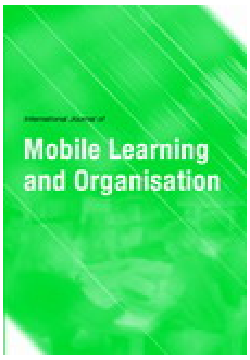

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Hiroaki Ogata, Rwitajit Majumdar, Brendan Flanagan, Hiroyuki Kuromiya

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Learning analytics and evidence-based K12 education in Japan: usage of data-driven services for mobile learning across two years

Hiroaki Ogata, Rwitajit Majumdar* and Brendan Flanagan

Academic Center for Computing and Media Studies,
Kyoto University,
Yoshida Nihonmatsu-cho, Sakyo-ku, Kyoto 606-8501, Japan
Email: ogata.hiroaki.3e@kyoto-u.ac.jp
Email: majumdar.rwitajit.4a@kyoto-u.ac.jp
Email: flanagan.brendanjohn.4n@kyoto-u.ac.jp
*Corresponding author

Hiroyuki Kuromiya

Graduate School of Informatics,
Kyoto University,
Yoshida Nihonmatsu-cho, Sakyo-ku,
Kyoto 606-8501, Japan
Email: kuromiya.hiroyuki.27z@st.kyoto-u.ac.jp

Abstract: Learning and evidence analytics framework (LEAF) is a technology framework for data-driven services in education. LEAF helps to form an educational eco-system with new digital technologies with capabilities such as integrating AI-driven models for learning recommendations and connecting learning logs through blockchain technologies to support lifelong learning. Since 2018, its implementation in Japan has led to more than 1,000 students of Japanese public schools using LEAF on mobile tablets for their daily learning activities both inside and outside school. The data collected at the school level in LEAF further enabled the creation of computational models to support teaching and self-learning. This article presents the data-driven services built on the platform and how it was used in Japanese K-12 Mathematics and English classes. This study evaluates the usage and user perception of data-driven educational practices in the Japanese context and discusses its greater implications and challenges for learning analytics research.

Keywords: evidence-based education; learning analytics; K-12 education; e-book platform; AI-driven services; Japanese school; learning and evidence analytics framework; LEAF; BookRoll; Japan.

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Biographical notes: Hiroaki Ogata is a Professor at the Academic Center for Computing and Media Studies, Kyoto University, Japan. His research interests include learning analytics, evidence-based education, educational data mining, educational data science, computer-supported ubiquitous and mobile learning, CSCL and CALL.

Rwitajit Majumdar is a Senior Lecturer in the Graduate School of Informatics at Kyoto University. He received his PhD from IDP-ET at IIT Bombay in India. His research interests include technology-enhanced learning environment design, learning analytics and studying human-data interactions in educational contexts.

Brendan Flanagan is a Senior-Lecturer at the Academic Center for Computing and Media Studies, Kyoto University. He received his Bachelor's degree from RMIT University, Master's and PhD degrees from the Graduate School of Information Science and Electrical Engineering, Kyushu University. His research interests include: learning analytics, explainable machine learning, and language learning.

Hiroyuki Kuromiya received his BS and MS in Education from the University of Tokyo, Japan. He is a PhD student in the Graduate School of Informatics at Kyoto University. His research interests include technological support for evidence-based education through learning log analysis.

1 Background and research context

Learning analytics (LA) at school level education has grown from analysing the complex learning dynamics and their relationship to outcomes (Ebner et al., 2014) to supporting different stakeholders in understanding and improving their teaching and learning practices (Pardo et al., 2016). Across the globe, many countries have taken the e-learning infrastructure to the next level to integrate LA to inform and support their stakeholder's decision making. Some studies report those implementations in the educational context of the USA (e.g., Krumm et al., 2018), Spain (e.g., Martínez-Monés et al., 2020) and recent approaches adopted in the context of Bulgaria (Gaftandzhieva et al., 2021).

Mobile learning becomes important in that context where the user's educational needs are catered through mobile devices anytime and anywhere. It also makes learning log generation much more natural as a part of the activity itself without further burden to create them by the teachers, learners or other stakeholders. A recent review on mobile learning (Lai, 2020) also highlights those investigations conducted are quite low in the junior high and high school context (8% of the review articles) and only 2% considering home as a learning place and 4% consider tablet PC as a learning device. To throw some light on that unexplored area the current study focuses on K-12 education in the Japanese context where students were given a tablet PC that they could use at school and home to access learning materials uploaded by the teachers and participate in different learning activities.

1.1 State of mobile learning and LA in Japan

In Japan too, the Ministry of Education, Culture, Sports, Science and Technology (MEXT) focuses on the Global and Innovation Gateway for All (GIGA) School Program (MEXT, 2020) which aims to transform learning with the use of an ICT environment and one device per student. The program has rolled out and MEXT has already administered nearly 461 billion Japanese Yen over the fiscal year of 2019 and 2020 to build the capacity. However, it is quite early to find any research reporting of its usage and effects. Research on LA in Japanese secondary schools is still in its infancy, and to the best of our knowledge, there is no other English-language literature on this topic besides our research group. Although not a study of LA, some of the small number of papers submitted to domestic journals on the distribution of one-per-person tablets in classrooms. Sato et al. (2021), for example, used the ICT utilisation survey in PISA 2018 to identify the characteristics of Japanese elementary schools. The survey revealed that a higher percentage of children used websites and cloud applications in class, but a lower percentage of children used communication tools such as SNS. As described above, research on the use of learning tools is beginning to gather knowledge, but the discussion on how to utilise data such as the history of tool use is still in its infancy in Japan (for further policy documents related to the current status please refer to MEXT (2021), Digital Agency Japan (2021) and Science Council, Japan (2021).

1.2 Context of the current research project

This research discussed in this article stems from an earlier ministerial special innovative project (SIP) to effectively use big data and artificial intelligence in the domain of education. We present the components of the infrastructure built based on the learning and evidence analytics framework (LEAF); a LA driven infrastructure that has been used at the school level across three Japanese schools since 2019. The usage of LEAF and different use cases of the data-driven technologies for conducting and augmenting daily teaching and learning activities at the K-12 level are highlighted along with the reported research findings.

We investigate two research questions (RQ) in the research context for this reporting:

RQ1 What are the usage trends of the LEAF platform within and outside the school hours?

RQ2 What is the perception of the students and teachers who used the platform for two years?

1.3 Organisation of the current article

Based on the background and the research context presented in this section, the article is structured as follows: Section 2 provides the overview of the technology framework and its components. Section 3 elaborates specific case studies of LA enhanced mobile teaching and learning activities and compiles the research findings from the field implementation context. Section 4 analyses the statistics of usage and the learner perception of using the LEAF platform over a two years period. Section 5 discusses the challenges and the contribution of the learning and evidence analytics framework to the mobile learning and LA field.

2 Learning and evidence analytics framework

LEAF is an overarching technology framework that is conceptualised as a part of this research project. The framework aims to design technology components and features that are user friendly for learners and teachers from elementary school to university while using it in different devices and contexts such as within class or out of class, in groups or as individuals. It should be easily integrated into their current workflow and start collecting data that is made available for creating data-driven services to further support a lifelong learning process. For system architects and researchers, the framework aim to be flexible to integrate different behaviour logging systems and expand the different services that are built. Overall the data-driven paradigm needs to be in a natural teaching-learning context with minimising any further burden for the stakeholders. In light of the overall aim of the framework, the system architecture and the various components are described in the following subsections.

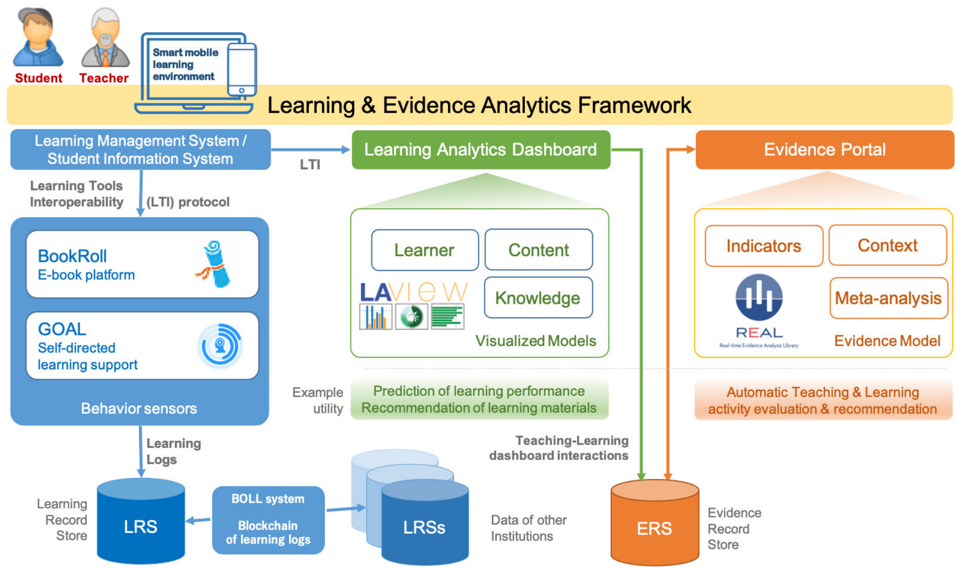
2.1 System architecture

LEAF is the overall technical framework that seamlessly integrates research and production systems together to enable educational data science research as well as AI-driven services for the users (see Figure 1). Our current stakeholders include the students, teachers, researchers and school coordinators. In the following section, we shall present each of the components of the framework.

2.2 Learning behaviour sensors

To capture the traces during teaching and learning episodes, LEAF incorporates behaviour sensor systems that can log students and teacher's interactions during such episodes. These user interactions can occur outside the learning management system (LMS) and take place both in formal and informal learning situations. Earlier development and research (Flanagan and Ogata, 2018) pointed to a seamless learning environment that bridged the production and research requirements to enable analytics with educational big data and develop services across the tools. Learning tools interoperability (LTI) protocol provided standardised and seamless authentication transfer from the LMS to any of the behaviour sensors or intelligent tutoring systems (ITS). It connects user interaction logs to anonymised unique user ids (UUID) that would help the research platform to use the data for advanced analytics and build services based on the log data. Two of such systems in LEAF is a digital learning material reader called BookRoll (Ogata et al., 2015) which acts as primarily a reading behaviour sensor. Another system is GOAL, a self-directed learning support platform to trace learner self-directed learning behaviours (Majumdar et al., 2018). An open-source statement API, xAPI (Advanced Distributed Learning xAPI, 2016) is used for outputting anonymised event logs to a centralised independent learning record store (LRS) from the behaviour sensors. An opt-out option is given to all the users on initial authentication if they do not consent to participation and will not have their interactions logged. However, data-driven services are also not available for those users.

Figure 1 The system architecture of LEAF (see online version for colours)



2.2.1 BookRoll: digital learning material reader

BookRoll is the e-book reading platform which in addition to serving as a learning material distribution platform, also is an important source of data for LA into the reading habits of students. The interaction events of the readers are recorded, such as: navigating the reading content (going to the next or previous page, jumping to different pages), annotating parts of the learning materials that are hard to understand or are of importance with memos comments, bookmarks, and markers. As shown in Figure 2, the user interface supports a variety of functions. Teachers can upload learning materials to BookRoll in PDF format, and students can access them in a wide range of devices through a standard web browser. Apart from a learning content reader, an audio upload function was developed to associate audio clips with each learning material. Teachers can easily upload their spoken lectures or any other tutorial audio associated with those materials. The students can control the audio, which plays automatically when the material is accessed. External links can be embedded in the recommender panel for the students. It can also contain simple multiple-choice quizzes that the teacher can create directly after uploading the content.

Table 1 presents a sample of e-book interaction logs extracted from BookRoll. For each user interaction in the learning environment, the user id, content id of the learning material, the operation's name, time, detail and the page number where it has happened can be extracted. For instance, OPEN means that the student opened the e-book file and NEXT means that (s)he clicked the next button to move to the subsequent page.

Figure 2 BookRoll digital learning material reader (see online version for colours)

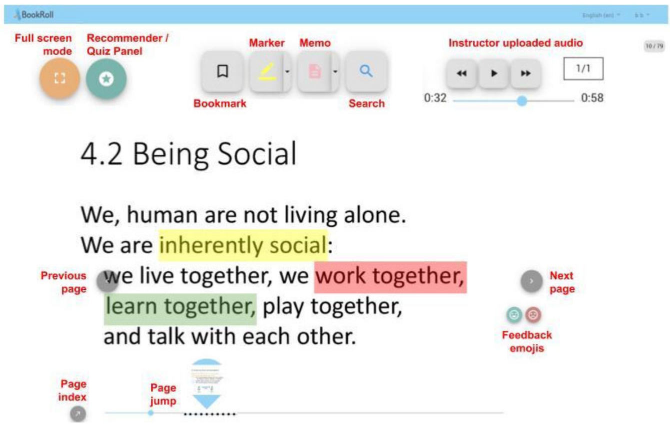


Table 1 A sample of events recorded from user interaction with BookRoll and its interpretation for LA

contents_id	*operation_name*	*operation_details*	*page_no*
1223_textbook	REGIST CONTENTS		0
1223_textbook	OPEN		1
1223_textbook	NEXT		2
1223_textbook	ADD MARKER	(255, 0, 0) work together	3
1223_textbook	ADD MEMO	Sample memo	3
contents_id	*user_id*	*operation_time*	*Interpretation for analytics*
1223_textbook	Teacher1	2021/01/22 18:10	Teacher 1 shared a content for the course
1223_textbook	Student1	2021/01/23 9:16	Student 1 accessed content for reading
1223_textbook	Student1	2021/01/23 9:20	Student 1 progressed to next page in the content
1223_textbook	Student1	2021/01/23 9:21	Student 1 added a red marker to identify important part of content
1223_textbook	Student1	2021/01/23 9:22	Student 1 added a memo as a part of the instructed learning activities or while self study

2.2.2 GOAL system

Goal oriented active learning system is a platform to support self-direction skills (SDS) with learning and physical activity data (Majumdar et al., 2018). Technological support to execute and acquire the skill of self-direction is limited. GOAL bridges this gap by synchronising learners' daily activity data related to learning and physical activities and then providing the environment to create plans and monitor them while executing. The learning activity data is extracted from the BookRoll logs providing the amount of time spent on reading and the number of pages reads to then plan and monitor. Similarly, physical activities like steps taken and sleep time can be automatically synchronised from wearable sensors such as Garmin and mobile applications such as Google Fit and Apple Health. For the current implementation at the junior high school, we have distributed Garmin vivoactive 4 bands to the students. They can wear it anytime and at any place and use their tablets to synchronise the data with the Garmin mobile application. The GOAL system automatically synchronises their steps, stress level and sleep time and aggregates the daily average values. While the physical activity data analysis if still under progress, in this article, we shall report about the effects of using the GOAL system while doing self-directed extensive reading (ER) activities by junior high school students.

2.3 Learning record store

Data from the various behaviour sensors are collected in a central standardised LRS in real-time. This allows stakeholders and LA tools to have access to all event data from across the platform. Due to the open nature of the standard, the xAPI format was adopted as the mode of transferring and storing learning behaviour data from other systems to the LRS thereby reducing information silos tied to individual tools. It also increases the availability of data for analysis from a common source. In the LEAF platform, we automate the extract-transfer-load (ETL) process by taking incremental log analysis from the LRS as data arrives and pre-processing it in the database of the LAViEW dashboard which is introduced in the following section.

2.4 LA engine and dashboard

Learning analytics visualisations and evidence widgets (LAViEW) (Majumdar et al., 2019a) is the LA engine in LEAF that analyses the log data in LRS and extract features for further data-driven services and visualising in the dashboard in near real-time. Similar to the behaviour sensors LTI automatically handles the user roles and display different panels of graphs with customisable views for teachers and learners. While using the users need to first select the learning content and the time period, they want to analyse from the context selector panel (see Figure 3 as reference). The data is visualised data in every panel is populated. An overview panel provides aggregated statistics about selected course material. In this section, both teachers and students can see the average statistics of the class on the bottom and selected student's records on the top. The current dashboard provides information regarding learners as a group or individuals regarding their engagement in the BookRoll content, learning traces such as annotations and learning outcomes such as performance in the quiz associated with any BookRoll content.

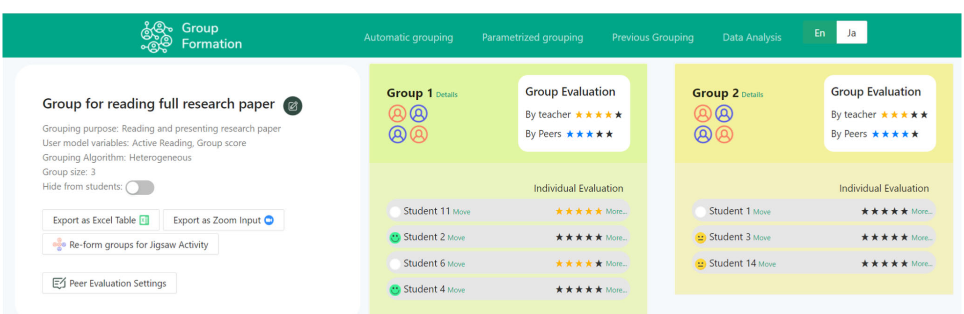
The dashboard also serves as a landing page to bridge different data-driven services such as the group work support module (Liang et al., 2021a) and the knowledge map visualisation (Flanagan et al., 2019). Student and content models created from LRS learning logs of the BookRoll system and Moodle platform are utilised by those services. For instance, in the group work module, the learner model is the input to generate various algorithmic groups (Boticki et al., 2019; Flanagan et al., 2021). The module further assists the students to conduct peer evaluation after the group work (Liang et al., 2021b).

All the data regarding the formation of the groups, teachers and peers' evaluation scores and comments are all also exported and recorded to the LRS. The data of prior group work can be reused for subsequent group formation or evaluation phases. Figure 4 presents the interface of the group work support module.

Figure 3 LAViEW dashboard (see online version for colours)

Source: Majumdar et al. (2019a)

Figure 4 Group work support module in LAViEW (see online version for colours)



Source: Liang et al. (2021a)

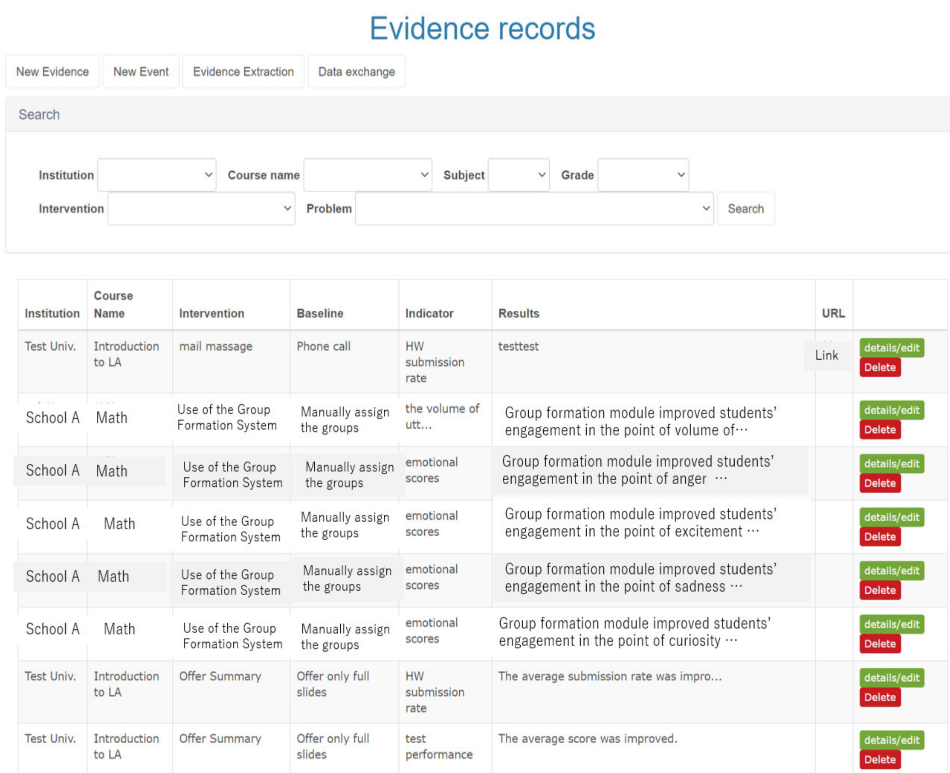
2.5 Data-driven and distributed educational infrastructure

While the above-mentioned tools and platform help the teachers and students in their own course, the overall framework also aims to connect learning logs from multiple similar contexts for mining trends and evidence. The evidence portal and a blockchain-based solution, BOLL in LEAF fulfil that requirement.

2.5.1 Evidence portal

The evidence portal is a platform where teachers and researchers share their experiences on LEAF. Users can access evidence portal via LTI authentication from LMS. Currently, an evidence database is implemented as a MySQL database (Kuromiya et al., 2020, 2021). Course and user information will be added automatically via LTI parameters. Evidence portal automatically meta-analyses the effect size of the interventions that have the same category_id and indicator (see Figure 5).

Figure 5 Screenshot of evidence portal (see online version for colours)



2.5.2 BOLL for connecting learning logs through blockchain

Digital learning systems are increasingly being used in various institutes and aspects of education, from early childhood to higher, corporate and adult education. Often, different systems and platforms are employed to deliver learning materials, collect and analyse interaction behaviour logs, and provide feedback to key stakeholders, such as students, teachers and administrators. When a student starts to learn at a new educational institution, the learning system will not contain any information about the student's past education, leading to a cold-start problem for most learner model-based systems. Also, a student could be studying at multiple institutes at the same time; however, each learning system would be unaware of the study or achievements from other institutes, for example, a student attending a cram school whilst studying at a high school. A centralised system to collect and distribute learning data could be constructed; however, there are also stakeholder privacy implications that need to be considered. To overcome the problem of educational data linking and distribution while protecting stakeholder data privacy, a blockchain-based system called BOLL, blockchain of learning logs, was proposed to facilitate the necessary functions and infrastructure (Ocheja et al., 2018, 2019). Smart contracts for the control and distribution of educational data were defined, allowing students and teachers as data owner's direct control over the authorisation data transactions on the blockchain network. This mechanism protects the rights of data owners while allowing access to previous learning data at institutes that are part of the BOLL consortium and visualising them (Ocheja et al., 2021, 2022).

3 Case studies

We implemented the system at a public school in Japan. Teachers in Mathematics and English subjects used the system extensively in their daily classes. Figure 6 provides an instance of using LEAF platform within a regular junior high school classroom. Students use their own tablets for activities and the teacher also uses the system if required to project it on the screen placed in the front of the class.

Figure 6 Using LEAF platform in Japanese public junior high school (see online version for colours)

We provide different affordances of the LEAF platform that were used as mini case studies. For each case, we describe the learning context, the affordances of the system used to orchestrate teaching and learning activities, and the effect of those activities.

Table 2 The organisation of the case studies

Purpose	*Use case*	*Outline description*	*LEAF components*	*References*
Supporting Mathematics learning inside and outside the classroom	Determining stuck points in math problem-solving	Students solved maths problems using handwritten memo and the stroke data was used to identify stuck points.	BookRoll and LAViEW	Yoshitake et al. (2020)
	In-class Jigsaw activities	Jigsaw group activities are conducted and evaluated with group utterance data collected during group work.	Group work module in LAViEW	Liang et al. (2021a, 2021b)
Supporting English learning inside and outside the classroom	Data-driven active reading (AR)	AR using the affordances of BookRoll and reflection using the LAViEW dashboard.	BookRoll, LAViEW, Group work module	Chen et al. (2019a, 2019b) and Toyokawa et al. (2021)
	Self-directed ER	With access to more than 500 e-books in BookRoll, GOAL system supported planning, monitoring and reflection of ER.	BookRoll and GOAL	Li et al. (2021a, 2021b, 2022)
	Reading recommendation for ER	Based on the reading patterns of the learners further ER contents are recommended.	BookRoll and knowledge map based recommendation	Takii et al. (2020, 2021)
Data-informed decision making in educational context using cross-platform systems	Connecting lifelong learning logs through blockchain technology.	Learning logs across institutions are connected and data sharing permissions are maintained using blockchain.	BOLL, LRS	Ocheja et al. (2018, 2019, 2021, 2022)
	Automatic extraction of evidence from learning traces.	Analysis of the effectiveness of a particular practice by statistical computation of attributes of learning logs.	REAL, LRS	Kuromiya et al. (2020, 2021)

3.1 Supporting Mathematics learning inside and outside the classroom

3.1.1 Determining stuck points in math problem solving

In some circumstances, handwriting input still is an important part of the learning process for students even in digitised education environments. For example, while there have been advances in input methods, particularly in Mathematics, it is advantageous for young students to use intuitive pen-based input. BookRoll supports the input of handwritten memos and answers to quizzes as shown on the left in Figure 7, and the pen stroke data is collected as time series vectors which are stored in the LRS in xAPI format. To support teachers in classes utilising this input process, a pen stroke analysis module was developed for the LAViEW dashboard as shown in the centre and right in Figure 7 (Yoshitake et al., 2020). Usually, when examining a handwritten answer on paper, a teacher can try to determine the points in the answering process where the student struggled or had difficulty. However, the teacher cannot know how long a student took to finish different sections of the answer process or parts that were erased and revised, both of which can be indications of sections in which the learner had some difficulty or stuck point. By analysing the pen stroke data from students' answers, the time between strokes can be visualised to show potential stuck points that would otherwise be impossible to detect from paper-based answers. Additionally, teachers often source worked examples for the answers of students in mathematics classes, and this usually involves the time-consuming process of reviewing all of the previous answers. To support this process, a clustering function and example visualisation was developed to enable the quick selection of ideal examples for an explanation. An experiment was conducted over three months with 360 students to determine the effectiveness of the system from the perspective of two teachers. An interview was conducted after the experiment period and both teachers highly rated the system for identifying at-risk students, reviewing student's answers, detecting stuck points from the visualisation of delayed stroke analysis, and understanding typical answers from high and low performing students. The teachers also expressed a high desire to continue using the system in their classes.

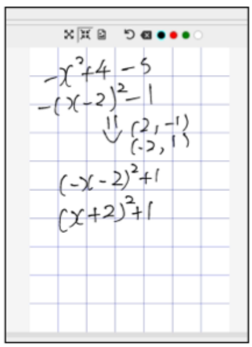
3.1.2 In-class group work

While conducting group work for cooperative learning has various advantages (Kyndt et al., 2013), implementing it in a classroom has various logistic considerations which often make it difficult for the teachers to orchestrate. To support this process a data-driven group formation module was developed in the LAViEW dashboard. The system assists the teachers to create groups based on the learner model within LEAF (Liang et al., 2019).

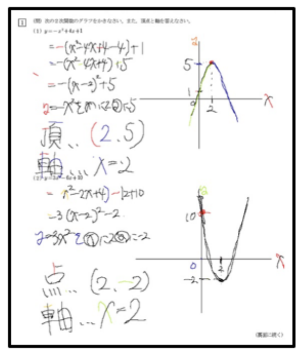
The system was used in the context of primary school mathematics class where group work was conducted during problem-solving exercises in seven topics. Two different teachers were in charge of two different classes but orchestrated the same topic. To compare the usefulness of the module, initially, three topics were conducted with teacher-formed groups, and for later four topics, groups were formed by using the group work module in LAViEW. The study (Liang et al., 2021a) highlights the difference in the group work when the groups were formed by teachers based on their experience versus prior data-driven ones. It was found that groups had more individual utterances and duration of utterance also increased in the computer-based groups. Thus, for idea exchange activities, system formed grouping considering prior attributes of students helped to arouse motivation and facilitate engagement of students. The parameters for group formation would be a key factor and it was found that the diversity of communication skills, prior knowledge of the topic, and previous academic performance might have catalysed the atmosphere and facilitate interaction for idea exchange within heterogeneous groups.

Considering affective states, positive and negative emotions were extracted from their utterances. Students acted significantly more positively in the system-formed groups where their utterances showed more positive affective states such as joy and vitality. Also, negative affective states were less expressed, where students were less reserved and irritated in the experiment groups as is indicated by the higher scores of calmness and low score of anger. According to the teacher, it indicated that the novelty of the new group combination motivated students to speak more and participate more actively. The teachers also appreciated the friendship-priority grouping strategy that can be done by uploading the friendship network in the group module. It was effective for the lower grades in school where from their practice they found to reduce the conflict within group members who had trust relationship and fostered willingness to handle group work challenges. It was also found to positively related to individual student's group work self-efficacy.

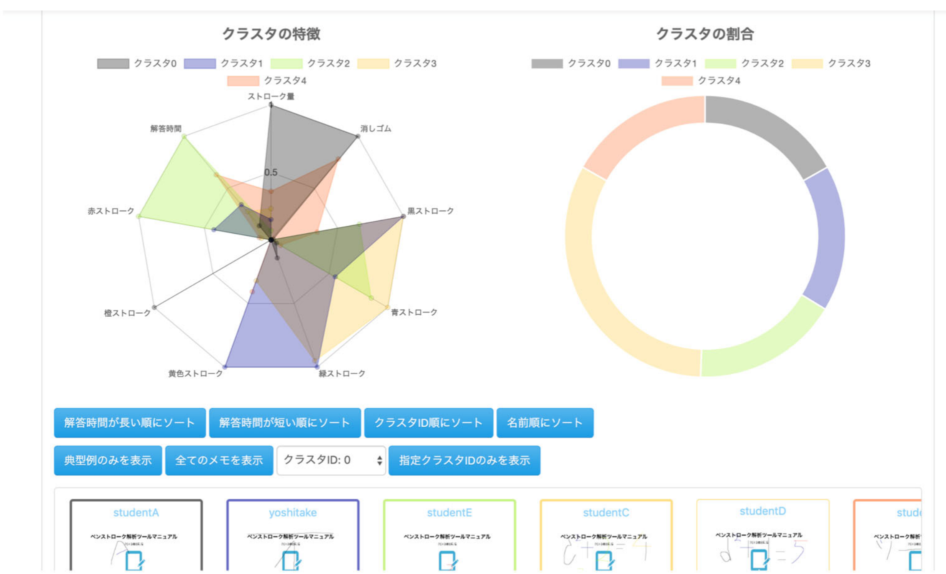
Figure 7 (a) Handwritten answer as a memo (b) Coloured pen strokes by delay analysis (c) Visualisation of clustering analysis and characteristics (see online version for colours)



(a)



(b)



(c)

3.2 Supporting language learning inside and outside the classroom

3.2.1 Data-driven AR strategies

Reading comprehension is a core competency in learning a language. While there exist many AR strategies to support reading comprehension, many of them are orchestrated with paper-based activities for individual students. In our context, a classical AR strategy SQ4R (Wong, 2009; Khusniyah and Lustyantie, 2017) was modified to have individual tasks using the affordances of BookRoll e-book reader and that of the LAViEW analysis tool and further include group learning phases. The overall activity flow, the corresponding LEAF system used and the connection to the SQ4R activity are presented in Table 3.

Table 3 AR using affordances of LEAF

	Jigsaw+ phase	*Platform*	*SQ4R task*
1	Content prediction	BookRoll using memo	Survey/(question)
2	Jigsaw pre-activity	BookRoll using markers, DicoDico and memo	Question/read/record/
3	Jigsaw expert activity	BookRoll using memo	Read/recite/record
4	Jigsaw activity	BookRoll using memo	Read/recite/review
5	Review and Evaluation	In-class listening activity	Review

Source: Toyokawa et al. (2021)

This approach leverages the data-informed paradigm for supporting teaching and learning. The students' learning attempts in the flipped learning phase are visualised in the AR panel of the dashboard. In a classroom implementation study (Toyokawa et al., 2021) it was found that the learning achievement improved significantly for both the advanced and standard learner groups.

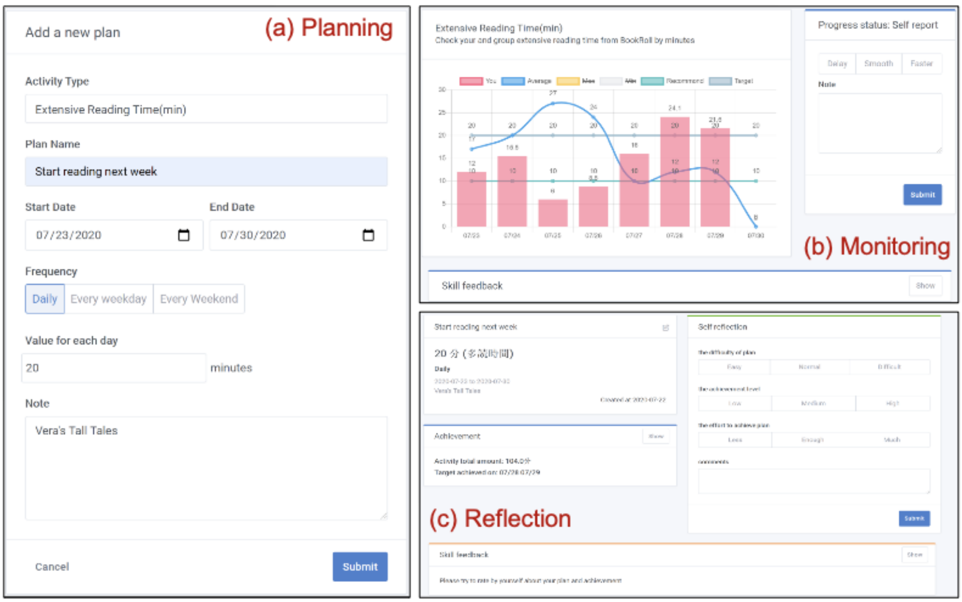
3.2.2 Self-directed ER

ER is recognised as an effective way to develop learner's language proficiency in English as a foreign language (EFL) and L2 (second language) research. ER is a way of learning a language through a great amount of reading on learners' own choice and pace (Day et al., 1998). Two of the key concerns are that teachers lack time to launch the ER program and guide students' reading activities (Brown, 2009) and students' autonomy for self-directed reading (Blachowicz and Fisher, 2014) are difficult and usually they lose their directions before forming a good reading habit if they have not their own goals in the ER program (Day and Bamford, 1998).

To support the students to conduct self-directed ER activities, more than 500 English picture books were uploaded in the BookRoll environment. The GOAL system was used by the students to set a plan to read the books by themselves (interface presented in Figure 8). Over an extended period, the study was to examine the relationship between SDL ability, SDL behaviour, and reading outcomes in the context of ER and to further explore the process of planned behaviour in SDL.

It was found that high SDL ability students had significantly more reading engagement, SDL behaviours, motivation and autonomy for ER than those with low SDL ability (Li et al., 2021a). Further, by applying cluster analysis and transition analysis methods it was possible to differentiate groups of learners with different planning behaviours (Li et al., 2021b) during a short term (one-week reading plan) and longer term (one-month reading plan). The result emphasised the use of systems like GOAL to foster their SDL ability in the context of language learning.

Figure 8 GOAL system interfaces for (a) planning, (b) monitoring, and (c) reflection (see online version for colours)



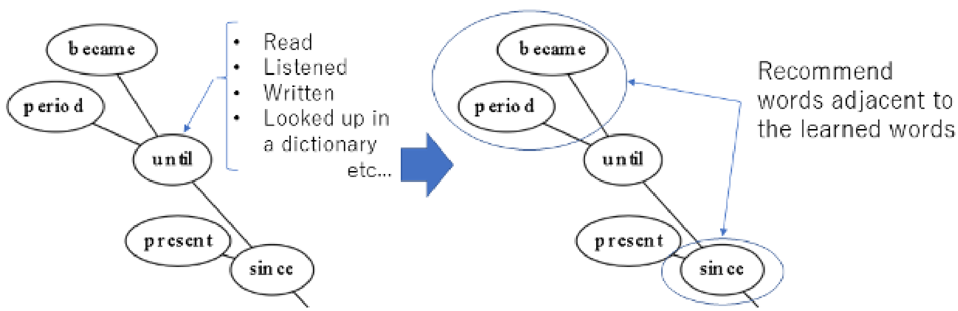
Source: Li et al. (2021a)

3.2.3 *Knowledge map-based reading recommendation for ER*

The knowledge map used for recommendation is based on a method proposed by Flanagan et al. (2019) to automatically construct a vocabulary knowledge map generated from words included in learning materials. This method creates links based on the strength of semantic and contextual similarity between nodes of the map that represent vocabulary. Learning materials and books that contain the vocabulary from the map nodes are then linked, and the amount of engagement a student has had while studying a particular vocabulary can be estimated by analysis of learning behaviour logs collected with LEAF. A personal knowledge map that is weighted with the history of study engagement of vocabulary is created for each learner. As the map closely associates vocabulary that occurs in similar contexts, recommendations can be generated by identifying low weighted nodes that are adjacent to high weighted nodes which the learner has studied. An example of this method is shown in Figure 8, where logs that represent study behaviours, such as reading, listening, writing, and searching for the meaning of the vocabulary in a dictionary, are analysed to estimate the amount of engagement with the word ‘until’. If the node ‘until’ has sufficient engagement when compared to other nodes in the knowledge map, learning materials and books that are associated with the adjacent nodes ‘became’, ‘period’, and ‘since’ will be recommended for study to the learner as shown on the right of Figure 9.

The learner can then select from the list of recommended studies generated and shown in different parts of the system where students monitor and reflect on their studies, such as LAViEW and GOAL. As the learner reads, listens, writes or looks up words in a dictionary using LEAF, their personal knowledge map is automatically updated by the system as new learning behaviour logs are collected. This ensures that students are provided with relevant and timely recommendations based on the course of the studies.

Figure 9 An example of a vocabulary knowledge map based recommendation for ER (see online version for colours)



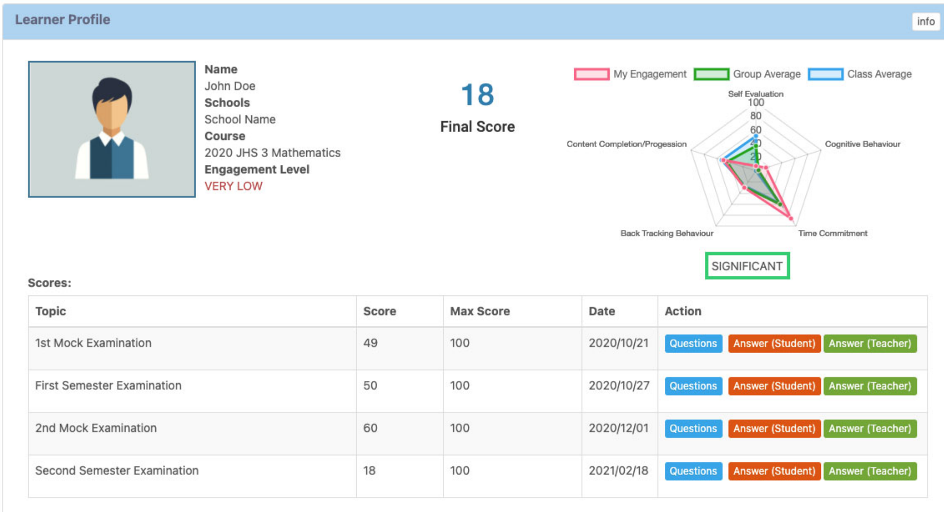
Source: Takii et al. (2020)

3.3 Advanced technologies for data-informed decision making in the educational context

3.3.1 BOLL for connecting learning logs across junior high school and high school

The BOLL system was used to connect learning systems at two different schools through the blockchain to enable the transfer of learning footprints across both schools. Connecting data from a junior high school to another high school through blockchain-enabled teachers to provide indicators for prior engagement of their learners in a particular subject. Access to such prior engagement information of learners can be useful in enabling personalisation, learning content design and early identification of problematic prerequisite topics. The students’ prior engagement behaviour and possible actionable insights are presented to the stakeholders on dashboards (example in Figure 10). Specifically, engagement behaviour in this context is defined based on five metrics: self-evaluation, cognitive behaviour, backtracking behaviour, time commitment and content completion rate (Ocheja et al., 2021).

Figure 10 BOLL dashboard presenting a prior profile of a learner to the teacher in a new school (see online version for colours)



Source: Ocheja et al. (2021)

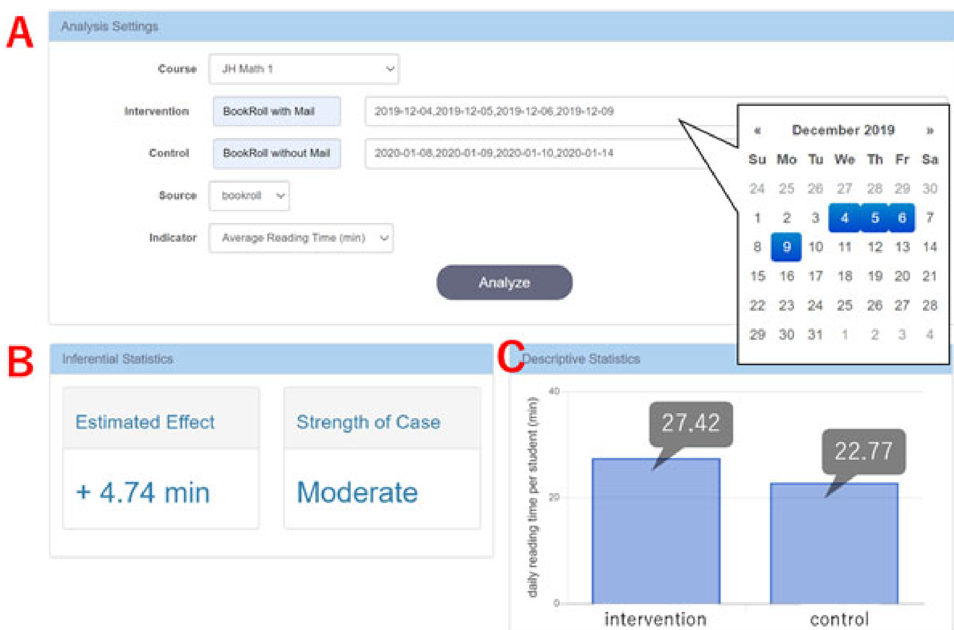
3.3.2 REAL for sustaining evidence-based educational ecosystem

REAL was used in the target school in a mathematics class of 60 first-grade junior high school students while they studied two different topics (Kuromiya et al., 2020). To encourage students' learning motivation, the teacher sent six e-mail messages to the students during the intervention period. Five out of six messages contained the notification of the next class's requirement, with an assumption that it would encourage students to preview and review the learning materials outside of the class. Each e-mail was sent to all students. The message sent to the students was shown in Table 4. The intervention was conducted during the first topic (data utilisation in statistics) during the first week of December, 2019 and the control period (no e-mail messages were sent) was later during teaching second topic (polynomial in algebra) on second week of January, 2020. The analysis highlighted the effect of the e-mail messages to enhance students' learning activities. A specific dashboard (Figure 11) for comparing BookRoll usage during the intervention period and control period presented the effectiveness of the intervention. The workflow of extracting evidence from learning data is as follows. First, the class activity schedules were entered in the system. Figure 11(a) presents the settings for the analysis. The overview panel [Figure 11(b)] showed the effectiveness of the intervention. It highlights that e-mail intervention increased the reading time on e-book by 4.74 minutes compared to the control period with a moderate confidence level. The amount of effect was retrieved from a mixed-effects model and the confidence level was determined based on the p-value of the dummy variable which stands for the existence of the intervention. The descriptive statistics panel [Figure 11(c)] presents the mean reading time indicating that the reading time on the e-book reader was longer (mean: 27.42 minutes) in the intervention period than that in the control period (mean: 22.77 minutes). Using REAL this analysed results can be logged in the evidence record store (ERS) via an API to create a corresponding teaching-learning case (TLC).

Table 4 Messages sent to the students

Date	*Message*
3 December	How was the test? Do not worry about the results. Reviewing is important!!
3 December	Good morning! For today's class, you will need a tablet, a class notebook, and a STEP notebook. Prepare during your break time.
4 December	Today's homework. 1. Put two types of prints on your notebook. 2. Prepare for textbooks p.206 (relative frequency) * For students who use the bookroll, it is good to draw a marker. 3. STEP 1 and 2 * If you want graph paper to create a histogram, please tell me! There are many but do your best!
5 December	Confirmation of today's homework 1. Read textbook p.208 and review! 2. Solve the problems in STEP 10! It is Friday, but it is the deadline to submit the STEP check sheet. By the start of the first term, please come to the staff room to submit.
8 December	Good morning!! Did you have a nice weekend? It seems that people have reviewed in STEP. Great! Submit your retest notes (including your reflections) and prints today. Bring a tablet, classroom notebook, and STEP notebook.
9 December	Good morning! The e-mail is once over today. Thank you for checking every time. Today is a class using print. Have your writing utensils, tablets and STEP notebook ready. Friday is the date of the B-line test. Study hard and ask questions if you do not understand.

Figure 11 Effectiveness of e-mail messaging (see online version for colours)



Note: Registering a teaching-learning case.

Source: Kuromiya et al. (2020)

4 Platform usage and user perceptions

To evaluate the usage of the system we investigated the usage statistics of the LEAF platform over the two academic years. Further, a survey of the students was conducted at the end of the second year to understand their perception towards using the system.

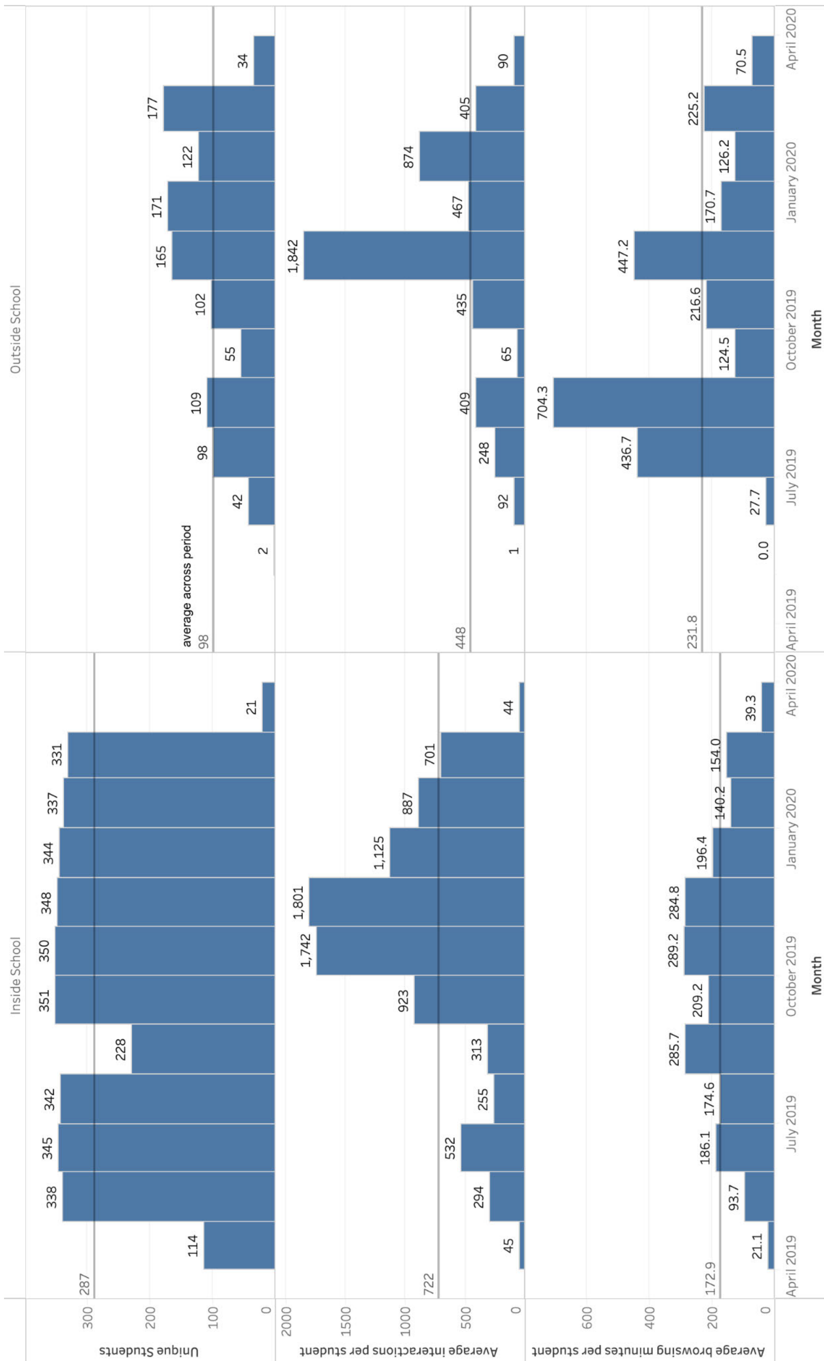
To answer RQ1 about the usage of the system we extracted the log data from the LRS and accumulated monthly usage in the English or mathematics courses. The period of extraction was set from April 2019 to March 2021. The usage of the system in both the subjects is presented in Section 4.1. Further, the log data is separated according to usage within and outside the school hours.

To answer RQ2 about the perception of the students, a questionnaire-based survey was created with items adapted from the self-directed learning instrument (Cadorin et al., 2017). While the survey was deployed across all the classes of the junior high school (n = 348), the students who used the LEAF infrastructure across the two periods were selected for the current analysis (n = 228). This included the batch of 2018 who was in junior high 2 (n = 112) and the batch of 2019 junior high 1 (n = 116) respectively. The performance data, learning logs and the questionnaire response could be linked for 204 students. The 24 students whose dataset was incomplete (either missing questionnaire response or without learning logs) were not considered in the current analysis. Four constructs were focused on and had 19 items answered on a five-point Likert scale. The constructs related to self-efficacy (three items, reliability = 0.909, example item 2: I am confident that I will study using BookRoll/Moodle), usage of the platform for reviewing, summarising and organising learning (five items, reliability = 0.902, example item 5: it is convenient to use BookRoll/Moodle when preparing), social usage of the platform (three items, reliability = 0.835, example item 9: Bookroll/Moodle is convenient to teach and study problems with friends) and perceived effect after the use of the platform (eight items, reliability = 0.931, example item 16: using BookRoll/Moodle for a year, the learning time outside the school has increased since last year). The perception of the two batches that used the system for two consecutive years is presented in Section 4.2.1 and the perception of the teachers is presented in 4.2.2.

4.1 LEAF usage across two academic years

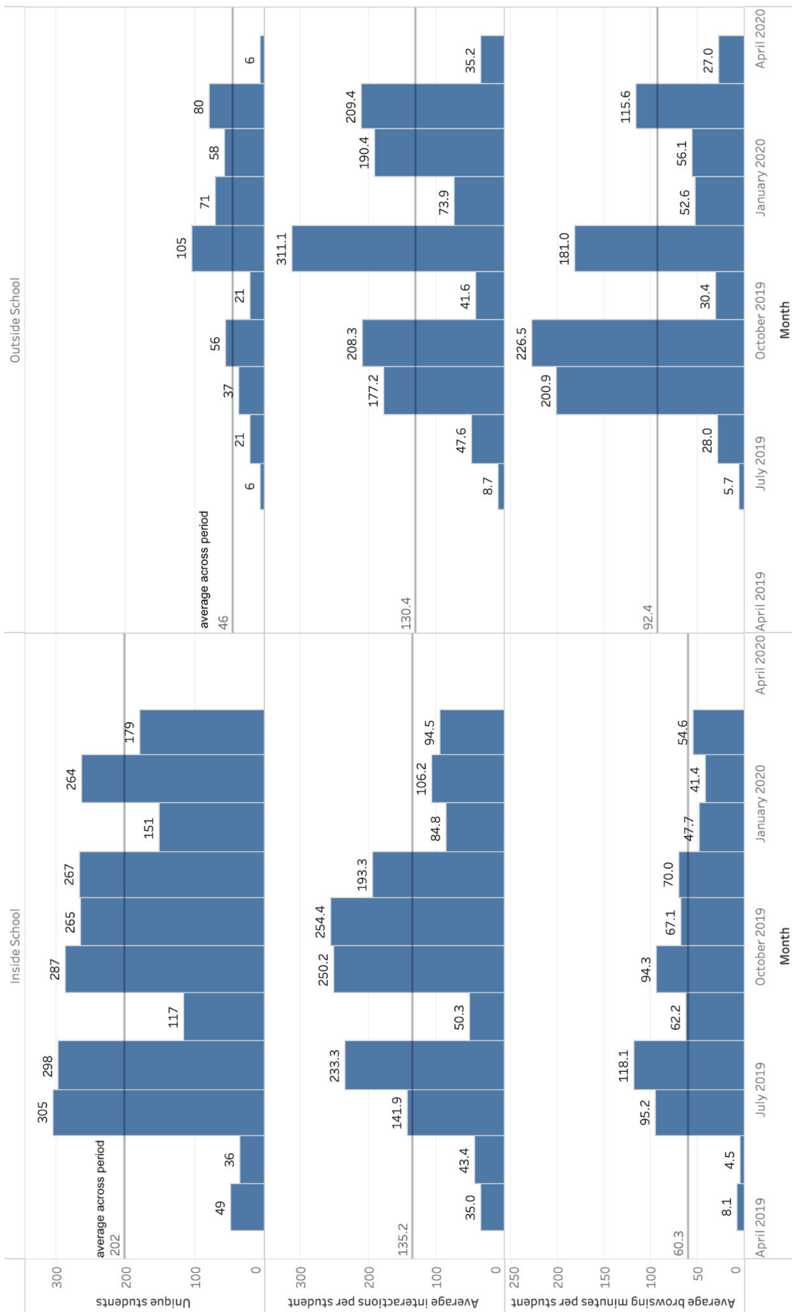
The logs of usage of BookRool were extracted from the LAViEW dashboard. Figure 12 presents the overall monthly usage in the 2019 [Figure 12(a) Mathematics, Figure 12(b) English] and 2020 [Figure 12(c) Mathematics, Figure 12(d) English] academic year. Average interactions and time spent per student inside the school and outside the school each month are reported. The average monthly value over the year is represented by the reference line. In the English courses in the second year, there was a significant increase in out of the school engagement with the platform specifically with respect to a number of active students (t = 7.56, p < 0.001, Cohen's D = 3.09), interactions (t = 2.571, p = 0.018, Cohen's D = 1.05) and browsing time (t = 2.31, p = 0.03, Cohen's D = 0.94).

Figure 12 (a) Logs in mathematics course during 2019 academic year (b) Logs in English course during 2019 academic year (c) Logs in mathematics course during 2020 academic year (d) Logs in English course during 2020 academic year (see online version for colours)



(a)

Figure 12 (a) Logs in mathematics course during 2019 academic year (b) Logs in English course during 2019 academic year (c) Logs in mathematics course during 2020 academic year (d) Logs in English course during 2020 academic year (continued) (see online version for colours)

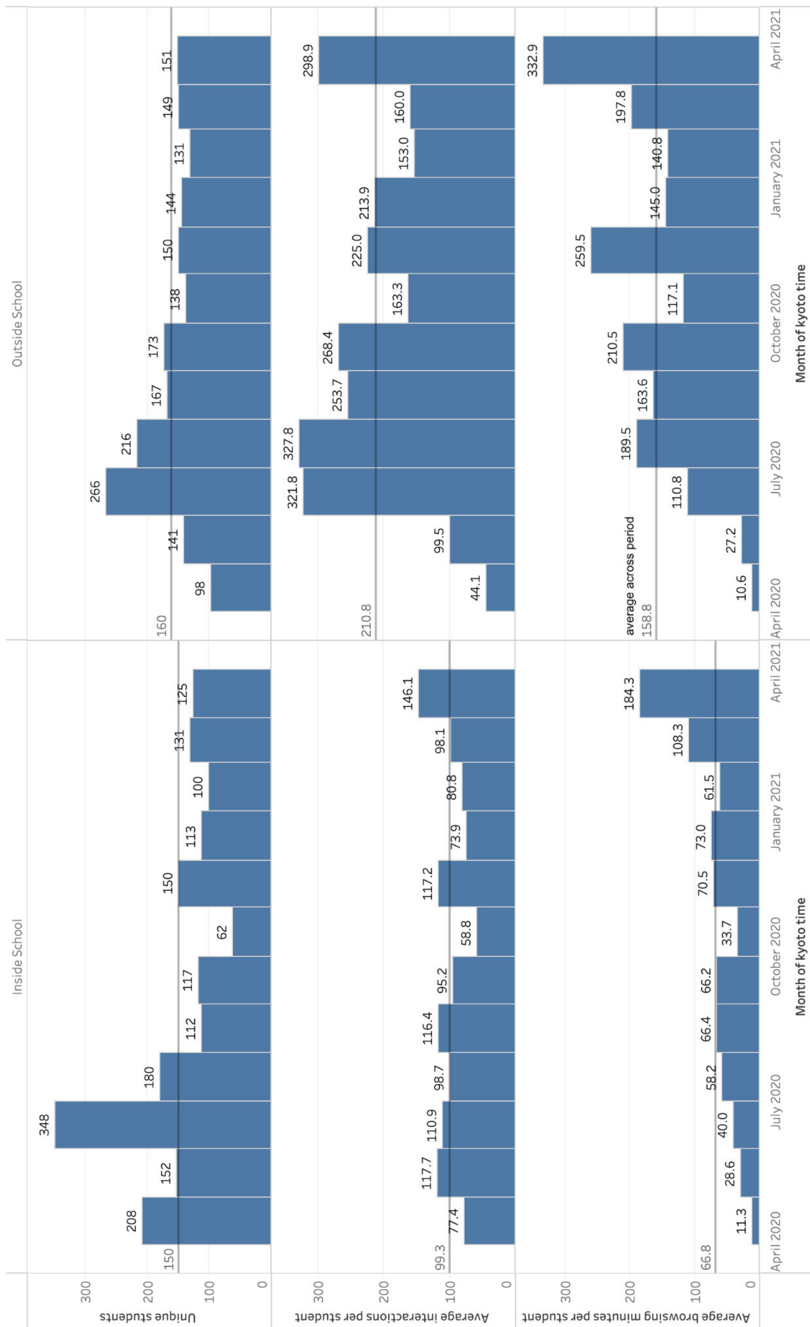


(b)

Figure 12 (a) Logs in mathematics course during 2019 academic year (b) Logs in English course during 2019 academic year (c) Logs in mathematics course during 2020 academic year (d) Logs in English course during 2020 academic year (continued) (see online version for colours)

(c)

Figure 12 (a) Logs in mathematics course during 2019 academic year (b) Logs in English course during 2019 academic year (c) Logs in mathematics course during 2020 academic year (d) Logs in English course during 2020 academic year (continued) (see online version for colours)



(d)

The key points are as follows:

- Mean unique students inside school vs. outside school decreased in 2020 when compared to 2019 for both English and mathematics suggesting less rigid timeframes for study.
- English classes saw a marked increase in 2020 of outside school average interactions per student and average browsing minutes per student when compared to inside school activity.
- A significant overall increase of inside and outside browsing time from 2019 to 2020 in mathematics.
- A significant increase from 2019 to 2020 in out of school engagement with the platform in English.

4.2 Perception of using LEAF

4.2.1 Students

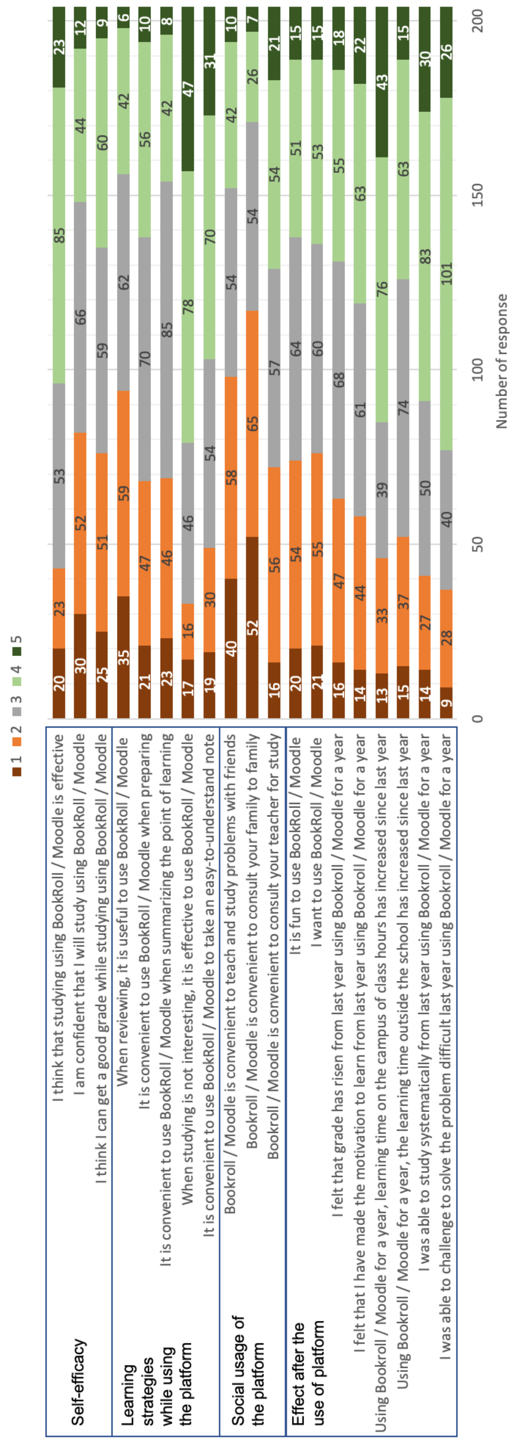
The compiled students' perception survey responses (n = 204) are shown in Figure 13. For self-efficacy the perception was that using the LEAF platform was effective (mean = 3.5, mode = 4), and confident of its use for studying (mean = 3.4, mode = 4). The perception regarding contribution to good grade by using LEAF was not clear (mean = 3.1, mode = 3). The use of the platform for reviewing (mean = 3.5, mode = 4) and preparing (mean = 3.2, mode = 4) was perceived as useful and convenient. However, the use for summarising (mean = 3.1, mode = 3), note taking (mean = 2.9, mode = 3) and using when studying is not interesting (mean = 2.9, mode = 3) was marginal.

The use of the platform to study with friends was marginally more convenient (mean, mode = 3) than the use with teachers (mean = 2.6, mode = 2) or family (mean = 2.4, mode = 2).

Regarding the effect of the use of the platform, it was perceived as fun to use (mean = 3.3, mode = 4) and preferred to continue using it (mean = 3.6, mode = 4). The perceived learning time out of school was marginally improved (mean = 2.9, mode = 4) than learning time inside school (mean = 2.6, mode = 3), however motivation to learn (mean = 2.9, mode = 3) and effect on performance (mean = 2.6, mode = 3) were not perceived to improve due to the use of the platform. Lastly, there was a moderate perception that while using the platform students solved challenging problems (mean = 3.3, mode = 4) and studied systematically (mean = 2.8, mode = 3). The key points of how students perceived LEAF are as follows:

- effective and are confident in its use for study
- useful and convenient for reviewing and preparing
- fun and preferred to continue using it
- participated to solve challenging problems systematically.

Figure 13 The perception of students ($N = 204$) after using leaf for their learning for two years (see online version for colours)

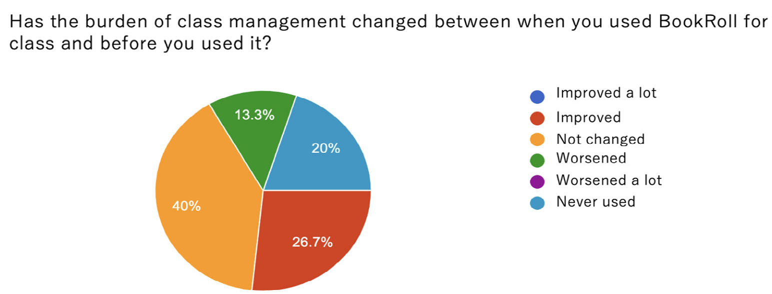


4.2.2 Teachers

We also conducted a perception survey of the teachers in August 2020. The survey consisted of three main components related to Moodle, BookRoll and LAViEW dashboard. The responses were collected via an online questionnaire. Fifteen teachers in the target school responded to our survey. Table 5 represents the frequency of using the tools on LEAF. Teachers' overall perceptions about our entire project were shown in Figure 14. Although some teachers noticed that class management became initially difficult by adopting the new practices in the project, no teachers mentioned that students' comprehension was adversely affected by the project. The key points of how a majority of teachers used and perceived LEAF are as follows:

- Used Moodle, BookRoll and the LAViEW dashboard at least once a week.
- When using BookRoll there was no change or improvement in class management burden.
- The use of BookRoll either had no change or did improve student's comprehension.

Figure 14 Teachers' perception ($N = 15$) about class management and students' comprehension (see online version for colours)



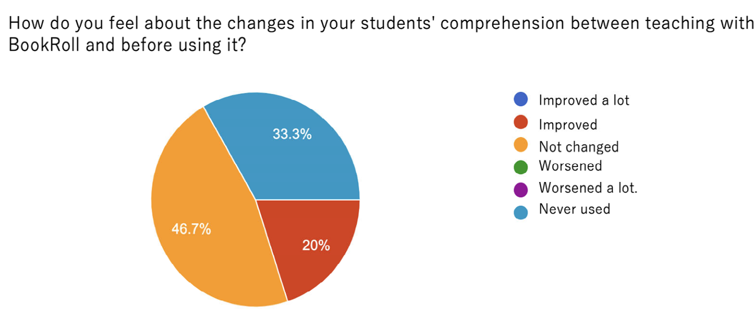


Table 5 Frequency of using the tool

	Never used	*Once a week*	*Two-three times a week*	*Four-five times a week*
Moodle	0 (0%)	7 (46.7%)	2 (13.3 %)	6 (40%)
BookRoll	1 (6.7%)	9 (60%)	2 (13.3%)	3 (20%)
Dashboard	3 (20%)	11 (73.3%)	1 (6.7%)	0 (0%)

5 Discussion and conclusions

5.1 Usage and perception of the LEAF platform

Current data analysis builds on the earlier study (Majumdar et al., 2020), that focused on the use of platform specifically the dashboard in the Junior high school context and its relationship to learning achievement. In this study it was observed that the utilisation of the e-book platform increased differently across the two years. In the mathematics courses the monthly utilisation from 2019 to 2020 academic year there was overall significant increase in both inside school browsing time (t = 3.24, p = 0.004, Cohen's D = 1.325) and outside school browsing time (t = 2.26, p = 0.040, Cohen's D = 0.9). While the increase in class students' numbers from 287 to 328 (in Figure 12) was not statistically significant, students accessing out of class were significantly more in the second year (t = 7.7, p < 0.001, Cohen's D = 3.14). Teachers started to provide specific learning activities based on the resources shared on the platform in the second year. For instance, in junior high school mathematics summer vacation tasks involved the students to use the platform and complete it and specifically report their level of confidence on the answer. It involved the use of a BookRoll panel quiz. Such planned activities also gave opportunities for students to explore the features of the system and possibly contributed to the larger effects in analysis (Cohen, 1988).

In the high school context, it was observed that some teachers already used e-learning tools in their course and readily started to think about how the LEAF platform be used in their own course context. This also involved providing flipped out of class reading activities in BookRoll. In junior high school, the students perceived the platform as useful for review and preparation but did not mention using it for taking notes and summarising activities. It was also used for interaction with peers rather than with teachers and family. Overall, the experience was positive for the students, however, they did not perceive the effect on their class grades due to the use of the platform but got interested in problem-solving which was provided in the Bookroll platform. At least 50% of teachers in junior high school used Moodle, BookRoll and Dashboard once a week in their class. While there was mixed response regarding their effort to prepare for class while using the technology, none of them perceived that the student's learning is adversely affected due to the usage.

The key points are as follows:

- 2020 saw teachers increasingly provide learning activities based on resources shared on LEAF, such as: flipped out of class reading activities and reporting confidence on answers as quizzes in BookRoll.
- Students perceive LEAF use as a positive experience but had no effect on class grades.

5.2 A LA development and research space

From the research case studies presented in Section 3, a possible conceptualisation of the LA research landscape emerges. We consider two aspects: the degree of practice-driven or theory-driven approach of a project and whether it aims for an engineering or scientific outcome. We consider Maass et al. (2018) discussions on practice-driven and theory-driven research, the challenges on each front and possible ways to resolve in the domain of information systems to draw the parallels in the context of the LA domain. Data-driven research uses exploratory approaches to analyse big data to extract scientifically interesting insights (Kitchin, 2014) whereas theory-driven research from a social science perspective focuses on identifying abstract constructs and the relationships among them (Andersen and Hepburn, 2016). In the context of LA research, data-driven approaches are the ones where the actual teaching-learning practices are focused and the availability of different data sources are considered within that practice. As the actual teaching-learning practice is the focus, we term it a practice-driven approach. The theory-driven approach in contrast considers the availability of technological or scientific theories which can be directly considered but the data in the specific teaching-learning context is sparse. Regarding outcome, an engineering outcome aims to develop novel solutions or propose a novel workflow in the given teaching-learning context. The scientific outcome aims at developing new knowledge or a new theory of teaching and learning based on the analysis of the gathered educational big data. The four categories which emerge is elaborated as follows with an example of representative cases (summarised in Table 6):

1 Practice-driven and engineering outcome – given the context of learning mathematics and using handwriting interactions to solve problems, there are possibilities to capture a large amount of stroke data. However, there exists a solution to utilise those stroke data to determine where the student is stuck in the problem-solving step. Thus, easy availability of data is ensured while practising stroke-based interactions and designing and developing a process to identify the student's difficulty would follow an engineering solution approach.

2 Practice-driven and scientific outcome – while reading based activities are conducted on an online BookRoll a lot of reading logs are generated, however, there is less focus on modelling the active learning strategies based on that new log data. The current scientific outcome is limited to paper-based and teacher-guided activities,

3 Theory-driven and engineering outcome – the existence of blockchain technology is available but its large-scale solution in an educational context is not developed yet. The research of the BOLL system utilises the existing blockchain theory and aims to design specific technology solutions distributing the authentication of collected learning logs across institutional boundaries securely. However, the current status of collected data in the BOLL system is still sparse and it needs to be adopted more in practice.

4 Theory-driven and scientific approach – the concept of evidence-driven education is existing, but few initiatives aim to develop new knowledge of how to establish evidence from analysis of learning logs itself. Hence such a project can be categorised as theory-driven aiming for new scientific knowledge using educational big data.

Table 6 Approach and outcome matrix to highlight the LA research space

	Engineering outcome (develop novel solution/practice using data)	*Scientific outcome (develop new knowledge from data)*
Practice-driven approach (data available but the theory is not developed yet)	Stroke analysis to identify stuck points in mathematics problem-solving.	Finding new AR strategies from reading logs.
Theory-driven approach (theory available but data is sparse)	Using blockchain technology to connect learning logs.	Evidence extraction from learning logs to support education.

5.3 Challenges and learnings

Introducing the platform to end-users of different levels to technology, pedagogy and content knowledge (TPCK) was challenging. While prior efforts to conduct workshops for the stakeholders mostly focused on university in-service teachers (Majumdar et al., 2019b), for the K-12 level, the available time for the teachers to engage in the training was limited. However, we offered face to face feature demonstration sessions to support smooth adoption into their practices. A coordination course for the teachers was also created in the respective Moodle of different schools where platform manuals and activity handouts were shared.

For initiating usage of the platform using the student's tablet pc, the course reading materials were uploaded in the BookRoll. It involved procuring or making contracts of the digital version of the materials with the publishers. For instance, for mathematics courses, the textbooks and their corresponding question bank were acquired and uploaded in the corresponding course. Similarly, more than 500 contents of ER materials were organised and indexed. The system then could use them to enable the recommendation of new reading materials for students.

As the system is being used for regular classes across the whole institutional level, there were different logistic challenges to overcome related to sudden technical issues. It also required coordination with teachers and school IT administration to pinpoint unanticipated system downtimes due to any technical issues. It was also required to have a quick turnaround time to deploy any system updates and check its efficacy for large scale usage. To handle these logistics, we maintained a planned maintenance and upgrade schedule which was decided in tandem with the school authorities.

On the research front, one of the challenges was to schedule study plans in the regular academic schedule of the school. For instance, the junior high school course was to proceed towards completion at an equal pace for each class in a grade and conducting a controlled study design was quite challenging (Bliesmer, 1970). However, the approach of extracting evidence from the actual log data helped to mitigate the study design problem, where even in some cases where all the students were introduced to the technology intervention, some of the students who did not use the system were considered as being controlled for the effect and the ones who adopted the intervention represented the other group.

Overall, a co-design paradigm with the stakeholders was challenging as well as rewarding regarding the insights gained. For technology outputs, teachers were involved during the conceptualisation of the technology where their context of the classroom was considered to design the technology features and its user workflow. Then conducting observational studies of the use of the technology in actual class settings or having a follow-up interview with the teachers about the degree of compliance with their mental model of the system was done. The redesign requirements were gathered for further development.

Similarly in projects focusing on scientific outputs too, we first shared the experiment design with the teachers and iterated till a mutually feasible plan emerged. The study protocol for in-class usage often included classroom observation to find details in the context which was not able to be identified from the data logs. After the analysis of the data, the findings were then shared with the teachers and the team of researchers discussed the interpretations in the specific educational context and the extent to which it is generalisable.

The framework proposed in this study is a platform involving different levels of end-users, which involved complex influencing factors, both in terms of participants and the preparation and practice of learning activities. The challenge remains to have uniform criteria and select assessment methods to evaluate the multiple components. However, to tackle this issue we had a pragmatic solution to develop an evidence portal that can store the evaluation findings of any of the teaching-learning practices that use the system components as teaching and learning cases.

In the post-pandemic era when the Japanese education system is aiming to move to the new normal (Educational Rehabilitation Post Pandemic, 2021) digital textbooks in a mobile learning environment have the potential to provide further opportunities for adoption and maintaining the daily teaching-learning activities from anywhere and at any time.

5.4 Contributions and future possibilities LEAF infrastructure

The article presented the LEAF developed to support and enrich teaching-learning interactions with data-driven services. The framework was instantiated with Moodle as LMS, BookRoll as the learning content reading platform and GOAL system to support learners' self-directed activities. It engineered a data-driven educational evidence portal and applied the technology of blockchain to connect learning logs for learners across their academic life in different institutions. The deployed technology is used in practice for two years in a K-12. The engagement and the user perception are reported. Earlier researchers have focused on personalisation and precision education with the data-driven infrastructure (Yang et al., 2021). The LEAF platform has the foundations to carry forward the research agenda at scale.

Acknowledgements

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