Learning Behavior and Performance of Asynchronous Distance Learning with Face Recognition System among In-service Teachers

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Abstract: -The purpose of this study focused on the learning behavior and performance of asynchronous distance learning with face recognition system among in-service teachers. Web set up the "distance learning – Excel practical course" for K-12 school teachers enrollment in-service education at the Nationwide Teacher In-service Education Information Web. There are 48 Participants. In this study, teacher's gender, age, job status, educational level, school level, and school district were analyzed to explore the differences in learning behaviors and performance. In addition, this study analyzed learning behavior on the learning effects.

Key-Words: Learning behavior, Asynchronous distance learning , Face recognition system, In-service teacher

1 Introduction

The asynchronous distance learning may manufacture the teaching material beforehand, speaking of the curriculum executor, is the safe way, therefore more universal use. Distance learning in higher education poses a great challenge as this mode of instruction delivery relies solely on the available information and communication technology infrastructure and doesn't confirm the real learning status of learners. A number of studies of dropouts from distance learning that reveal such reasons as job duties, course difficulty, and time constraints resulting from family duties [1]. Carries on the teaching by the network, what most was denounced is the curriculum comments the value way, including teaching resources, teaching material use, teaching transfer mode, learner actual participation rate and so on[2]. Regarding the teaching resources, the teaching material, the transfer mode is easy to solve, but is difficult regarding the learner actual participation rate to overcome[3].

Face recognition is one of biometric device, the main concept is to collect all kinds of different person face chief feature (e.g., the eye, the mouth). In this study, we use asynchronous distance learning with face recognition system to explore learners' learning behavior and performance.

2 Literature Review

2.1 Distance Learning Assessment

computer learning environment integrating the concept of learning and assessment[4].

(1) Portfolio: Personal files are the establishment of learners in the learning process of the study records, including logs, special reports, works the course of development records. Personal Profile is based on a more holistic point of view to assess

progress in the case of learners, help teachers to track learner growth curve.

(2) Summary statistics: Through the formative tests and summative tests in order to understand learner learning conditions, and based on these statistics, to revise teaching strategies to meet the needs of learners. With computer technology, the learners interact with the materials to obtain statistical data to help teachers diagnose learners to progress in the case, as well as to monitor each stage of the suitability of materials for learners.

(3) Diagnosis: Diagnosis based on many types of information, including personal files, statistical data, teachers and learners in the degree of progress and capacity evaluation, learner self-reflection, self-evaluation and so on. Is a continuous, dynamic nature of the evaluation methods, teacher analyze learner learning and teaching strategies to amend a timely manner to meet the learners in a real teaching situation in the learning needs.

Because the actual participation rate of learners is more worthy of taking into account the part of distance learning model is built on mutual trust between teachers and learners before a state can operate normally as a teaching method, they are inevitably some doubts, in the present study curriculum planning in order to "Study time total quantity", "average rate of facial recognition" and other learning behavior to understand the distance learning learners in the course of participation.

2.2 Learning performance

The indicators to measure the effectiveness of learning identified vary, it is, as described below.

(1)Learning Satisfaction: Learning satisfaction of learners in the learning process, the inner feelings of the whole, and this feeling comes from the course learning environment, the actual access to the learning content should be the value of the expected gap [5]. With learner learning satisfaction surveys as a measure of the effectiveness of the aim to understand the subjective assessments of their learners through the study, the right of teachers, teaching materials, curriculum and learning performance satisfaction. Factors on learner learning satisfaction construct, it should contain two elements, one for the overall experience, that is, the satisfaction factor constructed to cover learners in course learning to be the overall experience, including physical, psychological, outside school, and school learning experience for all of the other; The other question asked, namely, levels of construction of the factors to look at every aspect of the problem or really care about the core issues of curriculum implementation[6]. In this study, learning activities through the network involved in learning satisfaction content is divided into five categories, including teachers, teaching strategies, teaching materials, teaching administration, curriculum, learning environment, equipment[7].

(2) Mixed views: For web-based learning assessment criteria should include "regular classroom teaching" and "potential to classroom teaching" both to be assessed[8]. The former mostly based on test scores, while the latter, after learning of the affective emphasis on performance, it is not easy definition and measurement. This study used mixed views, both summative tests and learning satisfaction.

3 Methodology

3.1 Participants

The course was for K-12 school teachers and there were 48 participants. There were 17 males (35.42% of samples) and 31 females (64.58% of samples). The age composition of subjects was as follows: 12 subjects of 22-29years old (25% of samples), 23 subjects of 30-39years old (47.92% of samples), 13 subjects of above 40 years old (27.08% of samples).The job status was as follows: 36 qualified teacher (75% of samples), 12 on-qualified teachers (25% of samples). The educational level was as follows: 21 graduated from college (43.75% of samples), 13 were master or doctoral degree (27.08% of samples), 14 of others (29.17% of samples). The school level was as follows: 5 kindergarten teachers (10.42% of samples), 27 middle or elementary school teachers (56.25% of samples), 16 senior or vocational school teachers (33.33% of samples). The school district was as follows: 10 from north Taiwan(20.80% of samples), 2 from central Taiwan (4.20% of samples), 33 from south Taiwan (68.80% of samples), 3from east Taiwan(6.20% of samples).

3.2 Instruments

In this study, Moodle1.9 version and Luxand FaceSDK facial recognition technology built by Nationwide Teacher In-service Education Information Web-distance learning website (http://moodle.inservice.edu.tw/), and based on the number of e-learning standards Sharable Content Object Reference Model (SCORM). We used data from the login records of each participant when participants login to learn. facial feature detection processes as Fig. 1.

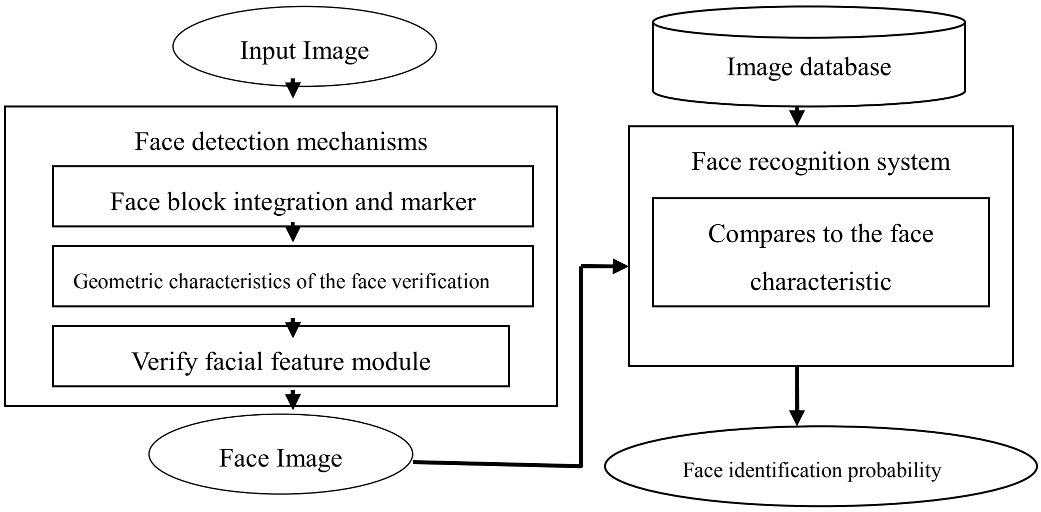

Fig. 1 Face recognition system process

In addition, we used on-line questionnaires to assess teachers' learning satisfaction. After taking courses, system sends questionnaire to each participant who has already take courses. There were 19 items and each item rated on bipolar agree-disagree statements on a 6-point Likert scale (1=strongly disagree, 6=strongly agree).

3.3 Data analysis

Data analyses were performed using SPSS for Windows 14.0. Statistical tests included independent-samples t test, independent-samples one-way ANOVA (using Scheffé method to compare), product-moment correlation analysis, and regression analysis.

4 Results and Discussion

4.1 Demographic characteristics effect on the learning behaviors

Table 1 presented the findings. Male subjects had higher login times than female subjects. Compare to past research findings, male teachers for the information input and interest in computers than female teachers in integrating information technology into the teaching level of participation and involvement is also higher than female teachers[9]. In addition, the society's general view that women should bear more family responsibilities, female participants in this study the average age of 34.65 years old, this age of the participants, perhaps because of, who have to care of children and deal with family, and limited the site to learn sign the opportunity. In addition, there were "age effect" in the "time spot of login (morning)" were significant. By post hoc comparison were found in the morning whose login times of distance learning website, above 40 years old subjects higher than 30-39-year-old subjects.

Table 1 Learners of different background variables in the learning behaviors of the difference analysis

	Login times	Time spot of login				Time total quantity of login	Study time total quantity	Summary examination average times	Average face identification rate	Participation modular unit number
		Early morning	Noon	Afternoon	Off work					
Gender	2.28*	0.64	1.31	-.21	0.69	1.39	-.12	-1.03	0.15	0.05
Age	1.97	5.78**	0.47	0.44	0.54	1.94	0.26	0.98	0.48	0.94
Job status	-0.12	0.26	-0.23	1.78	-0.41	0.94	0.48	-1.66	-1.07	0.11
Educational level	0.07	0.03	0.27	0.06	0.02	0.94	0.01	0.11	1.36	0.29
School level	2.29	0.19	0.26	1.15	0.21	0.18	1.19	0.09	0.23	0.49
School district	0.04	0.23	0.33	0.36	0.35	0.31	1.28	1.40	1.28	0.54

* $p < .05$ ** $p < .01$

The characteristics of learners are to design distance learning should be considered an important factor. The designers of Web-based Instruction will focus on multi-information technology can operate smoothly, and less attention to the characteristics of Web-Based Learning in the learner[10].

4.1.2 Demographic characteristics effect on the learning performance

Table 2 presents the findings. It showed there were no demographic characteristics effects on learning performance. Information literacy and online learning of experience in the first interaction has an impact on the network, but the explanatory power is not strong enough[11].

Table2 Learners of different background variables of the learning performance difference analysis

	Summary examination average scores F value	Learning satisfaction F value
Gender	2.79	1.54
Age	1.35	1.54
Job status	0.10	-0.27
Educational level	0.11	0.60
School level	0.09	2.85
School district	1.40	1.04

4.2 Relationship between learning behaviors and learning performances

Table 3 showed relationship between learning behaviors and learning performances. In terms of summary examination average scores, this positively correlated with login times, time spot of login (morning), time total quantity of login, study time total quantity, participation modular unit number. In addition, there was negatively correlated between summary examination average scores and summary examination average times. The reason may be some learners did not watch the study courses first and directly involved in the summative tests. In this study, there were 5 learners didn't take courses and first to take the exams instead. Therefore, in an ongoing trial and error learning learners to conduct multiple tests in order to reach under the eligibility criteria, making the number of tests the more conclusive test average scores, the lower the likelihood. Furthermore, in learning satisfaction, this positively correlated with time total quantity of login and average face identification rate.

Table 3 Learning behavior and learning performance of the correlation matrix

	Login times	Time spot of login				Time total quantity of login	Study time total quantity	Summary examination average times	Average face identification rate	Participation modular unit number
		Early morning	Noon	After noon	Off work					
Summary examination average scores	0.39*	0.40*	0.19	0.38	0.29	0.34*	0.36*	-0.32*	0.04	0.35*
Learning satisfaction	0.09	-0.01	-0.16	0.05	0.09	0.52**	0.00	-0.10	0.47*	0.19

$^{*}p < .05.$ $^{**}p < .01$.

4.3 Gender, age, and learning behavior predict summary examination average times

In this study, we used learner's background variables of gender, age as predictors. Gender, age, and learning behavior on the summary examination average scores of stepwise multiple regression as shown in Table 4.

Table 4 Gender, age, and learning behavior on the summary examination average scores stepwise multiple regression

Model	R	R^2	△R	F value	Unstandardized Coefficients	Standardized Coefficients
Summary examination average times	.89	.79	.79	41.99*** ***	-12.33	-.89

$^{***}p < .001$.

Only summary examination average times were significant prediction. The summary examination average times can predict the summary examination average scores 79% of the variance. The average number of tests standardized regression coefficient is negative, indicating the number of learners on average fewer tests, summative tests, the higher average scores.

5 Conclusions

In this study, we found that male subjects more often login to learn than female and login in the morning above 40 years old subjects more often than the age of 30-39 years old. In addition, the higher average face identification rate, the more learning satisfaction, subjects had more login times, login times in the morning, time total quantity of login, study time total quantity, participation modular unit numbers, the higher summary examination average scores. We also found subjects had more summary examination average times, the less summary examination average scores, subjects had more time total quantity of login, average face identification rate, the more learning satisfaction, and subjects' summary examination average times can predict summary examination average scores.

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