Doctoral Dissertation

Enhancing Students' Self-Direction Skill with Learning and Physical Activity Data

Huiyong LI
Supervisor: Hiroaki OGATA

January 2020

Department of Social Informatics
Graduate School of Informatics
Kyoto University

Abstract

The 21st century demands the explicit integration of learning and innovation skills, information literacy skills, and life and career skills. Self-direction skill (SDS) has been identified as an increasingly important skill in the education and health domains. Being self-direction would help students to prepare them for success in their future careers, and enables them to engage in lifelong learning. There is a great need for students to develop SDS following the shift from teacher-centered traditional classrooms to learner-centered approaches with advanced technologies.

However, students lack the contexts to practice their SDS, have difficulty with the objective assessment of their SDS, and lack the technological support to develop their SDS. To address these issues, a goal-oriented active learning (GOAL) system was developed. The GOAL system integrates theoretical and empirical knowledge of self-directed learning, self-regulated learning, quantified self, and learning analytics into SDS support components.

In this work, firstly an activity data-rich environment is built in GOAL by synchronizing students' everyday learning activity data, such as reading logs from an e-book reader and physical activity data such as sleep records from wearable devices. Secondly, affordances are designed in GOAL to engage students in self-direction tasks based on the DAPER (Data collection – Analysis – Planning - Execution monitoring - Reflection) model. Each of the five key sub skills of SDS is defined in a separate view to convey the importance of data sufficiency, status identification, smart planning, regular tracking, and strategic evaluation. While students execute any self-direction tasks with the support of GOAL, the system automatically generates their interaction logs. Thirdly, a scoring rubric for each the SDS sub skill is modeled considering students' specific activity data and general trace data. It has five levels from novice learner (level 0) to skilled learner (level 4) and visualised for the learner. Finally, an automatic adaptive feedback is generated based on the sub skill levels and delivered to learners. Therefore, students are systematically assisted in taking initiatives to "identify their status in contextual activities, set smart goals, monitor their progress, and reflect their strategies".

Furthermore, there has been much less understanding of the effects of SDS on learners' self-directed behaviors, activity-related outcomes, and personal attributes. To address this limitation, this thesis investigated the behavioral patterns in learning and health promotion contexts and further explored the effects of SDS on learners' behaviors, outcomes, and personality attributes. One exploratory study was performed to investigate the behavioral patterns of self-redirection without SDS support and find the needs of support. Three evaluation studies were designed and conducted in K-12 educational settings to investigate the effects of SDS on learners' behaviors, outcomes, and personality attributes.

The results of the exploratory study showed the importance of SDS for high English achievers and the support needs of SDS in order to prevent passive procrastination and maintain regular learning. The first evaluation study in learning found that setting specific challenging goals and regular reviewing had benefits on the successful English learning activity. The second evaluation study in health promotion found that self-tracking and self-planning had a crucial role on the sleep promotion activity. Furthermore, the final evaluation study in learning found that the perception of SDS was a critical factor of SDS, affecting self-directed behaviors, activity-related outcomes, and motivation for the activity.

Therefore, this thesis conducted a theoretical and empirical investigation of the technology support for SDS on needs, design, and evaluation. The findings suggest that a timely personalized feedback based on students' perception, behaviors and attributes in self-direction would be helpful to succeed in lifelong learning. The findings have implications for researchers studying SDS support environments and the effects of SDS on learning and health promotion contexts. Practically, the findings provide suggestions for educators seeking to improve students' learning and healthy activity with SDS usage.

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Acknowledgements

This thesis work was supported by many of researchers from different departments at Kyoto University and teachers at Saikyo junior high school in Kyoto. Without their powerful support, it's impossible for me to accomplish this thesis. I would like to take this opportunity to express my sincere appreciation to them.

I first thank my supervisor, Professor Hiroaki Ogata, who gave me infinite supports, encouragements, and inspiring advice. I appreciate that he spent much time and energy in discussing my research work every week. The guidance gave me more confidence to pursue further work to answer more research questions. It has been an honor to be his Ph.D. student.

I am especially grateful for Professor Takashi Kusumi, my Academic Adviser in both Informatics and Design at Kyoto University. He spent much time to instruct me as specialists in the educational domain in past three years. I received high-quality instruction from him, so as to ensure my research progress and achievements.

I also would like to thank Professor Tomohiro Kuroda to be the thesis committee member although he have a very busy schedule. I am especially grateful for his time, interest, and insightful comments. The discussion with him inspired me how a good researcher should be.

I am indebted to Associate Professor Kazuya Okamoto, my Academic Adviser in Informatics at Kyoto University. He always gave me professional suggestions as specialists in the Medical Informatics domain in past three years. I'm so lucky to be guided by his academic advisership, which speed up my research.

Dr. Rwitajit Majumdar always provided prompt advice and guidance when I got confused about research and experimental issues through my Doctoral Program. The advice was very critical to resolve my research and experimental issues, and it really made my research work faster than I had expected. Thank you Rwitajit Majumdar.

The members of the laboratory and the GOAL team have contributed immensely to my personal and professional time at Kyoto. They has been a source of friendships as well as good advice and collaboration. I thank the following laboratory members for helpful discussions and professional support: Brendan Flanagan, Akcapinar Gokhan, Mei-Rong Alice Chen, Hiroyuki Kuromiya, Lecailliez Louis, Tomoko Tanaka, Ayumi Nakagawa, and Noriko Nakajima. I am especially grateful for GOAL team members: Yuan Yuan Yang and Taisho Kondo. They put much effort into the design and development of GOAL system with me and made significant contributions on my research work.

For the experimental work, I particularly thank Miyabe-sensei in Saikyo junior high school. I have appreciated his collaboration and his impressive communication skill. He plays a significant role in the experimental design and execution with lots of helpful suggestions and practical improvements.

Lastly, I would like to thank my parents for all their love and encouragement. My parents raised me with a love of science and supported me in all my pursuits. They teach me not only to be an enthusiastic researcher but also to be a good human with a grateful heart. Thank you.

Chapter 1

Introduction

The 21st century demands the explicit integration of learning and innovation skills, information literacy skills, and life and career skills (Partnership for 21st Century Skills, 2016). Self-direction skill (SDS) has been identified as an increasingly important skill in the education and health domains (L. M. Guglielmino, 2013; Hill et al., 2020; Murad et al., 2010; Sumuer, 2018; Toh & Kirschner, 2020). Being self-direction would help students to prepare them for success in their future careers, and enables them to engage in lifelong learning. SDS is acquired through experience, training, and effort. The gain of experience and training depends on the degree to which learners engage in volitionally initiated processes. Since it's a cognitively, affectively and behaviorally complex task during executing SDS, more opportunities that learners engage in self-direction would benefit the development of SDS (Fahnoe & Mishra, 2013). There is a greater need for students to develop SDS following the shift from teacher-centered traditional classrooms to learner-centered approaches with advanced technologies (Toh & Kirschner, 2020).

1.1 Design of the support of SDS development

Three critical issues in the support of SDS development have been identified: learners lack the contexts to practice SDS (Barnes et al., 2007; L. M. Guglielmino, 2013; Robertson, 2011), learners have difficulty with the objective assessment of SDS (Araka et al., 2020; Spruijt-Metz et al., 2015), learners lack technological support to develop their SDS (Riley et al., 2011; Toh & Kirschner, 2020).

Opportunities for SDS training exist along a continuum in varying educational settings. Every learning situation has the potential to develop the attitudes and skills of self-direction, however, rarely is there opportunity for fully self-directed learning in educational contexts (Barnes et al., 2007; Glenn, 2000; L. M. Guglielmino, 2013). It is becoming a trend to utilize technologies in education, and students' learning behaviors in an online learning environment can be automatically recorded by learning systems (Daniel, 2019; Winne, 2017). On the other hand, available activity tracking data is rapidly increased since the development of mobile and wearable technologies (Swan, 2013). The self-tracking data expands the educational choices available for traditional educational settings. Such large learning records and physical activity trace data provide new contexts to capture and influence learners' general cognitive process and outcomes.

Self-report measures are mostly used to capture data on learners' self-direction so far (Cadorin et al., 2017; Slater & Cusick, 2017; Zhu et al., 2020). These instruments are static, intrusive, and time consuming. However, the assessments could be make through tracking activities and interactions with technology, especially in online learning environment (Araka et al., 2020; Winne et al., 2019). The assessment of frequencies and sequences of self-directed behaviors in learning environments provides a novel perspective on self-redirection that complements and potentially supersedes traditional self-report measures (Jansen et al., 2020; Wong et al., 2019).

Learning Analytics (LA) approach has potential to play a central role in supporting students' SDS (Buckingham Shum & Crick, 2016; Zhu & Bonk, 2019) as a metacognitive tool. The domain of LA can provide computational techniques and infrastructure to support self-directed learning and twenty-first century education by allowing learners to track their behaviour, choices, and learning progress through visualising patterns and providing rapid feedback using a computerised or mobile platform (Aldowah et al., 2019).

To address these issues, a goal-oriented active learning (GOAL) system was developed. The GOAL system integrates theoretical and empirical knowledge of self-directed learning, self-regulated learning, quantified self, and learning analytics into SDS support components. The system provides a data-rich environment with students' everyday learning and physical activity data, a quantitative measurement of SDS in phases and levels, and an adaptive feedback of SDS in phases and levels. The system aims to systematically assist learners in taking initiatives to "identify their status in contextual activities, set smart goals, monitor their progress, and reflect their strategies".

1.2 Impact of the support of SDS development

Previous studies on SDS in learning have focused on the general perceptions of SDS from students' perspectives (Fahnoe & Mishra, 2013; Kop, Fournier, et al., 2011; Loizzo et al., 2017) as well as the relations between elements of SDL in an online learning environment (Terras & Ramsay, 2015; Zhu et al., 2020). Although there are multiple approaches to capture data on learner's self-directed behaviors, self-report measures have still stayed dominant so far. Self-report measures of self-directed behaviors have been extensively studied for adolescents (Schweder, 2020), undergraduate students (Sumuer, 2018), and adults (Cadorin et al., 2017; Garrison, 1997) in K-12 schools (Timothy et al., 2010), universities (S.-F. Cheng et al., 2010), MOOCs (Li, 2019), and autonomous work environments (J. Choi, 2020). However, there has been much less understanding of the self-directed behaviors in contexts and the effects of SDS on students' behaviors, outcomes, and personality attributes.

Given this gap in the research, this thesis investigated the behavioral patterns in learning and health promotion contexts and further explored the effects of SDS on learners' activity-related outcomes, self-directed behaviors, and personality attributes. One exploratory study was performed to investigate the behavioral patterns of self-redirection without SDS support and find the needs of support. Three evaluation studies were designed and conducted in K-12 educational settings to investigate the effects of SDS on learners' behaviors, outcomes, and personality attributes.

1.3 Research questions

Therefore, there are research questions related to the design and evaluation of impact of the technological support for the development of SDS in this thesis:

Design questions:

1. How to integrate contextual activity data and objective SDS measures into a SDS support system?

1.1 What is SDS and what are its sub skills? what is the general process of SDS execution?

1.2 What kind of learning and physical activity data can be leveraged to develop SDS?

1.3 How to quantitatively measure SDS? How to technological support the development of SDS?

Impact evaluation questions:

2. What are the behavioral patterns of self-direction in learning without and with the SDS support?

2.1 What are the behavioral patterns in learning without the SDS support?

2.2 What are the changes of self-directed behaviors using the SDS support system in a learning activity (extensive reading)?

2.3 What are the changes of self-directed behaviors using the SDS support system in a health promoting activity (sleep)?

3. What are the effects of learners' perception of SDS on their activity-related outcomes, self-directed behaviors, and personality attributes?

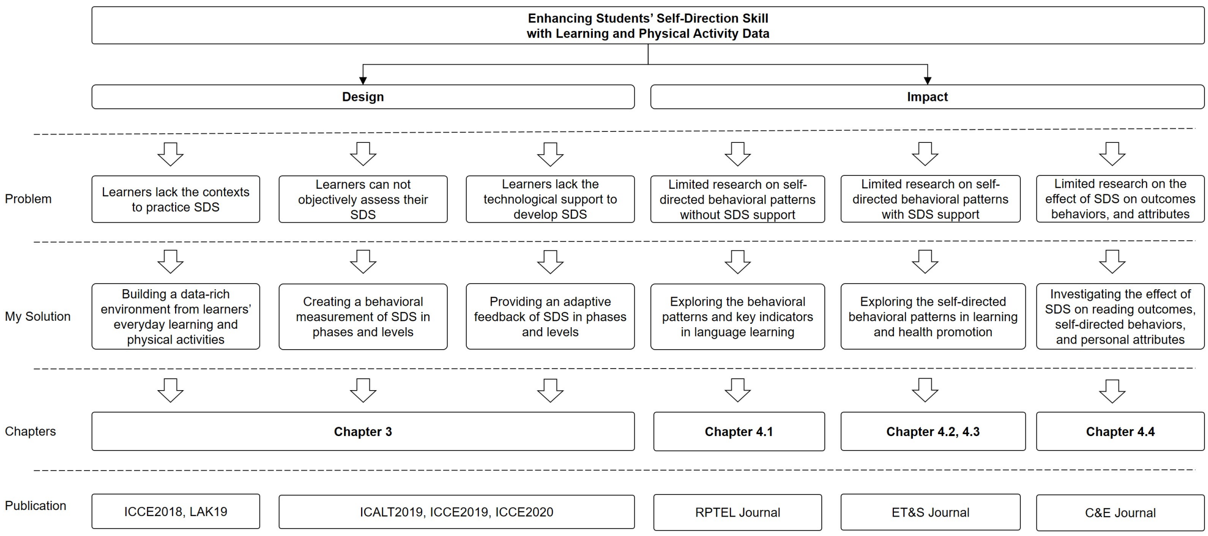


Figure 1.1: Thesis overview: Research objective, associated problems and proposed solutions

Chapter 2

Literature review

2.1 Self-direction skill

Self-direction skill (SDS) is relevant for learner's learning as well as their daily well-being. In the learning context such a skill is also studied as Self-Directed Learning (SDL) and Self-Regulated Learning (SRL).

The concept of Self-Directed Learning (SDL) has been recognized and researched for decades (Brockett & Hiemstra, 2018; Candy, 1991; Gibbons, 2002; Knowles, 1975). SDL is broadly defined as the process wherein individuals take the initiative, with or without others' support, to diagnose their learning needs, formulate their learning goals, identify human and material resources for learning, choose and implement appropriate learning strategies, and evaluate their learning outcomes (Knowles, 1975). According to Gibbons (2002), a learner who practices SDL initiates challenging activities and develop personal knowledge and skills to pursue these challenges successfully. Candy (1991) further discussed SDL and related it to learning strategies. He postulated that learning environments that foster SDL are believed to promote deep-level processing where learners seek meaning in the subject matter rather than surface-level processing in which learners are engaged in rehearsal and memorization. Brockett and Hiemstra (2018) identified learner self-direction as a behavior seen in instructional method processes (self-directed learning) and a personality characteristic of the individual learner (learner self-direction). Generally, SDL entails goal setting and task analysis, implementation of the plan that was constructed and self-evaluation of the learning process (Loyens et al., 2008).

In addition, a self-directed learner may exhibit various traits: motivation, goal orientation, locus of control, self-efficacy, self-regulation, and metacognition (Biemiller &

Meichenbaum, 2017; Lumsden, 1999; Renchler, 1992). Sze-Yeng and Hussain (2010) emphasized learner autonomy from the personal attribute perspective. Brookfield (2013) also emphasizes learners' decisions on what to learn, when to learn it, how much to learn, and whether something has been learned well enough. Such traits signalled that self-directed learners typically enjoy a high level of autonomy in learning (Brookfield, 2013).

SDL and Self-Regulated Learning (SRL) are two terms most frequently used in today's educational discourse on the learning process (Brockett & Hiemstra, 2018; Candy, 1991; Winne, 2017; Zimmerman, 2008). Saks and Leijen (2014) have highlighted their commonality and differences. Both SDL and SRL have 4 key phases: Defining tasks – Setting goals and planning – Enacting strategies – Monitoring and reflecting. SDL is mainly used outside the traditional school environment due to its adult education roots and involves designing learning environments. SRL, on the other hand, is mostly studied in the school environment that originated from cognitive psychology. The self-directed learner initiates the learning task, whereas, in SRL, the task is usually set by the teacher. While SDL is suggested to be situated at the macro-level, SRL is stated to be the micro-level concept. The macro-level SDL refers to the planning of the learning trajectory – a self-directed learner is able to decide what needs to be learned next and how the learning is best accomplished.

In order to conceptualize a general SDS in learners' everyday activities, we synthesizes the common elements in SDL and SRL. We call it DAPER (Data collection - Analysis - Planning - Execution monitoring - Reflection) model (Majumdar et al., 2018). DAPER model has five phases, the initial phase of data collection which gives learners the initiative in their contexts, followed by the other four phases: data analysis, planning, execution monitoring and reflection. Figure 2.1 provides an overview of the DAPER model of self-direction ability execution and acquisition with examples.

In the data collection phase of DAPER model, the learner takes the initiative to collect available activity data of interest in, such as learning logs from e-book readers or sleep time from wearable devices. In the analysis phase, the learner tries to identify the current status of activities through visualized activity information. In the planning phase, the learner creates SMART (Specific, Measurable, Appropriate, Relevant, and Timely) plans for the analyzed activity using a plan template. In the phase of execution monitoring, the learner checks the progress of the plan through visualized activity and plan information. In the reflection phase, the learner reviews the plan and achievements by evaluating the

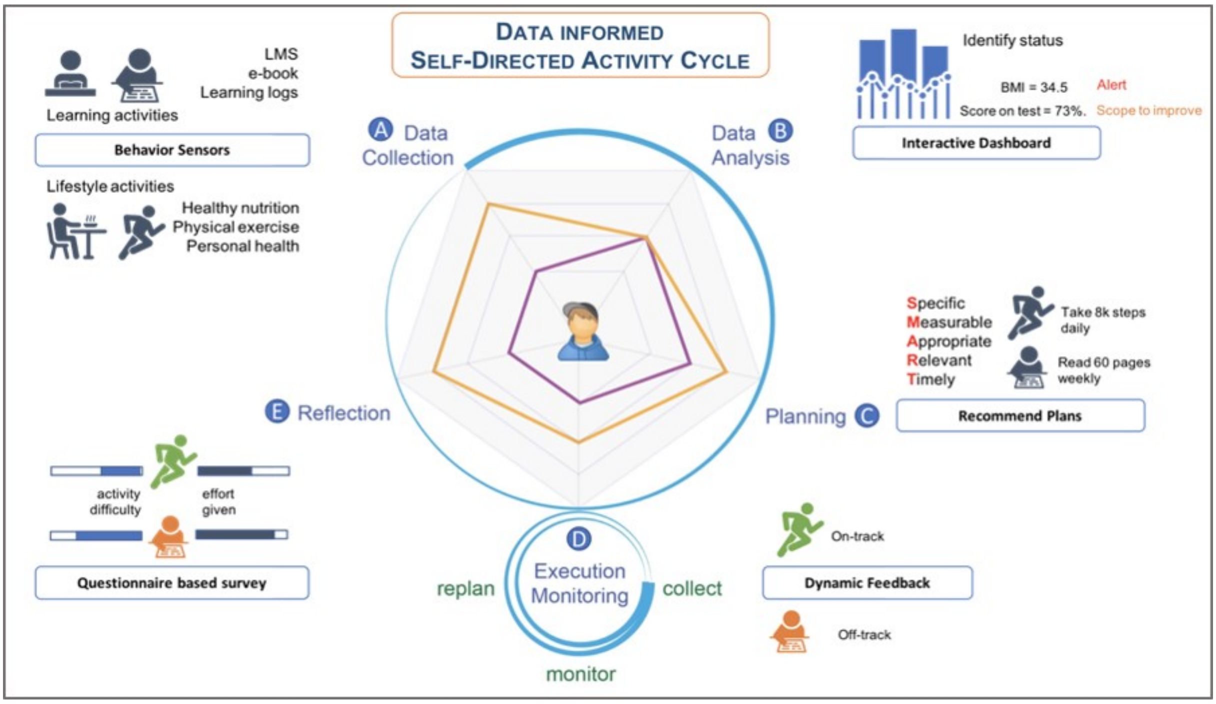


Figure 2.1: DAPER model of self-direction skill execution and acquisition

strategies in the whole self-direction process.

2.2 Goal-setting and planning in self-direction skill

A key phase in SDS is goal setting and planning (Brockett & Hiemstra, 2018; Stolk et al., 2010). Goal-setting is a crucial aspect of human behavior; it has a heightened role in all activities of modern individuals that require perseverance and planning (Hamari et al., 2018). Goal-setting refers to individuals' process of determining desirable end-states that they wish to achieve and intend to use in self-regulation (Burnette et al., 2013; Locke & Latham, 2002; Loock et al., 2013). Set concrete goals rather than wishful thinking are important for goal attainment. Thus, goal-setting has been extensively studied as the process (Elliot & McGregor, 2001; Freund et al., 2010; Mann et al., 2013), and it has been linked to improvements in performance in a variety of settings such as in education, health or personal development (Locke & Latham, 2002; Loock et al., 2013; Nahrgang et al., 2013; Wack et al., 2014)

Self-directed learners are expected to actively and autonomously engage in goal setting and planning. They demand a high level of goal setting and planning skills during the SDS execution process. Compared with assigned goals and plans, personal goals and plans produce higher goal commitment since the learners who are aware of their goals have high achievement expectations. Setting goals implies that a person has committed thought, emotion, and behavior to attain them for personal development, such as learning or well-being (Brunstein, 1993; Heimerdinger & Hinsz, 2008). Because goals refer to a future desired state that differs from the current state, goal setting can be thought of as a process that creates a expectation between what one wants to be like and what one is currently like (Inzlicht et al., 2014).

Researchers have examined the role of goal-setting and planning on physical and healthy behaviors (Greaves et al., 2011; Munson & Consolvo, 2012; Sullivan & Lachman, 2017). As a behavior change techniques, goal-setting are often included in fitness technology. The results suggest that goal setting, self-monitoring, and feedback are effective for increasing physical activity and healthy behaviors (Sullivan & Lachman, 2017). Specifically, self-regulatory behavior change techniques such as goal setting and self-monitoring were associated with better outcomes (Greaves et al., 2011). Self-monitoring of progress and goal achievement may lead to increases in self-efficacy and sense of control for exercise, which could encourage long-term lifestyle changes (Olson & McAuley, 2015). More researches need to examine that which type of goal is best for motivating individuals to be more active and to achieve recommended guidelines (Sullivan & Lachman, 2017).

Although goal-setting and planning play a critical role on self-regulation, limited researches on the dynamic transition of goal-setting and planning existed. Further research is needed particularly in the understanding for goal-setting behavioral processes in self-direction across the range of learning and health promotion contexts.

2.3 Measuring SDS

The researchers commonly assess learners' SDS using self-reported questionnaires, like PRO-SDLS (Stockdale & Brockett, 2011), SRSSDL (Williamson, 2007), SDLI (S.-F. Cheng et al., 2010), or self-direction measure for mental health care (de Vries et al., 2020).

Self-Directed Learning Readiness Scale (SDLRS) is the most widely used measures of self-directed learning which originally developed by P. Guglielmino (1995). The operational definition of SDL readiness was the degree to which an individual possesses the characteristics that are necessary for SDL abilities. The SDLRS has a 58-item, five-point scale and consists of eight dimensions: (1) openness to learning opportunities; (2) self-concept as an effective learner; (3) initiative and independence in learning; (4) informed acceptance or responsibility for one's own learning; (5) love of learning; (6) creativity; (7) future orientation; and (8) ability to use basic study skills and problem solving skills. It examines what individuals need to possess to pursue SDL. A high score on the SDLRS indicates a higher level of readiness for SDL.

Oddi Continuing Learning Inventory (OCLI) is another instrument that has been used frequently to measure self-directed learning developed by Oddi (1986). The OCLI contains 24 statements (e.g., "I work more effectively if I have freedom to regulate myself") with seven-point responses and measures three domains: (1) proactive versus reactive learning drive; (2) cognitive openness versus defensiveness; and (3) commitment to learning versus apathy or aversion to learning. A higher score on the OCLI represents a greater level of self-directed learning ability. The results at the development stage revealed a higher degree of reliability (coefficient alpha) of .87 and a 2-week test-retest correlation of .89. However, Harvey et al. (2006) suggested that the OCLI should be extended to four underlying domains. These are learning with others, learner motivation/self-efficacy/autonomy, ability to be self-regulating, and reading avidity.

Recent attempts at measuring self-directed learning saw developments of instruments for specific populations. S.-F. Cheng et al. (2010) developed the Self-Directed Learning Instrument (SDLI) for nursing education using a five-point Likert scale. It is comprised of 20 items categorised into four domains: "Learning motivation", "Planning and implementing", "Self-monitoring", and "Interpersonal communication". These four domains are consistent with Knowles's SDL theory (Knowles, 1975).

de Vries et al. (2020) developed a self-direction measure for mental health care. The developed questionnaire measures the degree to which people are experiencing self-direction in their lives, and their capability of solving their problems. A 31-item questionnaire was constructed that included six factors that measured actorship, commitment, demoralization, readiness, understanding, and monitoring progress and two broader underlying factors called gaining control and loss of control.

While these instruments provide a picture of each learner's skills at a certain moment in time, they do not continuously track learner's skills. Also, these instruments are intrusive and time consuming. The assessments could be make through tracking activities and interactions with technology, especially in online learning environment (Araka et al., 2020; Winne et al., 2019). Unlike self-reported measures in traditional learning contexts, online measures focus on assessing self-regulated learning processes and are based on actual learning behaviors in authentic contexts (Cicchinelli et al., 2018). Innovative online measures of self-redirection offer detailed information concerning the interrelation of various processes in real time through data traces (Jansen et al., 2020; Winne et al., 2019; Wong et al., 2019).

2.4 Technological support for SDS

The development of SDS are much emphasized by Glenn (2000), "Net Geners need self-directed learning opportunities, interactive environments, multiple forms of feedback, and assignment choices that use different resources to create personally meaningful learning experiences" (p. 2). Opportunities for SDL exist along a continuum in varying instructional approaches; every learning situation has the potential to develop the skills and attitudes supportive of SDL, but rarely is there opportunity for fully self-directed learning in institutional contexts (L. M. Guglielmino, 2013). It is argued that technology-rich learning environment can provide learners with great opportunities to be self-directed in their learning since it scaffolds the learners to be knowledgeable about the relevant resource selection and the appropriate usage of the learning strategies (Fahnoe & Mishra, 2013). The technology-rich learning environment can provide a conducive context to execute SDS effectively. The flexible structure of the learning environment enables learners to identify their own needs in their own time, place, and pace. Thus, the high flexibility and diversity in technology-rich learning environment make it possible for them to have more control over their own learning (Beach, 2017).

Technology may have direct impact on self-directed learning because it has greatly facilitated access both to information resources and to online expertise (Daniel, 2019). The technology approaches include capturing, storing, manipulating, displaying information, and making contact with skilled learners and experts around the globe in a timely manner. For the self-directed learners, it's important to be able to access a wide and unlimited range of information to accommodate their learning needs and interests (Candy, 2004).

Rashid and Asghar (2016) found that the use of technology has a direct positive relationship with students' engagement and levels of self-direction, which both are related to academic success. Moreover, Gabrielle (2003) found that technology mediated instructional strategies designed using motivation model and delivered via several technologies such as personal digital assistants, the Web, videos, and email had positive impacts on self-direction in learning. Consequently, technology-rich environments have the potential to provide flexible opportunities and capabilities for learners to facilitate SDS.

In the technology-rich environments, Learning Analytics (LA) approaches have potential to play a central role in supporting students' SDS (Aldowah et al., 2019; Zhu & Bonk, 2019) as a metacognitive tool. LA approaches in general offer different kinds of computational support for tracking learner behaviour, managing educational data, visualizing patterns, and providing rapid feedback to both educators and learners. A diverse range of LA tools and techniques can be deployed in the service of building 21st century competencies (Buckingham Shum & Crick, 2016).

Quantified-Self (QS) movement emphasizes 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 (Choe et al., 2014). The quantified-self technologies have advantages such as noninvasive, do not require much effort, and enable high-frequency user activity tracking. They also provide a means to foster strong awareness, motivation, and behavioral change, with lifestyle and fitness trackers being common examples (K. E. Arnold et al., 2017).

The research and design of quantified-self have grown as an interest area in information and learning sciences (Lee, 2019). The collection of student data via quantified-self apps can be transformative for students, especially those who are already familiar with activity-tracking mobile applications and quantified-self technologies (Giannakos et al., 2020). Having a quantified-self technology that enables a student to be aware of what effort she is putting into learning, so that she can work toward her own personal goal, by optimizing her behavior, is one approach to overcome common barriers of self-directed learning (K. E. Arnold et al., 2017). Quantified-self technologies have been placed as a scaffold of meta-cognitive processes in theoretical frameworks for student support and learning benefit (Eynon, 2015; Giannakos et al., 2020; Rivera-Pelayo et al., 2012). Despite this great potential for support learning, however, the direction remains rather under explored (Henrie et al., 2015). The potential of self-tracking data to support meta-cognitive process need to be investigated.

2.5 SDS and its effect in learning and health promoting contexts

In this thesis we focus on the English language learning as the learning context and the sleep promotion as the health promoting context. The key aspects of learning and health promoting contexts are introduced below: theoretical background in contexts and the relations with goal-setting in self-direction.

2.5.1 Extensive reading as a language learning context

Grabe and Stoller (2019) defined ER as an "approach to the teaching and learning of reading in which learners read large amounts of material that are within their linguistic competence" (p. 286). The following four elements of ER are commonly presented: a large amount of reading, easy materials, faster reading rate, and reading pleasure (Yamashita, 2015). Among them, most ER researchers take "a large amount of reading" as the essence of ER, as Day and Bamford (1998) stated, and regard the remaining three elements as a set of interacting factors that contribute to this essence.

Researchers have examined the effect of ER from different perspectives, including learners' motivation (Day & Bamford, 1998; Tanaka, 2017), reading comprehension and reading speed (Beglar & Hunt, 2014; Chang, 2010), sight vocabulary (R. Brown et al., 2008; Pigada & Schmitt, 2006), and grammatical knowledge (Song & Sardegna, 2014). ER has also been recognized by EFL and L2 researchers as an effective way of encouraging language growth and acquisition, in particular improving reading comprehension and vocabulary growth (Schmitt, 2008; Urquhart & Weir, 2014).

Although the benefits of extensive exposure to meaningful language have received strong empirical support, ER has not always received the kind of support that it deserves. Many ER educators in the schools are constrained by practical concerns that prevent them from achieving successful large-scale ER programs.

The first key concern is that teachers lack time to launch the ER program and guide students' reading activities (D. Brown, 2009). ER is often implemented as an out-of-class activity where it's difficult to provide sufficient on-going support to each student from teachers. Teachers need to be clear whether students are reading and what they are reading. However, after the initial enthusiasm, teachers may begin to feel overwhelmed by the amount of work related to the running of the program without sufficient support.

The second key concern is how to promote students' autonomy for independent reading, especially in a large-scale ER program (Blachowicz & Fisher, 2014). Students are expected to self-select their reading materials, read at their own pace, and have sufficient time for reading in a ER program. However, students usually lose their directions before forming a good reading habit if they have not their own goals in the ER program (Day & Bamford, 1998). Therefore, both teachers and students need to be supported to achieve the expected outcomes in the ER program.

One potential influence on ER motivation and engagement is the ability of autonomy. Jones (1998) emphasized the advantages of autonomy, such as strengthening intrinsic motivation and enabling personalized reading. Autonomy relates to the need for freedom or choice of one's behavior. Learners' autonomy provides a motivational basis for their behavioral engagement because of the choice of making decisions for participating in an activity (E. Skinner et al., 2008).

Moreover, another potential influence on ER motivation and engagement is the ability of goal-setting. Learners who are highly committed to specific, challenging, and attainable goals can perform better on goal-relevant activities (Locke & Latham, 2002). This is because people with specific, challenging, and attainable goals tend to exert greater effort and persistence than those with vague or easy goals.

2.5.2 Extensive reading and goal-setting

Recent studies on ER (McLean & Poulshock, 2018; Suk, 2017) have implied that setting a reading goal facilitated more reading. According to Locke and Latham's goal-setting theory, setting appropriate goals can enhance students' motivation (Locke & Latham, 2002). Mikami (2020) suggested that goal setting can exert a powerful influence on students' motivation for ER. Setting appropriate goals may be crucial in increasing students' motivation and reading amounts. The virtuous cycle through the effective use of goal-setting may be a key factor in ensuring the success of ER programs.

Klimas (2017) investigated the relationship between goal-setting and autonomy and revealed that goal setting is an effective strategy of to develop students' autonomy in learning. Helping students to create their own goals transfers responsibility for the success or failure of the activity from the instructors to the students. Letting students pursue their own goals transforms learning into more authentic and autonomous experience. Therefore, the usage of goal-setting could be a key factor in ensuring the success of ER programs.

Despite goal-setting playing an influential role in different educational settings, there has been little investigation on the effects of goal-setting for ER. Additionally, most participants have been university students or life-long learners, whereas few studies have been conducted in school settings (Jeon & Day, 2016). Therefore, there is a need to examine the effects of goal-setting on ER in the context of K-12 schools.

2.5.3 Sleep promotion as a health promotion context

Sleep is defined as a natural and reversible state of reduced responsiveness to external stimuli and relative inactivity, accompanied by a loss of consciousness (Rasch & Born, 2013). Sleep occurs in regular intervals and is homeostatically regulated (Borb & Achermann, 1999). Sleep serves several different functions, such as repair and growth, learning or memory consolidation, and restorative processes: all these occur throughout the brain and the body (J. Krueger, 2003).

It is well known that the integrity of learning and memory processes are fundamental in school achievement and academic performance, particularly in individuals like children and adolescents who are in a particular developmental phase (Wolfson & Carskadon, 1998).

Over more than a century of research has established the fact that sleep benefits the retention of memory (Rasch & Born, 2013). The initial theories posed a passive role for sleep enhancing memories by protecting them from interfering stimuli, current theories highlight an active role for sleep in which memories undergo a process of system consolidation during sleep (Diekelmann & Born, 2010; Klinzing et al., 2019).

The neuroscientists indicated that goal-directed action were particularly vulnerable to sleep loss, and this process involves the brain mechanism. Elucidation of the effects of sleep deprivation on decision-making emphasized the role of sleep in cognitive impairments and mental health (Chen et al., 2017).

As some literature reviews pointed out, learning abilities and consequent academic performance are particularly dependent on sleep patterns and sleepiness levels (Fallone et al., 2002). Studies with experimental manipulations of the amount and quality of children's sleep confirmed that poor or fragmented sleep is associated with behavioural and cognitive difficulties with reduced academic achievement and learning (Wolfson & Carskadon, 2003). Carskadon (2011) found that short school night-sleep also negatively affects school performance.

Very often, to cope with our many daily interests, we prefer to sacrifice some sleep time, in the hope that this will not induce dangerous effects but will enable us to carry out several other activities. Unfortunately, this is not true and sleep loss has various consequences, such as sleepiness and impairments in neurocognitive and psychomotor performance (Pilcher & Huffcutt, 1996). A marked increase in sleepiness that usually facilitates cognitive, emotional, behavioural and academic failure (Carskadon et al., 2004).

American Academy of Sleep Medicine suggested that teenagers 13 to 18 years of age should sleep 8 to 10 hours per 24 hours on a regular basis to promote optimal health (Paruthi et al., 2016). Studies indicate that adolescents obtain less sleep and experience increased daytime sleepiness (Hale & Guan, 2015). Sleep loss is frequently associated with poor declarative and procedural learning in students, and therefore the question of how to improve adolescents' sleep health behaviors becomes more important.

2.5.4 Sleep promotion and goal-setting

There are theory-based interventions that include goal setting as a key component, particularly in the context of sleep promoting (Wolfson et al., 2015). Goal-setting theory is used mostly in physical activity and health promoting domains (Kaipainen et al., 2010; Munson & Consolvo, 2012). Successful self-regulation entails selecting desired goals with appropriate criteria for success (i.e., goal setting), and engaging in those strategies and behaviors necessary to procure that outcome (i.e., goal striving) (Mann et al., 2013).

However, the Goal Setting Theory picture is complicated by a lack of consensus on the measurement of goal commitment (Hollenbeck et al., 1989) or indeed goal difficulty. When designing technological support with Goal Setting Theory, researchers should also take individual characteristics into account (Pinder et al., 2018). More measures and feedback of personal goals would help to enhance learners' goal achievements, such as informative instructions, self-monitoring, and feedback (Wolfson et al., 2015).

Health behavior motivation theories suggest that it is important to break long-term health behavior goals into short-term, specific, and achievable sub-goals; monitor progress; and provide relevant, timely feedback and guidance (Bandura, 2004; Strecher et al., 1995). Learning and cognitive theories emphasize the role of shaping (i.e., identifying and immediately reinforcing successively improving approximations of the target behavior (K. A. Krueger & Dayan, 2009; B. F. Skinner, 2019)) and teachable moments (i.e., natural opportunities for learning and improvement (Lawson & Flocke, 2009; McBride et al., 2003)) in the acquisition of a new skill. Therefore, these perspectives emphasize that timely provision of intervention scaffolds and prompts can capitalize on short-term natural opportunities to improve health and learning outcomes .

To address the above research limitations of sleep promotion, a sleep promoting intervention should synthesize the social learning theories and behavioral change approaches, such as personal goal-setting, informative instructions, self-monitoring, and timely feedback.

2.6 Summary of gap in previous work

The research gaps were summarized in this chapter. From a design perspective of the support of SDS development, theses issues are identified: 1) learners lack the contexts to practice their SDS, 2) learners can not objectively assess their SDS, 3) learners lack the technological support to develop SDS. From the evaluation of the impact of technological support on SDS especially on goal-setting skills, limited researches on self-directed behaviors and the effects of SDS on outcomes, behaviors, and attributes were found.

Apart from the literature review, an exploratory study was also conducted in this thesis in order to identify behavioral patterns and key indicators of self-directed learning activity without SDS support. The detail of the exploratory study is introduced in Chapter 4.

Chapter 3

GOAL system: the SDS support environment

In this chapter, the GOAL system and its modeling components will be introduced. The architecture of the GOAL system is descried firstly. Then, the modeling components are introduced in detail containing the activity model, DAPER model implementation, user interface, user interaction tracking, and SDS sub-skill model. Finally, the ethical considerations for the design of the GOAL system are given.

3.1 System architecture

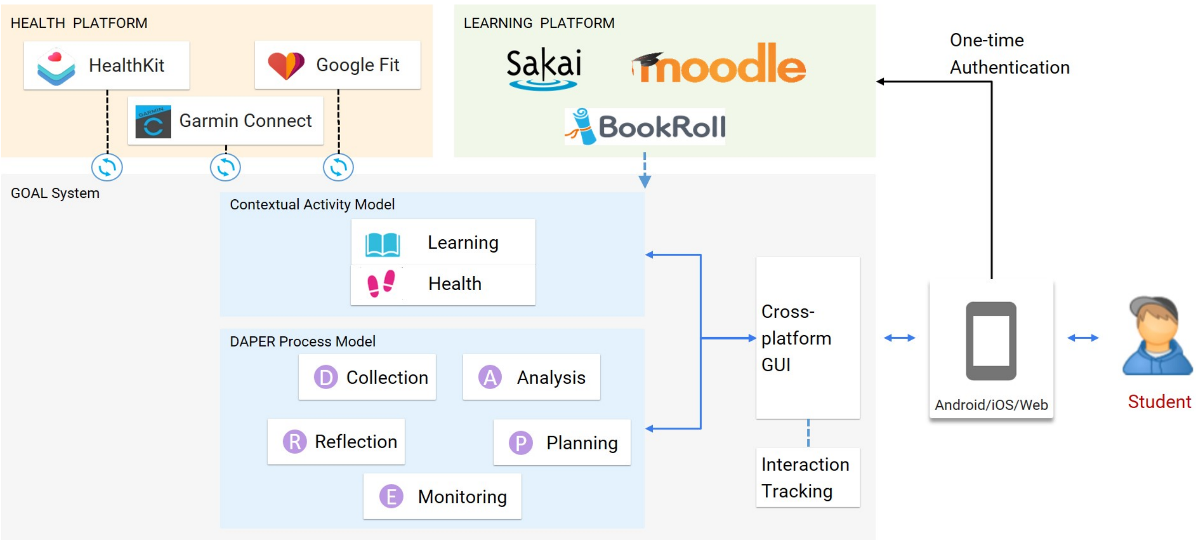


Figure 3.1: System architecture of GOAL system

The architecture of the GOAL system is shown in Figure 3.1. The GOAL system is a platform to support students' development of SDS: 1) builds a data-rich environment from learners' everyday learning and physical activities; 2) creates a quantitative measurement of SDS using online trace data; 3) provides an adaptive feedback of SDS in different phases and levels.

The GOAL system can be launched through the Learning Tool Interoperability (LTI) in a typical LMS such as Moodle. Learners can link automatically their learning activity data from the e-book readers or LMS, such as extensive reading logs, English learning logs, Math learning logs, answers of quizzes (Flanagan & Ogata, 2018). Learners can also synchronize physical activity data from mobile health platforms or wearable devices, such as data from steps taken, walks, runs, sleep, and stress. Furthermore, the interactions between learners and the GOAL system are logged as eXperience API (xAPI) statements in the GOAL server. The learning activity data is aggregated to contextual information by an activity aggregator. The contextual information is aggregated as various contextual indicators with hourly, daily, and weekly scales, such as daily reading time spent in extensive reading. Then SDS scaffoldings are implemented and provided to students using the DAPER model. The scaffolding includes self-direction tasks, interaction tracking, skill diagnosis, and skill-based adaptive feedback in phases. Self-direction tasks are contextual operations in phases, such as creating personal plans for extensive reading in planning; The interactions with the GOAL system are automatically tracked as eXperience API (xAPI) statements; The skills are diagnosed using the contextual information and interaction data; Adaptive feedback is generated based on the diagnosed skill level. Furthermore, a cross-platform GUI is provided for students to interact with the self-direction tasks and receive the skill-based adaptive feedback.

In a word, the GOAL system not only leverages learners' fine-grained data in self-directed activities but also provides computer-based scaffolding to promote learners' SDS in phases and contexts.

3.2 Modeling activity context

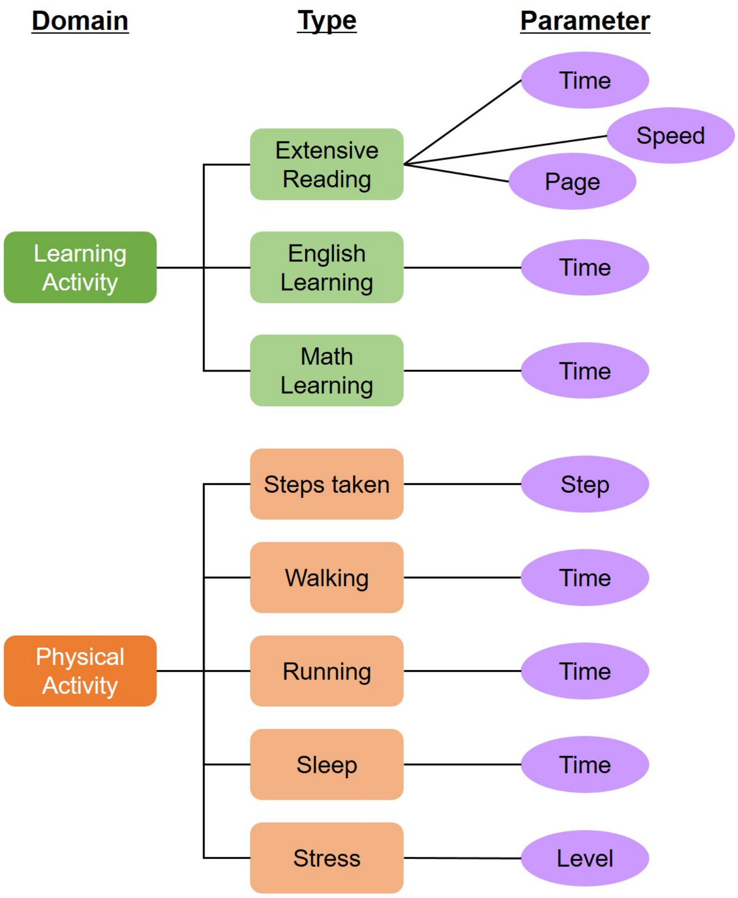


Figure 3.2: Activity model in learning and physical activity contexts

The activity contextual model has a set of self-activities and parameters which can be synchronized from learners' learning and physical behavior sensors (see Figure 3.2). Learning activities contain extensive reading, English learning, and Math learning. Physical activities include steps taken, walking, running, sleep, and stress. For each activity, the key parameters are extracted, such as reading speed for extensive reading or sleep time for sleep activity.

3.3 Implementing DAPER model

The DAPER model-based scaffoldings were implemented in the GOAL system. Table 3.1 indicates the phase, skill, description of DAPER model in the GOAL system.

A. Data Collection. Learners take the initiative to collect available behavioral data of their self-directed activities of interest in. Data from most of the activity context can be automatically recorded in GOAL through behavioral sensors, like e-book readers. For example, the time spent and pages read in extensive reading can be logged by BookRoll. Learners can also add their own activity data manually. Those manual inputs can supplement the automatic logging.

B. Analysis. Learners can conduct an analysis of visualized data to identify current status in any context. The analysis tasks are given by checking their own daily value in the previous week and comparing their value with the average value of the group in that context. For example, the learners can analyze their extensive reading status with respect to the average value of their cohort.

C. Planning. Learners set SMART (Specific, Measurable, Appropriate, Relevant, and Timely) goals in the analyzed context. They choose a specific context to prepare their own goals and create their own plans using a plan template. For example, learners can create a daily plan for time spent in extensive reading.

D. Execution monitoring. Learners can execute the plan and track the progress regularly. The progress of the plan is visualized by comparing the actual value of the selected context with the target value of the plan. This phase often includes multiple cycles of re-planning, execution monitoring and ongoing reflection.

E. Reflection. Learners review the outcomes of the plan and the whole planning-monitoring-reflection process. The details of the plan and achievements during the plan are shown to learners. Supported by these representative reference data, learners reflect on their strategies by rating key indicators in the planning-monitoring-reflection process, including the degree of plan difficulty, the target achievement rate, and the effort to achieve the plan. Furthermore, Learners can input unstructured thoughts in an additional comment area, such as the current problems, specific strategies, or further actions in extensive reading.

Therefore, the DAPER model-based implementations systematically assist learners in taking initiatives to “identify their status in contextual activities, set smart goals, monitor their progress, and reflect their strategies".

Table 3.1: Phase, skill, description of DAPER model in the GOAL system

Phase	**Skill**	**Description**
Data collection	Data sufficiency	Learners take the initiative to collect available activity data of interest in. Data can be automatically recorded in GOAL through contextual behavioral sensors, like e-book readers. For example, the time spent and pages read in extensive reading can be logged by BookRoll. Learners can also add their activity data manually as a supplement to the automatic logging.
Analysis	Status identification	Learners can conduct an analysis of visualized data to identify the current status in contextual activities. Analysis tasks are given by checking their own daily value in the previous week and comparing their value with the average value of the group in that context. For example, learners can analyze their extensive reading status in the analysis tasks.
Planning	SMART planning	Learners set SMART (Specific, Measurable, Appropriate, Relevant, and Timely) goals in the analyzed context. They choose a specific context to prepare their own goals and create their own plans using a plan template. For example, learners can create a daily plan for time spent in extensive reading.
Execution monitoring	Regular tracking	Learners can check the progress of the plan regularly. The progress of the plan is visualized by comparing the actual value of the specific context with the target value of the plan. This phase often includes multiple cycles of re-planning, execution monitoring, and ongoing reflection.
Reflection	Strategic evaluation	Learners review the plan and their achievements by evaluating their strategies in the whole planning-monitoring-reflection process. They can see the details of the plan and achievements during the plan and then reflect on their strategies using a reflection journal template. They can rate the degree of plan difficulty, the target achievement rate, and the effort to achieve the plan and noting the thoughts, such as the current problems, specific strategies, or further actions.

3.4 User interface

Figure 3.3 shows GOAL system interfaces for data collection, analysis, planning, monitoring, and reflection. Figure 3.3a shows the data collection view, learners take the initiative to collect available activity data of interest in, such as learning logs from e-book readers or sleep time from wearable devices. Figure 3.3b shows the analysis view, learners try to identify the current status of activities through visualized activity information. Figure 3.3c shows the plan template, which includes the activity type, plan name, start date, end date, frequency, value for each day, and notes. Figure 3.3d shows the monitoring view, which contains a visual graph and self-report form. Learners can track their detailed self-progress and compare them with the average of the group, recommendation, or target value. They can further report their progress status through self-rating and unstructured note-taking. Figure 3.3e shows the reflection view, which contains plan details, achievements, and self-reported reflection journal.

3.5 User interaction tracking

Table 3.2 presents a sample of trace data from user interaction with GOAL. In trace data, there are a variety of interactions, for instance, ADD ANALYSIS means that the student submitted a self-rating report in the analysis view and ADD PLAN means that the student created a personal plan in the planning view. The trace data makes it possible to quantitatively measure students' SDS in different phases.

Table 3.2: A sample of trace data from user interaction with GOAL

User id	**Action name**	**Action id**	**Date**
U1	ADD ANALYSIS	A1	2020/11/20 9:15
U1	VIEW ANALYSIS	A1	2020/11/20 9:21
U1	ADD PLAN	P1	2020/11/20 9:33
U1	VIEW PLAN	P1	2020/11/21 17:02
U1	ADD REFLECTION	R1	2020/11/27 18:21

A set of trace data for the extensive reading activity in the DAPER cycle is given in Figure 3.4. The tracking records have user id, action name, action id, and date attributes. With the unique action id, the action details are connected with each tracking record. For instance, a set of trace data can connect with a series of self-directed behaviors, i.e., initial

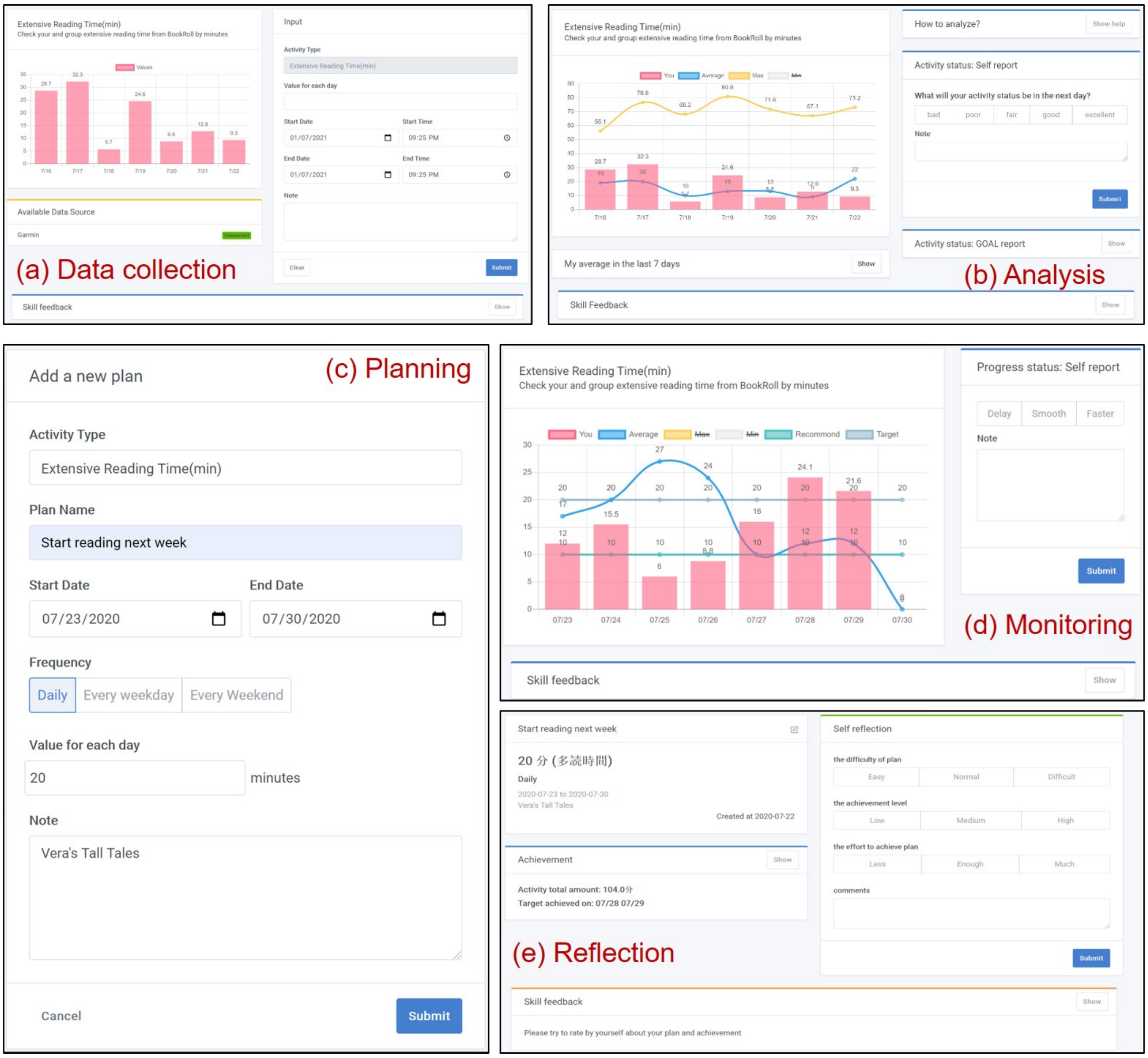
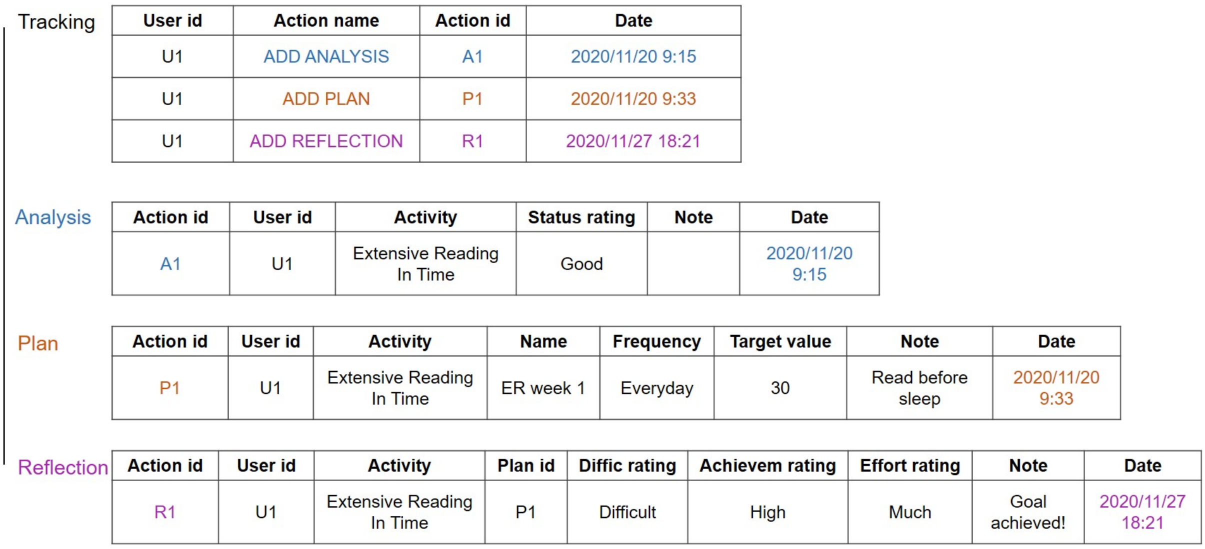


Figure 3.3: GOAL system interfaces for (a) data collection, (b) analysis, (c) planning, (d) monitoring, and (e) reflection

analysis, further planning, and final reflection.

3.6 SDS level measurement

Learners' SDS levels are measured by a 5-point scoring rubric using students' specific activity data and general trace data (see Table 3.3). Each SDS sub skill is divided into five levels from novice learner as level 0 to skilled learner as level 4. For example, the novice learner in planning skills means 'never plan' and the skilled learner is 'set appropriately challenging plan after analyzing their status of activity'.



Tracking

User id	Action name	Action id	Date
U1	ADD ANALYSIS	A1	2020/11/20 9:15
U1	ADD PLAN	P1	2020/11/20 9:33
U1	ADD REFLECTION	R1	2020/11/27 18:21

Analysis

Action id	User id	Activity	Status rating	Note	Date
A1	U1	Extensive Reading In Time	Good		2020/11/20 9:15

Plan

Action id	User id	Activity	Name	Frequency	Target value	Note	Date
P1	U1	Extensive Reading In Time	ER week 1	Everyday	30	Read before sleep	2020/11/20 9:33

Reflection

Action id	User id	Activity	Plan id	Diffic rating	Achievem rating	Effort rating	Note	Date
R1	U1	Extensive Reading In Time	P1	Difficult	High	Much	Goal achieved!	2020/11/27 18:21

Figure 3.4: A set of trace data for the extensive reading activity in the DAPER cycle

Table 3.3: The level and description of self-direction skills

Level	**Data sufficiency**	**Status identification**	**SMART planning**	**Regular tracking**	**Strategic evaluation**
4	76-100%	Check data and successfully identify status WITHOUT system recommendation	Set appropriately challenging plan after analysis	Check progress and successfully self-report regularly	Reflect by self-rating and further comments
3	51-75%	Check data and successfully identify status WITH system recommendation	Set too difficult plan after analysis	Check progress but DID NOT self-report regularly	Reflect by self-rating but DID NOT writing comments
2	26-50%	Check data but PARTIALLY identify status	Set too easy plan after analysis	Check progress but DID NOT self-report in detail	Reflect on personal plan and achievement
1	1-25%	Check data but DID NOT identify status	Set plan without analysis	Check progress but DID NOT self-report	Reflect on personal plan only

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Level	Data sufficiency	Status identification	SMART planning	Regular tracking	Strategic evaluation
0	No data collected	Never analyze	Never plan	Never monitor	Never reflect

Table 3.4 indicates the scoring rubric for planning skills with action description and computation criteria. Five levels of self-planning skills are diagnosed: no plan is set, set plan without analysis, set too easy plan after analysis, set too difficult plan after analysis, and set appropriately challenging plan after analysis.

Table 3.4: Scoring rubric for planning skills

Level	Description	Computation criteria
4	Set appropriately challenging plan after analysis	Count of planning and analysis interactions are above zero and plan difficulty is between zero and threshold value
3	Set too difficult plan after analysis	Count of planning and analysis interactions are above zero and plan difficulty is above threshold value
2	Set too easy plan after analysis	Count of planning and analysis interactions are above zero and plan difficulty is below zero
1	Set plan without analysis	Count of planning interaction is above zero but count of analysis interaction is zero
0	No plan is set	Count of planning interaction is zero

Table 3.5 indicates the scoring rubric for reflection skills with action description and computation criteria. Five levels of self-reflection skills are diagnosed: never reflect, reflect on personal plan only, reflect on personal plan and achievement, reflect by self-rating but no comments, and reflect by self-rating and further comments.

Table 3.5: Scoring rubric for reflection skills

Level	Description	Computation criteria
4	Reflect by self-rating and further comments	Check plan detail and achievement, rate indicators, and make comments
3	Reflect by self-rating but no comments	Check plan detail and achievement, rate indicators, but comment is empty

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Level	Description	Computation criteria
2	Reflect on plan and achievement	Check plan detail and achievement only
1	Reflect on plan only	Check plan detail only
0	Never reflect	Count of reflection interaction is zero

3.7 SDS level-based feedback

Learners are classified into 5 groups based on the diagnosed skill levels. They are given adaptive feedback through feedback prompts (see Table 3.6). The feedback prompts contain a brief description of current skill level and a actionable suggestion which support learners continuously to improve their skills.

Table 3.6: The level and adaptive feedback of self-direction skills

Level	Data sufficiency	Status identification	SMART planning	Regular tracking	Strategic evaluation
4	Good job! You have collected all the data. Please continue to do your best	Good job! You got a great analysis skill.	Good job! You already master the skill of planning. You have set appropriately challenging plan.	Good job! You already master the skill of monitoring. Please continue to do your best.	Good job! You got a great reflection skill.
3	Great! You have collected more than half of the data. Please try to collect all the data.	Great! Then try to analyze DO NOT check system help.	You have partly mastered the skill of planning. Please decrease the difficulty level of the plan to achieve timely.	Great! You have evaluated yourself well! Please take notes every time.	Great! Then try to reflect on your strategies and record it into comments.

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Level	Data sufficiency	Status identification	SMART planning	Regular tracking	Strategic evaluation
2	You have collected some data. Please try to collect a lot of data.	You have not checked the system help. Please check system help.	You have partly mastered the skill of planning. Please increase the difficulty level of the plan to challenge yourself.	You have evaluated yourself. Please also take notes next time.	You have checked your achievement. Please try to rate by yourself about your plan and achievement.
1	You have started collecting data. Please try to collect more data.	You have not reported the activity status. Please report your status.	You have initiated to acquire the skill of planning. Please analysis activity status before plan for it.	You have not evaluated the progress status. Please evaluate the progress status.	You have checked your plan. Please check your achievement.
0	You have not collected your own data. Please start to collect data.	You have not analyzed the activity status. Please check your activity status.	You have not shown the skill of planning yet. Please try to create a plan.	You have not checked your progress. Please check your progress.	You have not checked your plan. Please check your plan.

Table 3.7 indicates the adaptive feedback based on planning skill levels. For each diagnosed planning skill level, a timely feedback is generated. For instance, for the learner with planning skill level 2, he/she receives a description of current skill level as 'You have partly mastered the skill of planning' and an actionable suggestion as 'Please increase the difficulty level of the plan to challenge yourself'.

Table 3.7: Adaptive feedback based on planning skill levels

Level	Description	Feedback
4	Set appropriately challenging plan after analysis	You have set appropriately challenging plan You already master the skill of planning

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Level	Description	Feedback
3	Set too difficult plan after analysis	Please decrease the difficulty level of the plan to achieve timely You have partly mastered the skill of planning
2	Set too easy plan after analysis	Please increase the difficulty level of the plan to challenge yourself You have partly mastered the skill of planning
1	Set plan without analysis	Please analysis activity data before plan for it You have initiated to acquire the skill of planning
0	No plan is set	Please try to create a plan You have not shown the skill of planning yet

Table 3.8 indicates the adaptive feedback based on reflection skill levels. For each diagnosed reflection skill level, a timely feedback is generated. For instance, for the learner with reflection skill level 3, he/she receives a feedback prompt as 'Great! Then try to reflect on your strategies and record it into comments'.

Table 3.8: Adaptive feedback based on reflection skill levels

Level	Description	Feedback
4	Reflect by self-rating and further comments	Well done! You got a great reflection skill
3	Reflect by self-rating but no comments	Great! Then try to reflect on your strategies and record it into comments
2	Reflect on plan and achievement	Please try to rate by yourself about your plan and achievement
1	Reflect on plan only	Please check your achievement
0	Never reflect	Please check your plan

3.8 Ethical considerations

The consent need to be taken from users before they start to use the GOAL system. Also the authorization is taken from users to synchronize their learning and physical activity data. The GOAL system pushes the activity data only after the authorization. The learning data is synchronized from the BookRoll e-book reader and the physical activity data is from mobile devices such as Apple Healthkit or wearable devices such as Garmin smartwatches. The system allows to update the consent agreement to stop synchronizing the data. We also address issues on user privacy by creating an internal UUIDs to anonymously collect and analyze learner behavior while using the GOAL system.

Chapter 4

Experiment design and results

In this chapter, one exploratory study and three evaluation studies are presented. Firstly, an exploratory study on the self-regulated behaviors was examined to identify behavioral patterns and key indicators of self-regulation without SDS support. The context was self-regulated English learning in a university. Secondly, an evaluation study on the planning behaviors in self-directed learning was conducted to explore students' dynamic process of planning behaviors with the SDS support. The context was self-directed English extensive reading in a junior high school. Thirdly, an evaluation study on the planning behaviors in sleep promoting was performed to explore students' process of self-directed behaviors and improvement of SDS levels with the SDS support. The context was self-directed sleep promoting in a junior high school. Finally, an evaluation study was carried out to investigate the effects of SDS on activity-related outcomes, self-directed behaviors, and motivation for the activity. The context was self-directed English extensive reading in a junior high school.

4.1 Study 1: Identifying Behavioral Patterns of Self-Regulation in Computer-Assisted Language Learning

4.1.1 Aim and research questions

To measure self-regulated behaviors in computer-assisted language learning (CALL) courses and identify behavioral patterns and key indicators of self-regulation, such as procrastination and regular learning. There are two main research questions in this study:

1. What learning behavioral patterns of self-regulation exist in the trace data in CALL

courses?

2. Which behavioral factors significantly predict the final course point?

4.1.2 Setting and participants

Fifty mandatory CALL courses at a national university in Japan were employed in this research. The courses were provided to freshman students for self-regulated learning from the spring semester to the fall semester. Table 4.1 shows the course schedule for 1 year.

Table 4.1: Course schedule for one year.

Semester	Stage	Deadline	Learning materials assigned		
			Reading	Listening	Grammar
Spring	1	Week 5	Reading1	Listening1	Grammar1
	2	Week 10	Reading2	Listening2	Grammar2
	3	Week 15	Reading3	Listening3	Grammar3
	4(optional)	Week 21	Reading4	Listening4	Grammar4
Fall	5	Week 30	Reading5	Listening5	Grammar5
	6	Week 36	Reading6	Listening6	Grammar6
	7	Week 42	Reading7	Listening7	Grammar7
	8(optional)	Week 47	Reading8	Listening8	Grammar8

To increase students' motivation, four sub-deadlines were set in each semester. Students were required to complete the assigned materials from the first stage to the third stage, with the fourth stage as an optional one in each semester.

The e-learning materials of the CALL course contained grammar, listening, and reading sections. A total of 973 quiz units were included, with 493 quiz units in the spring semester and 480 quiz units in the fall semester, respectively. The difficulty of e-learning materials increased stage by stage. Table 4.2 indicates the details of the e-learning materials.

A total of 2631 freshman students participated in this study. Students were from all departments of the Art and Science faculties. Eighty-four students (3.19%) dropped out and did not access the learning materials at all during the whole year. Additionally, 93 students (3.53%) who scored 520 or more in the semester-initial TOEFL-ITP exam applied for exemption from the CALL course. Thus, the total data used in this study were from the remaining 2454 students (93.27%).

Table 4.2: Categories and unit numbers of learning materials.

Section	**Part**	**Category**	**Unit #**
Reading	1	Reading comprehension	6
	2	Reading comprehension	7
	3	Reading comprehension	6
	4	Reading comprehension	6
	5	Reading comprehension	6
	6	Reading comprehension	7
	7	Reading comprehension	6
	8	Reading comprehension	6
Listening	1	Short conversation	15
	2	Long conversation	14
	3	Long announcement	15
	4	Formal conversation	22
	5	Short conversation	15
	6	Long conversation	14
	7	Long announcement	14
	8	Formal conversation	21
Grammar	1	Grammar and word usage	95
	2	Grammar and word usage	89
	3	Grammar and word usage	98
	4	Grammar and word usage	120
	5	Grammar and word usage	84
	6	Grammar and word usage	81
	7	Grammar and word usage	106
	8	Grammar and word usage	120
		Total	973

4.1.3 Measures and data collected

The freshman students conducted the CALL course on a language learning management system named WebOCM, and the system had a function for tracing students' events. As students practiced quizzes online, the learning events were recorded in the server logs concurrently. Therefore, the trace data was retrieved from the server of the CALL course. There were three types of trace logs including access to learning materials (access logs), completed quiz items (completion logs), and quiz answers (answer logs). A total of 14,329,172 learning logs were restored for 1 year with 3,344,215 access logs, 2,199,340 completion logs, and 8,785,617 answer logs, respectively.

An example of the raw data contained in access logs is shown in Figure 4.1. The access logs presented information about the frequency and duration of actual learning behaviors, with columns such as user ID, quiz ID, start time, and end time. Besides these columns, a complete flag was included in the completion logs, and each answer for quizzes was stored in the answer logs.

User ID	Course ID	e-material ID	e-material Name	Quiz ID	Quiz Title	Start Time	End Time	Counter
xxxxxxxxxx	101	2614	Grammar1	2590	G_文初_22_強調	2016/04/24 00:13:54	2016/04/24 00:14:13	1
xxxxxxxxxx	101	2614	Grammar1	2589	G_文初_23_冠詞	2016/04/24 00:14:13	2016/04/24 00:14:42	1
xxxxxxxxxx	101	2614	Grammar1	2588	G_文初_24_冠詞	2016/04/24 00:14:42	2016/04/24 00:15:31	1
xxxxxxxxxx	101	2614	Grammar1	2587	G_文初_25_冠詞	2016/04/24 00:15:31	2016/04/24 00:16:24	1
xxxxxxxxxx	102	2041	Listening1	2033	LT_A6_プロポー	2016/04/24 00:16:35	2016/04/24 00:18:05	1
xxxxxxxxxx	102	2041	Listening1	2032	LT_A7_面接	2016/04/24 00:18:05	2016/04/24 00:18:58	1
xxxxxxxxxx	102	2041	Listening1	2031	LT_A8_カエル	2016/04/24 00:18:58	2016/04/24 00:19:40	1
xxxxxxxxxx	201	2614	Grammar1	2587	G_文初_25_冠詞	2016/04/24 00:20:24	2016/04/24 00:20:45	1
xxxxxxxxxx	201	2614	Grammar1	2586	G_文初_26_冠詞	2016/04/24 00:20:45	2016/04/24 00:21:01	1

Figure 4.1: An example of access logs

The behavioral measures from the raw data used in this study were as follows:

– Number of completed quizzes

– Total access time

– Reviewing time

– Score of completed quizzes

– Anti-procrastination

– Irregularity of study interval

– Pacing

All learning variables in this study are summarized in Table 4.3. Variables 1 to 7 are behavioral measures derived from the raw data, and variables 8 and 9 are used for course achievement.

Table 4.3: Summary of learning variables.

Variables	**Description**
1.Number of completed quizzes	The Number of quizzes a student has completed
2.Total access time (h)	The total hours spent on accessing learning materials
3.Reviewing time	The total hours spent on reviewing learning materials
4.Score of completed quizzes	An average score of all quizzes which a student has completed
5.Anti-procrastination	A degree of how early a student completes quizzes
6.Irregularity of study interval (d)	A standard deviation of study intervals
7.Pacing	A count of the number of quizzes which are completed as assigne
8.Mid course point	The exam point in the spring semester
9.Final course point	The exam point in the fall semester

Of particular interest in this study is the measuring of self-regulation patterns from the trace data such as procrastination and regular learning. Thus, three measures were specifically created to identify self-regulation patterns.

The first measure is “anti-procrastination.” It is calculated by comparing the total available days and the lead days when each quiz unit was completed, as shown in Equation 4.1.

$$AP = \sum_{i=1}^{N} \frac{1}{N} * \frac{D - D_{a_i}}{D} \tag{4.1}$$

Where N is the number of completed quizzes, a_i is one quiz unit, D_{a_i} is the days between the completed day of the quiz unit and the first day of the stage when the quiz unit is completed, and D is the total days of the stage. For each quiz unit, a score ranging from 0 to 1 is decided by comparing the completed day with the first day of the related stage. As shown in Figure 4.2, the student who completed all quiz units just at the first day of each stage would receive the highest possible value of 1, however, one who completed all quiz units just before the deadline of each stage would receive the lowest value of zero. Therefore, the anti-procrastination measure was used to determine whether the students completed the quiz units in advance and how early the students completed the quiz units.

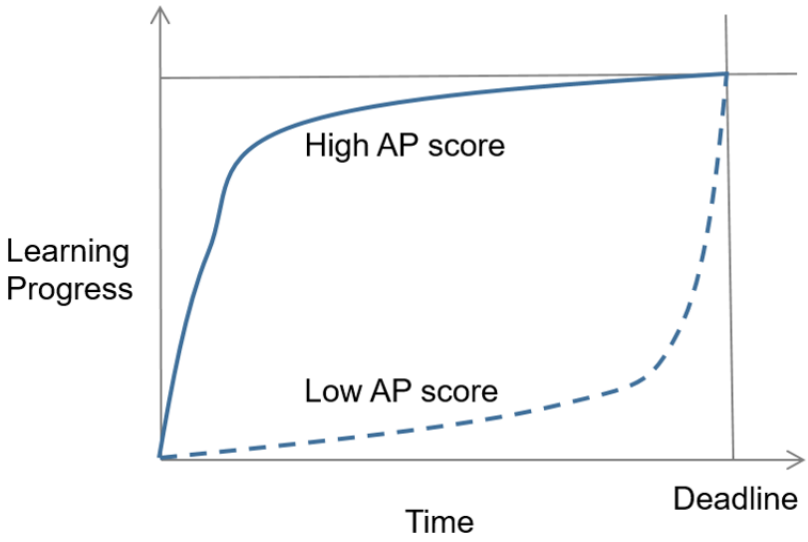

Figure 4.2: An example of high and low anti-procrastination (AP) scores

The second measure is the irregularity of study interval. It manifests how study intervals are dispersed. First, a set of daily activities of accessing learning materials were extracted per student. The study intervals in daily activities were then calculated. Finally, the standard deviation of study intervals per student was computed. A student who regularly learns would get a low score of the irregularity of study interval measure. This measure was used to determine the degree of continuous learning.

The third measure is "pacing." It refers to a count of the number of quiz units that were completed as assigned. As noted earlier, a course schedule informed students of the online materials that should be completed before the four given sub-deadlines. Ideally, students should complete quiz units stage by stage rather than cramming with all quiz units within several days. Thus, a value of 1 would be recorded to the pacing measure if the student completed one quiz unit within the scheduled stage. A high pacing measure would indicate that the student was keeping the learning pace as the assignment schedule. Since the number of quiz units was 973, the cumulative measure ranged from 0 to 973.

Moreover, the total access time is a broad measure of online activities and was calculated by summing the total time spent on accessing learning materials. The reviewing time is the cumulative time spent on reviewing learning materials. The number of completed quizzes is referred to the degree of course completeness. The score of completed quizzes is an average score of all quizzes which the student completed.

Finally, two exam points were used to evaluate the effects of learning pace patterns on student performance. The examinations were administered through an offline campus at the end of the spring and fall semester, respectively. They were graded in the form of five letter grades: A, B, C, D, and F. This grading scale is commonly used, where topical grades where A ranks the highest and F, short for failed, is the lowest. For the sake of easy computation, the grades of A, B, C, D, and F were digitized as 4, 3, 2, 1, and 0, respectively. The results of the first exam conducted in the spring semester are referred to as the mid course point, while the results of the second exam conducted in the fall semester are treated as the final course point.

4.1.4 Data analysis

To investigate the research questions, three phases of analysis were conducted.

First, descriptive statistics were performed for all behavioral measures, including "antiprocrastination," the irregularity of study interval, and "pacing."

Second, clustering analysis was applied to find answers to the first research question. The differences of learning pace would be examined based on "anti-procrastination" and the number of completed quizzes. The k-means algorithm was used to extract clusters from these two measures.

Finally, hierarchical regression analysis was chosen to identify significant behavioral measures related to course achievement. In the process of hierarchical regression analysis, a stepwise method was conducted. A significance level of .05 was used to test the hypothesis.

4.1.5 Results

In this section, we first discuss the results of descriptive statistics for all behavioral measures. Then, the result of clustering analysis is described. Finally, the model of hierarchical regression analysis for course achievement will be proposed.

Descriptive statistics

Table 4.4 contains descriptive statistics for all behavioral variables. The mid course point (M = 3.3, SD = 1.0) and final course point (M = 3.2, SD = 1.1) had high mean values and indicates that the majority of students completed the course with high points. Additionally, the reviewing time (M = 2.8, SD = 4.3) and anti-procrastination (M = 0.27, SD

= 0.14) varied widely. The distribution of the score of completed quizzes (Skewness = −0.28) was close to a normal distribution, whereas the distribution of the irregularity of study intervals (Skewness = 2.01) was skewed to positive. The results revealed that the majority of students completed the course with wide differences in learning pace as well as time management.

Table 4.4: Descriptive statistics of the behavioral variables (N=2454).

Variables	**Mean**	**SD**	**Min.-max.**
1.Number of completed quizzes	800.4	160.3	2-973
2.Total access time (h)	21.2	11.6	0.01-109.48
3.Reviewing time	2.8	4.3	0-60
4.Score of completed quizzes	65.6	12.1	0-98
5.Anti-procrastination	0.27	0.14	0.03-0.84
6.Irregularity of study interval (d)	16.6	8.3	0-90
7.Pacing	742.5	166.7	2-973
8.Mid course point	3.3	1.0	0-4
9.Final course point	3.2	1.1	0-4

Results of clustering analysis

Two measures were used in the cluster analysis: anti-procrastination and number of completed quizzes.

In order to determine the optimal number of clusters for the k-means algorithm, two main evaluation methods were computed: the elbow method and the silhouette method. According to the resulting evaluation, 7 was chosen as the optimum number of clusters.

The average of the clusters are given in Table 4.5. Cluster 1, cluster 2, and cluster 4 accounted for nearly half of the students (n = 1163, 47%), and they completed the course tasks in the last few days before each deadline. The behavior is known as procrastination, which means the delay of initiation or of completion of important tasks. The final course point average in three clusters increased with the number of completed quizzes. Besides, the students who reached the equal number of completed quizzes acted at different learning paces.

Out of seven original clusters, four typical groups for learning pace were identified: Early Completers, Late Completers, Early Dropouts, and Late Dropouts. The cluster

Table 4.5: Average of the clusters for learning pace.

	n	Number of completed quizzes	Anti-procrastination	Final course point
Cluster 1	526	674	.16	2.79
Cluster 2	558	870	.16	3.42
Cluster 3	282	924	.52	3.80
Cluster 4	79	360	.15	1.24
Cluster 5	529	754	.35	3.11
Cluster 6	38	298	.50	2.05
Cluster 7	442	961	.30	3.85

distributions and the final course point average of four clusters are shown in Figure 4.3.

1) Cluster green: Early Completers

This cluster includes students who started to access online materials at the early days of each stage and finally completed the required learning materials. Early Completers accounted for 11% of students in the course. They received an average of 3.80 final course points.

2) Cluster red: Late Completers

This cluster contains students who rushed to access online materials just before the last days of each stage and finally completed the required online materials. Late Completers made up the largest cluster, accounting for 23% of students in the course. They received an average of 3.42 final course points, which was 0.38 lower than Early Completers ($p<.001$).

3) Cluster black: Early Dropouts

These students started to access online materials at the early days of each stage but then dropped out of the course. Early Dropouts made up 2% of students in the course with an average of 2.05 final course points.

4) Cluster pink: Late Dropouts

These students rushed to access online materials just before the last days of each stage but failed to complete the required online materials. Late Dropouts made up 3% of students in the course with the lowest average of 1.24 final course points.

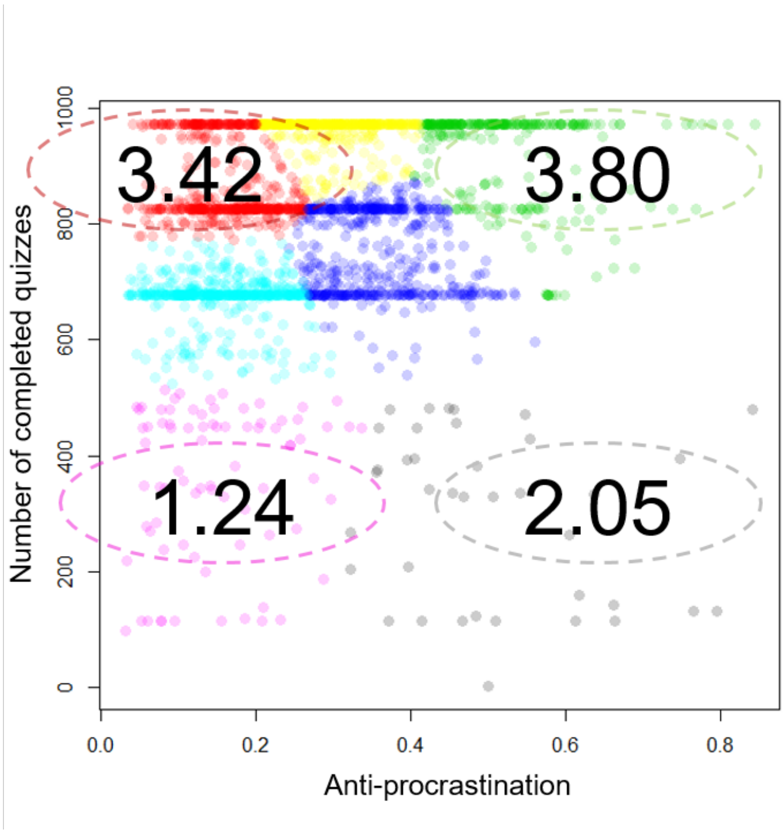

Figure 4.3: Cluster distributions for learning pace and the final course point average of four clusters

Results of hierarchical regression analysis

Hierarchical regression analysis was conducted to predict the final course point. The following variables were analyzed in the prediction: the number of completed quizzes, total access time, reviewing time, the score of completed quizzes, anti-procrastination, irregularity of study interval, and pacing. Furthermore, the mid course point was also selected as a predictor.

Results are shown in Table 4.6. The number of completed quizzes ($B = .002$, $p < .001$), the mid course point ($B = .265$, $p < .001$), irregularity of study interval ($B = -.022$, $p < .001$), the score of completed quizzes ($B = .010$, $p < .001$), total access time ($B = .010$, $p < .001$), and pacing ($B = .001$, $p < .001$) were significant. The regression model explained 40.5% of the variance in the final course point ($R2 = .405$, $F(6, 203) = 274$, $p < .001$). Note that the reviewing time measure was not significant since it was removed from the modeling process. The R2 value was slightly greater than 40% and is not so high to conduct precise course achievement prediction. However, this is an acceptable value when taking into account the fact that there is a large variation of personal behaviors.

A beta coefficient compares the strength of the effect of one behavioral variable to the final course point. The higher the absolute value of the beta coefficient, the stronger the effect. The result revealed that the number of completed quizzes ($\beta = .230$), the mid course point ($\beta = .231$), and irregularity of study interval ($\beta = -.158$) were the most important predictor variables.

Table 4.6: Hierarchical regression analyses results on the final course point.

Model	**Predictors**	**Final course point**			
		B	**SE**	β	R^2
M6	Number of completed quizzes	.002	.000	$.230^{***}$	.405
	Mid course point	.265	.021	$.231^{***}$	
	Irregularity of study interval	-.022	.003	$-.158^{***}$	
	Score of completed quizzes	.010	.002	$.104^{***}$	
	Total access time	.010	.002	$.104^{***}$	
	Pacing	.001	.000	$.116^{***}$	

*** p < .001.

4.1.6 Discussion

This study provided a quantitative account of self-regulated learning in CALL courses and advances the understanding of what learning behavioral patterns exist and which behavioral factors in the trace data can significantly predict the final course point. The results were based on log data from 2454 freshman university students over the period of 1 year. Because self-regulated learning is essential to online learning,measures that reflect the degree of self-regulation were specifically created, including anti-procrastination, irregularity of study interval, and pacing.

The results of clustering analysis revealed that students who took late action were more likely to achieved lower final course points. For learning pace, nearly half (47%) of students were procrastinators. In general, procrastination may lead to dropouts and can have negative effects on academic performance.

The regression model based on six variables explained 40.5% of the variance in the final course point. The number of completed quizzes and irregularity of study interval were strong predictors of course achievement. This clearly indicates the importance of self-regulation skill, in particular completion of assigned tasks and regular learning.

Students who took late action (procrastination) were more likely to achieve lower final course points, which could be explained by the previous studies on procrastination. Researchers has found that procrastination has a negative effect on learning performance (Hussain & Sultan, 2010). However, some researchers suggest the positive effects of procrastination and refer to this positive type of procrastination as active procrastination (J. N. Choi & Moran, 2009). Passive procrastination was negatively correlated with academic performance (Kim & Seo, 2015). Passive procrastination was also associated with planning and self-monitoring problems (Goda et al., 2015). Several studies found that younger college students tend to procrastinate more often than older college students (Kim & Seo, 2015). As a form of dysregulation, procrastination adversely affects young people's autonomy and well-being by limiting their personal growth. Supporting young students' autonomy, by facilitating self-regulation, may promote timely goal setting, initial goal pursuit, decision making, planning, and goal striving (Steel et al., 2018). Previous work also found that planning and self-monitoring were helpful to prevent procrastination (Prestwich & Kellar, 2014). Thus, the support for self-direction and self-regulation is needed, especially for procrastinators.

The present findings have implications for self-regulated learning in the context of CALL and similar online learning environments.

First, this study contributes to the identification of unconventional but more relevant self-regulated learning measures from the trace data and studies their effectiveness. The "anti-procrastination" variable is considered as an elaborate measure regarding learning pace. It is based on the timing of when a quiz is completed and then transforms the behaviors into a number. This variable could also be considerable in other online courses as a quiz could be extended to a task and a learning stage could be set to specific days. Future work could use this variable to easily identify procrastination so that the instructors would further understand their students' learning status.

Second, the measures of irregularity of study interval and pacing proved to be positive influence upon student performance. These findings support those of previous research, which has emphasized the quality of learning behaviors rather than the quantity of learning (Asarta & Schmidt, 2013; G. Cheng & Chau, 2016; You, 2015). The results are consistent with accounts from prior research in online courses. Successful students actively participate in their learning in terms of regularly accessing course notices, carefully studying and reviewing the course content, completing the assignments in a timely manner, and self-evaluating their learning. By contrast, unsuccessful learners are characterized by their failures in estimating the amount of time and effort required to complete tasks and their lack of time-management and life-coping skills (Yukselturk & Bulut, 2007).

Furthermore, these findings could be a foundation of further support for individuals during the whole self-regulated learning process. At the early stage of learning, these measures could be used to categorize learners and identify at-risk students based on their online action. For example, the students who are categorized as procrastinators could be periodically reminded to access the online materials at the remaining stages. At the end of learning, these measures are helpful to evaluate self-regulated learning behaviors for learners as well as for instructors. For example, a score of self-regulation could be sent to facilitate students' self-reflection by integrating learning pacing, consistency, and completeness.

4.2 Study 2: Analysis of Personalized Planning Behavior for Self-Directed Extensive Reading

4.2.1 Aim and research questions

This study investigates students' dynamic process of planning behaviors with the SDS support, including behavioral measures of planning, behavioral patterns after planning, and transition across planning periods. Accordingly, the following research questions were examined:

RQ1. How does learners' perceptions of self-directed learning ability affect their reading outcomes in an online reading environment?

RQ2. How does learners' perceptions of self-directed learning ability affect their planning behaviors in a goal oriented active learning system?

RQ3. What is the correlation between planning behaviors and reading outcomes?

RQ4. What are the students' planning skill levels and their characteristics related to reading amount, planning behavior, and plan achievement?

RQ5. What are the behavioral patterns after planning and their characteristics related to reading amount, planning behavior, and plan achievement?

RQ6. What are the transition dynamics of the cohort's planning behaviors across planning periods?

4.2.2 Participants and contexts

A total of 119 seven-graders (46 boys and 73 girls) aged around 13 years old in a junior high school in Japan participated in the study. The students were from 3 classes and instructed by the same English teacher. The students were divided into the high SDL ability and low SDL ability groups based on their perceptions of SDL in the pre-questionnaire (details in instruments and data collected section). Those who scored higher than the median were labeled as having high self-directed (n = 57), while those who scored lower than the median were considered as having low self-directed (n = 62).

Students self-selected and read e-books in BookRoll and engaged in extensive reading inside and outside of the school using BookRoll. The e-books were from more than 400 graded readers, which predominantly from the Magic Adventures series, the Vera the Alien Hunters series, the School Adventures series, and the Classic Readers series published by e-future. The levels of e-books were from level pre-A1 for beginners to level B2 for upper intermediates of the Common European Framework of Reference for Languages (CEFR) (Council of Europe, 2001).

4.2.3 Procedure

Figure 4.4 shows the experimental procedure of this study. In the beginning, all e-books were provided for the students in BookRoll and were free to access through the learning management system. In the first week, the students took the pre-questionnaire. Then they were guided to ensure that they understand the essence of the extensive reading activity. In the second week, the students were given instruction on how to select e-books by themselves in BookRoll. In the second and third week, the students were given an orientation of the GOAL system. In the fourth week, the students set a one-week plan in the GOAL system and continued to read e-books. In the following four weeks, after setting a one-month plan, the students are asked to engage in extensive reading and interact with the GOAL system at their own pace. They could review the plan, monitor progress, and reflect strategies in the GOAL system. All the reading activities were automatically recorded by the BookRoll e-book reader, and the interactions with the GOAL system also automatically tracked.

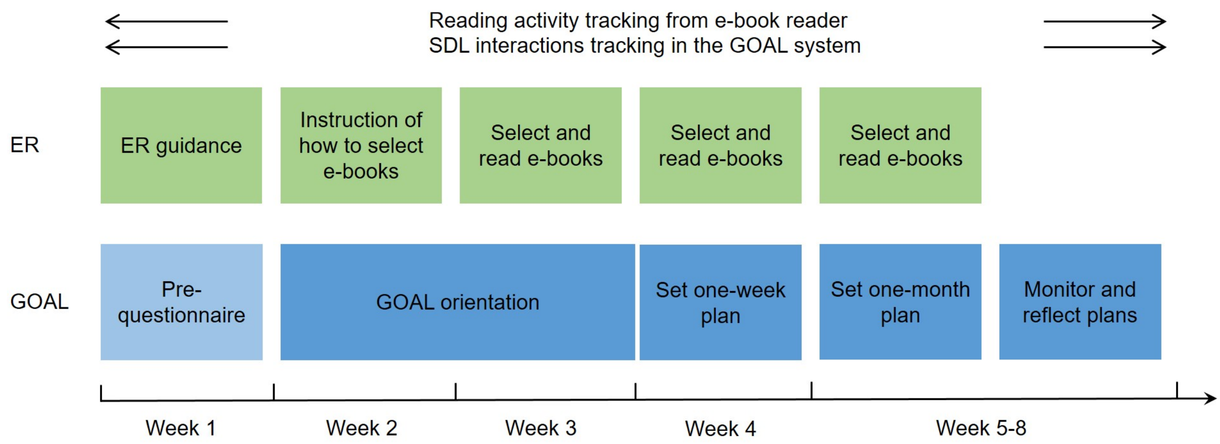

Figure 4.4: Experimental procedure of the study

4.2.4 Measures and data collected

The measures and their descriptions in this study are shown in Table 4.7. Three measures were mainly used: SDL ability, reading outcomes, and planning behaviors. SDL ability is measured by the pre-questionnaire. Reading outcomes contain the reading amount and reading days. Planning behavior, plan reviewing behavior, and planning skill level are measured by interactions with the GOAL system.

Table 4.7: Measures and descriptions in this study

Measure	Description
SDL ability	Sum of the self-reported scores of planning, implementing, and self-monitoring.
Reading amount	Count of completed books during the e-book reading activity.
Reading days	Count of days when the student read e-books.
Attempted days	Count of days when the student read within the plan period.
Achieved days	Count of days when the student achieved the daily target within the plan period.
Attempt rate	Ratio of the Attempted days to the total days in the plan period.
Efficiency rate	Ratio of the Achieved days to Attempted days in the plan period.
Plan achievement	Ratio of the Achieved days to the total days in the plan period.
Planning behavior	Count of GOAL interactions related to planning (create, edit, delete, review).
Plan reviewing behavior	Count of GOAL interactions when students reviewed their plan.
Planning skill level	Level of planning measured by the GOAL system.

The pre-questionnaire regarding SDL ability was developed based on the scale proposed by Cheng et al. (2010). Two dimensions of the questionnaire are used in this study with a total of 10 items, including 6 items for "planning and implementing" and 4 items for "self-monitoring." The questionnaire items were scored on a Likert-type 5-point scale, where 5, 4, 3, 2, and 1 represented "strongly agree," "agree," "neutral," "disagree," and "strongly disagree," respectively. The Cronbach's alpha values of the two dimensions were 0.68 and 0.70, implying acceptable reliability of the questionnaire.

During the experiment, students' reading activities were recorded as learning logs in the learning record store. The reading outcomes were computed from the learning logs. Moreover, students' interactions with the GOAL system were stored as trace data in the GOAL system. The planning behaviors with types were extracted from the trace data. Based on the reading outcomes and planning behaviors with types, the attempt rate, efficiency rate, and plan achievement were calculated for each student.

4.2.5 Data analysis

To answer the research questions, six analyses were conducted. First, a one-way ANCOVA analysis was conducted to assess the effects of the high and low SDL ability on students' reading outcomes. Second, an independent sample t-test was applied to investigate the effects of high and low SDL ability on students' planning behaviors. Third, a Pearson's correlation analysis was conducted to examine the correlation between planning behavior and reading outcomes. Fourth, descriptive statistics were performed for planning skill levels, reading amount, planning behavior, and plan achievement. Fifth, a clustering analysis was applied to reveal students' shared characteristics based on their plan reviewing behaviors. Finally, the Interactive Stratified Attribute Tracking (iSAT) approach was taken (Majumdar & Iyer, 2014) to investigate transitions of cohort's cluster membership in short-term and long-term plan periods for the high and low self-directed groups.

4.2.6 Results

Analysis of reading outcomes between high and low self-directed groups

One one-way ANCOVA was employed to examine the effects of SDL ability on the students' total reading amount, which refers to the count of completed books. The high and low self-directed as an independent variable, while the total reading amount in week 6-8 and the ones in week 1-3 were the dependent variables and covariates, respectively. The assumption of homogeneity of regression coefficient ($F = 2.39$, $p > .05$) was confirmed.

Table 4.8 shows the results of the difference in SDL abilities on reading amount. The adjusted means of the reading amount in the high and the low self-directed groups are 7.58 and 4.10, respectively. Moreover, the post-reading amount between the high and low self-directed groups reached a significant level with $F = 3.93$ ($p < .05$) with $\eta 2 = 0.04$, while controlling for the pre-reading amount, showing a medium effect size (Cohen, 1988).

Table 4.8: Difference in self-directed learning abilities on reading amount

Variance	**SDL ability**	**n**	**Mean**	**SD**	**F**	$\eta 2$
Total reading amount	High	57	7.60	12.60	3.93*	0.04
	Low	62	4.10	5.65		

Another one-way ANCOVA was employed to examine the effects of SDL ability on the students' total reading days, which refers to the count of days read. The high and low self-directed as an independent variable, while the total reading days in week 6-8 and the ones in week 1-3 were the dependent variables and covariates, respectively. The assumption of homogeneity of regression coefficient ($F = 2.99$, $p > .05$)) was confirmed.

Table 4.9 shows the results of the difference in SDL abilities on reading days. The adjusted means of reading days in the high and the low self-directed groups are 5.14 and 3.27, respectively. Moreover, the post-reading days between the high and low self-directed groups reached a significant level with $F = 3.81$ ($p < .05$) with $\eta 2 = 0.04$, while controlling for the pre-reading days, showing a medium effect size (Cohen, 1988). Consequently, it is concluded that the students who had high SDL abilities increased their reading amount and days significantly than those who had low SDL abilities.

Table 4.9: Difference in self-directed learning abilities on reading days

Variance	**SDL ability**	**n**	**Mean**	**SD**	**F**	$\eta 2$
Total reading days	High	57	5.30	6.17	3.81*	0.04
	Low	62	3.26	4.23		

Table 4.10 shows the average of attempt rate, efficiency rate, and plan achievement between the high and low self-directed groups. The averages of the measures in one-week and one-month plan periods were compared. The t-test revealed that high self-directed students attempted more to achieve the one-month plan than low self-directed students with $t = 2.32$ ($p < .05$)

Table 4.10: Difference in self-directed learning abilities on attempt rate, efficiency rate, and plan achievement

	SDL ability	One-week plan			One-month plan		
		Attempt	**Efficiency**	**Achievement**	**Attempt**	**Efficiency**	**Achievement**
Average	High (n = 57)	0.50	0.49	0.28	0.28*	0.38	0.13
	Low (n = 62)	0.48	0.43	0.23	0.18*	0.40	0.10

Analysis of planning behaviors between high and low self-directed groups

An independent sample t-test was employed to examine whether students' SDL abilities would affect their planning behaviors. The results showed that the difference between the high and low self-directed groups on planning behavior was significant ($t = 2.04$, $p < .05$) (see Table 4.11). More specifically, compared to the low self-directed students, the high self-directed students had significantly higher frequency of planning behaviors. The results revealed that the high SDL ability students engaged in more planning interactions in the GOAL system than the low SDL ability students.

Table 4.11: Difference in self-directed learning abilities on planning behavior

	SDL ability	**n**	**Mean**	**SD**	**t**	**Cohen's d**
Planning behavior	High	57	8.46	7.84	2.04*	0.37
	Low	62	6.05	4.76		

The comparison of detailed planning behaviors between the high and low self-directed groups is shown in Figure 4.5. The counts of creating plans in the high and low self-directed groups were 2.30 and 2.31, respectively. The counts of editing plans in the high and low self-directed groups were 0.28 and 0.10, respectively. The counts of deleting plans in the high and low self-directed groups were 0.46 and 0.37, respectively. The counts of reviewing plans in the high and low self-directed groups were 5.00 and 3.15, respectively. More specifically, the difference between the high and low self-directed groups on plan reviewing behavior was significant ($t = 2.19$, $p < .05$).

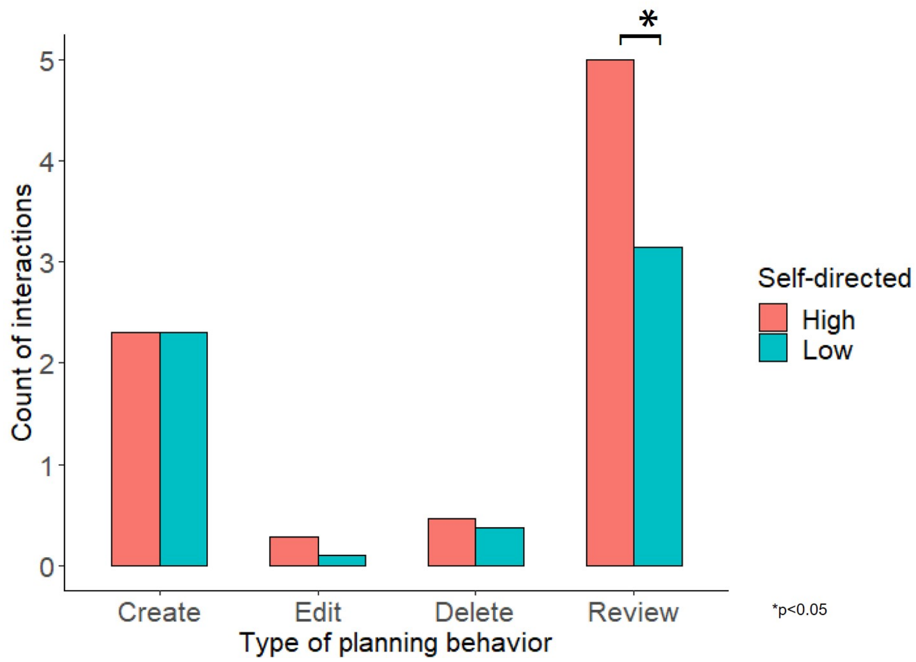

Figure 4.5: Count of detailed planning behaviors with types between high and low self-directed groups

Correlation between planning behaviors and reading outcomes

A Pearson's correlation analysis was conducted to examine the correlation of reading amount, reading days, planning behaviors, and plan reviewing behaviors. The results showed that planning behaviors had positive correlation with reading amount ($r = .27$, $p < .01$) and reading days ($r = .25$, $p < .01$) (see Table 4.12). Moreover, plan reviewing behaviors had positive correlation with reading amount ($r = .38$, $p < .001$) and reading days ($r = .31$, $p < .001$).

Table 4.12: Correlations of reading outcomes, planning behaviors, and plan reviewing behaviors

Correlations	**RA**	**RD**	**PB**	**RPB**
Reading amount (RA)	1			
Reading days (RD)	.77***	1		
Planning behaviors (PB)	.27**	.25**	1	
Plan Reviewing behaviors (RPB)	.38***	.31***	.97***	1

Analysis of the planning skill levels

Descriptive statistics were performed for planning skill levels, reading amount, planning behavior, and plan achievement. Table 4.13 contains descriptive statistics for planning skill levels, reading amount, planning behavior, and plan achievement. The results showed that students who set appropriate challenging plan (level 4) had the highest reading amount and plan achievements in both one-week and one-month plan periods. Students who never set plan (level 0) had the lowest reading amount and plan achievements in both one-week and one-month plan periods. Specially, students who set too difficult plan (level 3) had relatively low reading amount and plan achievements than other level students.

Table 4.13: Descriptive statistics of planning skill levels

Level	**Student #**	**Reading amount**	**Planning behavior**	**Plan achievement**	
				One-week	**One-month**
4	9	29	9.78	0.41	0.14
3	19	14.26	8.84	0.14	0.07
2	46	20.78	8.67	0.31	0.14
1	43	13.23	4.67	0.23	0.11
0	2	5	0.5	0	0

Analysis of the cluster of planning behaviors

A k-means clustering algorithm was applied to extract clusters from the plan reviewing behaviors. In order to determine the optimal number of clusters for the k-means algorithm, two main evaluation methods were computed: the elbow method and the silhouette method. According to the resulting evaluation, four were chosen as the optimum number of clusters. These four clusters that emerged in both one-week and one-month periods could be interpreted as the following groups: Never reviewed, One-time reviewers, Regular reviewers, Short-term reviewers. The pattern of the cluster for plan reviewing behaviors are visualized in Figure 4.6. The averages of the plan achievement are shown, and the ratios of the count of students who reviewed plans in the group in daily scale are colored.

Table 4.14 contains descriptive statistics of reading amount and plan achievement in clusters of one-week plan. Table 4.15 contains descriptive statistics of reading amount and plan achievement in clusters of one-month plan. Following are the description of clusters.

Cluster	N	achievement	d1	d2	d3	d4	d5	d6	d7
Regular Reviewers	20	26%	0.85	0.00	0.10	1.00	0.00	0.25	0.05
Short-term reviewers	10	34%	1.00	1.00	0.10	0.20	0.00	0.00	0.00
One-time reviewers	59	27%	0.98	0.00	0.02	0.00	0.10	0.03	0.00
Never reviewed	30	20%	0.00	0.00	0.00	0.00	0.00	0.00	0.00

a. week-long plan period

Cluster	N	achievement	d1	d2	d3	d4	d5	d6	d7	d8	d9	d10	d11	d12
Regular Reviewers	7	19%	0.14	0.00	0.00	0.29	0.00	0.14	0.00	0.00	0.43	0.00	0.14	0.00
Short-term reviewers	4	8%	1.00	1.00	0.00	0.25	0.00	0.25	0.00	0.00	0.00	0.00	0.00	0.00
One-time reviewers	57	11%	1.00	0.00	0.04	0.00	0.04	0.00	0.02	0.04	0.00	0.00	0.00	0.00
Never reviewed	51	11%	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

d13	d14	d15	d16	d17	d18	d19	d20	d21	d22	d23	d24	d25	d26	d27	d28
0.00	0.00	0.14	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.14
0.25	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.25	0.00	0.00	0.00	0.00
0.02	0.02	0.00	0.00	0.02	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.02	0.00	0.00
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

b. month-long plan period

Figure 4.6: Clusters based on plan reviewing behaviors and their average plan achievement in a. one-week period b. one-month period

For one-week plan period, Cluster 'Never reviewed' accounted for 25% of the students and they never reviewed their plans during the plan period. Cluster 'One-time reviewers' made up the largest cluster, accounting for 50% of the students. They only reviewed their plans once on the 1st day during the plan period. Cluster 'Regular reviewers' accounted for 17% of the students and they reviewed their plans regularly during the plan period. Cluster 'Short-term reviewers' made up 8% of the students and they only reviewed their plans on the 1st and 2nd days during the plan period. The plan achievement in Never

Table 4.14: Descriptive statistics of reading amount and plan achievement in clusters of one-week plan

Cluster	**n**	**Reading amount**	**Plan achievement**
Regular reviewers	20	9.4	26%
Short-term reviewers	10	7.6	34%
One-time reviewers	59	8.63	27%
Never reviewed	30	4.86	20%

Table 4.15: Descriptive statistics of reading amount and plan achievement in clusters of one-month plan

Cluster	n	Reading amount	Plan achievement
Regular reviewers	7	15.57	19%
Short-term reviewers	4	8.75	8%
One-time reviewers	57	8.88	11%
Never reviewed	51	7.10	11%

reviewed, One-time reviewers, Regular reviewers, and Short-term reviewers were 0.20, 0.27, 0.26, and 0.34, respectively.

For one-month plan period, Cluster 'Never reviewed' accounted for 43% of the students and they never reviewed their plans during the plan period. Cluster 'One-time reviewers' also made up the largest cluster, accounting for 48% of the students. They only reviewed their plans once on the 1st day during the plan period. Cluster 'Regular reviewers' accounted for 6% of the students and they reviewed their plans regularly during the plan period. Cluster 'Short-term reviewers' made up 3% of the students and they only reviewed their plans on the 1st and 2nd days during the plan period. The plan achievement in Never reviewed, One-time reviewers, Regular reviewers, and Short-term reviewers were 0.11, 0.11, 0.19, and 0.08, respectively.

Compared the plan achievement between one-week and one-month plan period, the short-term reviewers gained the highest rate of 0.34 in the one-week period, however, received the lowest rate of 0.08 in the one-month period. The regular reviewers gained the average rate of 0.26 in the one-week period and achieved the highest rate of 0.19 in the one-month period.

Analysis of the transition of planning behaviors

Figure 4.7 and 4.8 present the transitions of cohort's cluster membership in one-week and one-month plan periods respectively. The analysis takes the Interactive Stratified Attribute Tracking (iSAT) approach. The clusters of cohort are shown as columns in the SAT diagram and the transitions of cohort are shown as bands in the SAT diagram.

For the clusters of high self-directed learners, nearly half of the learners (n=29, 51%) only reviewed their plan one time and nearly a quarter of the group (n=13, 23%) didn't

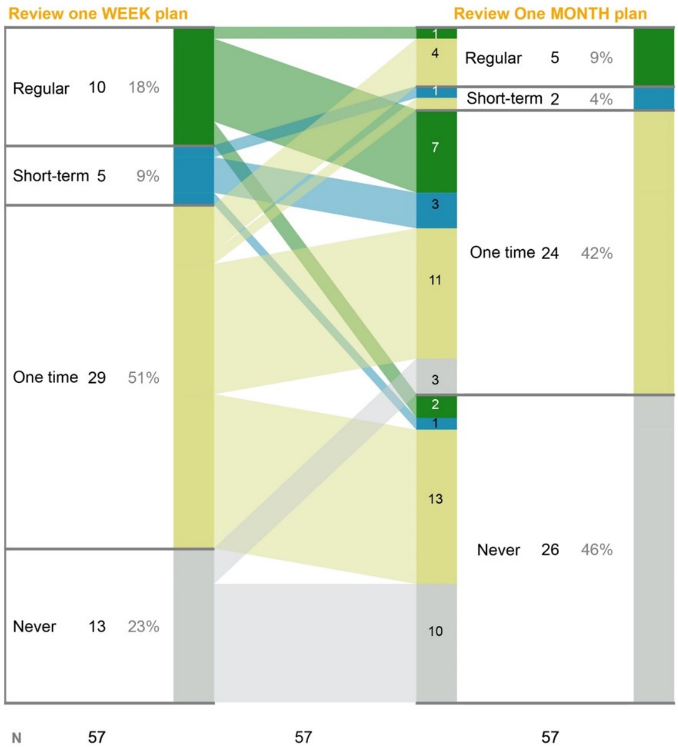

Figure 4.7: Dynamics of plan reviewing behavior across one-week and one-month periods for high SDL learner

review any plans during the one-week period. On the other hand, the regular reviewers and short-term reviewers accounted for 18% and 9% of learners during the one-week period respectively. For the transitions of high self-directed learners, 5% of never reviewed learners (n=3) shifted to one time reviewers during the one-month period. 23% of one time reviewers (n=13) fell in the never reviewed group during the one-month period, with the highest proportion. 7% of one time reviewers (n=4) switched the regular reviewers during the one-month period.

For the clusters of low self-directed learners, nearly half of the learners (n=30, 48%) only reviewed their plan one time and nearly a quarter of the group (n=17, 27%) didn't review any plans during the one-week period. On the other hand, the regular reviewers and short-term reviewers accounted for 16% and 8% of learners during the one-week period respectively. For the transitions of high self-directed learners, 11% of never reviewed learners (n=7) shifted to one time reviewers during the one-month period. 18% of one time reviewers (n=11) fell in the never reviewed group and 3% of them (n=2) switched

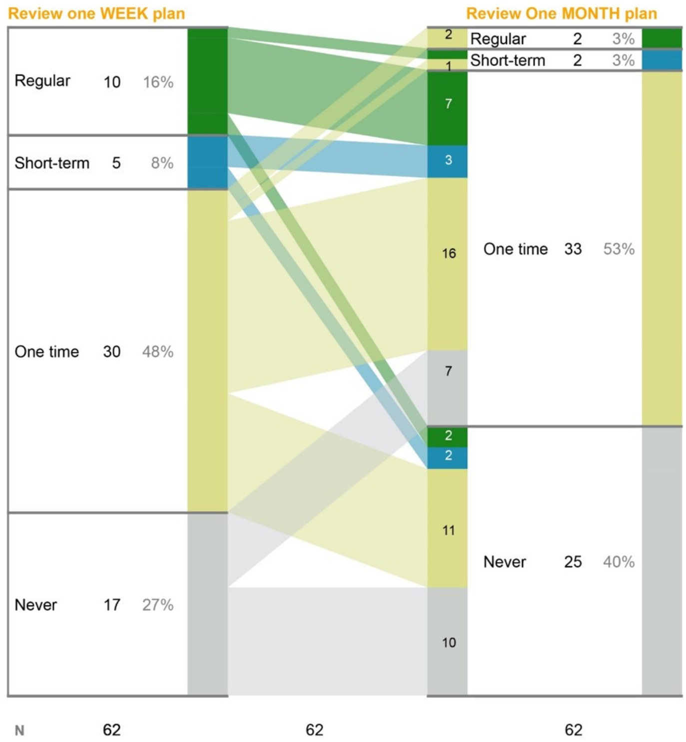

Figure 4.8: Dynamics of plan reviewing behavior across one-week and one-month periods for low SDL learner

the regular reviewers during the one-month period.

While cluster proportions of plan reviewing behaviors were similar in both high and low self-directed groups, it still can be identified the differences of the transition from short term period to long term period in two groups, in particularly for never reviewed learners and one-time reviewers.

4.2.7 Discussion

This study investigated the relations between perceived SDL ability, SDL behaviors, and reading outcomes using the GOAL system. The process of planning behaviors in SDL was also compared and discussed. The findings of this study reveal that the perception of SDL ability plays influential roles in the context of ER. There are six main findings of the study: (a) the high SDL ability students demonstrated significantly more reading outcomes, including reading amount and reading days, than the low SDL ability students; (b) the high SDL ability students engaged significantly more in SDL planning behaviors than the low SDL ability students, more specifically in reviewing plan behaviors; (c) SDL planning behaviors had significant positive correlation with reading outcomes of reading amount and reading days; (d) students who set appropriate challenging plan as skill level 4 had the highest reading amount and plan achievements in both one-week and one-month plan periods; (e) clustering of plan reviewing behaviors highlighted 4 dominant patterns both in short term and long term plan periods, and Regular reviewers read most books and had the highest achievement in one-month plan; (f) transition analysis differentiate the nuances of plan reviewing process in high and low SDL ability groups.

These findings suggest that the perception of SDL ability is a critical factor in the online reading environment, affecting reading outcomes, SDL behaviors and processes, but the degrees of the effects vary. The SDL support should provide personalized feedback in a timely manner based on students' SDL behaviors and processes.

Learners who had high perceived SDL ability tended to gain more outcomes in ER, which could be explained by the previous studies on online learning contexts (N. Arnold, 2009; Zhu et al., 2020). The online learning environment made it appropriate for SDL by breaking through the limitations of time and space, providing learners with abundant reading resources, and allowing learners to read at their own time and pace. The self-select reading and goal-setting allowed learners to take ownership and responsibility for their own learning. When students were unable to use goal-setting skills effectively, they repeatedly failed to achieve goals and could not keep pleasures to read. This could be the reason why the students with low SDL abilities had less reading engagement.

The experimental results also revealed that high perceived SDL ability learners engaged in more planning interactions in the GOAL system. The previous studies have shown that learners' SDL levels and information literacy can be quite different, such as that students' level of SDL correlated with the frequency of using digital tools for learning (Popa & Topală, 2018). The individual differences in SRL behaviors could also be identified in MOOCs (Hood et al., 2015). That is, higher perceptions affect more desirable behaviors in SDL.

4.3 Study 3: Analysis of Planning Behaviors for Health Promotion Activities

4.3.1 Aim and research questions

To explore students' process of planning behaviors and improvement of SDS levels in the sleep promoting activity with the SDS support. Accordingly, the following research questions were examined:

RQ1. What are the differences of self-directed behaviors in sleep promotion using self-tracking or self-planning strategies?

RQ2. What are the improvement of SDS levels in sleep promotion using self-tracking or self-planning strategies?

RQ3. What are the effects of self-planning behaviors on data collection behaviors in sleep promotion?

4.3.2 Participants and contexts

A total of 119 seven-graders (46 boys and 73 girls) aged around 13 years old in a junior high school in Japan participated in the study. Each student were distributed a wearable device, Garmin smartwatch. The smart watch can automatically track student's physical activities after students wore it, including steps taken, walking, running, sleep, and heart-rate based stress level. Students need to synchronize the physical activity data from their smartwatches to the Garmin platform through the Garmin Express application in their tablets. Students can see their own physical activity data in the GOAL system once they succeed to synchronize. Students self-set their plans of sleep time for sleep promotion in the GOAL system.

The students were divided into four groups based on their self-tracking and self-planning behaviors. Students who never track themselves and never set any sleep plan were considered as untracked novice (n = 37). Students who track themselves but never set any sleep plan were labeled as tracked novice (n = 36). Students who never track themselves but set sleep plans were considered as untracked planner (n = 11). Students who track themselves and set sleep plans were labeled as tracked planner (n = 35).

4.3.3 Procedure

Figure 4.9 shows the experimental procedure of this study. In the first week, the students were distributed to a Garmin smartwatch and then were guided on how to use the smartwatch. In the second week, the students were introduced to how to utilize smartwatch and GOAL system for sleep tracking and promoting. They were also guided on the basic usage of the GOAL system for sleep promoting. In the third week, the students started to track their sleep using the smartwatch and synchronize the sleep data on their own. They were also given a data collection and analysis task in the GOAL system. After the fourth week, the students set a sleep plan, monitored the progress of the plan, and reflected strategies in the GOAL system. All the sleep activities were automatically recorded by the Garmin smartwatch, and the interactions with the GOAL system also automatically tracked.

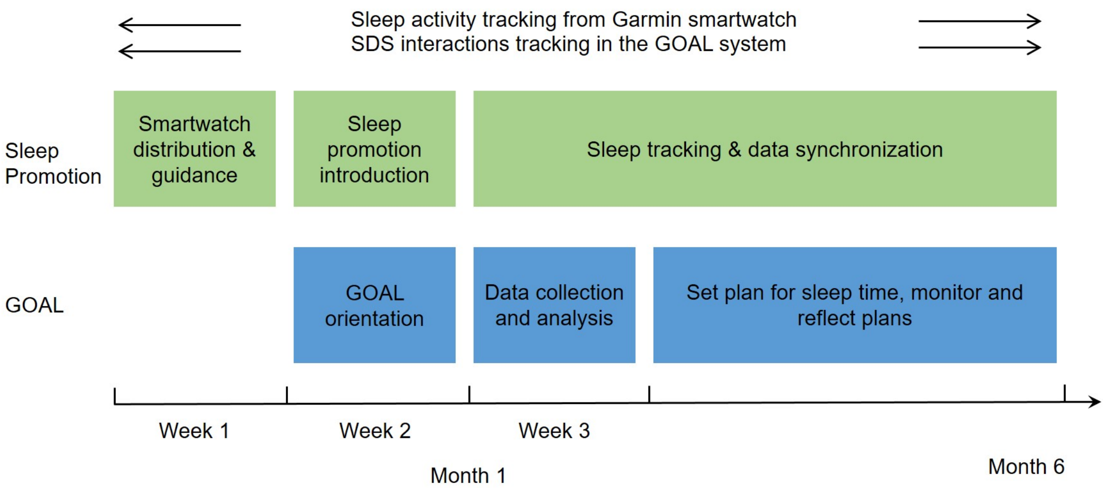

Figure 4.9: Experimental procedure of the study

4.3.4 Measures and data collected

The measures and their descriptions in this study are shown in Table 4.16. Four measures were used: self-directed behavior, SDS level, goal-setting behavior, and count of sleep record. Self-directed behavior, SDS level and goal-setting behavior are measured by interactions with the GOAL system. The count of sleep record is computed based on the sleep data which synchronized from students' smartwatches.

Table 4.16: Measures and descriptions in this study

Measure	Description
Self-directed behavior	Total Count of the interactions in data collection, analysis, planning, monitoring and reflection with the GOAL system.
SDS level	Level of self-direction in five phases measured by the GOAL system.
Goal-setting behavior	Interaction of planning in the GOAL system.
Count of sleep record	Count of sleep record from smartwatches in daily level

During the experiment, students' once synchronized the physical activity data from smartwatches, the records of sleep time were automatically push to the GOAL system. Moreover, students' interactions with the GOAL system were stored as trace data in the GOAL system. The self-directed behaviors extracted from the trace data. Based on the self-directed behaviors, the SDS levels were timely computed for each student.

4.3.5 Data analysis

To answer the research questions, three analyses were conducted. First, independent sample t-tests were applied to investigate the differences of self-directed behaviors for sleep promotion in four student groups. Second, independent sample t-tests were conducted to examine the improvement of SDS levels for sleep promotion in four student groups. Finally, a independent sample t-test was conducted to reveal the effects of goal-setting behaviors on data collection behaviors for sleep promotion.

4.3.6 Results

Analysis of self-directed behaviors in four student groups

Descriptive statistics were performed to summarize self-directed behaviors. Table 4.17 contains descriptive statistics for self-directed behaviors in four student groups. The untracked novice (M = 5.41, SD = 7.04) had lowest mean value and indicates that this group student were not active in self-directed interactions with the GOAL system. On the other hand, the tracked planner (M = 24.66, SD = 19.36) had highest mean value indicates that this group student were highly engaged in self-directed interactions with the GOAL system.

Table 4.17: Descriptive statistics of self-directed behaviors in four student groups (N = 119)

Group	**n**	**Mean**	**SD**	**Min.-max.**
tracked planner	35	24.66	19.36	1-83
untracked planner	11	11.45	11.43	1-40
tracked novice	36	9.89	14.84	0-81
untracked novice	37	5.41	7.04	0-34

Independent sample t-tests were employed to investigate the differences of self-directed behaviors for sleep promotion in four student groups. The results showed that the differences between the tracked planner and other three groups on self-directed behavior were significant with $t = -5.67$ ($p < .001$), $t = -3.54$ ($p < .001$), and $t = -2.14$ ($p < .05$), respectively. The difference between the untracked planner and untracked novice groups on self-directed behavior was significant ($t = -2.15$, $p < .05$) (see Table 4.18). The results revealed that the tracked and untracked planners engaged in more self-directed interactions in the GOAL system.

Table 4.18: Difference of self-directed behaviors for sleep promotion in four student groups

	Group	**n**	**Mean**	**SD**	**t**	**Cohen's d**
Self-directed behaviors	tracked planner	35	24.66	19.36	-2.14*	0.83
	untracked planner	11	11.45	11.43		
	tracked planner	35	24.66	19.36	-3.54***	0.84
	tracked novice	36	9.89	14.84		
	tracked planner	35	24.66	19.36	-5.67***	1.32
	untracked novice	37	5.41	7.04		
	untracked planner	11	11.45	11.43	-2.15*	0.64
	untracked novice	37	5.41	7.04		

Analysis of SDS levels in four student groups

Descriptive statistics were performed to summarize SDS levels. Table 4.19 contains descriptive statistics for self-direction skill levels in four student groups. The tracked planner had highest mean values in all SDS levels indicates that this group student gained relatively high SDS sub-skills in the GOAL system. On the other hand, the untracked novice had lowest mean values in all SDS levels and indicates that this group student had low SDS sub-skills in the GOAL system.

Table 4.19: Descriptive statistics of self-direction skill levels in four student group (N = 119)

Group	Skill	Mean	SD	Min.-max.
tracked planner	Data sufficiency	1.46	1.48	0-4
	Status identification	0.97	0.66	0-2
	SMART planning	1.66	0.97	1-4
	Regular tracking	1.00	1.03	0-4
	Strategic evaluation	1.09	1.34	0-4
untracked planner	Data sufficiency	0.09	0.30	0-1
	Status identification	0.64	0.67	0-2
	SMART planning	1.27	0.47	0-2
	Regular tracking	0.45	0.93	0-3
	Strategic evaluation	0.45	0.93	0-3
tracked novice	Data sufficiency	1.07	1.12	0-4
	Status identification	0.75	0.52	0-2
	SMART planning	0	0	0
	Regular tracking	0.54	0.51	0-1
	Strategic evaluation	0	0	0
untracked novice	Data sufficiency	0.17	0.38	0-1
	Status identification	0.75	0.44	0-1
	SMART planning	0	0	0
	Regular tracking	0.54	0.72	0-1
	Strategic evaluation	0	0	0

Independent sample t-tests were employed to investigate the differences of SDS levels in four student groups. The results showed that the difference between the tracked planner and untracked planner groups on the skill of data sufficiency was significant with t = -3.02

($p < .01$). The differences between the tracked planner and tracked novice groups on the skills of regular tracking and strategic evaluation were significant with t = -2.18 ($p < .05$) and t = -4.29 ($p < .001$), respectively. The differences between the tracked planner and untracked novice groups on the skills of data sufficiency, SMART planning, regular tracking, and strategic evaluation were significant with t = -4.16 ($p < .001$), t = -8.36 ($p < .001$), t = -2.38 ($p < .05$), and t = -3.97 ($p < .001$), respectively.

The differences between the untracked planner and tracked novice groups on the skills of data sufficiency, SMART planning, and strategic evaluation were significant with t = -2.84 ($p < .01$), t = -14.73 ($p < .001$), and t = -2.63 ($p < .05$), respectively. The differences between the untracked planner and untracked novice groups on the skills of SMART planning and strategic evaluation were significant with t = -13.59 ($p < .001$) and t = -2.43 ($p < .05$), respectively. The difference between the tracked novice and untracked novice groups on the skill of data sufficiency was significant (t = -3.78, $p < .001$).

The results revealed that the tracked planners achieved higher SDS level than other three groups in the GOAL system.

Analysis of the effects of self-planning behaviors on data collection behaviors

An independent sample t-test was employed to examine whether self-planning behaviors would affect data collection behaviors. The count of sleep record between tracked planner and tracked novice were compared. The results showed that the difference between the tracked planner and tracked novice on the count of sleep record was significant (t = -2.33, $p < .05$) (see Table 4.20). More specifically, compared to tracked novice, the tracked planners had significantly higher count of sleep record. The results revealed that self-tracking and self-planning students put more effort in collecting their sleep data than only self-tracking students.

Table 4.20: Difference in the count of sleep record between tracked planner and tracked novice groups

	Group	**n**	**Mean**	**SD**	**t**	**Cohen's d**
Count of sleep record	tracked planner	35	51.83	53.89	-2.33*	0.55
	tracked novice	36	27.22	33.05		

4.3.7 Discussion

This study investigated the differences of self-directed behaviors, the improvement of SDS levels, and the effects of goal-setting behaviors on data collection for sleep promotion in four groups using the GOAL system. The four groups were tracked planner, untracked planner, tracked novice, and untracked novice. The findings of this study reveal that both self-tracking and self-planning strategies play influential roles in the context of health promoting. There are three main findings of the study: (a) the tracked and untracked planner group engaged in more self-directed interactions in the GOAL system than the tracked and untracked novice group; (b) the tracked planner group achieved higher SDS level than other three groups in the GOAL system; (c) self-tracking and self-planning students put more effort in collecting their sleep data than those who only self-tracking without self-planning.

SDS requires learners to be active and purposefully harness a number of skills to maximize their learning and health promoting achievements. With the growing trend of preparing lifelong learning in the 21st century, the theory of self-direction has been increasingly applied in the context of learning and health domains. Previous studies on SDS in learning have found that the understanding students' self-regulated learning behaviors such as goal setting and monitoring were crucial to the students' success in an online learning environment (Sabourin et al., 2012), where students' are expected to use specific strategies for achieving their goals. The findings of this study extend the understanding to health promoting context. That is, self-direction skills such as goal setting and monitoring were crucial to the students' success in health promoting (Munson & Consolvo, 2012).

4.4 Study 4: Promote Reading Engagement, Self-Directed Learning Behavior, and Motivation in Extensive Reading

4.4.1 Aim and research questions

To investigate how students' perceptions of SDL ability affect their reading engagement, self-directed learning behaviors, and motivation for extensive reading. Accordingly, the following research questions were examined:

1. How do learners' perceptions of self-directed learning ability affect their reading engagement in a online reading environment?

2. How do learners' perceptions of self-directed learning ability affect their self-directed learning behaviors a goal oriented active learning system?

3. How do learners' perceptions of self-directed learning ability affect their motivation for extensive reading?

4.4.2 Participants and contexts

A total of 117 seven-graders (45 boys and 72 girls) aged 13 on average in a junior high school in Japan participated in the study. The students are from 3 classes and instructed by the same English teacher. The students were divided into the high self-directed learning ability and low self-directed learning ability groups based on their perception of self-directed learning ability in the pre-questionnaire (details in instrument and data collected section). Those who scored higher than the median were labeled as having high self-directed (n = 56), while those who scored lower than the median were considered as having low self-directed (n = 61).

Students were required to select picture books by themselves from more than 400 e-books in BookRoll and engaged in extensive reading outside the English course using BookRoll. The levels of e-books were from level pre-A1 for beginners to level B2 for upper intermediates of the Common European Framework of Reference for Languages (CEFR) (Council of Europe, 2001). Furthermore, students created their plans for extensive reading weekly, monitored the progress of plans, and reflected the strategies on their own paces during the extensive reading activity in the GOAL system.

4.4.3 Procedure

Figure 4.10 shows the experimental procedure of this study. In the beginning, all e-books were provided for the students in BookRoll. In the first week, the students took the pre-questionnaire for 15 minutes. Then they were guided for 35 minutes to ensure that they understand the essence of the extensive reading activity. In the second week, the students were given instruction on how to select e-books by themselves in BookRoll and orientation of the GOAL system. In the following four weeks, the students are asked to engage in extensive reading and interact with the GOAL system at their own pace. They could set plans, monitor progresses, and reflect strategies in the GOAL system. After the six-week experiment period, the students took a post-questionnaire for 30 minutes.

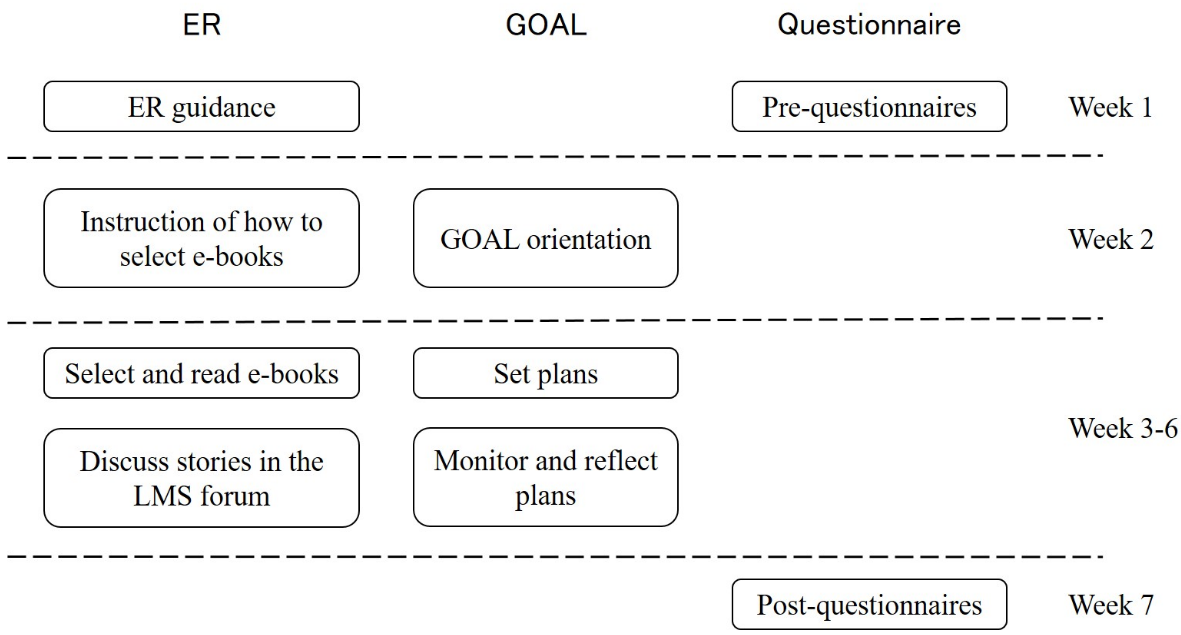

Figure 4.10: Experimental procedure of the study

4.4.4 Measures and data collected

The pre-questionnaire regarding self-directed learning ability was developed based on the scale proposed by Cheng et al. (2010). Two dimensions of the questionnaire are used in this study with a total of 10 items, including 6 items for "planning and implementing" and 4 items for "self-monitoring." The questionnaire items were scored on a Likert-type 5-point scale, where 5, 4, 3, 2, and 1 represented "strongly agree," "agree," "neutral," "disagree," and "strongly disagree," respectively. The Cronbach's alpha values of the two dimensions were 0.68 and 0.67, implying reasonable reliability of the questionnaire.

In addition, the post-questionnaire regarding the motivation and autonomy in extensive reading was adopted from Tanaka (2017). The motivation and autonomy in extensive reading scales were both measured through 5 items with a 5-point Likert-type scale. The Cronbach's alpha values of the two subscales were 0.73 and 0.74, revealing relatively high reliability of the scales.

During the experiment, the reading engagement was recorded in the learning record store, including total time read and total pages read. Moreover, the SDL behavior was tracked by the interactions between the students and the GOAL system, which contains planning, monitoring, and reflection behaviors. The total number of planning and monitoring interactions in the GOAL system is taken as a proxy of the students SDL behavior.

4.4.5 Data analysis

To assess the effects of the high and low SDL ability on students' reading engagement, a one-way ANCOVA was conducted. The independent variables were the students' high and low SDL ability, while dependent variables and covariates were their reading engagement in week 5-6 and reading engagement in week 1-2, respectively. Furthermore, independent sample t-tests were applied to investigate the effects of high and low SDL ability on students' SDL behaviors and motivation as well as autonomy in extensive reading.

4.4.6 Results

Analysis of reading engagement

A one-way ANCOVA was employed to examine the effects of SDL ability on the students' reading engagement, which contains the total time read and pages read. The high and low self-directed as an independent variable, while the reading engagement in week 5-6 and the ones in week 1-2 were the dependent variables and covariates, respectively. The assumption of homogeneity of regression coefficients for the total time read ($F = 0.23$, $p = .63 > .05$) and pages read ($F = 0.20$, $p = .66 > .05$) were confirmed. Table 4.21 shows the ANCOVA result.

Regarding the total time read, the adjusted means of the high self-directed and the low self-directed are 92.41 and 50.11, respectively; moreover, the post total time read between the high self-directed and the low self-directed reached a significant level with F = 5.94 ($p < .05$) with $\eta 2 = 0.05$, showing a medium effect size (Cohen, 1988).

Regarding the pages read, the adjusted means of the high self-directed and the low self-directed are 200.28 and 119.08, respectively; moreover, the post pages read between the high self-directed and the low self-directed reached a significant level with F = 5.02 ($p < .05$) with $\eta 2 = 0.04$, showing a medium effect size (Cohen, 1988).

Consequently, it is concluded that the students who had high SDL abilities increased more reading engagement significantly than those who had low SDL abilities.

Table 4.21: Different self-directed learning abilities on reading engagement

Variance	**SDL ability**	**n**	**Mean**	**SD**	**F**	$\eta 2$
Total time read	High	56	91.92	115.67	5.94*	0.05
	Low	61	50.56	73.53		
Total pages read	High	56	202.59	247.70	5.02*	0.04
	Low	61	116.96	134.83		

Analysis of self-directed learning behaviors

An independent sample t-test was employed to examine whether students' SDL abilities would affect their SDL behaviors. The results showed that the difference between the high and low SDL ability students on SDL behaviors was significant ($t = 2.00$, $p < .05$) (see Table 4.22). More specifically, compared to the low SDL ability students, the high SDL ability students' behaviors were significantly higher. The results revealed that the high SDL ability students engaged in more the planning and monitoring interactions in the GOAL system than the low SDL ability students.

Table 4.22: Different self-directed learning abilities on self-directed learning behaviors

	SDL ability	**n**	**Mean**	**SD**	**t**	**Cohen's d**
Self-planning and self-monitoring behaviors	High	56	37.68	39.99	2.00*	0.37

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	SDL ability	n	Mean	SD	t	Cohen's d
	Low	61	25.20	26.55		

Analysis of motivation and autonomy in extensive reading

An independent sample t-test was employed to examine the effects of SDL ability on the students' motivation and autonomy in extensive reading. The results showed that there were significant differences between the high and low SDL ability students' motivation and autonomy in extensive reading with $t = 3.27$ ($p < .01$) and $t = 4.41$ ($p < .001$), respectively (see Table 4.23). More specifically, the high SDL ability students perceived higher motivation and autonomy in extensive reading than those with low SDL ability.

Table 4.23: Different self-directed learning abilities on motivation and autonomy in extensive reading

	SDL ability	n	Mean	SD	t	Cohen's d
Motivation	High	56	4.29	0.45	3.27**	0.62
	Low	61	4.01	0.46		
Autonomy	High	56	4.43	0.48	4.41***	0.81
	Low	61	4.04	0.48		

4.4.7 Discussion

This study investigated how the perception of SDL ability affects students' reading engagement, SDL behavior, and motivation for ER using the proposed goal-oriented active learning system, GOAL. The findings of this study reveal that the perception of SDL ability plays influential roles in the context of ER. There are three main findings of the study: (a) the high SDL ability students demonstrated significantly more reading engagement, including total time read and pages read, than the low SDL ability students; (b) the high SDL ability students engaged significantly more in SDL behaviors than the low SDL ability students, which exhibited as planning and monitoring interactions in the GOAL system ; (c) the high SDL ability students demonstrated significantly higher motivation and autonomy for ER than the low SDL ability students. These findings suggest that the perception of SDL ability is a critical factor in the self-directed online reading environment, affecting reading engagement, motivation for ER, and SDL behaviors, but the degrees of the effects vary.

Learners who had high SDL ability tended to engage in ER, which could be explained by the previous studies on online learning contexts (N. Arnold, 2009; Zhu et al., 2020). The online learning environment made it appropriate for self-directed reading by breaking through the limitations of time and space, providing learners with abundant reading resources, and allowing learners to read at their own time and pace. The self-select reading and goal-setting allowed learners to take ownership and responsibility for their own learning. When students were unable to use goal-setting and monitoring skills effectively, they repeatedly failed to achieve goals and could not keep pleasures to read. This could be the reason why the students with low SDL abilities had less reading engagement.

The experimental results also revealed that high SDL ability learners engaged in more the planning and monitoring interactions in the GOAL system. The previous studies have shown that learners' SDL levels and information literacy can be quite different, such as that students' level of SDL correlated with the frequency of using digital tools for learning (Popa & Topală, 2018). Recent literatures examined the perception of planning, monitoring, and reflection in SDL activities. The correlation between reflection and planning, monitoring was identified in undergraduate students (Hill et al., 2020), however, no correlation between SDL readiness and the engagement in self-reflection, the need for self-reflection in MOOCs learners (Agonács et al., 2020). The influence factors of SDL behaviors such as self-reflection for young students is a future research question.

Learners with high SDL ability perceived higher motivation and autonomy for ER, which partially supports previous research on the importance of perceiving autonomy for ER in enhancing motivation for short in-class ER (Tanaka, 2017). Although it is reported that perceived autonomy had a positive impact on perceived motivation, leading to higher intrinsic motivation and identified regulation, no study has investigated the relationship between the perception of SDL ability and perceived motivation as well as autonomy for ER. One potential explanation for the result in this study and previous research is that learners' perceptions of SDL ability influence both perceived motivation and autonomy for ER. In the meantime, perceived motivation for ER is also positively correlated to perceived autonomy for ER.

Chapter 5

Discussion

In this thesis, we identified the need of the technology support for SDS in order to prevent passive procrastination and maintain regular learning in an exploratory study. We then designed and developed the GOAL system to support students' development of SDS. The system built an activity data-rich environment, created a quantitative measurement of SDS using online trace data, and provided an adaptive feedback of SDS in phases and levels. We finally explored the dynamic process of self-directed behaviors in learning and health promoting contexts and further investigated the relations between the perception of SDS, activity-related outcomes, self-directed behaviors, and personal attributes in three evaluation studies.

5.1 Finding summary

In the exploratory study on the self-regulated behaviors in computer-assisted language learning (CALL) courses without SDS support, we identified behavioral patterns of self-regulation using behavioral measures such as anti-procrastination and irregularity of study interval. The results of learning pace clustering analysis revealed that students who took late action were more likely to achieved lower final course points. For learning pace, nearly half (47%) of students were procrastinators. In general, passive procrastination may lead to dropouts and can have negative effects on academic performance. Furthermore, the number of completed quizzes and irregularity of study interval were strong predictors of course performance in the regression model. It clearly indicated the importance of self-regulation skill, in particular completion of assigned tasks and regular learning. Thus, technology support for SDS is needed to prevent passive procrastination and maintain regular learning.

In the first evaluation study on the planning behaviors in self-directed extensive reading with SDS support, we found that the high SDL ability students engaged significantly more in planning behaviors, that were found to be significantly correlated with reading outcomes, than the low SDL ability students. Setting specific challenging goals and regular reviewing were important for the successful English learning activity. Transition analysis also differentiate groups of learners with different planning behavioral patterns. These findings suggest that the perception of SDL ability is a critical factor in the online reading environment, affecting reading outcomes, SDL behaviors and processes, but the degrees of the effects vary. The SDL support should provide personalized feedback in a timely manner based on students' SDL behaviors and processes.

In the second evaluation study on the planning behaviors in self-directed sleep promoting with SDS support. we found that both self-tracking and self-planning skill play influential roles in the context of health promoting. The self-planning students engaged in more self-directed interactions in the GOAL system than the novice students. The self-tracking and self-planning students achieved higher SDS level and put more effort in collecting their sleep data than other students. The personalized feedback can be created using the self-directed behavioral variables and patterns in the environment.

In the final evaluation study on the effects of SDS on activity-related outcomes, self-directed behaviors, and personality attributes, we found that the high SDL ability students demonstrated significantly more reading engagement, SDL behaviors, motivation and autonomy for extensive reading than those with low SDL ability. It shows that the GOAL system could be exploited as a useful tool to support self-directed language learning in the schools; however, the affective and behavioral outcomes created by the environment were affected to varying degrees by the levels of students' SDL ability.

5.2 Causation and inference

The indicators of self-regulated behavior (i.e., irregularity of study interval and pacing) proved to be positive influence upon student performance. The finding supports those of previous research, which has emphasized the quality of learning behaviors rather than the quantity of learning (Asarta & Schmidt, 2013; G. Cheng & Chau, 2016; You, 2015). The results are consistent with accounts from prior research in online courses. Successful students actively participate in their learning in terms of regularly accessing course notices, carefully studying and reviewing the course content, completing the assignments in a timely manner, and self-evaluating their learning. By contrast, unsuccessful learners are characterized by their failures in estimating the amount of time and effort required to complete tasks and their lack of self-regulated and lifelong learning skills (Yukselturk & Bulut, 2007).

Learners who had high perceived SDL ability tended to gain more outcomes in ER, which could be explained by the previous studies on online learning contexts (N. Arnold, 2009; Zhu et al., 2020). The online learning environment made it appropriate for SDL by breaking through the limitations of time and space, providing learners with abundant reading resources, and allowing learners to read at their own time and pace. The self-select reading and goal-setting allowed learners to take ownership and responsibility for their own learning. When students were unable to use goal-setting skills effectively, they repeatedly failed to achieve goals and could not keep pleasures to read. This could be the reason why the students with low SDL abilities had less reading engagement. The SDL support take increasing responsibility for students' learning, and become mindful of such personal qualities as their sense of personal agency Buckingham Shum and Crick, 2016.

The high perceived SDL ability learners engaged in more planning interactions in the GOAL system. The previous studies have shown that learners' SDL levels and information literacy can be quite different, such as that students' level of SDL correlated with the frequency of using digital tools for learning (Popa & Topală, 2018). The individual differences in SRL behaviors could also be identified in MOOCs (Hood et al., 2015). That is, higher perceptions affect more desirable behaviors in SDL. Recent literatures examined the perception of planning, monitoring, and reflection in SDL activities. The correlation between reflection and planning, monitoring was identified in undergraduate students (Hill et al., 2020), however, no correlation between SDL readiness and the engagement in self-reflection, the need for self-reflection in MOOCs learners (Agonács et al., 2020). The influence factors of SDL behaviors such as self-reflection for young students is a future research question.

Learners with high SDL ability perceived higher motivation and autonomy for ER, which partially supports previous research on the importance of perceiving autonomy for ER in enhancing motivation for short in-class ER (Tanaka, 2017). Although it is reported that perceived autonomy had a positive impact on perceived motivation, leading to higher intrinsic motivation and identified regulation, no study has investigated the relationship between the perception of SDL ability and perceived motivation as well as autonomy for ER. One potential explanation for the result in this study and previous research is that learners' perceptions of SDL ability influence both perceived motivation and autonomy for ER. In the meantime, perceived motivation for ER is also positively correlated to perceived autonomy for ER.

5.3 Implications

The findings of this work have implications for researchers studying SDS support environments in learning and health promoting contexts. First, an data-rich environment has potential benefits if it integrates the learners' self-activity data. It not only provides learners with abundant resources in the context but can also support planning for the context. This can make learners select and practice planning skills in their own time and pace and consequently make it possible for them to have more control over their own learning and health promoting activity through planning. Second, the Learning Analytics approaches have potential to support SDS in both learning and health promoting contexts. The high perceived SDL ability students engaged significantly more in SDL planning behaviors than the low perceived SDL ability students, more specifically in reviewing plan behaviors. It's important to quantitatively measure the self-directed behaviors using such interactions as indicators and further provide timely feedback for learners. The measures and scaffolding would be useful to develop a personalized SDL intervention. Finally, these personalized interventions can be consider into other online learning environments, such as an blended learning in k-12 schools, a massively open online course, or a adult education course. Learners in these settings need to have SDS as a basic attribute to succeed in their current situation and future life.

The findings of this work also have implications for researchers studying ER environments. Compared with conventional reading, extensive paper books, reading extensive e-books in the self-directed online reading environment has potential environmental benefits. The environment not only breaks through the limitations of time and space but also provides learners with abundant reading resources. The benefits make learners select and read large amounts of books in their own time and pace and consequently make it possible for them to have more control over their own learning. In addition, the learning logs generated from e-book readers provide a quantitative measurement of ER engagement and a snapshot of learning status. The quantitative measurement can be an automatically and quantitatively objective metric for ER outcomes. The snapshot can be analyzed and further provided as feedback to learners using the learning analytics approach.

Practically, the findings of this study provide suggestions for educators seeking to improve ER with SDL strategy usage. First, instructors should consider learners' different levels of SDL ability, including self-planning and self-monitoring in the design and development of ER programs. It's necessary to encourage low SDL ability learners to make their own plans and monitor their progress toward their plans during the ER activity, such as creating a daily plan for reading time or pages. Second, since ER is a way of learning a language through a great amount of reading on learners' own choices and paces, more ER support should be provided for learners. The more technological support of SDL and autonomy learners received, the more self-directed opportunities they took. Accordingly, the support also reduces the instructors' workload in ER programs. Finally, ER support should consider learners' initial perceptions of SDL ability. If the scaffolding of SDL and autonomy can be adapted to different levels of learners, they could perform better in such personalized ER support environments.

The components of SDS support have rationality since they are built in learners' everyday learning and health activities. They have flexibility because of personality attributes are also considered. Since the measures are from not only the activity-related indicators but also the process data of behaviors, the adaptive feedback can be provided in a timely manner. The measures and feedback would be useful to build a personalized intervention for the development of SDS.

5.4 Limitations

Although the importance of investigating the effects of SDS on learning and health promoting are demonstrated, some limitations should be noted. First, the relationships among the factors and their effects may be altered in different learning environments, such as MOOCs or other forms of open and distance learning. Second, the participants of this study have a specific cultural background; therefore, it is suggested that future studies explore whether both the reading and cognitive outcomes from different cultural backgrounds reveal different levels of SDS. Finally, since the perception of SDS was one of the individual difference factors, there is a need to further consider other individual differences, such as age differences, gender differences, and information literacy skills. Such evidence would not only be helpful in promoting activity-related outcomes, but would also be useful to develop personalized SDS support systems.

Chapter 6

Conclusion and future work

To conclude, we will first present the main findings and contribution of this research and end by proposing directions for future research.

6.1 Objective and finding

In this thesis, we conducted a theoretical and empirical investigation of the technology support for SDS on needs, design, and evaluation. We aim to identify the research gap of SDS support, build a SDS support environment, GOAL, explore the dynamic process of self-directed behaviors in learning and health promoting contexts and further investigate the relations of perceived SDS, activity-related outcomes, self-directed behaviors, and personal attributes in the environment. The findings of this research show that setting specific challenging goals and regular reviewing were benefits on the successful English learning activity, self-tracking and self-planning had a crucial role on health promotion activity, and the perception of SDS was a critical factor of SDS by affecting behaviors, outcomes, and personal attributes. The findings suggest that a timely personalized feedback based on students' perception, behaviors and attributes in self-direction would be helpful to succeed in lifelong learning. The main findings related to research questions are as follow.

6.1.1 Finding 1: Design of SDS support

RQ1. How to integrate contextual activity data and objective SDS measures into a SDS support environment?

From the theoretical and empirical work of self-directed learning, self-regulated learning, quantified self, and learning analytics, we designed and developed these key scaffolds in the SDS support environment: 1) a data-rich environment from learners' everyday learning and physical activities; 2) a quantitative measurement of SDS in phases and levels using specific activity data and general trace data; 3) an adaptive feedback of SDS in phases and levels.

6.1.2 Finding 2: Impact of self-directed behavior

RQ2. What are the behavioral patterns of self-regulation in learning without the SDS support and What are the behavioral patterns of self-direction in learning and health promoting activity with the SDS support?

Firstly, the self-regulated behavioral patterns were identified in computer-assisted language learning environment without SDS support. Students who had procrastination behavior were more likely to achieve lower final course points. The regularity of learning behaviors is a strong predictor of course achievement. This clearly indicates the importance of self-regulation and self-direction skills and calls for further investigation and support for these meta-skills.

Secondly, students with high perceived SDS in learning engaged significantly more planning behaviors, specifically in reviewing plan behaviors than those with low perceived SDS in learning. The planning behaviors had significant positive correlation with reading outcomes of reading amount and reading days. Four dominant patterns of planning behaviors both in short term and long term plan periods were identified: Never reviewed, One-time reviewers, Short-term reviewers, Regular reviewers. Setting specific challenging goals and regular reviewing were important strategies for the successful English learning activity.

Finally, both self-tracking and self-planning skill play influential roles in the context of health promoting. The self-tracking and self-planning students engaged in more self-directed interactions in the GOAL system and put more effort in collecting their sleep data than only self-tracking students. The self-tracking and self-planning students achieved higher SDS level than other students.

6.1.3 Finding 3: Impact of the effect of SDS

RQ3. What are the effects of learners' perception of SDS on their activity-related outcomes, self-directed behaviors, and personality attributes?

In the self-directed extensive reading context, students who had high perception of SDS demonstrated significantly more reading engagement, self-directed behaviors, motivation and autonomy for extensive reading than those with low perception of SDS. These findings suggested that the SDS support environment could be exploited as a useful tool to support foreign language learning in the K-12 schools; however, the affective and behavioral outcomes created by the environment were affected to varying degrees by the levels of students' SDS.

6.2 Contribution in design and research of SDS

The findings of this thesis show the contribution of the proposed GOAL system for SDS support environments. First, the system gives contextual information support for learners by leveraging their learning and health activity data. The contextual information creates more opportunities for learners to take initiatives in SDS. It can impact the decision making of young learners in the beginning of SDS. Second, the system provides a better understanding of SDS behaviors in a variety of contexts. The interaction data in the system can be indicators to quantitatively measure learners' SDS in different phases, such as planning or reflection. That makes it possible to investigate the individual differences in SDS behaviors in detail. Finally, the system provides an exploratory environment to examine the design of SDS support for SDS development. Since it's a cognitively, affectively and behaviorally complex task during executing SDS, the design of SDS support needs better empirical evidence. Therefore, the GOAL system has potential significance to explore a paradigm to support the execution and acquisition of SDS.

The findings of this thesis also show the contribution of self-directed learning and behavior change technologies. With the growing trend of preparing students for lifelong learning, the theory of self-direction has been increasingly applied across domains in the higher education and K-12 school settings. The thesis addressed the research gap of limited research on self-direction behavioral mechanism and the effect of self-direction skills. The behavioral patterns of self-direction can contribute to categorize learners and further provide interventions to learners based on that. The behavioral patterns of self-direction were explored in both learning and health promotion contexts, which can be a foundation of further analysis of learners' general self-direction skills across contexts. The activity-related outcomes, self-directed behaviors, and personality attributes were significantly affected by the levels of students' SDS, which address the need for supporting students to develop SDS following the shift from teacher-centered traditional classrooms to learner-centered approaches with advanced technologies in the 21st century.

6.3 Future work

The findings and the current limitations motivate a set of future development and research agenda. Currently with the combined learning and physical activity data, we will explore the effect of SDS on simultaneous learning and health activity. We plan to investigate other SDS subskills except planning skills and the relation of different subskills, such as analysis, monitoring, planning and reflection. We will try to create more technology interventions for activity and behaviors, such as communication tools, teacher evaluation panel, or gamification. More empirical work of self-direction will be explored in other learning, health promoting, and behavioral well-being contexts, such as quiz answering in learning, walking challenge in behavioral well-being, sleep scheduling in health promotion, or stress reduction in health promotion.

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