

# The Impact of Learner Characteristics on Learning Performance in Hybrid Courses among Japanese Students

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**Abstract:** To improve the management of hybrid courses, the relationship between learner characteristics and learning performance was analyzed in two regular university courses. Undergraduate and graduate students participated in two 15-week hybrid courses which consisted of face-to-face lectures (Information Industrial issues), and the corresponding modules with online test. Subjects included 36 freshmen and 48 graduate students. Learner characteristics, consisting of motivation, personality, thinking styles and learners' impression of their e-Learning experiences were measured at the beginning and end of the term. Additional data was collected from the number of days attended, the number of modules completed, test scores and final grades for the course. Final assessment grades for the class were also analyzed. There was no significant difference in learner characteristics between bachelors and masters students who completed the course. There was no significant difference in learner characteristics between bachelor and master students, but there were some differences in conscientiousness scores between masters and bachelor students and between those who received a final grade of A and B. Scores on "learning strategy" as a factor to indicate learning experience were in favour of master students. Master students' evaluation of their e-Learning experience increased significantly throughout the course. Conscientiousness (one of the five factors in the personality construct) correlated positively with the number of e-Learning modules completed by master students ( $r=0.35$ ). They seem to understand better the benefits of e-Learning experience and being the more motivated students, they applied what they have learned from previous e-Learning experiences more effectively. Students with high grades evaluated their e-Learning experience positively and had significantly higher conscientiousness scores than master students who received lower grades ( $p<0.05$ ). For bachelor students, the number of modules completed correlates with both intrinsic and extrinsic motivation. Other learner characteristics did not affect learning performance. The reason may be that bachelor students have yet to understand well the benefits of e-Learning and still lack the learning strategies needed for university coursework. The causal analysis was conducted using Structural Equation Modelling (SEM) technique, and the result indicated that learner characteristics had an effect on learning experience and learning performance. These results suggest that understanding the benefits of e-Learning and learner characteristics, as well as knowing how to learn with e-Learning content could provide important key for promoting student success in online learning.

**Keywords:** learner characteristics, blended learning, learning practice, learning performance, path analysis

## 1. Introduction

The growing use of online technologies for teaching and learning is renewing the demand for (a) better understanding of student characteristics that affect learning and (b) the effective design of online instruction. Even in the traditional face-to-face class, teaching and learning management is not easy, because the interaction is often complicated by numerous factors which include characteristics of learners and the learning content. And when online learning activities are customized to meet individual characteristics and learning needs, the importance and need for the role of a tutor or mentor often emerges. Various personalized teaching/learning strategies can also be integrated in online course design to benefit learners (Koen 2005). Moreover, the use of online teaching components together with face-to-face teaching could help meet individual needs as well as increase the opportunities to assist students in their learning.

Despite the benefits that have been reported in the literature on online teaching, there are also other issues that have been identified in relation to online teaching, particularly about online learners. Recent literature on e-Learning indicates that not all students perform successfully in online courses. This may be caused by factors related to the learning environment and/or personal characteristics. Research reports have indicated that student success is influenced by factors such as learning styles (Diaz & Cartnal, 1999 ; Gagne, Briggs & Wager 1992; Terrell & Dringus, 2000; Zhang & Sternberg, 2001), self-directive competencies (Birch, 2002), and motivation (Pintrich & Schunk, 2002). Identifying learner characteristics for successful online experience was reported to serve the best interest of students (Wojciechowski & Palmer 2005) and should be part of any systematic design of instruction (Dick & Carey, 1996). Based on these findings, we have been conducting surveys of learners' attitude since 2005, and have reported initial findings on learner characteristics as factors affecting student performance in hybrid courses (Nakayama et al., 2006).

We expanded this 2005 survey on the relationship of learners' characteristics, learning experience and learning performance among university students by doing another survey and analysis of data collected from additional bachelors and masters students enrolled in a Japanese national university.

This paper will address the following objectives:

- To examine the impact of student characteristics on learning performance by measuring using various indices of learners who participated in regular hybrid courses in a Japanese university.
- To analyze the relationship among these indices, so that major influencing factors related to learner characteristics can be extracted
- To identify and examine plausible causal paths to learning performance from these characteristics

The goal was to extract effective management and instructional design methodologies for hybrid courses by investigating the above-mentioned relationships during an academic term when learners were engaged in the use of online materials. The rationale behind this goal is the need to support the "learning-to-learn" that takes place when students take hybrid courses, and to gain a better understanding of how learner characteristics may influence learning. As they move from a face-to-face to hybrid learning environment, students are often required to acquire new learning strategies and skills that go beyond the skills needed for the mastery of course content. Their learning and behavior undergo various forms of "shaping-up" as they go through the course. Therefore, focusing on the development process of e-learners in hybrid courses and understanding better their learning behavior or characteristics, can help obtain key points for effectively organizing hybrid courses in particular, or e-Learning in general.

## **2. Method**

### **2.1 Survey group**

Two credit courses which were offered during the Spring Term of 2006 were selected for this survey project. The first course was "Information Society and Careers", a 2-unit bachelor-level class for university freshmen, and the second course was "Advanced Information Industries", a 2-unit master's class for students on their first year of graduate work. For college freshmen, this is one of the first courses they take upon entering the university. Most of the students will be majoring in Engineering.

Both classes were taught by the same professor as 15-week hybrid courses at a Japanese national university. The hybrid courses consisted of regular face-to-face sessions, supplemented with e-Learning components in the form of corresponding online modules and tests. Students attended the face-to-face class and were able to access the online content from outside of class. Examples of a learning window and a testing window for the online content are presented in Figure 1 and Figure 2. Figure 1 shows a list of learning sessions which consist of modules that correspond to the course content covered in each face-to-face session. The modules include video clips of the instructor and the lecture for that session, plus the presentation slides which were used in the face-to-face lecture. Figure 2 shows a testing window which consists of test items for the learning content that was lectured in the face-to-face session. Most tests were conducted in the multiple-choice format. The learner can assess their responses and view their individual scores after completing the test. The learners are given as many opportunities as needed to retry and answer each question until they are satisfied with their own scores. This in turn motivates them to learn the course content well, using the accompanying video clips and presentation slides.

To encourage maximum participation in e-Learning, a benefit was explicitly provided to students: online test scores for modules will count towards their final grades in the course. Also, a student can make up for class absence by taking and passing the online test that corresponds to the face-to-face class session that was missed. This encouraged the students to do the online modules and test because missing a regular face-to-face class session often affects the students' final test scores and the evaluation of their learning experience. Most students are concerned about their performance and final grades. Thus, in these hybrid courses, online modules were counted as learning activities for the course and online test scores were also part of the grading system used for evaluating student final performance in the course. But more importantly, the online learning materials were designed to encourage students to catch-up with what they missed in class and to maximize their learning. This means that online modules for this course could become key learning activities for students.



Figure 1: An example of learning window



Figure 2: An example of testing window

Both classes were surveyed using the same constructs and questionnaires used in the earlier survey that was conducted in Spring 2005 (Nakayama et al., 2006). Also, the online materials used in the 2005 survey did not undergo any revisions when used in 2006, therefore learning content and materials were controlled. What may have changed are the instructor's teaching methodologies and learner's ability to learn in hybrid learning environments due to maturation effect. Also, there could have been an increase in the instructor's confidence in the effectiveness of online courses to promote student learning.

## 2.2 Survey instruments and data

To extract Japanese students' characteristics, four constructs were surveyed. These constructs were: motivation, personality, thinking styles, and self-assessment of online learning experience (Nakayama et al, 2006). The first construct is motivation, which was measured using a test inventory that was developed by Kaufman and Agars (2005), and which provided scores for "Intrinsic Motivation" and "Extrinsic Motivation" (Kaufman 2004). McCloy et al. (1994) defined motivation as "the combined effect of three choice behaviors: (a) the choice to expend effort, (b) the choice of what level of effort to expend, and (c) the choice to persist in the expenditure of the chosen level of effort." For the second construct, personality, the International Personality Item Pool (IPIP) inventory was used. Goldberg (1999) lists five personality factors and so for this construct, there were five components scores: "Extraversion", "Agreeableness", "Conscientiousness", "Neuroticism" and "Openness to Experience". There are multiple interpretations for these factors, for example, "Extraversion" suggests being sociable, "Agreeableness": being cooperative, "Conscientiousness": diligent or having a sense of responsibility, "Neuroticism": being very sensitive, and "Openness to Experience": relating to culture and intellect (Murakami & Murakami, 2001). Detailed inventory is available at the IPIP web site (International Personality Item Pool, 2001). For the third construct (thinking

styles), Sternberg's functions of Thinking Styles provides three scores : "Legislative Style", "Executive Style" and "Judicial Style" (Sternberg, 1997; Matsumura & Hiruma, 2000).

The original English versions of the three survey tools used in this study have been standardized, and their validity had been established. However, no Japanese version was available, except for Sternberg's Thinking Styles survey. Further, the validity of any version of the surveys translated into Japanese, had to be established. To generate the component scores from Japanese students, one of the authors (in collaboration with other colleagues) worked on the translation of all survey items into Japanese. A pilot test of the beta version of the translated versions was conducted with 28 graduate students prior to this study. Then, the translated surveys were revised based on student scores and feedback. To examine whether normal scores could be extracted from the Japanese survey data, the authors consulted with other psychologists about the possibility of this type of evaluation. The consultants agreed that the beta version can measure indices which can then be used as the extracted factors. The results were the Japanese versions of the three surveys which were developed and used in this study to collect data on learner characteristics.

The fourth instrument that was used to measure students' online learning experience consisted of a 10-item Likert-type questionnaire. Each item required the student to rate each item using a 5-point scale: from strongly agree (5) to strongly disagree (1). All subjects were asked to rate their overall impression of the online course and their own learning habits and learning strategies. This questionnaire was administered twice: during the second week of the term and at the end of the course. This survey instrument has been used previously by the authors to measure learner's attitude, and has been analyzed for its validity.

The students' final grade for the course was based on various learning activities, which included the final test scores, their learning attitude (i.e., the number of class days attended), and their online course learning experience with modules and tests. Three indices were identified and used as indicators of learning performance: the number of days attended (NDA), the number of completed modules (NCM), and the online test scores (OTS). In particular, the number of days attended (NDA) is considered by most Japanese university students as a key factor that affects their final grade. Therefore, most students are mindful of their total class attendance. In the surveyed courses, both the number of completed modules (NCM) and the online test scores (OTS) were taken into account for NDA as mentioned earlier, and the participants had to pay attention to all indices: NDA, NCM and OTS.

Also each student's final grade for the course (GRD), based on a 4-letter grading system, consisting of 'A' as highest grade to 'D' which is a failing grade, was used in this analysis. Since all students passed the course and received a grade of either A or B, they were divided into two groups, namely A-students (students who received a final grade of A) and B-students (students with a final grade of B).

### **3. Results**

#### **3.1 Learner characteristics**

Component scores for the three constructs were calculated from item responses according to the established factor structure. Table 1 presents a summary of basic statistical scores across the two learning groups, Bachelors and Masters, which are further classified as A-students and B-students.

The rating scale or range varies among the three constructs: 1-10 for motivation, 1-5 for personality, and 1-6 for thinking styles.

In comparing the mean scores between bachelor and master students, no significant differences were found. This result illustrates the presence of common characteristics within a cohort group. The means did not depend on their development during the university life. The differences between the two groups based on their final grades were also tested for further analysis. Results indicate that there is a difference in conscientiousness, a personality factor, for both bachelor and master students ( $p < 0.10$ ), suggesting that conscientiousness may have had an effect on the final grade of students. In other word, the diligent students made effort for learning to earn A-grades in both Bachelors and Masters levels.

**Table 1:** Personal characteristics for bachelor and master students.

	Bachelor		Masters	
	Grade=A (N=24) Mean (SD)	Grade=B (N=12) Mean (SD)	Grade=A (N=34) Mean (SD)	Grade=B (N=14) Mean (SD)
<b>Motivation (1-10)</b>				
Intrinsic motivation	7.20(0.83)	7.65(1.01)	7.44(1.06)	7.26(1.05)
Extrinsic motivation	5.56(1.27)	5.80(0.87)	5.63(1.02)	5.60(0.73)
<b>IPIP scale (1-5)</b>				
Extraversion	3.02(0.62)	2.88(0.79)	2.79(0.77)	2.93(0.64)
Agreeableness	3.42(0.50)	3.40(0.38)	3.49(0.52)	3.30(0.58)
Conscientiousness	3.29(0.53)	2.95(0.51)	3.37(0.60)	2.97(0.66)
Neuroticism	2.95(0.60)	2.64(0.59)	2.71(0.83)	2.76(0.75)
Openness to Experience	3.07(0.63)	3.00(0.38)	3.16(0.51)	3.16(0.76)
<b>Thinking Styles (1-6)</b>				
Legislative Style	4.21(0.92)	4.16(0.97)	4.48(0.85)	4.32(1.10)
Executive Style	4.18(0.60)	4.42(0.98)	4.58(0.97)	4.31(0.94)
Judicial Style	3.61(0.78)	3.57(0.70)	4.00(1.00)	4.00(1.02)

### 3.2 Online learning experience

Students' self-assessment of their online learning experience was conducted twice during the term, using a 10-item questionnaire. These ten questions were used to measure three factors: e-Learning overall evaluation, learning habits, and learning strategies (Nakayama et al., 2006).

There were 6 questions for Factor 1 (F1: overall evaluation of e-Learning experience), namely: Q1. e-Learning is easy to follow and understand, Q2. I learn better in online courses, Q3. Online materials are useful to me, Q4. It is easy to schedule online learning time, Q5. Online course content is interesting, Q6. Overall, online course is a favorable learning experience. For Factor 2 (F2: learning habits), the two questions were: Q7. I'm a conscientious student, and, Q8. It is my habit to do learning preparation and review; and for Factor 3 (F3: learning strategies), there were also two questions: Q9. I have my own method and way of learning, Q10. I have my own strategies on how to pass a course.

The scores that resulted from this survey were summarized according to these three factors. To compare the factor scores at the end of the term between the two learning groups (Bachelors and Masters), mean factor scores were summarized (see Figure 3). In this figure, the horizontal axis contains solid bars to represent the mean factor scores for L1, L2, and L3 for both bachelor and masters groups, and line bars are given at the end of the solid bar to represent standard errors. The mean scores for "e-Learning Evaluation" and "Learning Strategies" are distributed mainly around the mid-score of 3, which indicated a neutral rating or evaluation, while mean scores for "Learning Habits" were lower than the midpoint or neutral evaluation. This suggests that learners consider themselves to be insufficient in terms of having the necessary "Learning Habits". In comparing mean scores between Bachelor and Master students, results indicate a significant difference in F3: learning strategies ( $t(70)=3.05, p<0.01$ ). These results provide findings that freshmen do not seem to have sufficient learning strategies for university studies.

The university where this survey was conducted has been promoting online learning. Recently, some accredited online courses have been offered to masters and bachelor students, thus increasing the number of students who have taken online courses and an increase in the experience level of students as e-learners. Therefore master students, who have taken e-Learning courses in their undergraduate studies, may have gained and brought with them a useful understanding of the benefits of online learning and applied that understanding to this hybrid course. Masters students may have understood well the benefits of hybrid courses, however, the data analysis shows no significant difference.

To confirm the stability of F1 scores, data collected at the beginning of the term (April) were compared with data collected prior to the end of the semester (July). The results are summarized in Figure 4. The horizontal axis shows the month when the survey was conducted, and the vertical axis shows factor scores from 2 to 4. According to this figure, the factor scores for bachelor students were at the same level throughout the course, but scores of master students significantly increased as the course progressed, indicating that master students may have positively recognized the benefits of online courses, and have developed the strategies (e.g., access to online modules during that time of the day when they are most ready to study and learn) for e-Learning.

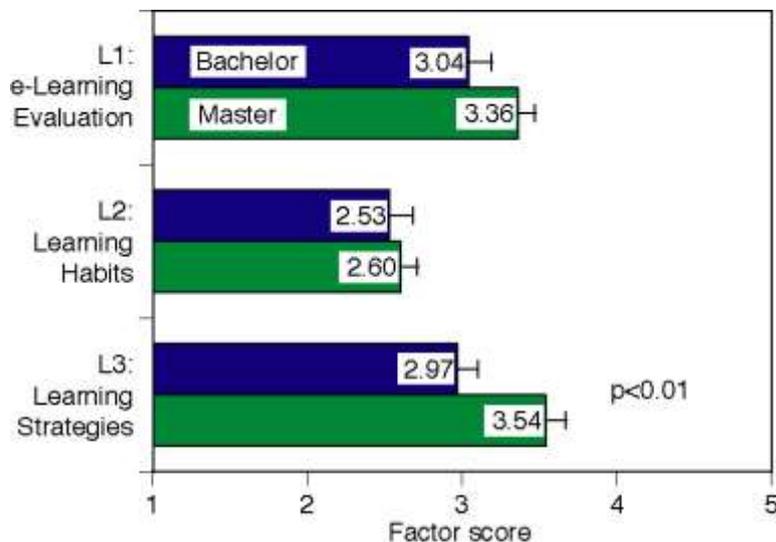


Figure 3: Comparing factor scores of learning experience

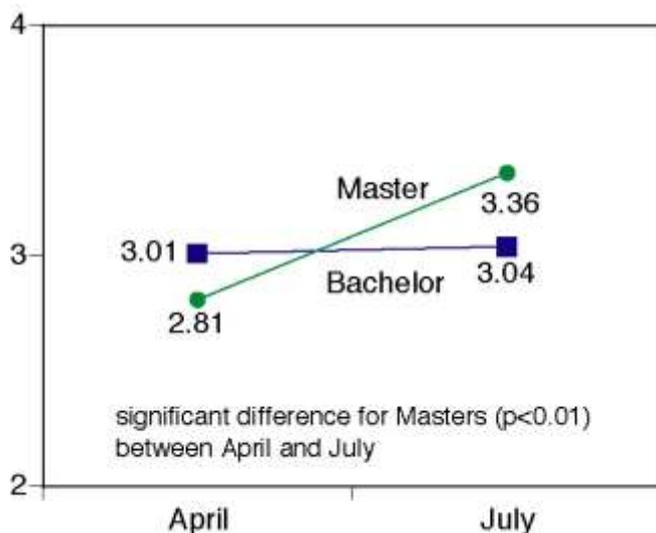


Figure 4: Comparing factor 1 (e-learning overall evaluation) scores.

Table 2: Correlation coefficients among three factors.

	Bachelors			Masters		
	L1	L2	L3	L1	L2	L3
L1		0.46	0.44	-	-	
L2	0.43		0.66	0.45		0.43
L3	0.53	0.60		-	0.37	

L1: e-Learning overall evaluation; L2: Learning habits;  
L3: Learning strategies

**Table 3:** Learner statistics for classes.

	Bachelor		Master	
	Grade=A (N=24)	Grade=B (N=13)	Grade=A (N=34)	Grade=B (N=14)
	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)
NDA	13.92(0.88)	13.23(2.17)	14.23(1.00)	13.36(1.60)
NCM	9.71(1.90)	8.00(3.11)	9.60(2.43)	6.18(2.40)
OTS	89.56(9.09)	73.05(24.81)	96.15(4.35)	90.57(7.61)

NDA: N of days attended; NCM: N of completed modules; OTS: online test scores

Results from further data analysis indicate that the F1 scores of A-learners increased significantly, but not the scores of B-learners. This suggests that the learner who recognizes the benefits of online learning gains to earn the highest possible final grade.

To examine whether the recognition of the benefits of online learning is based on one’s learning strategies, correlation coefficients among the three factor scores were calculated and are summarized in Table 2. The table shows lower triangular matrix for the beginning and upper triangular matrix for the end of class for bachelor students and master students respectively. As indicated in Table 2, for master students, there are no significant correlation coefficients between F1: e-Learning evaluation and F3: learning strategy. On the other hand, some bachelor students may consider online learning as another method or strategy for learning.

These results suggest that students acquire some skills that go beyond the learning of course content as they proceed and manage their own learning in hybrid courses, and that there are some differences in the performance of masters and bachelor students. This difference in student performance could be attributed to student’s previous experience with hybrid courses and to differences in learner characteristics. This point will be discussed further in a later section.

### 3.3 Learning performance

Results of the three indices for learning performance - namely, the number of days attended (NDA), the number of completed modules (NCM) and online test scores (OTS) -- are summarized in Table 3. The two classes that participated in this study are completely different, so that it is not easy to compare the data directly. However, most of the indices show similar tendencies.

In comparing the two groups of students based on their final grades, the means for A-students are all higher than the means for B-students, with most standard deviations (SD’s) for B-students higher than A-students.

There is no significant difference on NDA because most students have attended almost all face-to-face class sessions. The difference in NCM between A-students and B-students in the masters group is significant ( $p < 0.01$ ) but there is no significant difference for bachelor students. Most Masters’ A-students preferred to complete the online modules in addition to attending face-to-face class sessions, and they also sought to get high scores in the online test. Therefore, they had more opportunity to take online courses, but B-students only have occasional experience in learning with online courses. This learning pattern may have had an effect on the students’ final grade.

In terms of online test scores (OTS), there are significant differences because this index has a direct effect on final grades.

### 3.4 Relationship between learner characteristics and learning indices

**Table 4:** Correlation coefficient (r) between learner characteristics and learning indices.

	L1	L2	L3	NDA	NCM	OTS
OLJ	0.40	0.43	0.33	-0.12	0.15	0.18
B	0.43	0.34	0.43	0.00	0.21	0.13
M	0.34	0.53	0.21	-0.25	0.16	0.07
EAE	-0.06	-0.02	0.07	-0.17	0.05	-0.13
B	-0.16	-0.33	-0.17	-0.20	0.08	-0.08
M	0.04	0.22	0.27	-0.14	0.01	-0.06
MOTIV	0.20	0.38	0.07	0.02	0.16	0.12
B	0.06	0.34	0.18	0.20	0.43	0.18
M	0.37	0.42	0.04	-0.14	0.01	0.06
CONSC	0.33	0.39	0.28	0.07	0.26	0.19
B	0.30	0.36	0.34	0.30	0.15	0.19
M	0.37	0.43	0.29	-0.10	0.35	0.09

L1: e-Learning overall evaluation; L2: Learning habit; L3: Learning strategies

NDA: N of days attended; NCM: N of completed modules; OTS: online test scores

OLJ: Openness to Experience, Legislative Style and Judicial Style

EAE: Extraversion, Agreeableness and Executive Style

To examine the correlation between learner characteristics and learning indices, correlation analysis was conducted. A number of correlation relationships emerged: the number of completed modules (NCM) for bachelor students correlated with both intrinsic motivation ( $r=0.33$ ,  $p<0.05$ ) and extrinsic motivation ( $r=0.44$ ,  $p<0.01$ ); NCM for master students correlated with conscientiousness ( $r=0.35$ ,  $p<0.05$ ). All correlations were related to NCM for online learning. This suggests that some learner characteristics affect their learning performance.

To examine the causal relationship among learner characteristics, learning experience and learning performance, further analysis was conducted. There were many variables for this analysis. To reduce the number of variables (i.e., characteristics), three joint-factors (Nakayama et al., 2006) were introduced. Factor analysis was conducted for all variables, and as an outcome, five factors were extracted and the first three factors were joint-factors. The first factor "OLJ" consisted of "Openness to Experience", "Legislative Style" and "Judicial Style". The second factor "EAE" consisted of "Extraversion", "Agreeableness" and "Executive Style", which includes a factor of "positive emotionality" as "Extraversion" and "Agreeableness" (Five-Factor model, 2001). The two motivation scores were summarized as "MOTIV". The remaining two factors were the original "Conscientiousness" and "Neuroticism".

As previously mentioned, "CONSC" (Conscientiousness) is the key factor for learning. Because "Neuroticism" does not explicitly affect learning activity, relationships were analyzed between learning experience, learning performances and the remaining four factors as learner characteristics. The correlation coefficients are summarized in Table 4. The correlation coefficients for bachelor students and master students are also summarized in the same format. The significant coefficients are indicated with bold lines. According to this table, there are significant relationships for joint factors "OLJ" and "MOTIV", and "CONSC" with L1:"e-Learning overall evaluation", L2:"Learning habit", L3:"Learning strategies", and the number of completed modules (OTS). Also, there is significant difference on some correlation patterns between bachelors and master's students.

### 3.5 Path analysis

To summarize and to visualize the relationship among learner characteristics, learning practice and learning performance, path analysis was conducted using the Structural Equation Modelling (SEM) technique (McCloy et al. 1994, Kano & Miura 2002). The Optimized resolution was revealed by "CALIS" of SAS

procedure (Toyoda 1992). This technique was considered as an appropriate analysis to visualize the path diagram and to understand the causal relationship among variables. SEM has already been conducted to create a model of relationship for the survey data (Nakayama et al., 2006), which was used as the framework for this analysis.

As a result, a path diagram was constructed using correlation matrix (Table 4) and causal relationship of variables. The path diagram consists of two parts and these are illustrated in Figures 5 and 6. The variables are illustrated as boxes, while the path is displayed as an arrow line. Path coefficient is shown on each path for the total population, and for master students and bachelor students respectively. GFI (Goodness of Fit Index) as total model evaluation measure is also displayed in the figures. The diagrams are appropriate because the GFI's are higher than 0.9 and significant without a condition for bachelor students in Figure 5.

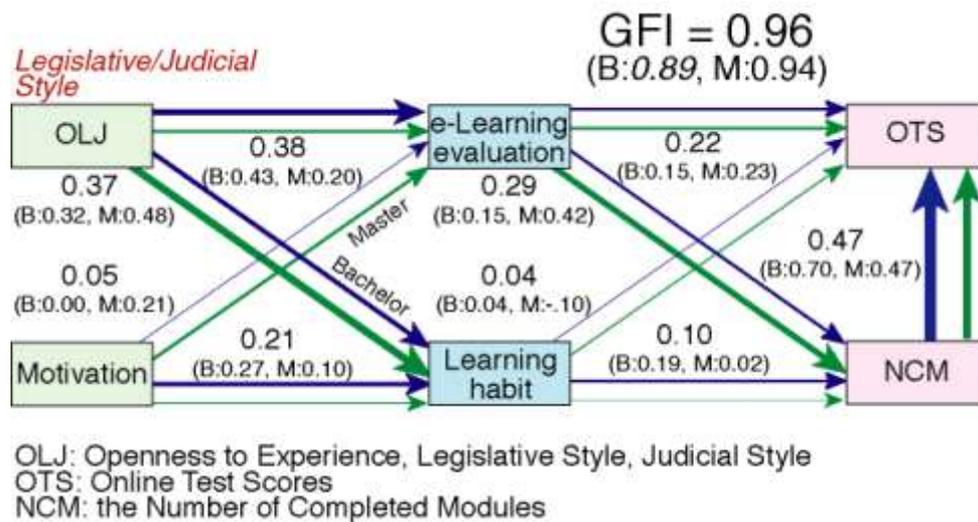


Figure 5: Path diagram based on thinking styles and motivation for Bachelor and Master Students.

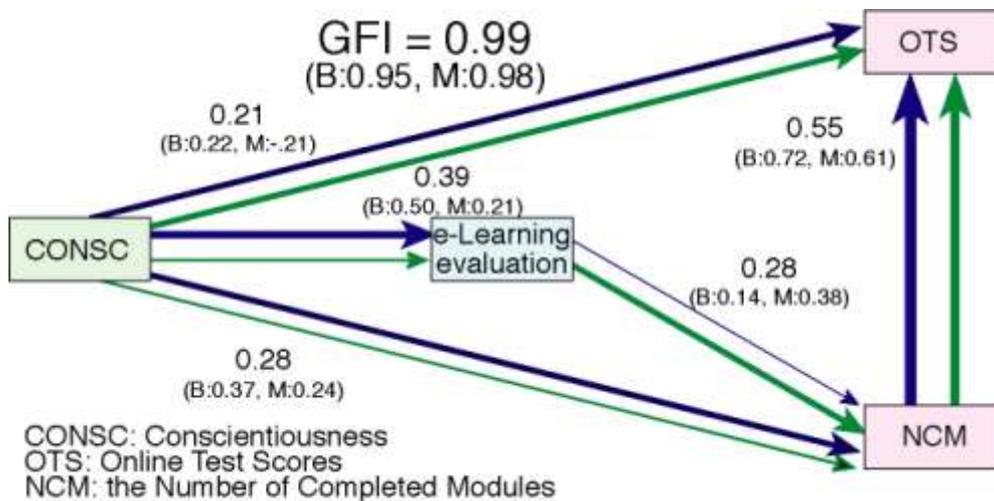
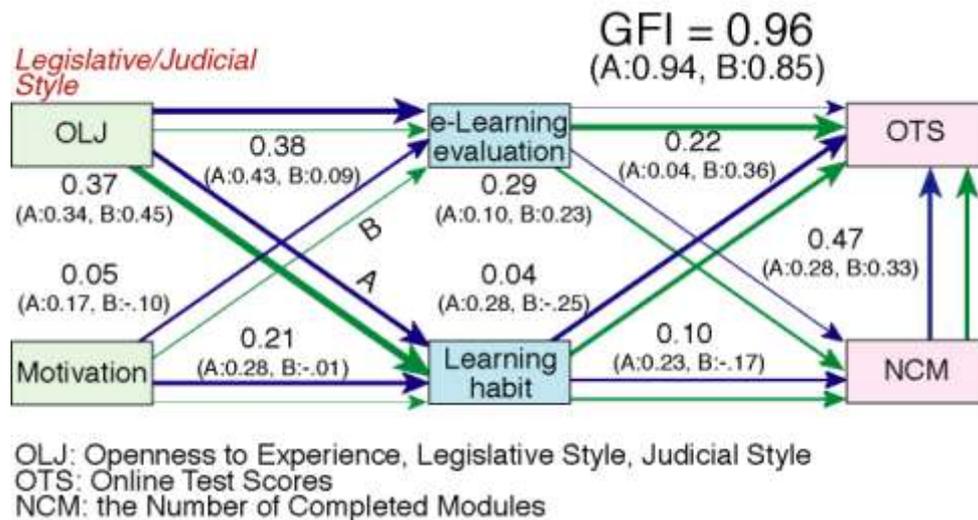
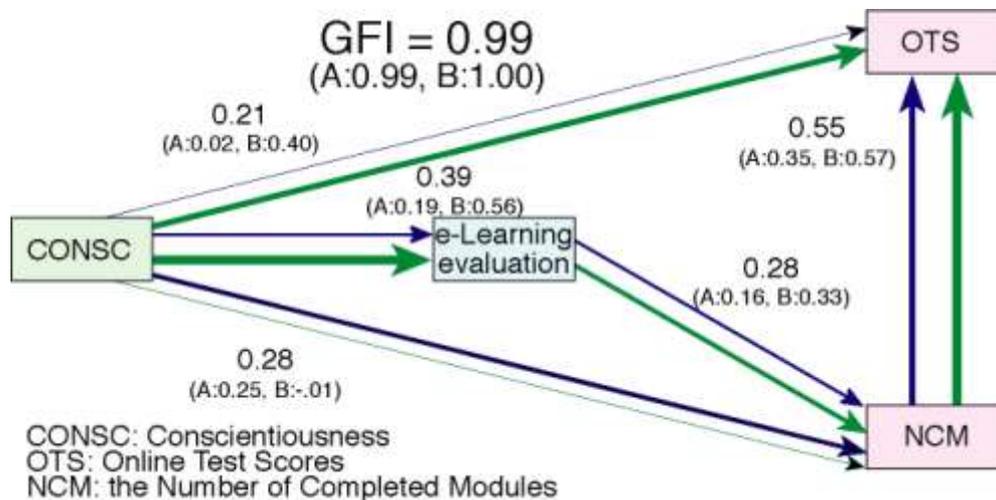


Figure 6: Path diagram based on conscientiousness for Bachelor and Master Students.



**Figure 7:** Path diagram based on thinking styles and motivation of A-students and B-students.



**Figure 8:** Path diagram based on conscientiousness of A-students and B-students.

According to the diagrams, the key personal characteristics are CONSC, MOTIV and OLJ as part of thinking styles. Factor 1 (F1: e-Learning evaluation) takes part in the causal relationship and affects mainly NCM in both diagrams. NCM relates strongly with online test scores or OTS.

The path diagram between A-students and B-students were also compared, and their causal relationships are summarized in Figures 7 and 8. It is interesting that the strength of links is different between the A-students and B-students, for example, among A-students, OLJ mainly affects Factor 1 (F1: e-Learning evaluation), but for B-students, it mainly affects Factor 2 (F2: learning habits).

These results suggest that learner characteristics affect learning experience and learning performance. Also, learning skills and knowledge acquired by students have repeated effects on their own learning behavior. Students mature or transform as they go through the course. In this study, some effects of this maturation or transformation process were investigated by doing an analysis of learner’s characteristics and learning experience. Other factors could very well affect learning behaviour and performance, and factors such as one’s recognition of the benefit of online course could be crucial. It is therefore important to consider learner characteristics and learners’ overall e-Learning experience in the instructional design and in the learning support provided in online courses in order to optimize the learning benefits that students can gain from hybrid courses.

The details of appropriate support programs for online courses will be the subject of further study.

## 4. Conclusion

This paper examined the impact of student characteristics on learning performance, while various indices of learners were measured under regular hybrid courses in a Japanese university. Differences between bachelor and master students were also examined further.

There were differences in conscientiousness between students with final grades of A and B for both bachelor and masters levels. This suggests that one of the personality scores affects the final grade. The score on "learning strategy" for master students was higher than the score of bachelor students. Master students' evaluation of their e-Learning experience also increased significantly throughout the course. Causal analysis was conducted using Structural Equation Modeling technique (SEM), and the results indicated that learner characteristics affected learning experience and performance. According to the results, transformation of learners' behavior could have taken place during the course, and data analysis indicated that learning performance was affected by this transformation.

An extraction of more stable causal models and creating appropriate support methodologies will be the subject of further study.

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