characteristics of the smartphone platform. Four elements in this framework are used as a basis for the design of *ATM*: (a) setting specific goals, (b) employing task strategies, (c) self-monitoring and self-reflection over performance outcomes, and (d) displaying high levels of self-efficacy and intrinsic motivation. Self-efficacy is defined as a belief in one's capabilities to mobilize the motivation, cognitive resources, and courses of action needed to meet given situational demands [16], and intrinsic motivation refers to taking an action because it is inherently enjoyable or interesting [17].

In our study, we address each element as follows.

- **(a) Goal setting and (b) Task strategy utilization:** We conducted a survey of 295 undergraduate or graduate students from various classes in a university in Korea [18]. Taking a bottom-up approach, we analyzed the survey results through open and axial coding [19] to identify students' goals and task strategies for achieving such goals. Our approach starts from designing the most fundamental parts, which are then combined to design the higher level [20].
- **(c) Self-monitoring and self-reflection:** We developed a smartphone application, *ATM*, to support students' time management, which was identified as the most important factor that supports the students' goals and task strategies. *ATM* is designed not only to collect smartphone sensor and usage data through a background service, but also to provide various real-time visualized and personalized usage reports.
- **(d) Self-efficacy and intrinsic motivation:** We measured self-efficacy and intrinsic motivation by using two reliable scales – generalized self-efficacy (GSE) [21] and intrinsic motivation inventory (IMI) [22] – which were used before and after a three-week field user study (pre- and post-evaluations).

Unlike previous studies that focus on students' mental health [23]–[25] and academic achievement [26], [27] by using a top-down approach (beginning from pre-defined ideas to small details), we conducted a survey [18] to explore students' goals and task strategies by using a bottom-up approach (beginning from the small details up to the whole idea; which more carefully considers students' various responses). We then derived three goals (i.e., academic achievement, health, relaxation) and seven task strategies (i.e., concentration, planning, attendance, adjusting smartphone use, exercising, eating regular meals, resting) by a coding procedure [19], and identified "time management" as a fundamental element for achieving such goals and task strategies.

Based on this, we developed *ATM* to effectively support (c) self-monitoring and self-reflection aspects of time management. We confirmed the effectiveness of various real-time personalized visualizations of *ATM* through a field study with 46 students. Most students (45 students, 98%) respond that they had a positive psychological or practical stimulation of time management through *ATM*, and 27 students (59%) show a decrease in total smartphone use hours during the study.

Specifically, the main contributions of our work can be summarized as follows.

- We propose a strategy for self-regulation on time management for college students based on a theoretically proven framework. Furthermore, we present an empirical study that transforms the theoretical understanding of self-regulation, which is famous as well as widely studied in the field of social sciences, into computing.
- To effectively support the self-monitoring and self-reflection aspects of time management, we designed and developed *ATM* to collect and analyze four types of smartphone sensor and usage data (i.e., notification, location, activity, the application's usage log) and calendar to provide seven visualization reports (i.e., individual and comparison reports of application usage and activities) for time management.
- We investigated the influence of *ATM* use on user's self-regulation on time management by conducting a field user study. The study's results highlight three primary experiences in time management that the students raised regarding their use of *ATM*: (1) *Awareness of unawareness*, (2) *Feedback preference*, and (3) *Contextual but obvious use*. Overall, 22% of the students reported having a positive experience self-regulating their time management after the study.
- Based on user feedback, we present three implications for designing a smartphone-based self-regulation management system: (1) *In real-time self-recognition*, (2) *Personalized feedback*, and (3) *No smartphone use mode* for supporting time management in a more effective fashion.

II. RELATED WORK

Given that our work is motivated by self-regulation and related to positive computing through a smartphone application, we outline prior research efforts in two research contexts: (1) *Self-Regulated Learning (SRL)* and (2) *Technology for Students' Well-being* and highlight how our work is distinct, yet substantiates results from previous studies.

A. SELF-REGULATED LEARNING (SRL)

1) Traditional Questionnaire Measures of Self-Regulated Learning

During the first wave of research on self-regulated learning (SRL), three representative evaluation methodologies were used in educational contexts (e.g., classes): the learning and study strategies inventory (LASSI) [28], the motivated strategies for learning questionnaire (MSLQ) [29], and the self-regulated learning interview scale (SRLIS) [30], [31].

The SRLIS relates to prospective answers to hypothetical learning contexts (e.g., interviews), whereas the LASSI and the MSLQ are both retrospective reports (e.g., emotion, anxiety, depression). According to [32], LASSI, MSLQ,

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and SRLIS can be classified as *aptitude measures* of self-regulation. In other words, they can be used to predict future behaviors and are designed to collect responses about self-regulation over time using ratings such as "is typical of me" or "most of the time."

2) Zimmerman's Three Cyclical Phases Model

To evaluate SRL, we used event measures, which define the SRL as a temporal entity with an identifiable start and end, as an alternative approach for assessing aptitude measures. A typical example of this event measure approach is an SRL phase model. To be more specific, social learning psychologists view the structure of self-regulatory processes as occurring in three cyclical phases: the forethought phase, the performance phase, and the self-reflection phase. These three phases refer to processes that occur before efforts to learn, during behavioral implementation, and after each learning effort, respectively [33], [34].

An SRL phase model is suitable for causal inference of changes in self-regulation in real-time and in various contexts because it can evaluate the sequential dependencies of responses. In addition, the model provides real-time detailed information about the interrelations between various processes including the impacts of target settings in the self-monitoring process [35].

3) Methodological Approaches

As the three cyclical phases model became widespread, changes also began to take place in the use of self-regulatory processes in education, and many studies evaluating students' SRL have been conducted. Reference [35] compiled related studies into five methodological approaches.

Among these five approaches, *structured diary measurements of SRL* [36], [37], *observed and qualitative measurements of SRL* [38], and *microanalytic measurements of SRL* [39], [40] presented effective methodologies for evaluating SRL online without having a designated computer tool. *Structured diary measurements of SRL* approach is based on SRL cyclic phases, and it uses a series of event questions regarding the student's study session. *Observed and qualitative measurements of SRL* uuse a variety of qualitative measures, such as observation from portfolio assessments and interviewing teachers and students, to studying changes in SRL during classroom learning events. *Microanalytic measurements of SRL* demonstrate the role of students' motivational feelings and beliefs in initiating and sustaining changes in their self-regulated learning.

The remaining two findings: *trace logs processes in computer-assisted environments* [41] and *think-aloud protocol measurements of SRL in hypermedia environments* [42] use a designated computer tool, namely "gStudy" and Microsoft "Encarta," respectively. *Trace logs processes in computer-assisted environments* provide students with many more ways to self-regulate their learning than are provided by traditional instructional software. *Think-aloud protocol measurements of SRL in hypermedia environments* report students' thoughts and cognitive processes while performing a task in a hypermedia learning environment.

To summarize, there have been many efforts to improve SRL since the advent of the three cyclic phases model. However, to support SRL effectively, it is desirable to use technology that enables in-real-time self-monitoring and self-reflection.

B. TECHNOLOGY FOR STUDENTS' WELL-BEING

IT technology has evolved with respect to collecting data from devices and accessing such data, and a considerable amount of research using sensor and usage data from smart devices has been conducted in various fields, such as smart city development [43]–[47] and well-being [48]–[53]. In the sections that follow, we focus on work related to student life by leveraging mobile technologies. In [54], the authors used smartphones and wearable devices to conduct a nine-week study of 83 college students. The authors found correlations between symptoms of depression and smartphone use and wearable passive sensor data and demonstrated that students with high PHQ-8 scores (a depression scale) were more likely to use their smartphones in the study places. The StudentLife study [55] demonstrated a relationship between passive sensing behaviors from smartphones, such as activity and co-location, conversation, and sleep with mental health outcomes, including stress, loneliness, and depression for 48 college students. [27] showed that grade point average and smartphone sensor data are correlated and suggested intervention methods to improve academic performance in a more effective fashion. In addition, [56] provided multi-dimensional feedback on well-being using a mobile application, "BeWell."

C. OUR RESEARCH CONTRIBUTIONS

While considerable research has been done on students' self-regulation over an extended period using traditional methods (e.g., surveys, interviews) or Web-based tools, to the best of our knowledge, *little research has been conducted to investigate how to support student self-regulation using smartphone technology*. As we have previously highlighted, since students use and carry their smartphones every day, and their behaviors are reflected in their smartphone use, studying ways of aiding self-regulation through smartphones is important. To do this, we developed a mobile application to support the self-monitoring and self-reflection aspects of the self-regulation on time management.

Many studies have analyzed behavior patterns related to student life, such as mental health and academic performance, by collecting smartphone sensor and usage data. However, most studies used the smartphone as a device for data collection and did not provide interfaces to support self-monitoring and evaluations. Compared to those prior studies, *ATM* is designed to provide students with easily accessible and straightforward statistics of usage patterns and reports through visualizations in real-time, allowing students

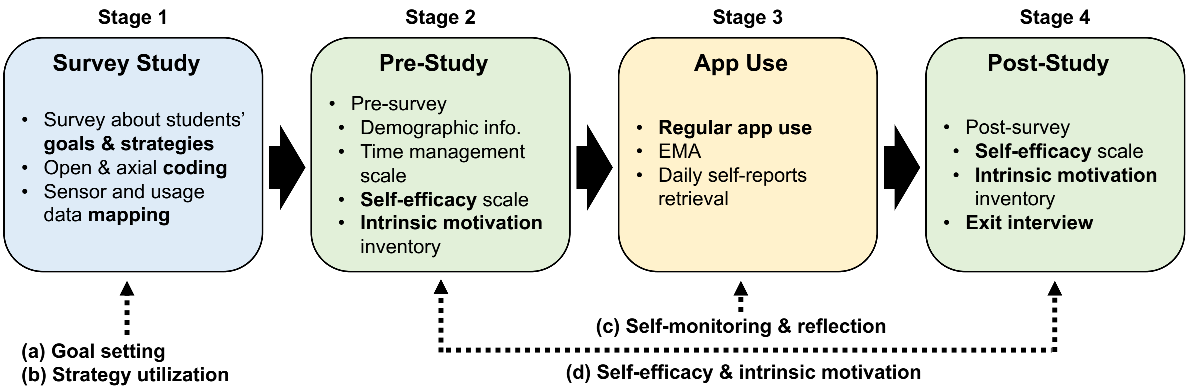

FIGURE 1. User study procedure. Our study consists of four stages.

to review and reflect on their smartphone use at any time and from anywhere.

III. OVERALL STUDY PROCEDURE

Fig. 1 shows the four stages of the user study. Each stage is composed of a single or a combination of four self-regulation element(s) – (a) setting specific goals; (b) utilizing task strategies, such as elaborating, organizing, and rehearsing; (c) self-monitoring and self-reflection on performance outcomes; and (d) displaying high levels of self-efficacy and intrinsic motivation – in our theoretical framework [14], [15].

IV. GOAL AND TASK STRATEGY SETTING

To investigate how students perform practices related to (a) goal-setting and (b) task strategy utilization as presented in Fig. 1, we first conducted a survey study [18]. For this purpose, we recruited undergraduate and graduate students from 13 different classes (e.g., social sciences, information and technology, liberal arts, nursing) at a university in Korea, and finally obtained a total of 295 participants. The gender ratio is 54.1% female and 45.9% male, showing that our sample is well balanced.

The survey questionnaire was revised and supplemented by conducting a pilot test with ten people who were not included in our final 295 respondents. The survey consisted of two primary sections. The first section has four items that examine goals and task strategies of the students. The second section has items that examine their demographics (i.e., age, sex, department, grade). We used both multiple choice and comments for question responses. The survey was conducted over one month, from April 9 to May 11, 2018. We collected a total of 397 responses. We then eliminated 102 incomplete or duplicated responses, leaving 295 complete responses for the analysis.

We looked at each response outlining goals and task strategies and grouped the responses. We employed axial coding to further generate categories and sub-categories [19]. Two authors of this paper refined themes and categories by an iterative coding process.

We confirmed that the majority of students (220 students, 75%) have a common goal of academic achievement and that some students (75 students, 25%) have secondary goals, such as health, relaxation. Seven task strategies were identified: concentration, planning, attendance, adjusting smartphone use, exercising, eating regular meals, and resting. From the students' responses to the question about the main element for achieving task strategies, we found that *time management* is a common response and the most fundamental element for achieving these task strategies and goals (Fig. 2). Therefore, we focused on time management in the study. The mapping procedure was carried out to determine the smartphone sensor and usage data that could support students' time management in order to develop the mobile application.

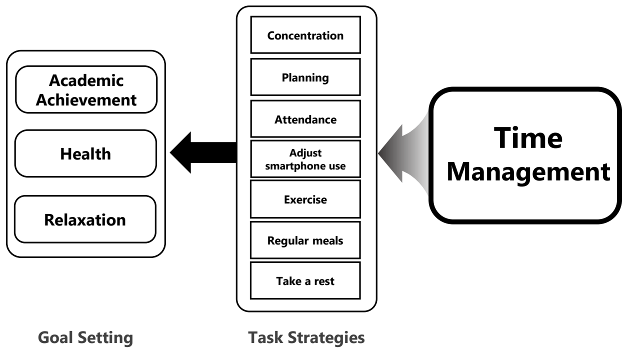

FIGURE 2. User survey showed that time management was a fundamental element for achieving task strategies and goals.

V. OVERVIEW OF ATM (AUTOMATED TIME MANAGER)

We developed *ATM* to promote users' self-regulation on time management by using their smartphones' automated sensing and data collection capabilities. *ATM* was also designed to collect additional course information, ecological momentary assessment (EMA), and self-reported data. EMA helps researchers to acquire ecologically valid data about behaviors, thoughts, and feelings over time in a natural setting while avoiding retrospective recall [57]. Smartphone sensor and usage data collection were implemented using Android's accessibility services [1], running in the background. The collected sensor and usage data include user activity (e.g., walking,

[1]https://developer.android.com/guide/topics/sensors/sensors_overview

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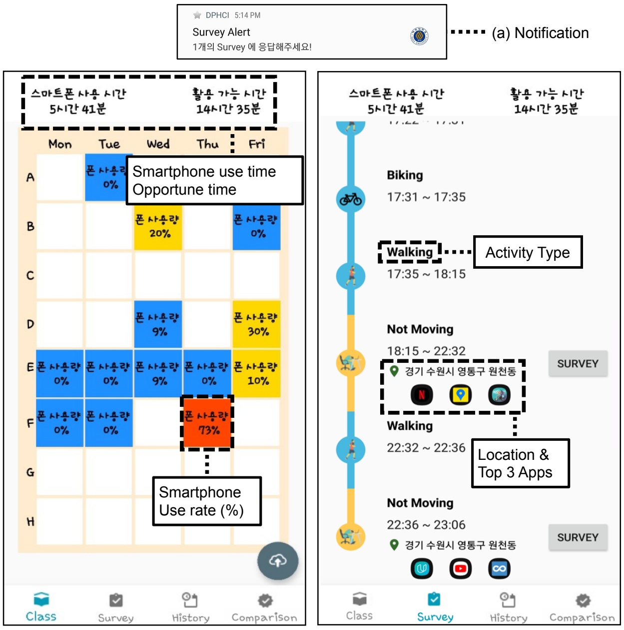
running, not moving), application usage log (e.g., application name, duration, start/end time), location, and notifications. We used Firebase [2] to automatically synchronize these sensor and usage data. Firebase is a real-time NoSQL database that stores data in a JSON format.



(b) Class (c) Timeline

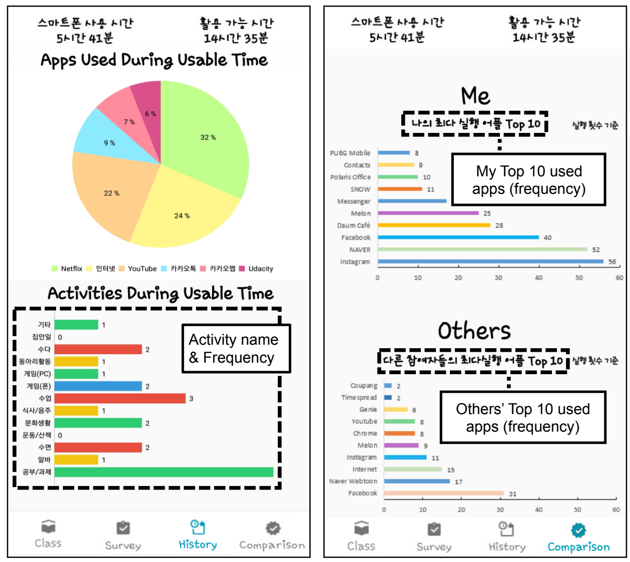
FIGURE 3. Screenshots of (a) Notification, (b) Class, (c) Timeline from *ATM*.

In addition, we collected students' course schedules and information data, EMA data related to opportune time (the stationary time of 30 min or more where sleeping hours were excluded), and self-reported data on students' day-to-day smartphone usage patterns. We collected the date, day, and start and end time information of the lecture to present a visualized summary of students' smartphone usage (%) during each class. Students gave direct input by touching the matched cells in the timetable. EMA data were collected when the opportune time ended. In other words, when a user starts using or carrying the smartphone again after at least 30 min of no detected movement, a notification (Fig. 3(a)) is sent to the user for collecting EMA data. Self-reported data was collected daily at every 9:00 p.m. by sending a notification to the students and asking for their feedback on the visualization reports on their day-to-day smartphone usage patterns.

ATM supports self-monitoring and self-reflection aspects of time management, and it consists of a fixed upper bar and four screens. We analyzed the collected sensor and usage data and provided different visualization reports from each screen to users as shown in Figs. 3, 4, and 5. The upper bar shows the total time of smartphone usage and the opportune time. Our goal of measuring this opportune time is to collect types of activities or application usage as well as to provide usage reports to users during that period. Through the usage reports, our intention is to give users an awareness of whether they use their time in a productive, useful way.

Regarding visualization feedback, *ATM* is designed to provide information related to (1) course (class), (2) timeline, (3) opportune time history, and (4) comparisons.

Class: The first screen (Fig. 3(b)) shows a visual summary of students' smartphone usage (%) during each class, where each cell represents 75 min of class time (e.g., Time A: 09:00-10:15; Time H: 19:30-20:45). Each cell uses three colors – blue (less than 10%), yellow (between 10 and 50%), and red (more than 50%) – depending on the degree of smartphone use during class. This screen is initialized to the default color (apricot) every Sunday at midnight.



(d) Opportune Time History (e-1) Comparison

FIGURE 4. Screenshots of (d) Opportune Time History and (e-1) horizontal bar graph for frequency-based top 10 used applications.

Timeline: The second screen (Fig. 3(c)) is designed to provide statistics on movement type and opportune time according to the student's timeline. The movement type is visualized using activity data collected by sensors, and the used activity type (e.g., walking, running, not moving, biking) is provided by Google fit [3]. Google fit provides integer constant values, and we used these values for consistency across applications. In the case of "not moving," if the duration of the activity exceeds 30 min, it is defined as opportune time in advance. Opportune time is displayed in yellow. Additional statistical information, such as location information and the most-used applications (top 3), is provided. Considering potential privacy issues, we exclude detailed location information in the visualization. Furthermore, at the end of every opportune time, the system sends a notification request asking the student to respond to a short questionnaire through

[2]https://firebase.google.com/

[3]https://developers.google.com/fit/

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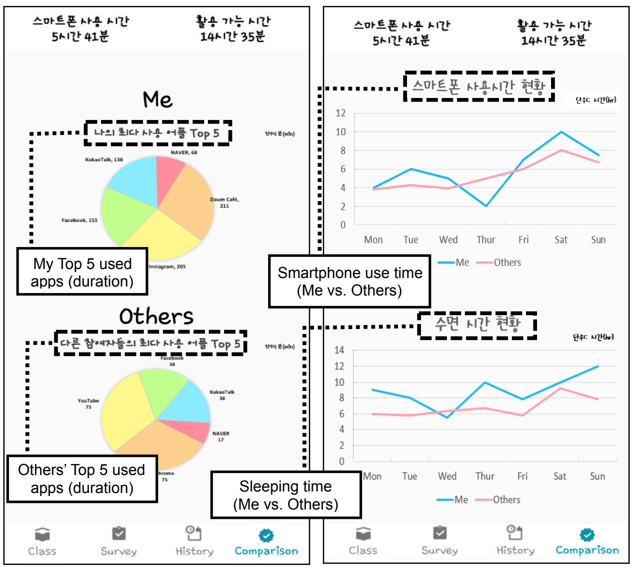
TABLE 1. Generalized Self-Efficacy (GSE) scale for the time management questionnaire

Q	Question
	Generalized Self-Efficacy Scale on Time Management
1	I can always manage my time if I try hard enough.
2	If something opposes me regarding time management, I can find ways to get what I want.
3	It is easy for me to stick to my schedules and manage my time.
4	I am confident that I could deal efficiently with unexpected schedules.
5	Thanks to my resourcefulness, I can manage my time for handling unforeseen situations.
6	I can solve most problems if I use my time efficiently.
7	I can remain calm when facing difficulties because of my time management skills.
8	When I am confronted with a problem, I can manage my time efficiently.
9	If I am in trouble, I can usually think of how to make priority of my work.
10	I can usually handle whatever comes my way.



(e-2) Comparison (e-3) Comparison

FIGURE 5. Visualizations for comparison from *ATM* in real-time.

EMA with the trigger method [58]. The EMA questionnaire consists of two questions asking which activity the student performed (e.g., studying, paying a video game, dining) and the student's satisfaction (5-point Likert scale where 1 means not satisfied at all and 5 means very satisfied) during the opportune time. Activities and their frequencies are presented as a horizontal bar graph on the third screen (Fig. 4(d)).

Opportune Time History: The third screen (Fig. 4(d)) shows the usage history of students' opportune time. We provide (1) a pie graph indicating the most-used applications (top 6) during the opportune time and (2) a horizontal bar graph presenting the performed activities during the opportune time. From the pie graph, we exclude applications that automatically run in the background and some health applications that are always running (e.g., cash walk [4]).

Comparisons: The fourth screen (Figs. 4(e-1), 5(e-2), and 5(e-3)) provides three visualizations that compare a student's personal smartphone data with the average of other students in real time. As shown in Figs. 4 and 5, the three visualizations consist of the most frequent running applications (top 10), the most-used applications (top 5), the most time-consuming activities during the opportune time, and the weekly trendlines of smartphone use hours and sleeping hours.

In this way, students receive a variety of visualization reports through the four interfaces and *ATM*-sent notifications every night (9:00 p.m.). Students can observe each screen of *ATM* and provide feedback related to their daily time management. In summary, through the design and implementation of *ATM*, we met factor (c), self-monitoring of and self-reflection on the performance, of our theoretically validated framework. We requested EMA and feedback using notifications to increase the periodic use of *ATM* and to empower self-monitoring and self-reflection aspects, and the effectiveness of (c) was proved through exit interviews.

VI. FIELD STUDY ON ATM USE

The main purpose of our field user study was to identify the viability of application-based self-regulation practice for time management among college students. In addition, we aimed to present design implications and other potential research questions that would guide future design and research directions.

TABLE 2. Intrinsic Motivation Inventory (IMI) for the time management questionnaire

Q	Question
	Intrinsic Motivation Inventory (IMI)
1	I enjoyed the activities for time management very much.
2	Time management was fun to do.
3	I thought scheduling was a boring activity.
4	The activities for time management did not hold my attention at all.
5	I would describe the activities for time management as very interesting.
6	I thought the activities for time management was quite enjoyable.
7	While I was scheduling, I was thinking about how much I enjoyed it.

We conducted a user study to verify the effectiveness of using *ATM* on (c) self-monitoring and self-reflection over performance outcomes and on (d) displaying high levels of self-efficacy and intrinsic motivation. We recruited 50 college students who use Android version 7 (Nougat) or higher

[4]https://play.google.com/store/apps/details?id=com.cashwalk.cashwalk

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smartphones via a bulletin board flyer, university research website, mailing list, and word of mouth.

We conducted a preliminary study as the second stage for the participating students. The questionnaire consisted of two sections: a section with questions about demographic variables (grade, gender, age range), and the other with questions related to GSE [21], IMI [22], and time management scale [59]. Tables 1 and 2 present the questionnaires of the two metrics: GSE and IMI. We conducted a pilot test with eight college students who did not participate in the user study and finalized the questionnaire after further correction and supplementation. The survey was conducted by sending survey URLs to students via email and text message, and the average response time of the survey was 5 min.

The third stage corresponds to an active use of *ATM*, including EMA and feedback responses for three weeks. At this stage, four students dropped out of the study halfway, and all data from these four students were immediately discarded. In the case of a feedback request, a notification was sent to all students daily at 9:00 p.m. If a student did not respond to an EMA, an additional notification was sent.

In the final stage, post-survey and exit interviews were conducted, which took 4 min and 20 min on average, respectively. The same questionnaires were used to examine the changes of (d) self-efficacy and intrinsic motivation. We conducted face-to-face exit interviews, asking open-ended questions regarding the effectiveness of time management and overall user experience with *ATM*.

A. PARTICIPANTS

All participants are Android smartphone users and were voluntarily recruited from a variety of sources, such as an university research website, and a mailing list. This study is approved by the university's Institutional Review Board. As the user study progressed, four students dropped out of the study halfway, and all the data from these four students were immediately discarded. Among the 46 students who completed the study from the pre-study to the exit interview, 44 students are undergraduates and 2 are graduate students. The college year demographics are as follows: 13 freshmen (28%), 9 sophomores (20%), 12 juniors (26%), 10 seniors (22%), and 2 graduate students (4%). They were from three colleges in Korea (university A (29 students; 62%), university B (15; 32%), and university C (3; 6%)). All of them were in their twenties, and 55% were male.

VII. USER STUDY RESULTS

A. THEMATIC ANALYSIS OF ATM USE

1) Awareness of unawareness

Many students spend the day with their smartphones, but there were some cases where they did not recognize their actual use behavior properly. Through *ATM*, we provided the students with information about smartphone usage time and the most-used apps, which allowed the students to recognize and be alerted to what they had been "unaware of."

TABLE 3. Smartphone usage trend slopes of the students (regression with a least square method). More than half of the students reduced their smartphone use.

PID	Smartphone Use Trend (Slope)	PID	Smartphone Use Trend (Slope)
1	-0.13	24	-0.01
2	0.15	25	0.18
3	0.08	26	0.09
4	-0.07	27	0.01
5	-0.04	28	-0.02
6	-0.08	29	0.13
7	0.23	30	0.00
8	0.00	31	-0.10^{*}
9	0.07	32	-0.01
10	0.06	33	-0.09
11	0.05	34	-0.01
12	0.02	35	-0.30^{*}
13	-0.02	36	0.01
14	0.05	37	-0.03
15	0.04	38	-0.07
16	-0.03	39	-0.14^{*}
17	-0.04	40	0.03
18	-0.10^{+}	41	-0.02
19	-0.01	42	-0.08
20	-0.01	43	-0.01
21	0.10	44	-0.07
22	0.06	45	-0.08
23	-0.10^{+}	46	-0.08

**p-value*$<$.05, $^{+}$*p-value*$<$*.10*

Surprise and awareness: The results of the exit interviews revealed that 45 students (98%) were surprised and alerted by the four compared statistics about their use of smartphones on a comparison screen. Consequently, 27 students (59%) achieved a decrease in total smartphone use hours during the user study period as shown in Table 3. In particular, five cells (students), highlighted in blue (P18, P23) and green colors (P31, P35, P39) in Table 3, showed statistically significant decreases. By looking at students' comments, we think that *ATM*'s visualization reports influence students' psychological factors such as surprise or increased awareness.

> *"Every time I turned on ATM, I felt a lot more aware of the timeline's colors and pie charts than I did, and I actually reduced my usage." (P37)*

> *"I have a feeling of psychological pressure like 'I wasted my times so badly' when the total smartphone usage time was shown. So, I pledged to reduce my smartphone usage time, and I think I actually reduced it a little." (P3)*

> *"I was alerted when I realized that I only use my smartphone for passing time." (P44)*

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TABLE 4. Top 10 applications used in a week. App usage logs normalized for each user and applications that were consistently in the top rank are gray. (R. refers to 'Rank,' and Prob. refers to 'Probability.')

Week 1			Week 2			Week 3		
R.	App Name	Prob.	R.	App Name	Prob.	R.	App Name	Prob.
1	KakaoTalk (Messenger)	0.53	1	KakaoTalk (Messenger)	0.53	1	KakaoTalk (Messenger)	0.51
2	Every Time (Community)	0.13	2	Every Time (Community)	0.12	2	Every Time (Community)	0.13
3	Naver (Browser)	0.09	3	Melon (Music)	0.08	3	Facebook (Social)	0.09
4	Facebook (Social)	0.08	4	Facebook (Social)	0.07	4	Naver (Browser)	0.05
5	YouTube	0.04	5	Naver (Browser)	0.04	5	YouTube	0.04
6	Internet	0.04	6	Instagram (Social)	0.04	6	Internet	0.04
7	Instagram (Social)	0.03	7	Internet	0.03	7	Instagram (Social)	0.04
8	Melon (Music)	0.03	8	Webtoon (Comics)	0.03	8	Message	0.03
9	Message	0.03	9	YouTube	0.03	9	Melon (Music)	0.03
10	Webtoon (Comics)	0.03	10	Gallery	0.03	10	TimeSpread (Schedule)	0.03

As mentioned above, the students were not exactly aware of their smartphone usage. The statistics and visualizations provided via *ATM* helped students understand their overall smartphone usage patterns.

Worse than the worst: All students (46) responded that EMA and self-reports, which were conducted for self-monitoring and self-reflection, helped them to realize their smartphone usage status and top-used applications. They said that they had decided to reduce their use of certain applications severely influencing on their daily lives and productivity. They consider those certain applications to be "the worst" applications based on their own standards. Interestingly, as students recognized and reduced the use of these applications, the use of the second most inferior applications increased greatly, making the total time spent on smartphones the same as in the previous usage time.

> *"I've deleted the most inferior application, and I expected that my total smartphone usage time would drastically decrease. However, the total usage time decreased only slightly as more time was spent on the second most inferior application." (P37)*

> *"In my case, I used the community app "Daum Cafe" the most. So, after I became aware of my smartphone usage status from the provided pie graph, I vowed to decrease my usage of the community application. Then, YouTube reversed the used app rank, and my total smartphone use time remained the same." (P35)*

Although students reduced their usage of the worst application on *ATM* for effective time management, they were not aware of their use of the second most inferior application.

2) Feedback preference

Students responded that their usage of applications is limited to a few as listed in Table 4, and some of these applications can be classified into three types: entertainment applications such as music applications (Melon) and YouTube, and social applications such as Facebook, Instagram, and community applications (Every Time). After analyzing the app usage logs for three weeks, we found that the apps used by the students and even the rankings did not show remarkable changes.

A narrow range of choices: We found that students mostly used 5 to 7 applications; thus, their smartphone usage pattern would be sufficiently reflected in those top applications. Therefore, the statistics for only the top used applications would be more helpful for examining the students' smartphone use.

> *"These days, we do a lot of activities on our smartphones, but only a few applications make me waste my time. So, I think it would have been better if the provided visualizations and statistics excluded some productive applications, such as alarm, voice recorder, and calculator." (P27)*

> *"I think that the applications that interfere with academic performance are always the same, which include YouTube and Facebook. Therefore, I think it will be a huge help to students if ATM can at least control those applications." (P23)*

Although students have several applications on their smartphones, they mention that there are only a few that are majorly used, and the applications that interfere with time management almost always remained the same. In addition, students have indicated that the system will be more advantageous if it limits the usage of these frequently used applications or provides real-time feedback on them.

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Differentiated feedback types: Based on smartphone sensor and usage data from the students, there are two major categories of applications that students mainly use: entertainment applications, including games and video streaming applications (e.g., Netflix, YouTube), and community applications including SNS (e.g., Instagram, Facebook, Every Time, which is an online university community application that only enrolled students can use) and weblogs. Entertainment applications have a relatively low running frequency but a long running time. On the other hand, students showed a tendency to unconsciously run community applications (as they feel a social connection when interacting with their peers).

> *"I think it's a good idea to give a reminder, like the online game, 'It's been several hours since you were playing,' rather than limiting the use of application itself." (P3)*

> *"I use smartphones mainly for Netflix and Instagram. I run Netflix once and use it for too long, while Instagram is habitually running. It would be more effective to let ATM know the total time spent on Netflix and tell me how many times Instagram has been running." (P33)*

It was noted by the students that to effectively enhance their time management skills, a system that helps them keep track of their smartphone usage and manage their time through a familiar feedback interfaces is needed.

3) Contextual but obvious use

It is difficult to judge whether students' self-regulation and learning is hampered by an increasing use of smartphones by the students. However, during the exit interview, students emphasized that smartphones are one of the biggest obstacles to self-regulation and learning, and smartphones served as a distraction during class time. The following two aspects demonstrate this.

Class usefulness: The results from exit interview revealed that 96% (44 students) of students used smartphones more than 10% (about 7 min) during class for something unrelated to the lecture. Therefore, the visualization criteria of yellow (between 10 and 50%) and red (more than 50%) can be a direct indication of low concentration during lecture.

> *"Generally speaking, students who use smartphones in class mean that they do not pay attention to the lecture. Sometimes, I search for English words and so on, but it only takes few minutes." (P37)*

> *"Nowadays, students usually use tablets or laptops in classes. But, from a student's point of view, using a smartphone during class is all about activities that are not related to classes." (P35)*

It is commonplace for students to use tablets and laptops in classes. However, they explicitly commented on the negative effect of smartphone use during lectures.

Uncomfortable rest: Several students mentioned that the quantity of their smartphone usages significantly increased when they experienced psychological pressure because of exams or assignment submissions. Such pressures gave them more free time (usable time) than usual as they tended to reduce the amount of time for outdoor activities, entertainment, or sleep. This naturally increased accessibility of their smartphones.

> *"The test period is a special period only for students who are obsessed with having to sit for longer periods than is usual. So, I feel like I'm still wasting my time using a smartphone while feeling uneasy." (P23)*

> *"Regardless of how hard students are studying during the test period, students lack sleep and make few appointments with their friends. That's why it's natural for students to have a lot of smartphone usage even during the test period." (P48)*

Although it was expected that students' smartphone usage should vary depending on context such as mid-term or finals period, students' use of smartphones did not differ much even during the test period.

TABLE 5. Differences in post- and pre-results of generalized self-efficacy and intrinsic motivation inventory. Cell in color (yellow for GSE, red for IMI) means an increase from the pre-results to the post-results. The highlighted cells indicate more than average post-pre values.

All Participants					
PID	**GSE**	**IMI**	**PID**	**GSE**	**IMI**
1	-0.33	0.17	**24**	-0.07	-0.11
2	-0.11	-0.04	**25**	0.04	-0.09
3	-0.27	0.06	**26**	-0.03	0.04
4	0.07	-0.17	**27**	0.02	-0.04
5	-0.08	-0.11	**28**	-0.11	-0.21
6	-0.01	0.11	**29**	-0.17	-0.28
7	0.11	0.16	**30**	0.18	0.05
8	-0.07	0.18	**31**	-0.27	-0.01
9	-0.26	-0.41	**32**	0.21	0.07
10	0.38	-0.19	**33**	-0.18	-0.28
11	-0.53	0.53	**34**	0.45	-0.09
12	0.37	-0.11	**35**	-0.55	-0.11
13	0.00	-0.76	**36**	0.13	-0.05
14	0.00	0.16	**37**	0.19	-0.10
15	-0.78	-0.17	**38**	-0.05	-0.27
16	0.09	-0.14	**39**	-0.21	-0.02
17	0.24	-0.18	**40**	-0.06	-0.52
18	0.03	-0.02	**41**	0.08	-0.14
19	-0.15	-0.02	**42**	0.15	0.32
20	0.00	0.18	**43**	0.02	0.07
21	-0.20	0.26	**44**	0.18	-0.04
22	0.07	0.00	**45**	0.23	0.01
23	-0.19	-0.24	**46**	-0.04	-0.05

B. PERCEPTION CHANGES IN SELF-REGULATION

Finally, as for completing (d) from the theoretical model, we measured the differences in the self-efficacy and intrinsic

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motivation reports between the pre and the post-surveys. Table 5 hows the differences between pre- and post-survey responses for all students for generalized self-efficacy (GSE) and intrinsic motivation inventory (IMI). We normalized post-pre values for the analysis. The highlighted results indicate more than average post-pre values, and there were few cases where both scales increased. There were many cases where one of the scales increased (GSE: 57%, IMI: 54%). This result demonstrates that effective self-control and self-reflection based on visualizations may be possible on a mobile application.

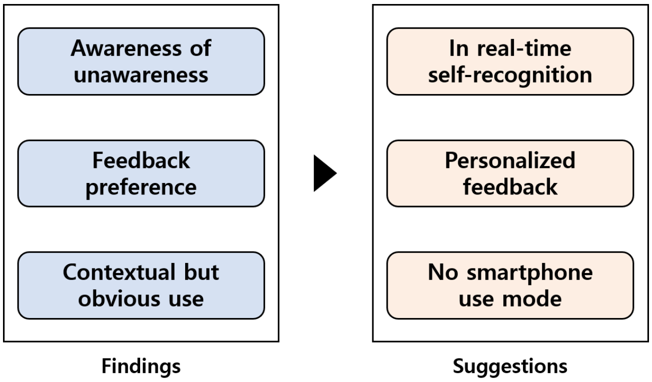
We further grouped the students into two based on the time management scale [59] from a pre-survey: low (below average) and high (above average). Subsequently, we analyzed each group's normalized post-pre values for the two scales. The results confirmed that the post-pre values from the low group (avg. of self-efficacy: 0.11, avg. of intrinsic motivation: -0.01) were higher than those from the high group (avg. of self-efficacy: -0.01, avg. of intrinsic motivation: -0.72). In particular, the post-pre values for self-efficacy on time management were statistically significant ($t(44)$ = 6.26, p = 0.016). In other words, both the changes of self-efficacy and intrinsic motivation in the low time management group exhibited greater changes than those in the high time management group. This partially indicates that *ATM* is quite effective on students who needed to regulate themselves on time management.

VIII. DISCUSSION

A. FEEDBACK DESIGN IMPLICATIONS

In section VII - *A*, we highlighted three primary experiences in time management: (1) *Awareness of unawareness*, (2) *Feedback preference*, and (3) *Contextual but obvious use*. As shown in Fig. 6, we identified aligned design implications that give more effective ways to support "time management" for students in the future through the post-survey and exit interviews.

FIGURE 6. Findings and their corresponding suggestions.



1) In real-time self-recognition

Students appreciated the fact that *ATM* provides real-time statistics and visualizations, as well as comparative analyses with others. In addition, students responded that it would be a more effective tool for time management if *ATM* could provide real-time statistics and visualizations easily and more conveniently.

> *"ATM does not have a compulsory function, but it compares my usage time with that of others in real time, so I tried to change my habits. Furthermore, I hope ATM will send me more notifications so that I can be made aware of my smartphone usage patterns more frequently." (P2)*

> *"I liked that EMA asked me what I did at the end of my opportune time in ATM. As I had to reflect on how I wasted my time, I tried to spend my next opportune time in a better way." (P17)*

We have confirmed that students want to be more easily and frequently aware of their smartphone usage behaviors to better manage their time. As students are positive about the self-monitoring aspects of *ATM*, it would be desirable to provide proactive yet unobtrusive feedbacks to them. For example, the system can be designed to have a fixed status bar or display a prompt window, showing a report on the user's smartphone usage for a certain time period, so that they can quickly view their usage reports. Although a similar function is provided by Apple's Screen Time [5] or Android's Digital Wellbeing [6] applications, those applications only rely on and show the reports of "application" usage.

2) Personalized feedback

Each student has different applications that he/she mainly uses; however, the number of such applications is somewhat limited (5-7 applications). We found that there are two major categories of such applications: *entertainment* and *community*, and the students have a preferred notification type for each category. For Entertainment, students mentioned that it is more effective to give feedback on total usage time. For community, students mentioned that it would be more effective to provide feedback on the execution frequency rather than total usage time.

> *"I mostly use YouTube and Instagram, and I think it would be nice if I can set the total usage time limit for YouTube and the frequency limit for Instagram because the ways to use them are different." (P44)*

> *"I found out through ATM that I run SNS more than 50 times a day. It would be better if I can get an additional report from ATM on heavily-used apps like Facebook in my case." (P13)*

As mentioned above, students desired statistics and visualizations of their frequently used applications. Furthermore, if *ATM* provides different (or more user-preferred) types of feedback based on the type of the application, it will provide more effective statistics and visualization for time management.

[5] https://apple.co/2OuXELS
[6] https://bit.ly/2RvvL7S

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3) No smartphone use mode

Students were highly skeptical about the advantages of using smartphones during class hours. Even during test periods, students' smartphone usage behaviors did not differ greatly. Therefore, the students responded that, during certain times and places, they needed some degree of coercion (e.g., locking the smartphone) so that they are not distracted by their smartphones.

> *"I'd like ATM to help me avoid my smartphone at least during lectures since I always regret using my smartphone in class later." (P21)*

> *"I cannot control my own smartphone usage even during the test term. So, I hope I get more notifications about smartphone usage, at least during the test term." (P31)*

As mentioned above, most students viewed their smartphone usages while being engaged in class-related tasks or activities (e.g., during lecture, working on assignment), which had negative impacts. They wanted to enforce self-monitoring and self-reflection aspects of *ATM* more than usual, especially for such class-related tasks or activities.

B. MISCELLANEOUS IMPLICATIONS

1) I need my private time

Students did not want to be notified about all types of smartphone usage, and before and after specific activities. Based on the interview results, interestingly, most of the student participants said they did not want to be disturbed by any feedback or notifications for some time before going to bed. They mentioned that they felt relaxed during that time and did not want to be interrupted or alerted assuming they were doing something wrong.

> *"I always watch YouTube for one or two hours before I go to sleep. I wish that no one would disturb me at this time." (P48)*

> *"I watch Netflix to compensate for my hard work for at least an hour even in the test period. I want to finish the day in my own way." (P27)*

However, there were those who wanted to be alerted if they used their smartphones excessively before bedtime. Thus, it would not be the best strategy to simply allow students to use their smartphones without any restrictions. As we found that several students were positive about receiving comparison reports on their smartphone use, it might be useful to identify the time that most students use their smartphone excessively and provide comparison reports on smartphone use during that period. This might help some students regulate their smartphone usage during a specific time period (such as before bedtime).

2) 60 minutes: Minimum minutes for productive activity

In response to the minimum amount of time required for self-defined productive activities, 61% (28 students) of the students answered 60 min (30 min (15%), 90 min (13%), 120 min (11%)). Students who chose "60 min" said that most of the classes were between 50 and 75 min, and the personal preparation time required for concentration was at least 10 to 20 min.

> *"If you start something, even though it is simple, it takes more than 10 minutes to prepare. I think 30 minutes is too short to call something productive." (P27)*

> *"I feel like 30 minutes is too short to do something and I have not been able to concentrate well for over an hour. I think 60 minutes is appropriate for me to do something productive." (P31)*

We found that students' preparation time for a certain task varies from one student to the other, and that the opportune time of 60 min would be the most appropriate for our future work. However, we do not believe such a time range would be applicable to every user. Given the fact that people tend to have different criteria, it would be more reasonable to allow them to manage and track their usable (or opportune) time in a more flexible way.

C. LIMITATIONS

While our study presents many insights and potentials about self-regulation on time management, we acknowledge some limitations.

First, our study results may not be generalizable because we performed the user study with 46 students for only three weeks. Because of this, our study may not strongly influence students to actually alter their behaviors. For example, a statistically significant decrease in total smartphone usage time during this user study period was only seen in five students, although 27 students (59%) achieved a decrease in total smartphone usage hours during the user study period. In this regard, we plan to conduct a large-scale study (with more users and longer time period) on self-regulation of time management. In addition, we believe a large-scale study will present more potential and design implications for self-regulation of time management through a smartphone.

Second, although we recruited students with various backgrounds, most of them (29 students, 62%) attended the same college, so the population diversity in our study was slightly limited, and the study findings are not generalizable for all college students. To address this, we are planning to conduct a multi-campus user study to derive more comprehensive results, as a future work.

IX. CONCLUSION

Although students' excessive use of smartphones is indeed a problem in our society, we need to acknowledge that students' smartphone use is inevitable; therefore, restriction on its use would not be a good solution. Prior work has emphasized the key role that self-regulation of behavior changes plays in achieving positive outcomes and experiences. Our research is motivated by the lack of studies on students' self-regulation of smartphone usages and is grounded by a theoretical framework to support such a psychological aspect.

We identified time management as a common strategy for students to achieve their goals by a bottom-up approach, and developed a mobile application, *ATM*, to support self-control and self-reflection aspects of self-regulation. Using *ATM*, we conducted a field user study and collected demographic information, course information, smartphone sensor and usage data, EMA, and self-reported data for a three-week period from 46 college students. As a result of the user study, we identified three findings: (1) awareness of unawareness, (2) preferred feedback, and (3) contextual but obvious use. Lastly, we presented future design implications for supporting self-regulation of time management in a more effective fashion.

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