Prototype Verification for Co-creation of an Experiential Value Platform for E-learning Skill-Based Education Service

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Abstract
E-learning is an effective e-business approach; however, it does not perform well for skill-based education involving body motion and implicit knowledge, typically neglecting experiential value which has a strong relationship with changes in the psychological status of the receiver and provider. The current study introduces a platform for co-creation of experiential value (CcEV) and a proposed prototype app named e-training analyzer. A pseudo e-learning experiment was conducted using the app to test the CcEV concept. We utilized a teaching-timing assistance (TT-assist) method, because suitable teaching-timing corresponds to changes in learners’ short-term experience value during practice. Moreover, an algorithm for objectively estimating the users’ feeling-of-satisfaction from the brain wave measurement was implemented in the app. Using three evaluation methods, we confirmed that the TT-assist method was able to enhance learners’ skill level as effectively as normal teaching (Welch’s t test : t(38.28) = 0.04, p = 0.03). In addition, TT-assist significantly enhanced learners’ subjective feeling-of-satisfaction (t(20) = 3.86, p < .001, d = 0.66), and maintained learners’ objectively estimated feeling-of-satisfaction. Taken together, the results suggest that the prototype CcEV platform was effective for overcoming the difficulties of e-learning for skill-based education.

Keywords
Skill education service, E-learning, Experiential value, Co-creation, Feeling-of-satisfaction.

1 INTRODUCTION

Education services are activities that provide knowledge and skills to students (service receivers) from teachers (service providers). The global education market reached a value of $4 trillion in 2001, and the rate of increase from 2000 to 2011 in the USA was as high as 34.2% (Sakai 2013). In many other countries, the increased growth rate of the education market has exceeded the growth rate of gross domestic product (GDP). This growth has been caused by the informatization of education businesses, including e-learning. E-learning can markedly enhance service productivity, significantly reducing time and cost for both service providers and receivers (Saito and Kim 2009). In Japan, e-learning has significantly advanced since 2005 (METI 2008), facilitated by regulation of usage environments for e-learning, including improvement of learning management systems (LMS), popularization of cloud services by information technologies, and the development of sophisticated light smartphones and tablets. Industrialized countries have introduced e-learning aggressively; 80% of all Japanese enterprises have introduced LMS, and 95.8% of companies with over 3000 employees use LMS (JMA 2016). In the field of education, massive open online courses (MOOCs) such as Coursera (Stanford) and edX (MIT and Harvard) have been launched, providing an important global innovation enabling free and borderless education.

1.1 Challenges for education services involving skill-based e-learning

Most of the successful cases mentioned above, however, are focused on knowledge education, rather than skill-based education. In short, for skill-based learning involving body motion, orthodox e-learning approaches often cannot work well, particularly in cases of machinery processing operations (Mori 2005), nursing care operations (Peate 2010), and sports (Lyle and Cross 1999). This challenge is related to several factors, including the gap between a learner’s cognitive level and actual motion (Kidman and Hanrathan 1997), or the need for implicit knowledge that cannot be recognized, even by the instructor themselves (Polyanyi 1966). Because these factors are difficult to verbalize, instructors and learners implicitly depend on non-verbal communication like gesture, facial emotion, and nuance of voice to express their feeling and to impart information. Because of these challenges, even long-term use of on-line e-learning systems cannot communicate as effectively as in-person one-on-one communication.

Few previous studies have investigated skill-based education in management and marketing, which are considered stakeholders of the education service. However, skill analysis methods (e.g., Therblig (Price 1990) and SAT (Mori 2005)) and coaching methods (Cheng et al. 2011) have been studied. In contrast, a number of previous studies have examined e-learning from the viewpoint of marketing:
e-learning standard SCORM (SCORM 2017), LMS (Solihadin and Bandung 2016), study-support methods (Baneres et al. 2014), a training model (Kou and Wan 2009), and an interaction method between teachers and students (Yengin et al. 2010). These studies, however, are intended for knowledge education or enterprise training, and have not focused on skill-based education. Overall, research examining both skill education and e-learning from the perspective of service science is extremely rare.

1.2 Characteristics of skill education service

In investigations of the characteristics of e-learning skill-based education service from the standpoint of serviceology, the following three points have been highlighted as unique factors compared with orthodox knowledge education services (Asama et al. 2014):

- C1. Multiplicity
- C2. Propagatability
- C3. Experiential-value basis

Multiplicity (C1) refers to a structure involving a third factor, in which learners apply their own skill in addition to the two roles of service provider and receiver. For instance, in case of the three fields mentioned above (manufacturing, nursing business, and sports), the third factor corresponds to the quality of products, the care-receiver’s sense of security, and the joy of the audience, as shown in Figure 1. In short, comprehensive evaluation of certain skill education services depends not only on the instructor’s teaching skill, but also the effects of the third factor brought by the learners who received the original skill education service.

![Figure 1: Multiplicity in three representative areas of skill-based education.](image)

Propagatability (C2) is the extent to which the learner, as the service receiver, becomes a new provider capable of transferring the skill they have mastered, enabling the service to be propagated from one person to another, as shown in Figure 2. Such a repeatable process of learning and teaching constitutes a transfer of technology. If the process is successful, the instructor is satisfied with the teaching result, and the learner satisfies their end customers, propagating the feeling-of-satisfaction. Thus, it is important for an e-learning education service to transfer not only the skill but also feeling-of-satisfaction to learners, who will be future instructors.

Unfortunately, existing skill-based education activities cannot consciously utilize propagatability, because they tend to use service designs based on orthodox economic criteria, focusing on use value and exchange value (Vargo et al. 2008) while neglecting the important components of experiential value that are emotional and instinctive, such as sensation and satisfaction (Grönroos 2007). For instance, a good instructor infers the degree of learners’ understanding from their emotional state when the instructor attempts to give advice (Daniel et al. 2010). Learners also implicitly convey feelings of misgiving via non-verbal communication when they do not think they have mastered the correct action. These factors suggest that a user’s willingness to use the learning service cannot be increased if learners do not feel agreement with the guidance techniques used. In such cases, the service receiver will be dissatisfied with the service. The instructor is also likely to feel insecure about the adequacy of their teaching method. Consequently, it may be difficult to maintain a high level of service quality, because both providers and receivers affect the service activities via their sense of dissatisfaction. Thus, experiential value should be used as an axis to evaluate and improve education service quality, as indicated by point C3.

1.3 Co-creation of experiential value

As explained in the subsection above, we have previously proposed a new concept for the co-creation of experiential value (CcEV) in our previous research, while developing an e-learning education service, focusing on multiplicity/propagatability and experiential value (Asama et al. 2014). The CcEV indicates interactive and cooperative features about the process to form experiential values in both instructors and learners. An illustration of the concept is shown in Figure 3.

![Figure 2: Propagatability of the skill education service.](image)

![Figure 3: Concept of co-creation of experiential value.](image)
The CcEV concept is an expansion of the so-called S'FIRE model (Murakami 2013), by making the flows between an instructor and a learner bidirectional. According to the concept, the learner obtains satisfaction through the utilization of a skill-based education service, and the experience through the utilization itself becomes the learner’s value. Meanwhile, an experience of teaching becomes the instructor’s value, since they teach adaptively depending on the learner’s characteristics and circumstances. Repeating such mutual interaction, both parties increase their experiential value and satisfaction, and the sustainability of the service is maintained.

We conducted the present study to test the effectiveness of the proposed CcEV for e-business designers of a skill-based education service. The concrete aims of the current study were as follows:

P1. Identifying the functions needed to produce a successful CcEV, and specifying the development of an information technology services (ITS) platform to achieve them.

P2. Examining mental status estimation as a core technology of the platform, and prototyping an e-learning tool for skill-based education.

P3. Performing a pseudo e-learning experiment and evaluating it using the prototype, to investigate the potential applications of the CcEV platform.

To achieve P2, we developed an app for recording experience during the practice of a skill involving user’s body motion, and corresponding changes in mental status. The app utilized a combination of brain signal measurement and machine learning, providing advice to the instructor according to each learner’s experience during practice. Moreover, a new algorithm for estimating the feeling-of-satisfaction objectively from a subject’s brain waves was developed and implemented in the app. To achieve P3, three types of evaluation were statistically applied to data obtained in the pseudo e-learning experiment: a questionnaire analysis of learners’ subjective feeling, an objective assessment of learners’ skill by a specialist, and verification of the feeling-of-satisfaction estimation with a newly developed algorithm.

In Section 2, we describe the details of the CcEV platform. In Section 3, we describe a method for estimating subjects’ mental status, providing an example of assistance based on the estimation, and reporting the details of the developed app. Section 4 explains the pseudo e-learning experiment, and Section 5 describes the results of three evaluations. Finally, Section 6 summarizes our conclusions and discusses possible future applications of the CcEV-platform.

2 PLATFORM FOR CO-CREATION OF EXPERIENTIAL VALUE

2.1 Required function for co-creation

Learning and teaching, which are the main activities of any education service, are associated with each skill and each experience of instructors and learners. Therefore, two-by-two different conditions must be considered to determine the functions required for co-creation of experiential value. The required functions are summarized in Table 1.

Table 1: Required functions for co-creation of experiential value in education service.

<table>
<thead>
<tr>
<th>Value activity</th>
<th>Value of knowledge and skill</th>
<th>Experiential value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Learning</td>
<td>a) Sharing of information regarding the intended skill and knowledge in learners’ community</td>
<td>b) Measurement and recording of learners’ experience during the learning process</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Detection of the changing points of the learners’ experience</td>
</tr>
<tr>
<td>Teaching</td>
<td>c) Sharing of teaching skills (know-how) between instructors</td>
<td>d) Measurement and recording of instructors’ experience during the coaching</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Detection of the changing points of the instructors’ experience</td>
</tr>
<tr>
<td></td>
<td></td>
<td>e) Enhancement of interaction between instructors and learners</td>
</tr>
</tbody>
</table>

Functions a) and c) correspond to systematization of the educational content regarding the intended skill, and the maintenance of the teaching methodology, respectively. If these functions are prepared adequately, both instructors and learners can access the correct information and knowledge, and ensuring an appropriate foundation for education. The resulting positive circumstances lead to a sense of connection between people in communities of instructors and learners. Such favorable circumstances establish a climate of innovation, because new value can be created by the main stakeholders’ new actions. On the other hand, functions b) and d) correspond to the data mining process, suggesting areas for the enhancement of experiential value by examining characteristic events in the experiences of both instructors and learners.

Most typical LMSs involve aspects of function a); however, most of them lack function c), which helps the sharing of teaching skills (i.e., know-how) between instructors. For instance, in the field of nursing, the teaching method of care has been reported to depend on each instructor’s style, and even professional caregivers do not have a common approach (Yasuda 2014). Functions b) and d) are often practically unrealized, because most existing LMSs cannot record experiences of the progress of learning/teaching. Instead, such LMSs only record after-the-fact data obtained by questionnaires and/or examinations. Therefore, function b) is a basic but critical function for the CcEV platform, enabling real-time recording of the user’s experience during the practice of a skill involving their own body motion, and corresponding changes in mental status.

2.2 Realization of the CcEV platform

Based on the factors discussed above, an ITS configuration for embodying the functions indicated in Table 1 for a CcEV platform is shown in Figure 4. Unlike existing LMSs, the proposed platform enables real-time measurement of both body motion and mental status during the training. Body motion is recorded by a motion analyzer comprising video and a motion capture system. These information technology devices and wearable appliances have recently become available to consumers. In contrast, mental estimation is less widely used, but is technically feasible, and several approaches such as brain wave monitoring and gaze measurement are available on the market. A database is used to accumulate information from learners and instructors, and required information is transmitted between providers and receivers using ITS technologies.
Realizing the platform shown in Figure 4 could enhance the service quality of the education service by enabling propagatability. Specifically, if certain signs that a learner/instructor experienced difficulty during the learning/teaching process can be identified from the recorded experiences, the pattern of these signs can be available for other instructors to facilitate improvement of their teaching skills. Such a chain-reaction corresponds to effects of functions c) and d) on the teaching side. Thus, new value is created as the establishment of effective coaching methods through analysis of previous learners’ and instructors’ experiential values.

The following section focuses on a key function b), involving the measurement of body motion and mental status, and the development of an app as a prototype.

### 3 PROTOTYPING OF CCEV-PLATFORM

#### 3.1 Measurement of mental status

Psychological measurement using electromyogram (EEG) was adopted from several methods enabling estimation of mental status. EEG is a method for measuring electrical signals produced by the activity of the cerebral cortex, enabling flexible and noninvasive measurement of human brain activity with high temporal resolution. In the current study, an EEG-based emotion estimator called Kansei-analyzer (Dentsu SJ 2017) was utilized. This device has a minimal burden for participants, requiring only a single measurement location, and wireless data transmission is suitable for real-world environments. Kansei-analyzer can automatically estimate five types of psychological status: like, interest, concentration, drowsiness, and stress (Ito et al. 2009). An algorithm for discriminating these psychological states was developed based on a sophisticated machine learning technique using EEG data collected from more than 10,000 subjects; hence, the reliability of the system is high, and it has been used in various practical fields. Because the algorithm is robust against noise induced by facial muscle activation, such as electromyogram and electromyogram signals, the device is also appropriate for measuring the mental status of a person who is moving the own body during motion training.

#### 3.2 Development of an app for skill-based e-learning

Before developing the app, we considered e-learning styles to determine appropriate specifications for the system. The system was designed to work with three styles of learning, as shown in Figure 5. Style A is self-directed study, corresponding to the learner downloading some content via the online e-learning service, and studying by themselves. Style B is mutual learning based on asynchronous communication between a learner and an instructor. In this style, communication between the learner and instructor is performed via a database, and the learning/teaching history is recorded in addition to downloading content and performing a web-based exam. This learning style is widely used in standard e-learning systems. Style C corresponds to real-time interactive communication, such as a online chat.

![Figure 5: E-learning styles.](image)

From the perspective of development of an information-communication technology system, style B can be considered a hybrid of style A and C, because the main functions of style A (i.e., a data server containing educational materials, and a viewer) and style C (i.e., mutual data transfer and communication between two access points through a server or the internet) are required for style B. Therefore, by assuming a scenario for style B, we determined the utilization procedure for the app, as shown in Figure 6. Because the system structure shown in the figure is as simple as a typical LMS, it can be easily introduced into existing e-learning systems.

![Figure 6: Utilization procedure for the app.](image)

In step ① in Figure 6, the learner’s body motion and mental status during skill operation were simultaneously measured with a camera and an EEG measurement device. Both were uploaded to a database at step ②. The instructor then downloads the data, and confirms the learner’s practical motion and mental status graph by watching the downloaded video (step ③). At that time, the instructor enters several comments (i.e., advice) corresponding to scenes recorded in the video. The instructor then re-uploads the modified video embedded with the comments to the server. The learner receives the modified video via the server, and practices again by referring the video and comments (step ④).
Based on the steps mentioned above, we developed an e-learning app called e-training analyzer with Dentsu Science Jam Inc. (Suzuki et al. 2016), as shown in Figure 7.

Figure 7: E-training analyzer.

3.3 Teaching-timing assistance

In teaching a skill-based operation, pinpointing corresponding to learner’s body movement can be an effective method (Sugihara 2008). Thus, we inferred that adequate timing of effective pointing corresponded to changing points of the learner’s short-term experience during the practice. Here, note that the term “timing” is used to express a moment during the learner’s practice of the movements involved in the skill operation. Therefore, as an example of function b) shown in Table 1, new functionality for showing the appropriate timing based on the estimated mental status of a learner was implemented in e-training analyzer.

Specifically, we focused on the points at which negative emotions (i.e., stress) and positive emotions (i.e., interest) changed to determine the teaching-timing (TT) points, because the psychological effects of short-term variation of experiential value are thought to be synchronized with changes of mental status. Based on this hypothesis, in our previous studies (Suzuki et al. 2014; Nakajima et al. 2015; Suzuki et al. 2015), we performed a comprehensive analysis of teaching-learning of polishing skills using grind stones to determine the judgment conditions for TT with the following three steps. First, the brain waves and gaze of both experts and beginners were measured during polishing work, and the transition of several types of mental status was estimated using Kansei-analyzer. Second, transitions of learner’s subjective mental status during the work were visualized as a hand-drawn graph using a video feedback analysis that reminded them of their subjective feelings at that time. Third, checking the subjective transitions, the objective measures of mental status estimated with the Kansei-analyzer, gaze information, and learners’ body motion, we extracted several characteristic patterns of learners’ mental transitions. As a result, the following three conditions were specified as possible TTs (Nakajima et al. 2015):

- TT1: The moment when stress rises.
- TT2: The moment when the value obtained by dividing interest by stress rises.
- TT3: The moment when concentration rises after interest rises.

These three qualitative conditions were formulated into the following quantitative criterion:

\[ I_p = \left\{ \frac{x_{(\text{max})}}{x_{(\text{min})}} \mid x_{(\text{max})} - x_{(\text{min})} > \sigma \right\}, \]

where \( t \) is time, \( x(t) \) is time-sequence data concerning each type of mental information mentioned above, \( \sigma \) is the standard deviation of \( x(t) \) for all \( t \), and \( x_{(\text{max})/\text{min})} \) is time at \( k \)th local maximum/minimum of \( x(t) \). \( x_{(\text{max})/\text{min})} \) values are detected from all time-sequence data \( x(t) \) using the findpeaks function in MATLAB software. The teaching-timing computed using Eq. (1) with respect to TT1, TT2, and TT3 were used in the pseudo experiment described in Section 4.

3.4 Development of objective estimation of the feeling-of-satisfaction

The feeling-of-satisfaction is an emotional response to experience (Westbrook 1981; Oliver 1989), and varies depending on both negative and positive emotion (Oliver 1993; Dube 1990). Previous studies suggest that our proposed approach mentioned above, focusing on positive and negative emotion, is adequate. Better still, if the feeling-of-satisfaction can be objectively estimated, experiential value itself can be easily quantified. This method is appealing because satisfaction is a significant factor in a customer’s sustainable purchase behavior (Oliver 1980), and new methods for objective measurement of brain waves are likely to become standard practical service measurement.

Although several types of mental status have been estimated using EEG in the field of emotional engineering, to our knowledge an algorithm for estimating the feeling-of-satisfaction has not yet been established. Hence, we sought to develop an algorithm to quantify feeling-of-satisfaction, which we verified through the pseudo e-learning experiment, as described in next section. See the Appendix for the details of the development procedure.

4 EXPERIMENTAL VERIFICATION OF CcEV-PLATFORM PROTOTYPE

4.1 Learning task

Chair-carrying motion was selected as a learning task for the pseudo e-learning experiment. This type of motion is simple to master, as a form of “no-lifting nursing care” (JNA 2017), which places importance on the avoidance of back pain problems during nursing care (Hirohashi and Tsujino 2005). A learning video was edited using Transcribe app (Suzuki and Mitsukura 2015) with a supervisor from the Japan No-lifting Association via an interview and discussion. Transcribe app enables a user to generate thumbnails from the video scene by touching the app buttons, providing easy video playback by touching the screen. Using the app, we visualized the sequential motion of chair-carrying motion, and produced a learning video.

Samples of snapshots from the video teaching material of chair-carrying motion are shown in Figure 8. To perform the motion correctly, the upper body should be kept vertical, the arm should be kept close to the center-of-gravity of the waist, and all actions should be performed smoothly.
4.2 Design of a pseudo e-learning experiment

The pseudo e-learning experiment was designed by focusing on the learner’s experience. The main purpose of this experiment was to verify the effectiveness of TT-assist, which was designed by considering the changing points of experiential value. Specifically, participants were divided into two groups of learners without their knowledge, and differences in learning effects between the two groups were statistically tested. We investigated differences in the method for selecting the teaching timing; one method was based on automatic detection by TT-assist, and the other method was based on human judgment by the instructor. All other conditions were the same, and the same instructor coached each of the two groups. As an instructor, we chose a beginner coach who was not a professional caregiver, because propagatability was one of the properties we sought to incorporate in a skill education. The instructor joined the e-learning experiment after another professional caregiver trained the beginner coach to perform the chair-carrying motion.

The scenario of the pseudo e-learning training consisted of three phases: a self-study phase, a teaching phase, and a review phase, as shown in Figure 9. In phase-1, the learner watched the video teaching material for 2 minutes to study the chair-carrying motion by themselves (step 1a in Figure 9). The learner then practiced the motion for 1 minute as their first trial practice. During the practice, the learner’s body motion and EEG signal were recorded using the learner’s e-training analyzer (1b). After the initial practice, the learner answered the questionnaire regarding their own chair-carrying motion at the first trial for later evaluation (1c). The recorded video and EEG data were then uploaded to the database (1d).

Phase-2 was the instructor’s turn, and corresponded to step ②, as shown in Figure 6. The instructor downloaded the video file and mental status data from the database (2a), and evaluated the learner’s practice performance by checking transition in their mental status using the instructor’s version of e-training analyzer (2b). The instructor gave advice by adding comments to the video file that was recorded in the learner’s self-study phase. At that time, the method for determining teaching-timing was changed according to which of the following two groups each learner belonged to: an assisted group (AG) and a normal group (NG). For learners in AG, the instructor commented at the teaching-timings that were automatically detected by TT-assist (assist mode).

Three teaching-timings were selected using Eq.(1) for each condition of TT1-TT3, and a total of nine timings were indicated to the instructor. In contrast for learners in NG, the instructor commented at teaching-timings selected by the own judgment without using TT-assist, as in a typical synchronous e-learning system (i.e., usual mode). The number of comments was $9 \pm 1$, rather than restricting the number to 9, to avoid disturbing the instructor’s own initiative. The comments were then uploaded to the database again.

Phase-3 was assumed for step ④, as shown in Figure 6, and was the learners’ second turn. Each learner downloaded the reply video of their own first practice with embedded comments written by the instructor (3a). The learner read the instructor’s advice by watching the video using the learner’s e-training analyzer for 2 minutes as a review phase (3b). The learner then practiced again for 1 minute as a second trial (3c). The second trial practice was also recorded, and the data were used in skill assessment for later evaluation. Finally, the learners answered the questionnaire again, regarding their second trial, using the same format (3d). This e-learning experiment corresponds to just one cycle of step ① to ④, as shown in Figure 6, because we wished to focus on short-term experiential value as a preliminary study for developing the e-learning skill-based education service.

It should be noted that AG and NG involved identical condition in terms of the following points: i) all learners received advice from the same instructor, ii) no learner knew whether the instructor used TT-assist or not, and iii) all learners had no previous experience using e-training analyzer. Because of the last condition, there was no difference between AG and NG in the effect of novelty. To avoid large differences in customer expectation, all participants were engineering students (importantly, none were medical students or caregivers) who did not have any experience of caregiving, to avoid any experience-related differences. Other conditions, including the room used for training, the chair type, and camera angle were identical for all participants in both AG and NG. The content and procedure of the experiment were approved by the Tokyo Denki University human ethics committee.
**5 EVALUATIONS**

To confirm whether the proposed TT-assist system was able to enhance the quality of skill education service, we performed three types of evaluation:

E1. Assessment of learners’ skill operation by a specialist
E2. Learners’ subjective self-assessment of skill operation to evaluate their feeling-of-satisfaction
E3. Objective measurement of learners’ feeling-of-satisfaction using a brain monitoring method

The main product of e-learning is the upskilling of learners, which was confirmed by E1, E2 and E3 were conducted to investigate customer satisfaction using subjective and objective methods, respectively. Moreover, E3 provided proof of the proposed algorithm for estimating the feeling-of-satisfaction from brain signals.

The number of participants in E3 was smaller than in E1 and E2, because an additional version of *e-training analyzer* was used to implement our newly developed algorithm for E3. A first group of 19 participants (18 males and one female, 20–24 years old, $M = 21.3, SD = 1.09$) participated in E1 and E2. Another 22 participants (19 males and three females, 20–24 years old, $M = 22.4, SD = 1.10$) then participated in all three evaluations (E1-E3). Thus, in evaluations E1 and E2 there were 20 participants in for NG and 21 participants in AG. In evaluation E3, there were 11 participants in NG and 11 in AG. The following subsections describe the details and results of each evaluation.

### 5.1 Assessment of motion skill by specialist (E1)

In this first evaluation, all movements performed by all learners were gauged objectively by a professional physical therapist who was not the instructor in the pseudo e-learning experiment. The specialist had more than 10 years’ experience and was approved as a coordinator of no-lifting care. The specialist watched all practice scenes recorded in the self-study phase (first trial before teaching) and at the review phase (second trial after teaching), and scored 20 items on a 0–100 point scale, as shown in Table 2.

<table>
<thead>
<tr>
<th>Segment</th>
<th>Check point</th>
<th>Detail</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lifting up the chair</td>
<td>Posture</td>
<td>Keep the backbone vertical</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Stabilize the upper body</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Keep the arms close to body trunk</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Keep center-of-gravity (CoG) of body lower by spreading legs back and forth</td>
</tr>
<tr>
<td></td>
<td>Motion of lifting up the chair</td>
<td>Grasp the backrest and tilt the chair around the chair’/front leg by pushing it</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Bend the front knee and descend CoG</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Roll up the chair in front/upper direction by kicking the rear leg</td>
</tr>
<tr>
<td>How to grasp the chair</td>
<td></td>
<td>Carry the chair by grasping the armrest</td>
</tr>
<tr>
<td>Angle of chair’s seat</td>
<td></td>
<td>Hang the chair naturally</td>
</tr>
<tr>
<td>Carrying the chair</td>
<td>Posture</td>
<td>Keep the backbone vertical</td>
</tr>
<tr>
<td></td>
<td></td>
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</tr>
<tr>
<td></td>
<td></td>
<td>Keep the arms close to body trunk</td>
</tr>
<tr>
<td></td>
<td>How to grasp the chair</td>
<td>Carry the chair by grasping the armrest</td>
</tr>
<tr>
<td>Angle of arm</td>
<td></td>
<td>Almost 90 degree</td>
</tr>
<tr>
<td>Angle of chair’s seat</td>
<td></td>
<td>Hang the chair naturally</td>
</tr>
</tbody>
</table>

The results of the assessment are shown in Figure 10. The bar graphs (a1)-(a3) and (b1)-(b3) indicate the averages and standard deviations of the subtotal scores on the first and second trials for three segmented motions (lifting the chair, carrying the chair while walking, and putting down the chair) for NG and AG. The graphs (a4) and (b4) show the averages and standard deviations of the total scores. The results confirmed that all averages on the second trial were larger than on the first trial. Next, the corresponding scores were compared using paired t-tests to check whether each learner’s skill level was increased after teaching. The results revealed significant differences in all cases: lifting-up ($t(19) = 6.03, p < .001, d = 1.24$), carrying ($t(19) = 5.63, p < .001, d=1.38$), and putting-down ($t(19) = 4.93, p < .001, d = 1.21$) for NG, and lifting-up ($t(20) = 5.95, p < .001, d = 1.35$), carrying ($t(20) = 4.83, p < .001, d = 1.24$), and putting-down ($t(20) = 4.41, p < .001, d = 1.31$) for AG. All effect sizes were large, indicating that teaching both with and without the TT-assist had a strong effect on the development of learners’ skill.

Further, to examine the difference between the effect of training with and without TT-assist, the increase in total skill scores from the first to second trials was analyzed using a 2-sample t-test. No significant differences were found (Welch’s t-test : $t(38.28) = 0.04, p = .97$), indicating that the TT-assist was able to enhance learners’ skill as effectively as normal teaching, without harmful effects.

![Figure 10: Comparison of motion skill assessment between “before” (first trial) and “after teaching” (second trial): (a) for normal group (NG), (b) for assisted group (AG), and (c) comparison of increases of total scores.](image)

### 5.2 Subjective self-assessment of learners’ skill operation (E2)

Maintaining a user’s willingness to use a skill education service requires not only successful mastering of a skill but also an enhancement of learners’ subjective feeling of agreement with the guidance techniques used. Hence, the second evaluation included a self-assessment questionnaire to measure learners’ subjective feeling-of-satisfaction concerning their own motion. Table 3 shows all questionnaire items. Participants were asked to score each item out of 10 using increments of 0.5 points, immediately the physical practice of the chair-carrying motion.

<table>
<thead>
<tr>
<th>#</th>
<th>Question (0 to 10 points)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>How well did you master the carrying-chair motion totally?</td>
</tr>
<tr>
<td>2</td>
<td>How well did you master the motion of lifting the chair?</td>
</tr>
<tr>
<td>3</td>
<td>How well did you master the motion of carrying the chair?</td>
</tr>
<tr>
<td>4</td>
<td>How well did you master the motion of putting down chair?</td>
</tr>
<tr>
<td>5</td>
<td>Could you understand motions by relating the skill knowledge?</td>
</tr>
</tbody>
</table>

Table 3: Questionnaire items of subjective self-assessment.
5.3 Objective measurement of learners’ feeling-of-satisfaction (E3)

The last evaluation was conducted to assess the performance of the proposed algorithm for estimating the feeling-of-satisfaction from brain-wave measurement. If adequate performance was achieved, the result would have important implications for service science, enabling a method for monitoring service-customers’ feeling-of-satisfaction in real time.

After the pseudo e-learning experiments, we analyzed the feeling-of-satisfaction data estimated with the proposed algorithm. Averages and standard deviations of the estimated feeling, measured for 1 minute in each trial for all learners, are summarized in Table 4. Tables 4(a) and 4(b) show the data for learners in NG and AG, respectively.

Table 4: Averages of the estimated feeling-of-satisfaction.

| Participant No. | NG (Normal group) | | AG (Assisted group) | |
|-----------------|-------------------|-------------------|
|                  | 1st trial | 2nd trial | 1st trial | 2nd trial |
| #N1             | 82.0 (17.5) | 74.3 (24.2) | #A1 | 86.5 (13.3) | 78.5 (19.0) |
| #N2             | 94.5 (11.3) | 94.2 (10.6) | #A2 | 84.0 (20.2) | 88.6 (15.4) |
| #N3             | 92.3 (14.3) | 96.4 (18.8) | #A3 | 83.1 (16.3) | 83.5 (14.0) |
| #N4             | 86.2 (18.4) | 80.3 (18.9) | #A4 | 88.8 (13.3) | 92.3 (13.9) |
| #N5             | 79.1 (16.5) | 77.7 (18.4) | #A5 | 86.3 (14.0) | 83.3 (16.8) |
| #N6             | 99.6 (3.3)  | 82.3 (17.0) | #A6 | 76.2 (18.7) | 61.3 (24.6) |
| #N7             | 94.5 (10.6) | 79.4 (17.2) | #A7 | 88.9 (16.8) | 81.0 (17.1) |
| #N8             | 92.0 (13.9) | 92.8 (12.9) | #A8 | 86.8 (15.7) | 76.1 (21.7) |
| #N9             | 70.4 (21.8) | 75.4 (20.1) | #A9 | 78.5 (17.9) | 64.8 (22.4) |
| #N10            | 94.5 (10.4) | 72.4 (22.9) | #A10| 83.2 (19.5) | 89.5 (12.4) |
| #N11            | 95.9 (10.9) | 91.4 (14.6) | #A11| 78.8 (20.9) | 89.0 (14.4) |

Because individual differences make it difficult to identify tendencies of AG and NG at a glance from Table 4, we used a paired t-test to detect differences between the first and second trials using data in the table. Figure 13 shows the results as a bar graph with error bars showing the standard deviation. For NG participants, the ratios of feeling-of-satisfaction decreased significantly (t(10) = -2.05, p = .068, d = 0.65), and no difference was confirmed for AG (t(10) = 1.00, p = 34, ns). Thus, the estimated feeling-of-satisfaction was maintained with the TT-assist but decreased without it. This significant effect indicates that the proposed TT-assist method had a mild effect on maintaining service-customers’ feeling-of-satisfaction.

![Figure 13: Averages of all learners’ feeling-of-satisfaction estimated by brain activity measurement.](image)

In conclusion, three evaluation methods (E1, E2, and E3) revealed that both objective skill and subjective feeling in learners were enriched by the proposed TT-assist method. Moreover, it was shown that learners’ feeling-of-satisfaction could be monitored objectively with a new brain-wave measurement method.
6 DISCUSSION AND CONCLUSION

The current study examined an important aspect of education service in the currently growing e-business and e-learning skill-based education market. After analyzing several challenges involved in skill-based e-learning education, we investigated which experiential values are effective in e-learning service, and developed a co-creation of experiential value (CeEV) platform to address these issues. After considering the required functions of the CeEV-platform, an e-learning skill education support tool was prototyped by utilizing estimation of mental status related to the experiential values. A pseudo e-learning experiment which participants learned a nursing operation was then conducted to validate the concept.

A teaching-timing assistance (TT-assist) method was used to determine the appropriate timing for each learner’s practice, by checking learners’ mental status, and an app named e-training analyzer was developed. Moreover, an algorithm for estimating the feeling-of-satisfaction, which is important for understanding the customers’ mental status, was developed and implemented in the app. We performed three evaluations: an assessment of learners’ motion, a subjective self-assessment of learners’ skill operation, and an objective measurement of learners’ feeling-of-satisfaction. As a result, qualities of learners’ skill could be improved to a similar extent, both for the assisted group (AG: t(20) = 4.41–5.95, p < .001) and the normal group (NG: t(19) = 4.93–6.03, p < .001). These results suggest that the assistance method enhanced learners’ skill as effectively as normal teaching, with no harmful effects. The second evaluation demonstrated that assistance significantly enhanced (t(20) = 3.86, p < .001, d = 0.66) learners’ subjective feeling-of-satisfaction, while normal teaching did not (t(19) = 0.10, p = .93, d = 0.02). Moreover, the third evaluation revealed that the estimated feeling-of-satisfaction was maintained with the TT-assist but decreased without the TT-assist. The results also revealed that the objective measurement of learners’ feeling-of-satisfaction was successful, since the change in subjective feeling indicated the same tendency in subjective feeling. The results suggest that the main reason the app satisfied users was the implementation of teaching-timing, in accord with our previous comprehensive analysis (Suzuki et al. 2014; Nakajima et al. 2015; Suzuki et al. 2015) using brain/gaze measurement. Summarizing the findings presented above, instruction support based on estimation of learners’ mental status from brain wave measurement was able to enhance learners’ subjective feeling-of-satisfaction. This is a significant findings for e-learning education services, because effective teaching-timing could be automatically and objectively detected from the estimation of learners’ mental status, which could then be utilized by the instructor.

This positive verification of the CeEV-platform demonstrated two important features of the system for skill education service: First, the TT-assist improved not only the service quality of the teaching effect, but also the service efficiency (i.e., reducing the number of hours required to teach for all learners). Second, the establishment of the estimation algorithm for users’ feeling-of-satisfaction is extremely useful in a service scenario, enabling customer satisfaction to be monitored on-site in real time. Thus, these features contributes to research on Serviceology.

However, it may be difficult to popularize the CeEV platform in the near future, because of the high cost of the brain monitoring app while in the research and development phase. Fortunately, the net cost of the main device is inexpensive compared with other conventional EEG measurement devices. We hope to achieve further cost reduction with future development of manufacturing technology to resolve this difficulty.

In addition, future research should address i) customer expectations, ii) sustainability, and iii) instructor’s experiential value. First, customer expectations were not sufficiently considered in the current study, although the satisfaction level was determined by balancing between ex-ante expectation and ex-post satisfaction (Surpremant 1977; Manstead and Tetlock 1989). Second, the long-term experiential value corresponding to service sustainability was not considered, because we focused on the short-term experiential value in the pseudo e-learning test. It is, however, technically straightforward to evaluate the long-term experiential value by accumulating the data measured by the proposed app and related measurement devices. Third, the instructor’s experiential value was not examined in the current experiment because we focused on propagaatability form a beginner coach to confirm effects of assistance. Future studies should investigate the experiential value of more than one caregiver through further analysis.

The e-training analyzer was developed as a special app for e-learning in skill-based education, with following functions: a) recording of the learner’s body motion during skill operation, b) estimation of the learner’s mental status, c) extraction of adequate teaching-timing for instruction based on mental estimation, d) support for the instructors, enabling them to input advice into recorded video for learners, and e) enhancement of feeling-of-satisfaction of learners who reviewed the advice delivered via the commented video. To our knowledge, no previously developed app is able to perform these functions.

As mentioned above, there are a number of issues remaining be addressed in future research, given the complexity and diversity of education services. As such, we propose that many researchers in diverse fields should focus on addressing these important issues in future studies.

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8 REFERENCES


Appendix. Construction of algorithm for estimating the feeling-of-satisfaction

Because the frontal cortex is related to satisfaction, like/dislike, pleasure, and displeasure (Edmund 2000), the EEG signal was measured over the left frontal cortex. Because EEG time-sequence data to whether a person felt accomplishment were necessary for constructing the estimation algorithm, an experiment for measuring EEG data was conducted using the Trump Tower game. Participants were 21 (14 males and seven females aged in their twenties) and played the game by speaking their feelings freely. From video monitoring during the game, utterances concerning satisfaction (e.g., “get it”, “alrighty”, and “whoopie”) were noted, and the periods in which participants appeared to be experiencing “satisfaction” were extracted as the satisfaction-window. Non-satisfaction-windows were also chosen randomly from data intervals outside of the satisfaction windows.
Using the prepared EEG data set, the optimal condition of frequency components and pattern recognition algorithms for mental estimation were customized. The design of the procedure is shown in Figure 14. First, the EEG signals were translated into EEG spectra using a short-term FFT with the detected satisfaction/non-satisfaction windows, as shown in Figure 15. The multiple EEG spectra were averaged one-by-one, for each participant, to intensify the spectrum features. Second, several spectra contaminated by a high level of noise, induced by body motion, were eliminated using principal component analysis (PCA) and multiple regressions analysis for pre-processing. Third, a statistical analysis to remove blinking-related artifacts was applied using a factor analysis (Shibata 1976). Finally, in the fourth step, the best frequency components were searched using the genetic algorithm (GA), and discrimination between satisfaction and non-satisfaction was performed by pattern recognition using a support vector machine (SVM). Thus, the optimal combination of frequency components for the SVM discrimination accuracy of satisfaction estimation was examined with an expectation-maximization algorithm of GA.

In the seeking phase, the EEG spectrum was treated as a histogram, with a combination of frequency bins from 4 to 22 Hz per second, and the histograms were treated as feature individuals for the GA. The GA revealed that the most effective combination of frequencies for classifying the EEG signal into “satisfaction” or “non-satisfaction” categories were 4, 6, 7, 10, 12, 16, 19, and 20 Hz. A classification accuracy of 82.1% was achieved by the final classifier.

In the e-training analyzer app, the SVM classifier using the frequency components mentioned above was implemented, and the app displayed the fitting ratio to the SVM as the value of the estimated feeling-of-satisfaction.