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Effects and acceptance of precision education in an AI-supported smart learning environment

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Abstract
The research presents precision education that aims to regulate students' behaviors through the learning analytics dashboard (LAD) in the AI-supported smart learning environment (SLE). The LAD basically tracks and visualizes traces of learning actions to make students aware of their learning behaviors and reflect these against the agreed goals. This research aims to realize the digital transformation of the learning space, thereby improving students' learning outcomes with the assistance of the learning dashboard. To examine whether there was a close relationship between the frequency of using the whole platform and academic results, the data was collected from 50 first-year university students who registered with the innovative thinking course. Based on the data, we constructed the Technology Acceptance Model (TAM) questionnaire and interview guide to realize the students' acceptance and feedback towards the SLE. Students were clustered into high-mark and low-mark groups based on their final results. The Wilcoxon rank-sum test is used to identify a significant difference between the two groups using the precision education platform. Subsequently, the partial least squares structural equation modeling (PLS-SEM) is further utilized to analyze the relationship between system quality, perceived ease of use, and perceived usefulness on behavioral intention and learning transfer.

Keywords Architectures for educational technology system · Improving classroom teaching · Teaching/learning strategies

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1 Introduction

Teachers, as facilitators in the Problem-Based Learning (PBL) classroom, must evaluate group work regularly to ensure student collaboration and learning. However, most teachers cannot observe and record the learning behavior of every student at the same time when in the traditional classroom as their individual role as teacher is limited and they are unable to support students and intervene in the students' learning process. Recently, learning analytics (LA) has been introduced to support digital transformation. The shifting paradigm underlies the collection of student behavior data but applies it in a SLE whereby students can get immediate feedback in the PBL classroom which ensures equal attention for every student who can likewise set agreed learning goals. However, some research has combined PBL and LA, focusing on the virtual environment rather than the physical classroom. As a result, the research explores students' acceptance towards a SLE and its effect upon students.

A wave of digital transformation took place in higher education institutions, where universities adopted innovative teaching by integrating multiple techniques to help students achieve better learning outcomes. Teachers or school administrators can track the learning status of certain students in detail, help them adjust learning goals, and carry out precision education (Lu et al., 2018). For example, the concept of rational agents is the heart of AI technology "perceiving its environment through sensors and acting upon that environment through actuators". In doing so, AI in the PBL classroom can assist teachers in classroom observation and student behavior recording. Obviously, the task of AI as an agent is not to completely replace the teacher as a facilitator, but to resolve the fact that the teacher cannot fully observe the students or cannot hire an assistant teacher for recording work with a limited budget. Therefore, an AI-supported precision education learning environment is expected to provide more agile and stable feedback of learning history records to teachers and students, thereby enriching students' learning experience in PBL classrooms.

In recent years, the development of smart classrooms has begun to integrate AI technology, and to automatically recognize and record most learning events and behaviors on the spot, so as to provide immediate feedback to teachers and support students' adaptive learning, but most research is still in the initial and feasible test development stage (Southgate et al., 2018).

The AI-supported SLE discussed in this research integrates technologies such as applying AI in facial recognition, image and behavior recognition, data visualization, and educational chatbots. Students in the SLE are given the right to freely review their learning process in the classroom through a visualized report generated automatically by the smart classroom system for each individual student. At the same time, the designed chatbot indicates the specific area for improvement and reminds students of the expected standard of performance after class, thereby being able to review and regulate their learning behaviors in line with the agreed improvement actions. In this research, students' self-introspection process supported by the smart classroom is considered as a precision education mechanism that can help them identify their behaviors in collaborative learning. Relevant literatures have shown that students' reference to the digital portfolio of their learning journey can facilitate their self-adjustment of learning (Yastibasa & Yastibas, 2015) and influence them positively (Chang et al., 2018). It is an effective tool for introspection (Slepcevic-Zach & Stock, 2018), which can also increase learning efficiency (Barisa & Tosun, 2013). The SLE discussed in this research collects data automatically and provides students with visualized dashboards reflecting their learning journey. It also reminds students to reflect, introspect, set goals, and take actions through the educational chatbot.

2 Literature review

2.1 Digital transformation and precision education

Digital transformation (DT) has extended to business and educational circles since the fourth industrial revolution (Verina & Titko, 2019). Although DT can improve the usability and accessibility of the education sector (Fonseca et al., 2017), it is not limited to improving the convenience of the sector (Newman & Beetham, 2017), and should be used to improve the efficiency of education (Marcelo-García et al., 2015). Many scholars have put forward their own definitions for the DT of education. Table 1 illustrates typical definitions taken from the literature.

OECD (2018) proposed the so-called people-driven approach to DT that sheds light on digital transformation: "If we lose sight of the individual and the need for all individuals to be engaged and benefit from the digital transformation, the transformation cannot be positive and inclusive." This suggests that teachers and students are the main clients of DT and teachers should emphasize how to meet the learning needs of every student in the educational practice of DT. In the context of DT, many teachers have paid attention to the development of precision education. In 2015, former U.S. President Barack Obama proposed the concept of precision education (Hart, 2016). The definition of precision education is interpreted as "an approach to research and practice that is concerned with tailoring prevention and intervention practices to individuals based on the best available evidence" (Cook et al., 2018).

Table 1 Definitions of the term "DT"

Author(s)	Definition(s)
Kaminskyi et al. (2018)	"DT of the university education system should have a broader focus and must include the modernization of corporate IT architecture management, which could provide an important contribution to structuring the efforts of innovation in education."
Fleaca (2017)	"The modern developments in the area of modernizing educational system with the aid of ITC technology and applied process thinking principles in the attempt to capture and model interrelated activities required to integrate digital technologies in teaching, learning, and organizational practices."
Abad-Segura et al. (2020)	"DT is a process that requires evolution in the way it is taught and adaptation to the new learning needs of the student."

Its core value highlights the value-added application of improving the academic performance of specific students (Sukhija et al., 2015). As far as the precision education is concerned, the student-centered approach is essential for the development of adaptive learning (Starčič & Vukan, 2019). Through learning analysis, teachers can quantify the learning process of students (Wilson & Scott, 2017), developing teaching methods, facilitating reflection and decision-making processes (Cook et al., 2018), and providing timely intervention to prevent failure (Johnson et al., 2011). The conduit for AI, if being applied in the learning environment, accentuates its statistical aspects of data mining to collect and analyze learners' behaviors (Du Boulay, 2019). This enables teachers to identify blind spots individually in the SLE where facial recognition, image, and behavior recognition to name a few are used to realize precision education. The SLE features a digitized application to track students' learning behaviors in the classroom. In order to speed up this data-driven decision-making process, data visualization presents learning information in the dashboard which is becoming more and more popular in many teaching contexts. The visual dashboard can also help readers gain a deeper understanding of the results (Sarikaya et al., 2018).

Recent PBL research has found the merits of DT and precision education. Saqr and Alamro (2019) collected the data in the learning management system (135 students and 15 PBL groups of the interaction data) and assisted teachers to identify isolated and active students through SNA visual and LA. They further indicated that "students' level of activity and interaction with tutors are positively correlated with academic performance". Other research relating to physical space utilizes multimodal data collection and analysis techniques (MMLA) to collect student behavior data by using infrared imaging, eye tracking, biosensors and wearable cameras (Blikstein & Worsley, 2016).

2.2 Smart learning environments

The SLE features digital transformation that can provide teachers with data on student learning behavior. In doing so, the intelligent learning environment can help teachers build up learners' profiles, automating the assessment and providing dynamic feedback on the learning progress (Vesin et al., 2018). This provides a good opportunity for the researcher engaging in the DT of education to explore how to design a meaningful information disclosure and feedback mechanism to enrich the learning experience and learning effectiveness of individual students, and that is precision education. According to Hwang et al. (2008), SLE is defined as a learning environment supported by the intelligent technologies. Students' learning behaviors can be adjusted in the right place and at the right time in accordance with their needs. Based on this, it could provide appropriate support, such as guidance, feedback, tips or tools.

Because the SLE can collect student learning data through a variety of integrated technologies, this also allows teachers to use more data to analyze student behavior. It can be closer to the actual situation, and resolve the fact that teachers can only observe because of the limited energy of personal observation and recording limitations of single or other indicators. In recent years, the breakthrough of AI in face and image recognition has also been used as a technology for the SLE to track learner behavior. For example, AI is used to automatically record student behavior and identify individuals (Andrejevic & Selwyn, 2020). It could also recognize gestures and body movements (Cukurova et al., 2018), and pinpoint information about social interaction and emotional state (Sullivan & Keith, 2019). These data are transformed and visualized into interpretable dashboards, and then sent to students via LMS or LA systems (Duval, 2011) or educational chatbots (Mubin et al., 2013). Another advantage of the SLE is to support students' spontaneous learning (Ribbe & Bezenilla, 2013). Based on the analysis information and feedback mechanism provided by the SLE, students are able to focus on weak units, such as deep learning (Azevedo et al., 2011) and reflection on the learning process (Hattie, 2013).

Students' engagement analysis is one of the SLE research areas in recent years, such as emotional engagement and behavioral engagement. For example, Spikol et al. (2017) automatically collected six groups (three people in each group) of 18 engineering students' behavior data in cooperative learning tasks through the SLE. These behaviors include the capture of objects, positions of people, hand movements, faces, audio levels and video. In addition, some researchers also indicate that 11 students voluntarily wear smart wristbands to observe their behaviors during cooperative learning in the group, including activities of hand-writing, typing and touchpad use (Preston et al., 2018). The contribution of this research is that teachers can use smart bracelets to collect individual student behaviors and track the overall performance of cooperative learning and the team. They further suggest this can help teachers and students reflect on the process of cooperative learning by establishing LADs and notifiers at the individual, group and class levels.

2.3 Technology acceptance model

The use of emerging educational technologies has increased in recent years, but the acceptance and use of technology is a challenge for educational institutions (Berrett et al., 2012). For many years, researchers have been using Technology Acceptance Model (TAM), Planned Behavior Theory (TPB), and Unified Theory of Acceptance and Use of Technology (UTAUT) to explain the adoption of technology systems. The TAM is the most commonly utilized model based on Theory of Reasoned Action put forward by Fred D. Davis in 1989. The main purpose of the TAM is to explain and predict users' behavior and acceptance of technology products. The basic assumption is that the user's behavioral intention and actual system use are directly affected by external variables (Straub et al., 1995). If believing the information technology is easy to use, they will be more willing to continue using it in the future (Davis et al., 1989). On the other hand, if users believe that the information technology is useful for work, this will also positively affect their intention to continue using it (Agarwal & Prasad, 1999).

Compared to TAM, the Planned Behavior Theory(TPB) is also a model for exploring human intentions and behavior Ajzen(1991). The theory comprises three main factors that affect behavioral intention and actual behavior adoption:

attitude, subjective norms, and perceived behavior control. TPB was not used in this study because it contains human and social factors. However, many researchers do not support that social norms affect behavioral intentions(Chau & Hu, 2002; Shih & Fang, 2004; Venkatesh & Davis, 2000). Venkatesh et al. (2003) integrated different models and theories to propose the UTAUT model. UTAUT model takes performance expectancy, effort expectancy, social influence, and facilitating conditions as the four factors for predicting user behavior intentions and takes gender, age, voluntariness, and experience as four moderators. Since this research focuses on the newly developed AI-supported SLE system, and the factors that affect students' acceptance of the new system are discussed, in the early stage, whether the factors of the new system design will affect the acceptance of students is our concern. However, neither the TPB model nor the UTAUT model explores the system's design's core factors. Besides, there are relatively few AI-supported SLEs on campus. Students and their significant others have no similar experience, so it is not appropriate to include subjective norms in this current model. Finally, because this study has limitations in recruiting participants and study design, it is not applicable to include these moderators, such as age (the subjects are all the same age), voluntary (this study is not mandatory). Lagstedt et al. (2020) also questioned the UTAUT model's exploration of social influencing factors. They argue that this not only moves the model to the organizational level but also points out that social influence is difficult to assess in advance. The reason is that all the different characteristics of a new technological system do not necessarily need to be known in advance.

Since the TAM has been verified, it can explain the decisive factors in the user's technological acceptance and at the same time explain the user's technological use behavior. Researchers can adjust external variables and expand the model as needed (Venkatesh & Bala, 2008), such as including job relevance, output quality, result demonstrability and other represented system characteristics (Venkatesh & Davis, 1996). Therefore, the TAM has been widely used in research on technology adoption and is one of the most cited models in the literature. In addition, Weng and Lyau (2018) used the TAM to explore students' acceptance of acupressure devices, and found that the quality of the system had a key impact on cognitive usefulness, and the intention of use also affected students' subsequent learning satisfaction. The TAM has been regarded as a stable tool across cultures and technologies (Van der Heijden, 2003).

This study adopts TAM, although it is simple and can not explain the difference between students' intention to use an AI-supported SLE system and the explanation made by UTAUT. However, Rahmana et al. (2017) compared the three TAM models, TPB, and UTAUT and found that TAM performed best in modeling acceptance TPB. Besides, other studies have also found that the percentage of variance explained by TAM is the same as UTAUT (Mathieson, 1991).

2.4 Research questions

Therefore, in this article, we will focus on the help of an AI-supported SLE for students' learning behaviors and answer the following questions:

- How does the frequency of use by students affect their grades?
- What are the factors that affect students' use of the AI-supported SLE system ?
- What are the suggestions made by students after using the AI-supported SLE?

2.5 Development of hypotheses

2.5.1 The influence of output quality on PEOU and PU

In this study, SLE aims to provide students with helpful information to support them in adjusting their learning behaviors. Davis (2000) pointed out that organizing data into appropriate information forms can play a role in people's current and future decisions. The quality of information output can measure by reliability, comparability, and relevance (Khorashadi Zadeh et al., 2017). The quality of perceived information output affects the perceived usefulness and perceived ease of use (Valaei & Baroto, 2017; Zheng et al., 2013). It means that if students find that the information they receive from AI feedback is highly consistent with actual behavior. The report's content can help them adjust their learning styles and meet the needs of comparison with their peers. Then, they will perceive that the output quality is good. The better the quality of the information that SLE feedbacks to students, the higher their perceived usefulness and ease of use. Based on the explanation, thus the hypothesis can be explained as follow:

H_1: Output Quality affects PEOU positively.
H_2: Output Quality affects PU positively.

2.6 PU, PEOU, and behavioral intention

It is essential to confirm whether students will continue to use new educational technology. In this study, behavioral intention refers to the continuous intention to use AI-supported SLE. AI-supported SLE is not designed for students as a one-time use tool but is expected to help students track their performance systematically and provide continuous support. Users can be encouraged to continue using technology only by exploring the intention of using technology (Alzougool, 2019; Bölen, 2020).

For students, when AI-supported SLE is declared by teachers to be designed based on learner needs. How students perceive whether they can effectively improve their learning performance will affect their intention to continue using SLE. In other words, if students think that AI-supported SLE is useless to adjust their learning behavior or improve their learning performance, they will not have the intention of continuing to use it. Some studies have pointed out that PU is related to behavioral intentions (Venkatesh & Morris, 2000), PU will affect users' behavioral intentions (Phua et al., 2012), users are aware of the benefits and increase the adoption of technology (Cheung et al., 2019). Besides, AI-supported SLE is a new technology for students. If it is too complicated, it may affect students' willingness to use it. Some studies have pointed out that PEOU will directly affect users' Behavioural Intention of new technologies (Almaiah et al., 2020; Sathye et al., 2018; Sun et al., 2008).

Therefore, this research further identifies and measures the factors influencing students' intention to continue using AI-supported SLE. In recognition of the existence of these relationships, the following hypothesis can be formulated as follow:

H_3: PEOU affects Behavioral Intention positively.
H_4: PU affects Behavioral Intention positively.

2.7 The influence of behavioral intention on transfer of learning

Intention can predict behavior (Ajzen, & Fishbein, 2005; Conner & Sparks, 2015; Zhang & Guterrez, 2007). However, the AI-supported SLE developed by this research institute is an integrated technology that supports students to improve their learning behavior in the classroom, so it is expected to be applied to different subjects and other classrooms. Therefore, our final dependent variable is Transfer of Learning, not the actual system use in TAM. It allows us to explore possible factors that influence students to transfer this AI-supported SLE experience to other subjects or classrooms.

H_5: Behavioral Intention affects Transfer of Learning positively.

The SLE TAM of this research puts forward the following hypotheses(see Fig. 1):

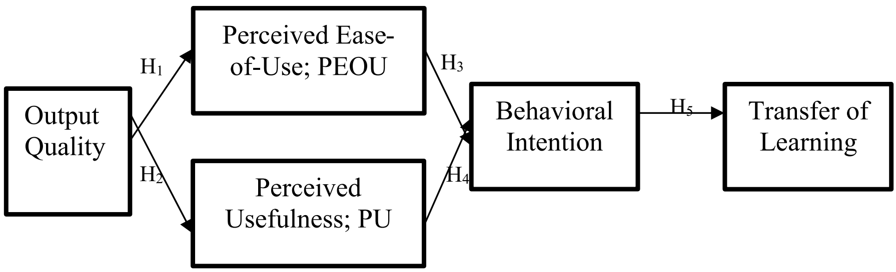

Fig. 1 SLE Technology Acceptance Model of this research

3 SLE Structure of this research

The SLE in this research is student-centered. The equipment includes webcams, while the technologies integrated include facial, image and behavior recognition, data visualization, educational chatbot, etc. In addition, this research established a precision education platform to assist students in viewing dashboards and setting their own learning goals.

3.1 Webcams

In this research, webcams are used mainly to constantly collect students' behaviors and biological characteristics of their face in the SLE. Photos are used for facial recognition as well as image and behavior recognition.

3.2 Facial, image and behavioral recognition

This research adopts the Face 8 facial recognition API services. Based on the actual teaching needs of this research, the authors customized eight behaviors of students in the classroom and applied Convolutional Neural Network (CNN) to train the model of image recognition.

In this research, the design of group activities in the SLE classroom is based on Group-Investigation (GI). Developed by Sharan in the mid-1970s, it was constructed to cultivate high-level cognitive abilities (Johnson et al., 2000). According to the method, team members not only need to determine how the research is going to be conducted but also gather or share information with others to complete the project report by means of discussion and analysis. Students could compare notes and exchange ideas concerning the project. Therefore, the seven behaviors of students using laptops, notebooks, mobiles, talking, standing, using microphones and raising hands in the classroom are observation indicators. However, sleeping is a behavior that needs improvement and is the eighth observation indicator.

Within the framework, three convolutional layers were used to extract the characteristics, while three pooling layers were used to choose specific characteristics, and seven connection layers were used for categorization. In the end, all Accuracy (ACC) surpassed 86%.

3.3 Dashboard

The dashboard in this research presents the results calculated in 3.1 and 3.2 using JavaScript (version 2.73) Chart.js. The dashboard presents the statistics of individual students, groups, and the entire class. This could urge students to learn about reflection, introspection, and goal settings.

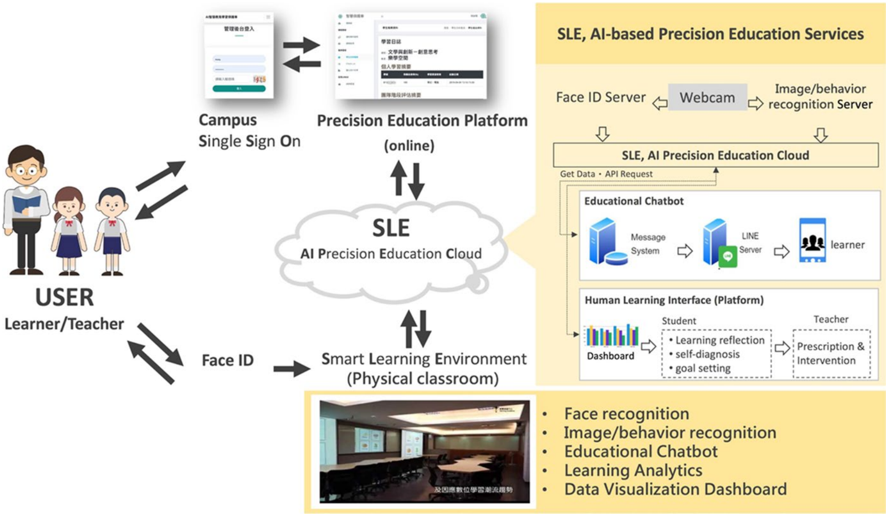

Fig. 2 SLE framework of this research

3.4 Precision education platform

This research also uses PHP to set up a precision education platform. This platform is equipped with functions to record students' reflection, introspection, and goal setting processes. As part of precision education, it supports students and teachers to log into the platform and view results via the school's Single sign-on (SSO).

3.5 Educational chatbot

The educational chatbot in this research is an automated learning reminder mechanism within the SLE structure. It reflects the characteristics of precision education. This educational chatbot lies between students and the platform and serves to represent teachers to send out messages and goal setting notifications.

The SLE framework of this research is shown in Fig. 2.

4 Methods

The first step after the integration of the AI-supported SLE was for students to sign up for precision education platforms. This procedure is pre-task in precision education, which allows students to link their personal account with the entire SLE system, and the sign-up process is as follows: upload personal photos and download educational chatbot to their mobile.

After connecting the SLE with students' personal identities, precision education was implemented. At this stage, students can log in to the precision education

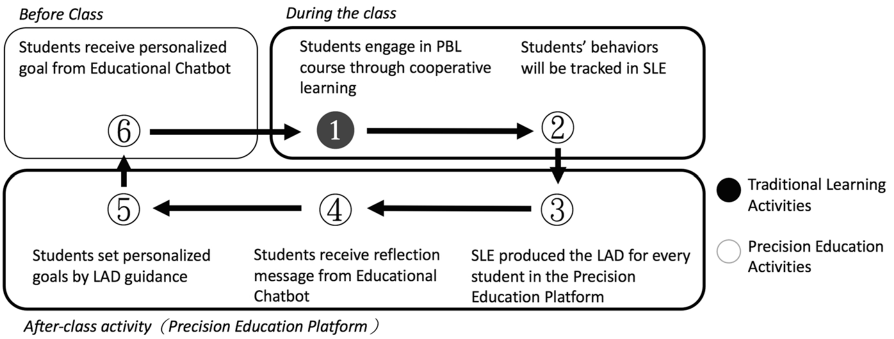

Fig. 3 Precision education activities

Table 2 Values of Cronbach Alpha, CR and AVE

Constructs	Cronbach's Alpha	CR (> 0.7)	AVE (> 0.5)
BI	0.922	0.951	0.865
TL	0.912	0.934	0.738
PEOU	1	1	1
PU	0.904	0.94	0.839
OQ	1	1	1

platform to view their learning journey, self-reflect, and self-assess after participating in the discussion sessions held by the PBL team each week. Students can define the objectives for the next session on the platform and request guidance from teachers via the platform.

Additionally, based on students' self-assessment and objectives, teachers can make tutorial plans for the next group learning session or intervene. Furthermore, the educational chatbot can represent teachers and guide students in self-adjusting their learning, remind students via mobile of their objectives set previously before each course, and notify them of the release of the latest information of the week in their learning journey.

In this research, the precision education service provided by the AI-supported SLE is to automatically assist students in recording their individual behaviors in the classroom during collaborative learning with group members during each class, and to guide students to use it through the educational chatbot after class and reflect on the precision education platform and LADs (including: self-evaluation of behavior, setting behavior goals, etc.). In addition, students will be reminded again of their customized behavior goals ten minutes before class to ensure that they can approach the expected goals in the subsequent cooperative learning process (Fig. 3).

Finally, the authors collected the number of times students used the precision education platform and their course results to see if students with different course results had different frequencies of using the precision education platform. In addition, with questionnaires and focus interviews, the authors gathered students' acceptance and advice regarding the SLE. For this research, a structured questionnaire was developed based on similar instruments (Davis et al., 1989). The instruments had 27 items to obtain information from the participants regarding their opinions on output quality (OQ) (6 items), PEOU (6 items), PU (5 items), BI (4 items), and TL (6 items). All items required five-point Likert-style responses ranging from 1 = "strongly disagree" to 5 = "strongly agree." The internal consistency of the instrument was determined using Cronbach Alpha coefficients. An overall Cronbach Alpha coefficient of 0.93 was obtained for the instrument. In addition, the higher the correlation between items of the same dimension, the better the convergent validity of the representative scale. This research used Component Reliability (CR) and Average Variance Extracted (AVE) to test the convergent validity. Fornell and Larcker (1981) suggested that the value of CR should be greater than 0.7, and the value of AVE should be greater than 0.5. The CR value in this research is between 0.934 ~ 1, and the AVE value is between 0.738 ~ 1, which shows that the questionnaire in this research has good convergence validity (see Table 2).

4.1 Participants

This research involved 50 first-year students of the case school, of which 35 were male (70%) and 15 were female (30%). In one semester of a creative thinking course, they were asked to complete a freshman project in groups composed of five to eight students.

4.2 Data analysis

4.2.1 Students' learning outcomes and SLE

It is a challenge to understand whether an AI-supported SLE can help students improve their learning outcomes through precision education mechanisms. Thus, the research examined this by looking into students' course results and their frequency of using the precision education platform. Therefore, the research collected students' final grades and classified their grades through K-means clustering. The purpose of clustering was to organize a set of data into clusters whose elements were similar to each other and different from those in other clusters. In this research, students were classified into high and low groups to examine whether there was significant difference between the two groups of students in using the precision education platform. Since cluster analysis consists of categorizing data to establish clusters for similar groups (Omolewa et al., 2019), it was appropriate for use in this research to group students by their course results.

Next, having considered that the research was unusual and had a small sample size and that the median number was often the same as the average number in which checking the median difference would be the same as checking the average difference (R Core Team, 2013), the researcher tracked students with different course results for the differences in their frequency of using the precision education platform with the Wilcoxon rank-sum test.

4.2.2 Acceptance study with SLE

This research not only examines students' learning outcomes and the SLE, but also importantly whether the students, as the subject of learning, can accept the SLE. After all, the school should not design a useful but unacceptable SLE. Classroom designs should also take students into consideration (Slotta, 2010). This research carried out path analysis by adjusting questionnaires, which mainly analyzes the relationship between different research dimensions and defines whether the path coefficient reached statistical significance to verify whether the hypotheses of this research are correct. PLS-SEM is a non-parametric method since it does not have any distributional assumption. The statistical significance level test is performed by re-sampling (Garson, 2014). As a result, it is suitable for a small sample size. The bootstrap method is used to carry out model verification and the significance of the path coefficient via t values is estimated (Henderson & Russell, 2005). The boot-strapping method is to randomly select sub-samples. The more sampling times, the

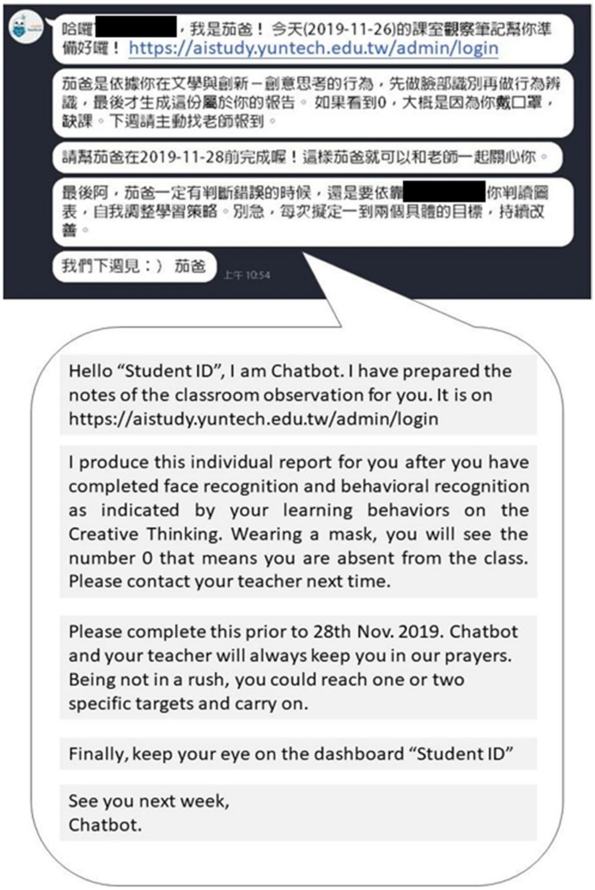

Fig. 4 Screenshot of educational chatbot – message

Fig. 5 Screenshot of precision education platform—student log

higher the stability of the sample (Hair et al., 2014). Since this research uses smart PLS 3.0 analysis, the bootstrap method is used for estimation.

5 Results

5.1 Students and SLE

During the first 15 weeks of the course, students received notifications from the educational chatbot (shown as Fig. 4). Students were able to log into the platform, review information of their learning journey in the LAD, and reflect, self-assess, and set goals for their learning (shown as Fig. 5).

Table 3 Average frequency and average course result

Frequency	Number of students	Average course result	Standard deviation	Minimum value	Maximum value
Lower than average	29	79.572	17.951	33.400	98.200
Higher than average	21	86.966	6.508	73.300	98.200

*N = 50, **Average Frequency: 4.32.

5.2 SLE and learning outcomes

5.2.1 Descriptive statistics

According to the statistics, the average frequency of students logging into the platform and completing the process of learning reflection, self-assessment, and target setting was 4.32 times. The authors divided the students into two groups based on their completion frequency. The analysis showed that the completion frequency of 21 students (42%) surpassed class average. Their average course result was 86.966 marks (standard deviation was 6.508). Twenty-nine students had below class average completion frequency, and their average course result was 79.572 marks (standard deviation was 17.951). As the completion frequency and the average and standard deviation of course result showed, students whose completion frequency surpassed class average had a higher course result with smaller standard deviation as shown in Table 3.

5.2.2 Difference between clusters

This research divided students' results into two groups (high and low) based on K-means clustering. The group with high marks had 86.78 on average (standard deviation was 7.84), whereas the group with low marks had 45.70 on average (standard deviation was 7.65), as shown in Table 4.

As the data do not conform to the expected hypothesis, the researcher verified the results using the difference in the medians of the two independent samples. Results

Table 4 Results of high- and low-marks groups

Results	Number of students	Average result	Standard deviation
High-marks group	45	86.78	7.84
Low-marks group	5	45.70	7.65

Table 5 Difference verification

Groups	w value	p value
High-marks group—Low-marks group	52	0.0072 **

*$p < 0.05$ **$p < 0.01$

Table 6 Path analysis

Hypothesis	Hypothesis	Path coefficient	SD	t value	p value
Output Quality—> Perceived Ease-of-Use	H_1	0.706	0.086	8.22	***
Output Quality—> Perceived usefulness	H_2	0.570	0.159	3.57	***
Perceived Ease-of-Use—> Behavioral Intention	H_3	0.405	0.125	3.23	***
Perceived usefulness—> Behavioral Intention	H_4	0.531	0.104	5.21	***
Behavioral Intention—> Transfer of Learning	H_5	0.578	0.103	5.36	***

$^{*}p<0.05$ $^{**}p<0.01$ $^{***}p<0.001$.

showed that the two groups of students differed significantly ($p<0.05$) in their frequency of using precision education platforms, as shown in Table 5.

5.3 Acceptance of SLE

This research uses the bootstrap method to verify the model and uses the t value to estimate the significance of the path coefficient to determine whether the hypothesis of this research is valid (Henderson & Russell, 2005). In the SLE Acceptance model, Output Quality positively affected Perceived Ease-of-Use ($p<0.001$); Output Quality positively affected Perceived usefulness ($p<0.01$); Perceived Ease-of-Use positively affected Behavioral Intention ($p<0.01$); Perceived usefulness positively affected Behavioral Intention ($p<0.001$); and Behavioral Intention positively affected Transfer of Learning ($p<0.001$). Path coefficients were 0.706, 0.570, 0.405, 0.531, 0.578. The adjusted R^2 of the model was 0.303. The t values of the hypotheses in this research were all significant. Thus, different dimensions are influential, as shown in Table 6.

5.4 Feedback for the system

From the feedback of students, we get their experience and suggestions on using the AI-supported SLE. First of all, students are very impressed by the ability to obtain personal LADs immediately after class, and that they can refer to the evidence materials after class, set their behavior goals in the next class, and then adjust their learning, which is very important to PBL.

> "I think this AI-supported SLE is very cool, because I can see my learning record. This is very helpful for me to complete the project with my team members in the classroom next time, especially to know which side to adjust. Because the course did not provide LADs, I would neglect my own learning behavior in the team. However, I know that the behavior of each team member is very important to everyone's ability to complete a project. In fact, it really helped me a lot (h7-4)"

In addition, some students provided observation indicators of eight behaviors for this research, and made suggestions for subsequent projects that could be expanded, such as personal and group atmosphere. According to the students, teachers can use this real-time data to actively intervene in class.

> "I suggest that students' responses in class be included in the smart classroom system so that the system can also remind teachers of the learning atmosphere in class, especially for instructing type of courses in the school (h9-7)"

Some students even suggest extensive integration of an SLE system for their uses.

> "There are many e-learning management systems in schools, but none of them are integrated. If the AI-supported SLE system can be integrated with the leave system or course calendars system that students often use, it will be more convenient to use (h14-12)"

Some people also said that the reason they would use this system less was because they had no similar learning experience in the past. It is suggested that teachers can share some successful cases before class.

> "I know this is a free-to-use system, which is great. I suggest that teachers can disclose some past use cases in the course for students to refer to. This may allow some students to wait and see like me, and increase their willingness to use".

One student pointed out an issue that had nothing to do with the quality of the system, but affected his use of the system. The student's feedback indicated that he could understand the function and value of the system, but he did not use it because he was aware that there was no problem with the interaction with the group partners.

> "I like the interaction with my group partners. It feels good. This is the reason why I haven't actively used it. However, if you carefully analyze the information on LADs, anyone will find that there are some behavior indicators that must be improved immediately, but I do ignore. If I want to improve the system, in my situation, I would suggest that the educational robot directly send the information on the indicators of backward behavior to the students. In this way, you will not be ignorant because you should take the initiative to check LADs. Improve learning (h30-8)."

6 Discussion

The AI-supported SLE developed by integrating multiple technologies in this research aims at laying the foundation for precision education in smart classrooms and providing students with personalized learning journey dashboards that support their learning reflection, self-assessment, and goal setting.

The first question in this research was to understand whether students were able to gain learning support in the AI-supported SLE and improve learning outcomes. The researchers collected student course results data, observed students' goal-setting frequency on the platform, and analyzed the correlation and difference between the two metrics. The researcher also regrouped the students by their course results and analyzed their goal-setting frequency on the platform.

Both analyses showed that the SLE, as a strategy of precision education, for students who used the platform more than average, delivered higher academic performance and smaller standard deviation. In addition, there are statistically significant differences in the academic performance of the students in the high-marks group and the low-marks group. Although this is only a small sample study, from the perspective of student interaction with the AI-supported SLE, teachers can actively collect students' learning behaviors in the AI-supported SLE and entrust educational chatbots to help provide accurate care and guidance for students in self-adjustment of learning.

The preliminary findings of this research will allow follow-up studies to create AI-supported SLE practical precision education, and provide some materials for further discussion. Yoo et al. (2015) reviewed the effectiveness of ten smart learning education dashboards and pointed out that the establishment of an SLE learning management system can support students to receive real-time, personalized and automatically generated information through LADs. Long and Aleven (2013) pointed out that this feedback information is very important for students, because it can not only increase their awareness, but also reflect on their learning performance and allocate learning time. Furthermore, Aguilar et al. (2018) proposed a concept of defining LA tasks as services in their latest research. The core of the learning analysis task is to analyze the data collected and accumulated by an SLE and support the needs of learners. They advocate that an SLE with technology integration (e.g. AI) can improve the learning process in physical classrooms.

The second question of this research was the level of acceptance of the AI-supported SLE by students. Knowing what influences students in using this system is important for subsequent development and refinement of an AI-supported SLE. Therefore, the authors conducted the investigation using a questionnaire, with results showing that Output Quality was an important external factor, and Perceived Ease-of-use and Perceived usefulness affected students' Behavioral Intention. The findings were consistent with those of previous studies (Zaharias & Poylymenakou, 2009).

As far as the future may gradually develop AI-supported SLE in K-12 and university campuses, students are expected to receive the assistance they have never had in the past and make adjustments to their learning behavior based on evidence-driven learning. This study has found that output quality is an external factor. Besides, the biggest difference between this study and other studies that use AI to provide student assistance is that AI-supported SLE is aimed at students' learning behavior in the classroom, rather than delivering direct learning materials and indirect guidance (e.g., tuition or Replace the role of teacher to answer students' questions). This not only guarantees student-oriented learning but also reminds technology integrators of smart classrooms to pay attention to PU and PEOU. Today, most classrooms are just a teaching space, without integrating technology to record students' learning behavior and the automated mechanism to guide students to self-adjust their learning. It is difficult for school institutions and teachers to conduct learning analysis conducive to improving students' learning effectiveness. It is also unfavorable to form conditions for precision education. However, in some virtual classrooms for online learning, emerging studies have also confirmed the positive benefits of AI to support students' learning behavior adjustment(Hussain et al., 2018; Yan, Lin, & Kinshuk, 2020; Zapata-Rivera, 2020). However, this study's explanative power is 30%, which means that some unknown factors affect students' acceptance of the AI-supported SLE system. Although this is a small sample of preliminary research, this discovery still reminds technical engineers that other unknown factors can explore and affect students' acceptance of AI-supported SLE. Also, the enlightenment for policymakers and stakeholders is that we can't just integrate technology and equipment in the classroom environment, even if we see some preliminary results, or have the ability to apply new technologies (such as AI) to transform classrooms and Propose possible solutions (that is, AI-supported SLE). However, there are still influencing factors that have not yet been discovered and are worth studying.

From MacLeod et al. (2018) in their latest study of 462 college students with an average age of 19, it also confirmed that Perceived Ease-of-Use and Perceived usefulness are factors that affect whether students accept smart classrooms. In addition, other factors that affect student preferences are also proposed, such as Student Negotiation, Inquiry Learning, Reflective Thinking, Functional Design, Connectedness and Multiple Sources. The study also further discussed gender factors, and the results showed that both genders equally appreciate the smart classroom with similar levels of preference.

The third question of this research was to discuss student feedback and suggestions for an SLE. In the field of technology-enhanced learning, the system framework should be designed to help humans make decisions, rather than make decisions for humans (Phillips-Wren, 2014).

The AI-supported SLE system in this research aims to actively provide students with personal learning behavior data to help them adjust their learning behaviors. In addition, users can expand functions and integrate other systems in the future, they also suggest possible directions on how to increase the frequency of students' use, such as explaining successful cases from an AI-supported SLE at the beginning of the course, or simplifying the steps to obtain learning behavior data. Based on the AI-supported SLE feedback mechanism, examples are as follows. Bull (2004) studied the degree of students' preference for feedback content, and found that it was mainly for information content that could help reflect on how to change performance, such as feedback about their weak points, current performance level, misconceptions, etc. Just like the suggestions that students want to reduce the complexity of process acquisition or information, in fact, students do not necessarily carefully review the feedback information they receive (Kay, 1997). Tanimoto's (2005) research further argued that the reasons why students might refuse to use feedback information may be related to the complexity and way the information is presented.

7 Conclusions

As the education community began to correctly and effectively discuss the application of artificial intelligence, recent literature has published empirical studies on AI-supported SLE online courses. There is very little research on classrooms. This study collected and analyzed data from 50 students who received precision education services during a semester to explore the learning effects and the acceptance of AI-supported SLE. This automatic process is applicable and helps to reflect on student behavior in class. Studies have shown that more students use the SLE system than average, their course grades are better, and the standard deviation is smaller. According to their course results, students are further divided into high and low groups, which shows a significant difference in their frequency of using the platform.

Because this study's preliminary conclusions come from a small sample, this study suggests that future researchers can conduct experimental studies that expand the sample size or include a control group. From the ratio of explainable variation to total variation ($R^2 = 0.303\%$), it is recommended to include other influencing factors in future studies. This research shows how to transform the traditional classroom into AI-supported SLE and achieve a precise educational framework.

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Data availability Due to the nature of this research, participants of this study did not agree for their data to be shared publicly, so supporting data is not available.

Code availability (software application or custom code) Not applicable.

Declarations

Conflicts of interest/Competing interests We have no conflict of interest to declare.

Ethics approval (include appropriate approvals or waivers) Ethical approval for this study was obtained from Human Research Ethics committee at National Chung Cheng University on July 25, 2019 (Approval No. CCUREC108070801).

Consent to participate (include appropriate statements) Written informed consent was obtained from all subjects before the study.

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