GOAL: Supporting Learner's Development of Self-Direction Skills using Health and Learning Data

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Abstract: For the 21st century learner, self-direction skill is crucial for developing both intellectual abilities and maintaining one's healthy lifestyle. While there are technology supports for specific self-regulated learning tasks and health monitoring, research is limited on how to support development of the meta-skill of Self-Direction itself. Our work bridges Learning Analytics (LA) and Quantified-Self (QS) research to enable technology support for self-directed activities of learners. We propose DAPER (Data-Analyze-Plan-Execution monitoring-Reflect), a data-driven Self-Direction skill execution and acquisition model. To support synchronize-visualize-analyze multisource data regarding learners' learning and physical activities, we are developing the GOAL (Goal Oriented Active Learner) system. In this paper we present our DAPER model, the initial implementation of the GOAL system based on that model and pilot study regarding the need and context analysis of this research.

Keywords: Learning Analytics, Quantified Self, Self-direction skills, wearable and mobile technology, GOAL system, DAPER model

1. Introduction

Self-direction skills (SDS) are considered a necessary skill in this 21st century (P21 framework, 2015; enGauge 21st century skills 2003; SCANS report 1991). University students often carry out multiple activities in their daily lives and SDS would be crucial to maintain academic performance as well as healthy lifestyle. But we did not find any research work which supports SDS skill acquisition for those individuals based on their own context and data. Currently the health and the learning data are often collected in separate data silos. Wearable technologies such as smart bands and watches (e.g. Fitbit, Apple watch, etc), assist to automatically log user's physical activities like number of steps taken, calories burned, and physiological parameters like heart beat rate, pulse rate, etc. On the other hand, Learning Analytics (LA) focuses on data logs from various technology enabled teaching learning environments. Learning logs from eBook environments such as reading patterns and annotations made can be analyzed with respect to learner's engagement and learning outcomes (Akçapınar G. et.al, 2018). Our overall research agenda is to find how data-driven technology can support SDS acquisition.

In this paper we propose DAPER (Data-Analyze-Plan-Execution monitoring-Reflect), our model of data-driven SDS execution and acquisition. We develop the GOAL (Goal Oriented Active Learner) system to support DAPER model. The technology synthesizes personal health and learning data logs from multiple sources and present it to the learners. We report finds of pilot surveys done during the need and context analysis of this GOAL project.

2. Background and related works

Our context revolves around the process of learner's acquisition of SDS. We first synthesize the definition of SDS from current literature. Our approach to support SDS acquisition is by providing learners their own data to reflect on. So, we look at existing techniques from the domain of

Quantified Self (QS) and Learning Analytics (LA). We highlight some limitations of existing mobile applications to motivate our work to design and develop a system that can support SDS execution and acquisition.

2.1 Self-Direction Skill

Discussions around the 21st century skills emphasize that individuals in general and learners in specific need to develop the skill to be self-directed. According to P21 framework (2015), *Initiative and Self-Direction* requires monitoring one's understanding and learning needs, demonstrating initiative to advance professional skill levels, defining, prioritizing and completing tasks without direct oversight and demonstrating commitment to lifelong learning. According to enGauge 21st century skills (2003) *Adaptability, managing complexity and self-direction skills* includes students being able to set goals related to learning, plan for the achievement of those goals, independently manage time and effort and independently assess the quality of learning and any product that result from the learning experience. It also requires students to handle multiple environments, goals, tasks, and inputs while understanding and adhering to organizational or technological constraints of time, resources, and systems. According to SCANS report (1991) *Self-management* assesses own knowledge, skills, and abilities accurately; set well-defined and realistic personal goals; monitors progress toward goal attainment and motivates self through goal achievement; exhibits self-control and responds to feedback unemotionally and nondefensively. It leads the learner to be a "self-starter".

While 21st century skills are more generic framework of overall skills required in this age, Self-directed learning (SDL) and Self-regulated learning (SRL) explores the various phases in the process of acquiring the necessary learning skills and designing pedagogical supports. Literature highlights their commonality and differences (Loyens, S. M., Magda, J., & Rikers, R. M. 2008; Saks, K., & Leijen, Ä, 2014). Both SDL and SRL have 4 key phases: Task definition – Setting goals and Planning – Enacting strategies – Monitoring and Reflecting. They assume intrinsic motivation and goal orientation. While SRL is rooted in educational psychology and is mostly studied in school level learners our context of university students is more near to the SDL. We conceptualize Self-direction Skill (SDS) as a meta skill and consider the phases of the process similar to SDL.

2.2 Quantified-Self and Learning Analytics

Quantified-Self movement (Choe et.al. 2014) emphasizes on the importance of the regular collection, processing, and presentation of data on behavioral indicators, environmental indicators or biological indicators as measures to evaluate personal performance so that individuals can better achieve progress in their areas of interest. Individuals with focus on the setting process-oriented goals are often interested on the stream of data regarding their own activities during that process to monitor goal accomplishment and if necessary re-plan. But keeping track of variables of interest is often time consuming as data collection is not unified in one application.

Learning analytics research on the other hand has generated infrastructure to assist gather and analyze data from teaching learning context to improve learning experience and understand how learning happens. In our context, we have previously developed learning tools to support both in-class and out of class learning. BookRoll is an e-book reader which supports in-class teaching (Yin, C. et.al, 2015). It can be integrated into university's Learning Management System (LMS) through Learning Tools Interoperability (LTI) standards to give students access it through LMS directly. SCROLL (Ogata et al. 2011) is an informal language learning tool ubiquitous learning tool to support language learning. These systems log learning footprints such as learner actions in the tool and their generated artifacts. To analyze these log data for research and visualize it for students and teachers the LA dashboard is built within the LA framework (Flanagan B. & Ogata H., 2017). The current work extends the scope of the framework to include learner's health data and support with goal setting and monitoring based on that unified dataset.

2.3 Related works

Recently developed QS applications assists users to collect, analyze and plan with their personal data. But most of these applications are very focused on tracking single function and hence limited in the type of data that they deal with. Some of them are physical activity trackers (Google Fit, Apple Health, FitBit Applications, Nike+, Pedometer++) and uses sensors in the mobile devices like accelerometers and GPS. Applications like Lose It!, Lifesum, MyNetDiary Calorie Counter focus on dieting and use features like calories counter, online diet logs, personalized diet plans for weight loss. Sleep cycle alarm clock and Sleep better are applications which track sleeping habits but still doesn't support goal setting. In the context of vocabulary learning some applications like Studyplus, TEDICT, Mondly help students to set goals and review their vocabulary achievements. But most of them are not based on any research paradigm. We only found, StudentLife (Wang, R. et.al. 2014) as a mobile application developed for an academic research study. It collected 48 student's data over 10 weeks from their mobile phone use to build predictive models for assessing student's mental health and study correlation of behaviors and academic performance. Our research focuses on supporting SDS acquisition by integrating both learning and physical activity data of learners, which to our knowledge it is a novel endeavor by itself. In the next two section we present our model of SDS acquisition and its associated support application.

3. DAPER model of Self-Direction skill execution and acquisition

We present the DAPER model to conceptualize the process of SDS execution and acquisition. It has five phases which can be informed by data and supported with different ICT tools and applications. Figure 1. introduces the model and the associated features at each phase.
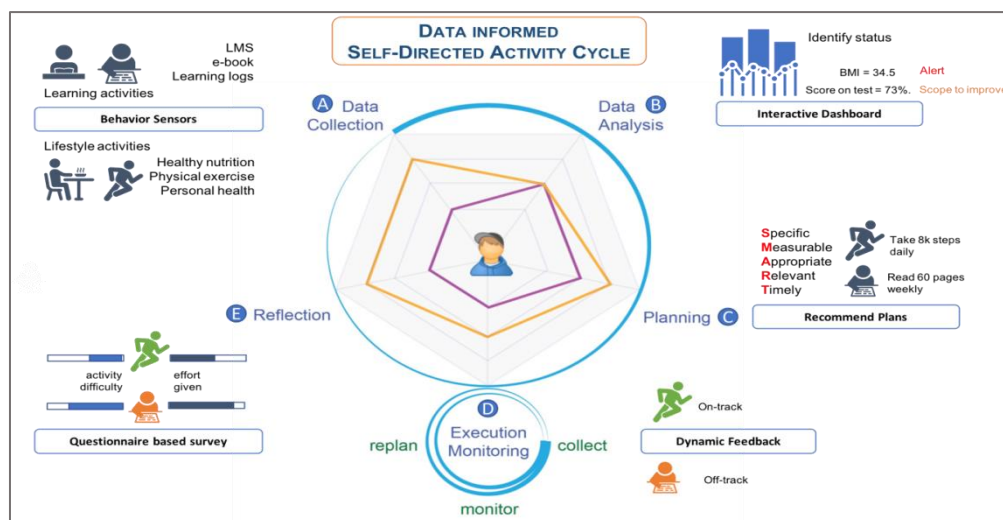

Figure 1. DAPER model of self-direction skill execution and acquisition

A. Data Collection

In the data collection phase, the individual collects initial behavioral data regarding the activities which they want to execute in a self-directed mode. Some of those data can be automatically logged with the help of physical sensors like the gyroscope in a wearable or mobile device which is used to compute steps taken from the user's movements data. On the other hand, virtual sensors are the applications which can log interaction behaviors of the users. For example, e-book readers like BookRoll, logs readers interactions such as reading time and annotating on e-books. Apart from automatic logging from multiple behavior sensors, users can also add their own log manually in the data collection phase. For instance, logging their calorie intake after a meal or time to go to bed for sleep.

B. Analysis

After data collection, in the analysis phase the individual can conduct simple analysis tasks to understand their activity trends and identify problems if any. Broadly these tasks deal with comparing the collected data with standard levels or with the group and understand trends. For

example, given their recorded sleep data, learners can analyze whether their sleeping time is maintained around the same hour or varies. Given their learning data, such as past quiz scores in a subject they can check their performance trends.

C. Planning

In the planning phase the individual sets SMART (Specific, Measurable, Appropriate, Relevant and Timely) goals regarding any activities whose data was analysed. Being aware of their own trends from the analysis phase aids them to plan accordingly.

D. Execution monitoring

In this phase the plan is executed and the individual collects data to monitor progress. For example, an individual may monitor their heart rate during a specific physical exercise. In the learning scenario, a student might monitor the completion of their course content before an upcoming assessment. This phase often includes multiple cycles of re-planning and execution monitoring.

E. Reflection

In the reflection phase the individual reviews the whole process of the SDS execution. It involves evaluating the ease of each tasks and their efforts given for their chosen activities. The individual further reflects on the effectiveness of their set plan, identify if any specific strategies were used to execute the plan and their note benefits and costs based on the outcome of that activity.

4. GOAL system

Goal Oriented Active Learner (GOAL) system supports the DAPER model of SDS acquisition and execution. We chose two domains to scope data collection in context of self-directed activities, one related to e-book based learning and other maintenance of healthy life style. In this section we describe the overall architecture of the system, and the user workflow with its associated mobile application.

4.1 Architecture

The GOAL architecture is given in Figure 2. It includes cross platform applications and an analysis server. The users open a common web user interfaces through the mobile application (iOS, Android) or on web browser of any device. User requires a one-time authentication via their LMS. For instance, in Kyoto University students authenticate through the Sakai LMS to open the application for the first time and then the UUID token generated by the LMS is used for anonymously linking user data. This follows our previously implemented LA framework to bridge production and research system (Flanagan B. & Ogata H., 2017).

Native applications such as Apple Health or Google Fit records the physical activity data like steps taken. Our GOAL client directly synchronizes data with the native app and pushes the data to the analysis server. The learning data will be accessed in real time from the learning platform by using APIs. In upcoming version user can also input records manually.

The analysis server consists of four modules: plan, activity, analysis and recommendation module. The plan module handles users' goal management. The activity module collects the log of learning activities and health activities. The analysis module synchronizes the actual learning and health activity logs with their corresponding goals. The recommendation module will recommend plans and feedback based on the tracked data.
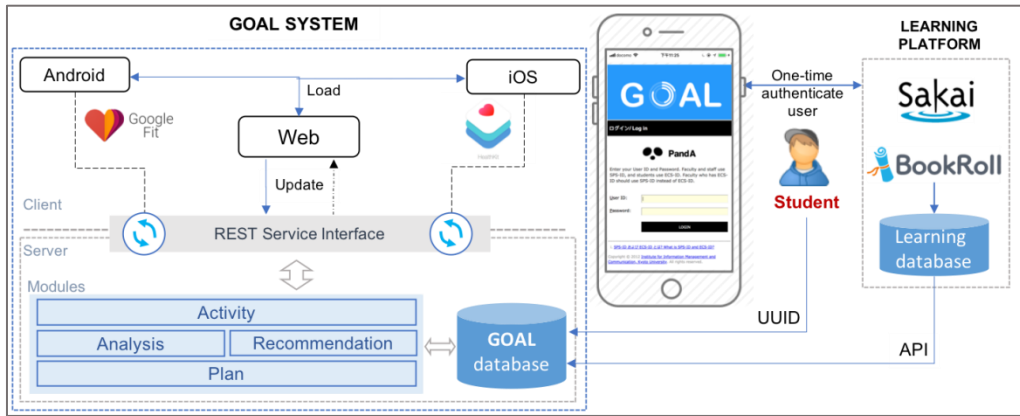
Figure 2. Architecture of the GOAL system

4.2 iOS Mobile Application

For the pilot study, we developed the iOS application as the front end. This decision was taken based on an entry survey where 54% of the interested participants said they use iPhones and 63% wanted to use Apple watch and Apple Health application to synchronize their activities. We also had in-house expertise of iOS development.

After installation of the application and the user can do a one-time login via authenticating through the set university LMS credentials. Then home screen displays the percentage completion of specific activities that are being tracked and can has options for the users to set Goals and Monitoring details of activities (Figure 3a. below). The Goal setting menu leads to selecting the frequency of the goal (Figure 3b.) and then setting the specific activities related to it (Figure 3c.).

a.   b.   c.

Figure 3. a. Home screen *b.* Goal frequency selection *c.* Activity value setting

For the monitoring function the user has two modes. The first mode is temporal monitoring. Here the graph visualizes the presence or absence of specific activities in a given hour of day via a simple heatmap (Figure 4a.). The other mode is completion monitoring. Here the recorded value is displayed as a bar chart (Figure 4b.). For the reflection phase we are currently developing a spider graph (Figure 4c.) to visualize users rating on each of the five subskills of SD.
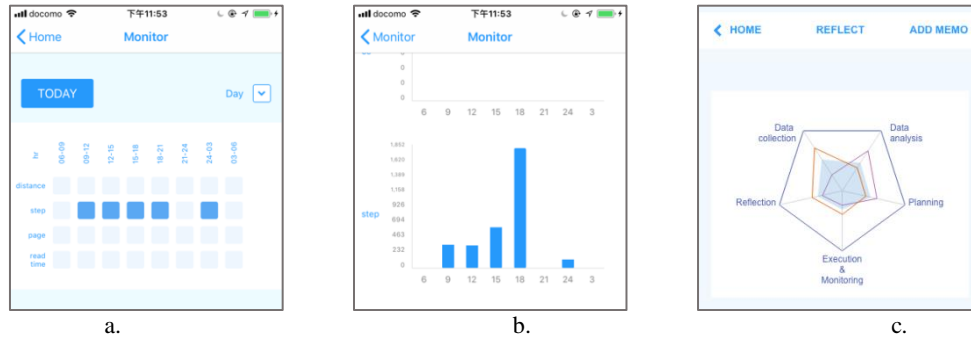
| a. | b. | c. |

Figure 4. a. Temporal monitoring *b.* Completion monitoring *c.* proposed Reflection graph

4.3 User Consent and Agreement for Data Collection

Apart from the initial consent taken from the user the current GOAL app also takes user's authorization to synchronize with iOS Healthkit. The GOAL app pushes the data log only after the authorization. The data is synchronized from the fitness module (steps and the distance logs) and the body measurements module (weight, height) of Healthkit. The system allows to update the consent agreement to stop logging the data.

5. Pilot Study

5.1 Research Questions

Our overall research object is to *design technology platform to support learners' self-direction skill acquisition with data-driven techniques.* We scope the domain of the self-directed activities to students learning and physical activities. To conduct the need and context analysis of our research objective we have the following three research questions (RQ):

RQ1: What is the intrinsic value and current ability of self-direction skill for the participants?

RQ2: To what extent and why did the participants take technology support for the various phases of self-directed activities prior to the exposure to GOAL system?

RQ3. To what extent did the participants practice health-promoting lifestyle?

5.2 Methods

Sample
We give an open call of participation to the new students of social informatics graduate school at Kyoto university. This included a 5 minutes presentation during the freshmen orientation sessions, separately for the Japanese students and the international students. There were 14 participants who participated in the ongoing pilot study (9 Masters students, 3 Doctoral students, 2 Postdoctoral fellows). There were 4 females and 10 males representing 9 different nationalities.

Introduction Session
The GOAL project was introduced to the participants and the application workflow was demonstrated to them. We organized monthly face to face reflection sessions with the participants to gather surveys response, feedback and conduct co-design activities to update the features of the application as found fit.

Data and Analysis
All the RQs were answered by conducting surveys with the participants. For RQ1, we solicited participants' perception regarding the importance of each SDS phase corresponding to the DAPER model (1-Not at all important to 5-Very important) and their current skill set in the activities in those phases (4-Excellent, 3-Good, 2-Adequate, 1-Needs improvement). We analyzed transitions in responses for each participant with iSAT (Majumdar R. & Iyer S, 2014).

For RQ2, we asked the participants whether they used technology to support SDS phases during any of their learning, physical or health care activities and if yes, why.

For RQ3 we used the Health-Promoting Lifestyle Profile (HPLP II) survey (Walker, S., Sechrist, K., & Pender, N. 1995). Out of the six dimensions in HPLP II, we selected twenty five items from five dimensions that focus on Nutrition, Physical activities, Health responsibility, Stress management and Spiritual growth. The participants responded their frequency of specific item (Never, Sometimes, Often, Routinely) related to these dimensions. Each item is scored based on the frequency on a scale of 4. We report the average score in each dimension and total score of everyone.

5.3 Results

To answer RQ1, the mean rating of importance across all the SDS phases is 4.36 (s.d. 0.44) and their mean rating of ability perception was 2.59 (s.d. 0.69). This was the aggregated value for all the participants (N=14). iSAT highlighted specific cohort dynamics with respect to the transition proportion of ratings across perceived importance to their own skill level corresponding to each SDS phases. Figure 5a. and 5b. gives the transitions for the data collection and the data analysis phases. For instance, 57% participants perceived data collection was very important (rated 5) and out of them 75% perceived they were good (rated 3) at data collection. Similarly, out of 57% of the participants who rated data analysis important (rated 4), 62.5% believed to have adequate skill (rated 2).
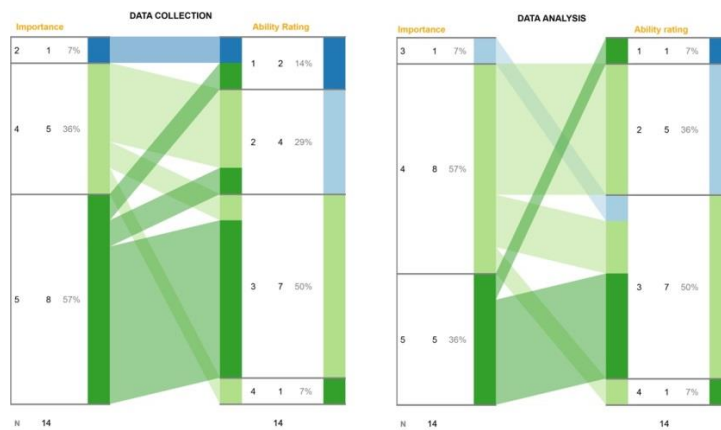

Figure 5. Survey response transitions for a. Data Collection and b. Data Analysis

Figure 6a, 6b and 6c highlights the transitions for planning, execution and reflection phases.
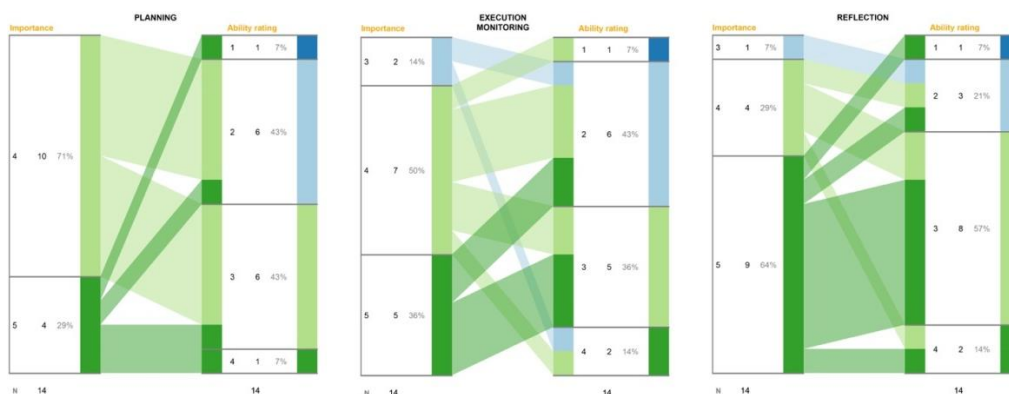

Figure 6. Survey response transitions for a. Planning b. Execution monitoring c. Reflection

To answer RQ 2. the survey results are given below in Table 1. It describes the number of participants who used technology to support phases of SDS in either learning, physical or health related activities prior to the use of GOAL system. We found more than half of the participants did not utilize technology previously for any specific SDS tasks. The ones who used, mostly collected in the context of physical activities and used in planning and monitoring. In the context of learning, 3

(21%) participants used technology for monitoring and reflecting. In Table 1 we also list the specific example activities that the participants mentioned to track and use their data in each phase of SDS.

Table 1. *Prior extent of technology use in different phases of SDS execution*

(N=14)	Data Collection	Data Analysis	Planning	Execution Monitoring	Reflection
None	8 (57%)	13 (93%)	10 (71%)	9 (64%)	9 (64%)
Learning	2 (14%)	1 (7%)	1 (7%)	3 (21%)	3 (21%)
Physical	4 (29%)	1 (7%)	3 (21%)	4 (29%)	2 (14%)
Health	4 (29%)	1 (7%)	1 (7%)	2 (14%)	1 (7%)
Activities used for	Collect LMS data, Steps, Menstrual cycle, Calorie counter, Heart beats	-	Scheduling lectures and meetings, Menstrual cycle, dieting	Vocabulary learning for JLPT, Steps	Vocabulary learning performance

To answer RQ 3, Table 2 reports the results of the health promoting lifestyle survey for each participant. The items in each dimension are clubbed together and its average value is reported. 4 indicates 'Routinely' (desirable) and 1 indicates the undesirable 'Never' response. The heatmap can be viewed as a reference to identify trend across dimension for a participant (column wise) or each dimension (row wise). For example, it could be inspected that one of the MS students gave the lowest self-rating in four dimensions but rated 3 in *Growth* dimension. Also, *Health Responsibility* had lower ratings among dimensions.

Table 2. *Results of Health Promoting Lifestyle survey*

Item # in HPLP II	Dimensions and items	MS	MS	MS	MS	MS	MS	MS	MS	MS	PHD	PHD	PHD	PDF	PDF
2, 8, 14, 20, 26, 32, 38, 44, 50	**Nutrition** Choose diet, controlled eating, eat breakfast, read labels to identify diet components	2.7	3.0	3.3	2.6	2.1	2.7	2.2	2.1	1.3	3.4	2.3	2.0	2.6	3.0
4, 10, 16, 22, 28, 34, 40, 46	**Physical Activities** Follow planned exercise, take part in physical activities, Check pulse rate, etc.	2.9	2.9	2.3	1.9	2.0	1.8	2.0	2.1	1.1	3.0	2.5	2.3	1.8	2.9
3, 9, 45	**Health Responsibility** Read, browse or attend programs related to personal health, report unusual sign to doctor	2.0	2.3	1.3	2.0	1.7	1.7	1.3	2.0	1.3	2.7	1.7	1.7	2.0	2.0
5, 11, 35, 41	**Stress management** Balance time, enough sleep, relax, meditate	3.5	2.3	2.0	2.0	2.3	2.0	3.0	2.3	1.8	2.3	2.5	2.5	2.5	2.0
30	**Growth** Work toward long-term goals in my life.	4.0	3.0	4.0	4.0	3.0	2.0	2.0	3.0	3.0	3.0	2.0	4.0	1.0	3.0
	Total Score	79	77	71	63	58	59	61	60	39	83	65	61	61	74

5.4 Discussion

The answers to the three research questions seeks an understanding of the context of SDS while assessing status amongst the participants. To answer RQ1, *What is the intrinsic value of self-direction skill for participants and their current ability?,* iSAT analysis highlights trends regarding participant's perception of importance of certain phase of SDS and their current ability rating. On an average 44% perceived each of the 5 phases is very important. For self-rating on an average 43% were either adequate or required improvement in their skill. It highlights both the opportunity to support students who believe they have the skill and train others who wants to improve.

Though participants perceived that the phases were important and they had the ability to execute the required actions in the phase, their actual practice was reported low. To answer RQ2, *To what extent and why did the participants take technology support for the various phases of self-directed activities prior to the exposure to GOAL system?,* we found most participants didn't use the technology support for any of the phases. Some reported to use in learning context for vocabulary learning using mobile applications. They could plan how many new vocabularies they would learn and monitor progress and reflect based on formative assessments in the application. In the context of physical activities, some tracked steps and calorie burn during workouts. One participant collected data regarding her menstrual cycle in the context of health-related activities.

This indicates the need of specific contexts with further activity task design to enable the users to actively engage for developing their SDS skills.

This observation led us to investigate a specific context regarding the personal health and lifestyle of individuals. To answer RQ3, *To what extent did the participants practice health-promoting lifestyle?,* we choose items from HPLP-II survey (Walker, S., Sechrist, K., & Pender, N. 1995). We found items related to health responsibility has lowest frequency across participants. This profiling would further help us to cluster the participants and track their app usage patterns and compare behavior outcomes.

Though this need and context study had only 14 participants, still it was crucial for overall systematic design of GOAL system. With initial response of only 8 participants, the reported average SUS score of usability was 65.4 (s.d. 17.4) indicating marginally high acceptance (Bangor A., et.al. , 2008). The monthly meetings with the participants and their feedback helped to take design decisions during the development process and further refine our plan for the next longitudinal study. The ongoing pilot study highlights a gap in learning context to support planning-monitoring-reflection aided with personal data. Current availability of fitness trackers, already exposes users to tracking and monitoring physical activities. Hence, with the GOAL system, integrating the health and learning data would help us test common training design modules for SDS taking both health (more exposed) and learning (less exposed) as contexts.

6. Conclusion and Future work

6.1 Contribution

We proposed a five-phase DAPER model of Self-Direction Skill execution and acquisition. It is informed from prior models of self-directed and self-regulated learning but explicitly emphasizes on data driven phases. We scoped to health promotion and learning activities related data. This paper describes the design and development of the GOAL system to synthesize health and learning data from multiple source. The primary focus of the system is to help learners collect, analyse, plan and monitor their physical and learning activities, having full access to their data. We used the LA infrastructure established in the Kyoto university and augmented the developed iOS application in it via LTI to collect the required health data. This also ensures data privacy by anonymizing the user identity following established LA framework (Flanagan B. & Ogata H., 2017). A sample of the collected data for one participant through the GOAL system is presented in Figure 7. It visualizes a temporal view across the day where each activity value is aggregated ever hour.
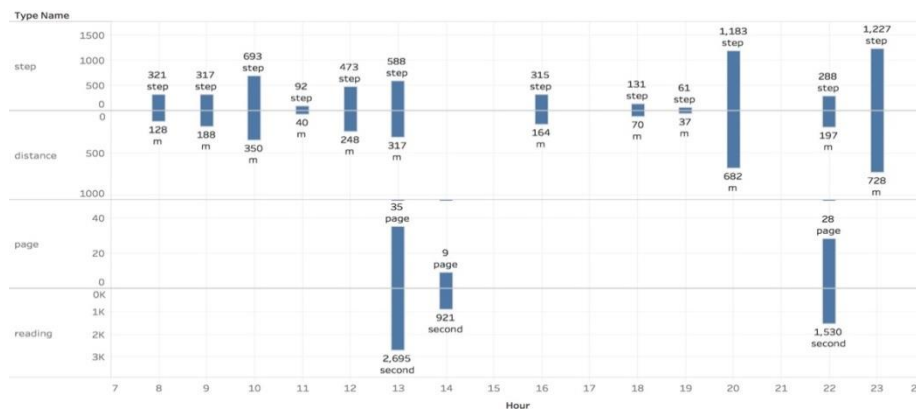

Figure 7. Sample dataset of one student as synchronized by GOAL system

6.2 Future work

In this pilot study we focus on the university students, but considering the super-aging society in Japan, SDS in the context of learning and health are relevant for users across all age groups. It is necessary for a lifelong learner and to maintain healthy lifestyle. The GOAL project aims to contribute to the societal wellbeing by supporting the different task associated with the five phases of self-directed lifestyle. The work initiated with conceptualization of the DAPER model and

developing the iOS application, opens various future development and research agenda. Our next development work includes analysis of the pilot users' feedback to modify or implement additional functionalities in the GOAL system. Next, we want to create a common web-based application which can be integrated with both android and iOS platform. After the ongoing pilot with current participants, we plan to develop valid metrics to identify learner behaviors and strategies based on their logged data. Identifying any such indicators potentially gives us scope to visualize them in the analytics dashboard to assist users to monitor and reflect on their behavioral trends. Based on the trends we can also decide about feedback strategies to the learners. The goal is to make learners self-directed independent of any technology support. Hence, further research is required on designing and studying scaffolding and fading strategies for meta-skills like self-directedness. Continuing with this research agenda, GOAL will then be introduced to a cohort of enrolled students in one course in the fall semester of 2018. We plan to conduct longitudinal study to investigate effectiveness for self-direction skills practiced by the learners and theorize regarding technology affordances to support it.

Acknowledgements

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