Towards Supporting Multigenerational Co-creation and Social Activities: Extending Learning Analytics Platforms and Beyond

Shin'ichi Konomi[1(✉)], Kohei Hatano[1], Miyuki Inaba[1], Misato Oi[1], Tsuyoshi Okamoto[1], Fumiya Okubo[1], Atsushi Shimada[2], Jingyun Wang[3], Masanori Yamada[1], and Yuki Yamada[1]

[1] Faculty of Arts and Science, Kyushu University, 744, Motooka, Nishi-ku, Fukuoka 819-0395, Japan
konomi@artsci.kyushu-u.ac.jp

[2] Graduate School of Information Science and Electrical Engineering, Kyushu University, 744, Motooka, Nishi-ku, Fukuoka 819-0395, Japan

[3] Research Institute for Information Technology, Kyushu University, 744, Motooka, Nishi-ku, Fukuoka 819-0395, Japan

Abstract. As smart technologies pervade our everyday environments, they change what people should learn to live meaningfully as valuable participants of our society. For instance, ubiquitous availability of smart devices and communication networks may have reduced the burden for people to remember factual information. At the same time, they may have increased the benefits to master the uses of new digital technologies. In the midst of such a social and technological shift, we could design novel integrated platforms that support people at all ages to learn, work, collaborate, and co-create easily. In this paper, we discuss our ideas and first steps towards building an extended learning analytics platform that elderly people and unskilled adults can use. By understanding the characteristics and needs of elderly learners and addressing critical user interface issues, we can build pervasive and inclusive learning analytics platforms that trigger contextual reminders to support people at all ages to live and learn actively regardless of age-related differences of cognitive capabilities. We discuss that resolving critical usability problems for elderly people could open up a plethora of opportunities for them to search and exploit vast amount of information to achieve various goals.

Keywords: Pervasive learning · Learning analytics
Multigenerational co-creation · Elderly people · Learning environment
Super-aging societies

1 Introduction

As smart technologies pervade our everyday environments, they change what people should learn to live meaningfully as valuable participants of our society. For instance, ubiquitous availability of smart devices and communication networks may have reduced the burden for people to remember factual information. At the same time, they may have

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increased the benefits to master the uses of new digital technologies. In the midst of such a social and technological shift, we could design novel integrated platforms that support people at all ages to learn, work, collaborate, and co-create easily.

In this paper, we discuss our ideas and first steps towards building an extended learning analytics platform that elderly people and unskilled adults can use. By understanding the characteristics and needs of elderly learners and addressing critical user interface issues, we can build pervasive and inclusive learning analytics platforms that trigger contextual reminders to support people at all ages to live and learn actively regardless of age-related differences of cognitive capabilities. We discuss that resolving critical usability problems for elderly people could open up a plethora of opportunities for them to search and exploit vast amount of information to achieve various goals.

We believe that such a platform can play critical roles in addressing the societal challenges in the age of declining population and super-aging societies by increasing the mobility of human resources and expanding the working population. Their impact can be substantial in many countries. For example, Japan has more than 6 million "potential workers," who do not have jobs despite their willingness to work, and more than 28 million active seniors without the need of caregiving. Learning support systems for these populations would increase their opportunities to participate in various social activities, thereby potentially making a major societal and economic impacts.

2 Limitations to Conventional Systems

There is increasing interest in exploiting distributed, ambient and pervasive digital infrastructures including mobile devices, wearable devices, and IoTs to support learning and intellectual work. In addition, the rise of crowdsourcing and sharing economy platforms is enabling a novel and flexible means to connecting with and participating in various social activities. However, conventional technological environments for supporting learning and intellectual activities could not fully cater to the needs and opportunities arising in this context. One of the key components in designing distributed, ambient, and pervasive learning environments is arguably the data generated and consumed by inter-connected people, things, and spaces. Indeed, data-driven approaches such as *leaning analytics* is increasingly popular in the research and practice of learning-support technologies. Existing learning analytics platforms however are inherently limited in capturing the whole picture of learning and its relevant contexts.

Many conventional learning analytics environments go as far as analyzing patterns of learners' access to digital learning materials. One can argue that this is only a first step towards understanding learners and their contexts to improve learning. We argue for the need to collect more data by using sensors, etc., so as to gain the holistic view of learners and their environments. Doing so would enable timely and appropriate feedback to learners and teachers.

The recent advances in sensing and IoT technologies made it easier to create such systems and environments. Multimodal learning analytics [4] for example employs sensing devices to extend conventional learning analytics for classrooms. This however is insufficient for supporting adults and elderly people as their learning would often take place outside classrooms.

3 General Approach

Our goal is to build a learning-support system that interacts with learners and teachers by exploiting sensing and data analysis techniques. In doing so, we focus on the needs of elderly people and unskilled adults.

As shown in Fig. 1, the system considers different learning environments including classroom lectures, peer learning, and learning through practice. The development process first focuses on an e-learning platform and improve it to facilitate acquisition of new skills. We will then support adaptive learning and acquisition of informal knowledge. We expect that this development effort will lead to various learning-support services targeting different occupations and skills.

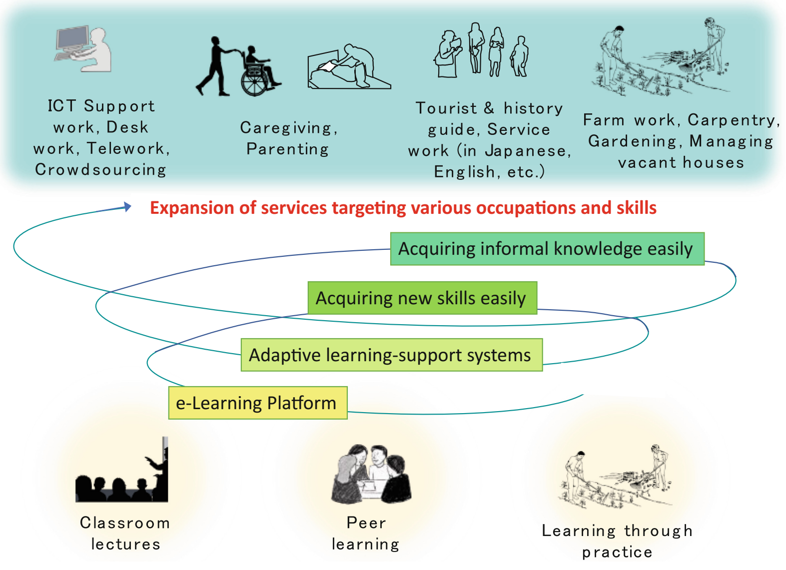

Fig. 1. Overview of the development of extended learning analytics platform.

In order to address the bottlenecks of learning and social activities by elderly people, we plan to exploit a quantitative approach to examine the bottlenecks in collaboration with brain and cognitive scientists. For example, we can measure arousal of consciousness or degree of concentration based on brain-wave and eye-gaze data in different contexts. Such quantitative measures can be useful for not only analyzing learning behaviors but also triggering contextual reminders at the right time (e.g., triggering proper reminders when consciousness is aroused.) We can then explore and examine the right timing to trigger different types of reminders in terms of effective memorizing and recalling. Although reasonably reliable brain-sensing devices could not be used "in the wild", we could explore other contextual information as proxies for brain and cognitive activities. We focus on the kind of contextual information that can be measured easily by using commodity devices including mobile, wearable, and stationary sensors. We can derive locations, presence, activities of people and physical objects as well as learning contexts and social networks based on their data.

Our research efforts focus on the kinds of practical learning that leads to increased opportunities for social participation. They include acquisition of the skills to use digital technologies fluently or the skills of caregiving. These kinds of learning require more than just remembering pre-packaged knowledge as they require acquisition of what we might consider as "living knowledge." Acquisition of such skills by elderly people and unskilled adults can be an important starting point for addressing the challenges of decreasing labor force.

There are three user interface issues that must be addressed to extend learning analytics platforms successfully:

1. *Designing for all*: As this type of learning-support platforms could have significant long-term impacts on people's quality of life, they should be accessible, usable and useful for everyone. Thus, the system should be designed for inclusiveness from the very beginning. To develop inclusive user interfaces, we can employ user-centered and participatory design processes and exploit pervasive off-the-desktop computing technologies. We also have to design *push*-based user interfaces for people with declining cognitive capabilities. This can be extremely challenging if they have difficulties providing appropriate feedback to system designers. In this case, we can look into people's "honest signals" based on various sensors in commodity devices as well as physiological sensors (e.g., EEG sensors, eye trackers, etc.).
2. *Sustaining continuous use*: For a data-driven approaches such as learning analytics to work, systems must collect and accumulate a large amount of relevant data. In our effort to extend learning analytics, systems must collect data by encouraging, motivating and sustaining continuous uses by elderly and unskilled learners.
3. *Support for learning communities*: Although elderly people may not be good at memorizing things and quickly getting used to new environments, they can play important roles in learning communities [1]. An interesting challenge in this context is the development of social user interfaces that help people to collaborate, co-create, and learn effectively in learning communities. These communities and groups would involve elderly people having similar skills and experiences, elderly people having different skills and experiences, or multigenerational people characterized by a wide range of capabilities and experiences.

Again, we aim to support learning and social activities by elderly people and unskilled adults by accumulating and using the data from different learners in different contexts. We can also exploit such data to match people and jobs, thereby potentially creating workforces at companies, local communities, and homes (e.g., telework).

4 Understanding Elderly Learners

We have reviewed relevant literature to understand the characteristics of elderly people as learners and examined their implications for designing digital learning-support environments [1]. Although elderly people may not be very good at memorizing things or getting used to new things quickly, they have a good potential to play important roles in learning communities. Thus, we consider two strategies in designing learning-support technologies for elderly people, i.e., (1) facilitating the perception of the self that recognizes learning as a self-behavior, and (2) supporting collaborative learning.

Collaborative learning provides a way of building knowledge through activities of collaboration with others such as group work. We have examined the impact of group composition on group work-based learning involving university students [2], which has some implications for designing group learning environments for elderly people with diverse experiences, knowledge, and learning styles, each of which can be quantified for recommending optimal group compositions.

To cope with insufficient memory abilities, people often utilize external memory aids and routines in everyday life situations. This means that information is often remembers not simply in the head of a person but also in the environment surrounding the person (cf. [5, 6]). If people have good tools and environments for the support of living and learning, their potential to learn and live active lives can increase substantially. This is relevant to not only elderly people but also many people at all ages. As we extend learning analytics platforms for people at all ages, we can consider not only optimization of teaching methods and learning materials but also optimization of support tools and environments for learning and living (i.e., broader context of learning). In this context, it is critical to understand elderly learners from the perspective of their capability to organize and utilize external tools and environments effectively. In the coming years, the capability to utilize the Internet, mobile and wearable devices, social media, and AI tools effectively will likely be of critical importance to improve learning for all. Elderly people who are not yet fully exploiting digital technologies could expand their potential substantially by optimally restructuring their tools and environments for learning and living. As we will discuss later, addressing the digital divide is then of critical importance.

5 Sensing the Contexts of Learners

In order to sense and compute the contextual information of learners, we can exploit various sensors that can be used in lab settings or in everyday environments. We use the following two types of devices in a lab setting to sense learners' physiological activities in relation to their context:

1. EEG sensor (Cognionics Quick-20) for measuring brain waves of learners and quantifying alertness, etc.
2. Eye tracker (Tobii Pro Spectrum 150 Hz) for measuring eye movements of learners and quantifying degrees of concentration, etc.

We consider the following sensing technologies to sense learners in everyday environments:

1. *Absolute and relative locations of people and physical objects.* For example, we could obtain sub-meter location information by using QZSS (Quasi-Zenith Satellite System)/RTK-GPS (Real Time Kinematic GPS) in outdoor spaces and WiFi CSI (Channel State Information) in indoor spaces.
2. *Presence of people, things, information, spaces, and events in proximity.* For example, we can use WiFi and/or Bluetooth signals to capture co-presence automatically, or employ a human computation approach based on crowdsourcing. We have discussed the potential of wearable devices such as smartwatches [3].
3. *Body movements.* Mobile and wearable sensors as well as IoT devices can be used to recognize people's activities and detect anomaly quickly.
4. *Learning behaviors and experiences.* These can be captured based on the log data generated by various learning support systems. This is the kind of data that is mainly used in conventional learning analytics platforms, and may include the scores of tests for measuring the outcomes of learning.
5. *Social networks of learners.* We can derive various social networks based on learners' locations, presence, body movements, and learning behaviors. We can analyze and use them to support collaborative learning.

6 Contextual Reminders

There has been extensive previous work in the area of context-aware reminders. The *comMotion* environment [7] allows users to create reminders using a graphical user interface that resembles paper to-do list, and delivers them based on location and time. The CybreMinder tool [8] extends the range of contextual information by using Context-Toolkit [9]. More recently, push services are available on most smartphone operating systems [10], making it extremely easy to develop applications that send notifications based on mobile context. Commercial services such as Nixle allow authorities to send notifications to local residents via SMS, web and email [11].

Researchers have run field studies of location-based personal reminders to examine their usage patterns. The exploratory study of Place-Its [12] suggests that location can be a convenient proxy for context that cannot be easily captured. The field study of PlaceMail [13] shows that people's preferred delivery points of reminders can be affected by situational factors such as patterns of human movements and the geography of corresponding areas. Also, recent studies of mobile notifications show that people view Android notifications typically within minutes [14] and that recipients' perceived values of notifications are different for different app categories [15].

Studies on mobile interruptions show that the content of a message plays an important role in influencing users' receptivity to mobile interruptions [16], and that notifications received after an episode of mobile interaction, such as calling someone or reading a text message, are responded more quickly [17]. Other researchers discuss that notifications received at the transition of physical activities, such as sitting and walking, are perceived more positively [18]. The Memory Glasses project proposes to send reminders based on the user's activity using body-worn sensors [19]. Similar approaches exploit sensing devices to cope with the problems [18, 20]. Recent proposals focus on smartphones and/or exploit machine learning [21–24]. Hatano discusses machine learning techniques to provide contextual feedback to elderly learners [25].

A relevant genre of context-aware applications is *mobile guides*, which provide tourists and museum visitors with relevant information to support their experiences *in situ* [26, 27]. Magitti is a mobile guide that recommends leisure-related information based on the categories of activities including Eating, Shopping, Seeing, Doing or Reading [28]. There are also mobile guides that combine context awareness and personalization [29].

Existing mobile guides and context-aware reminders often focus on the mechanisms to deliver information rather than the process to create content. In practice, a "curator" would have to create information content in many cases. This approach to content creation does not necessarily scale, as an expert is needed to create content. Also, these are usually one-way information channels (i.e., users just "consume" content, and they cannot generate content). Therefore, it is not easy to transfer a system to a new location/community. "Bottom up" approaches to generating contents may have an interesting potential as the recent web-based experiment with the production of personal city guides suggests [30]. Community Reminder take advantage of communities and discuss how reminders can be created and received in relation to collective concerns of a community [31].

Although reminders are typically triggered by automated mechanisms, it often requires some human skills to design and utilize them effectively by weaving them into the lives of different people. The notion of tools for living and learning [32] is important for understanding the uses and the design of reminders as some reminders are intended as memory aids for living (e.g., reminder to take a medicine), and other reminders are intended as support for learning (e.g., reminder to learn to take a medicine, which can disappear when the recipient finishes learning it). The skills to use reminders fluently can be extremely useful for living and learning actively regardless of age-related differences of cognitive capabilities.

7 Pervasive and Inclusive Learning Analytics

Pervasive computing in its ultimate form makes computers disappear physically and mentally. This would effectively make digital divide disappear. Smartphones, tablets, wearables, interactive surfaces, networked actuators, digital fabrication tools, and various other IoTs could be seen as transient forms of less and less obtrusive interfaces to computational services. Some of these devices such as tablets has already made computing services more accessible to everyone including elderly people. Thus, pervasive learning analytics is not merely about increasing sensor data for analysis but also about reduction of physical barriers for accessing computing services.

Existing research on internet skills and the digital divide shows that age may only affect some internet skills but not all [33]. What age may affect are operational and formal internet skills. Operational internet skills concern with operating software tools by typing URLs in the browser's location bar, etc. Formal internet skills concern with navigating websites without being disoriented, etc. These are the skills that can be influenced by specific implementations of the browser's user interfaces. Improving user interfaces by designing them for inclusiveness can minimize the negative impact of the decline of these skills. What seems encouraging is that age may not affect content-related internet skills [33]. Content-related internet skills include information internet skills and strategic internet skills. Information internet skills concern with the search processes involving choosing a website or a search engine, defining search options and queries, selecting information, and evaluating information sources. Strategic internet skills concern with developing an orientation towards a particular goal, taking the right action to reach this goal, making the right decision to reach this goal, and gaining he benefits resulting from this goal. All in all, improving the usability sufficiently for elderly people can open up a plethora of opportunities for them to find useful information and achieve their various goals.

8 Conclusion

We have discussed our ideas and the first steps towards building an extended learning analytics platform that elderly people and unskilled adults can use. By understanding the characteristics and needs of elderly learners and addressing critical user interface issues, we can build pervasive and inclusive learning analytics platforms that trigger contextual reminders to support people at all ages to live and learn actively regardless of age-related differences of cognitive capabilities. Existing research suggests that resolving usability problems for elderly people could open up a plethora of opportunities for them to search and exploit vast amount of information to achieve various goals.

We have begun to collaborate with the city of Itoshima to test the feasibility of such a platform. Our first exploratory trials exploited an existing learning analytics platform and involved 48 elderly people with varied computer skills.

We intend to support acquisition of informal as well as formal knowledge in the future to pave the way for the learning-support infrastructure of the future, which maximizes the potential of people at all ages to work and create together effectively.

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