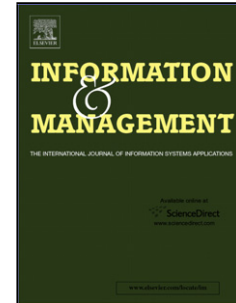


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Enhancing e-Learning Effectiveness Using an Intelligent Agent-Supported Personalized Virtual Learning Environment: An Empirical Investigation

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ABSTRACT

Virtual Learning Environments (VLEs) developed under constructivism and embedded personalization learning functions have the potential to meet different requirements of different learners, and thus increase e-Learning effectiveness. We formulated internal personalized learning mechanisms by implementing intelligent agents in a VLE under a constructivist learning model, and further developed an e-Learning effectiveness framework by integrating educational and IS theories. An empirical field experiment involving 228 university students was conducted. The findings suggested that personalized e-learning facilities enhance online learning effectiveness in terms of examination, satisfaction, and self-efficacy criteria.

Keywords: virtual learning environments, personalization, adaptive e-learning, e-learning effectiveness, intelligent information systems

1. Virtual Learning Environments

Online learning in virtual learning environments (VLEs) has grown in recent years. Most online education programs still adopt a traditional homogenous learning model with one single set of learning materials for all learners, though they have different backgrounds, learning styles, and cognitive capabilities. This lack of flexibility in a homogeneous model could be one reason that VLEs supporting those online education programs have not been as successful as expected [5, 6, 9, 23, 24, 27, 29].

Applying the constructivist learning theory, each individual learner has developed his or her own method of understanding and using learning materials, depending on his or her ability and learning style. This suggests that a VLE should personalize learning

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materials to match each learner's individual cognitive capability and style. Such a VLE should help online learners learn more and feel satisfied with the learning process.

Recent research in the field of Intelligent Tutoring Systems (ITS) forms a major part of research into VLEs. With the growth of computing capabilities, more researchers have focused on VLEs to provide tailored learning material, instruction, and instant interaction to suit individual learners by using intelligent agent technology [12, 15, 21, 28]. Intelligent agents are autonomous and can engage in flexible, high-level interactions. A multi-agent system is a collection of autonomous agents that work together to solve problems that are beyond the capabilities of individual agents. They offer a new and appropriate way of developing complex systems, especially in open and dynamic environments.

ITSs are intelligent learning systems whose components reflect the values of the particular view that they emphasise about the nature of that knowledge (the domain model), the learning model, and the teaching model. These emphasize the philosophy of learning under objectivist learning theory. However from the constructivist view, intelligent systems should provide a learning environment to meet the individual learner's needs. This type of ITS is flexible, giving rise to a Personalised VLE (PVLE), which supports e-learning by recognizing an online learner's learning stage and providing tailored instruction, including personalized learning materials, tests, instant interactions, etc.

The literature suggests that instructional methods matching an individual's learning style are most effective for learning, and a computer-based education system with a personalizing component might be superior to a non-personalized one. We noted and decided to address the lack of investigation into personalization mechanisms implemented by intelligent agents.

2. Theories of Learning and Instruction

Most work in the instructional design of VLEs is grounded in the objectivist learning model, a traditional approach that states that any mechanism that enhances the communication of knowledge should enhance knowledge transfer. This model is based on Skinner's stimulus-response theory and treats the world as real, structured, external to people, and independent of personal experience; it is assumed that the mind mirrors this independent reality. The principle of this model is that the goal of learning is to understand this reality and modify behaviour accordingly. In terms of instruction, the model assumes that the goal of teaching is to transmit knowledge from an expert to a learner. Direct instruction is the ideal process in which students absorb and repeat information to gain knowledge. Learning instruction structures reality into abstract or generalized representations that can be transferred to and then recalled by students.

However, Jean Piaget said the basic idea of constructivism is that the learner must construct knowledge; the teacher cannot supply it. The constructivist learning model is viewed as a learner-centered and active process of knowledge construction. Learners can

operate more effectively and meaningfully in an environment where their ideas are explored, compared, criticized, and reinforced through talking and listening to others.

Good pedagogy is commonly assumed to be related to personalized learning that relies on constructivism of understanding learning as the process in which persons actively construct knowledge, concepts, and competences through interacting with their environment [17]. Students come to highly personalized understandings and interpretations of the knowledge they are taught. Personalization fosters the learners to construct their own knowledge. A personalized curriculum necessitates a constructivist pedagogy that takes into account students' prior knowledge and how they generate connections between existing knowledge and new forms of learning.

Several learning models (the collaborative, the cognitive information processing, and the socio-cultural) follow the constructivist learning model. Constructivist learning is assumed to occur as an individual interacts with objects, whereas collaborative learning occurs through the interaction and cooperation of individuals. Learning emerges through shared understandings of more than one learner through interaction with others. Knowledge is created as it is shared, and the more it is shared, the more is learned. In the cognitive information processing learning model, learning involves the processing and transferring of new knowledge into long-term memory until that knowledge is effective and reliable enough in problem-solving situations. Learners differ in terms of their preferred learning style. In summary, the major characteristics of these learning models are illustrated in Table 1 of Appendix 1 [2, 7,8].

3. Prior Studies on Personalized e-learning

E-learning is shifting from being instructor-centric to learner-centric so that personalization (learning according to individual's interest, knowledge base, and style), and learning flexibility (time and location) are enhanced.

Most of the work in the instructional design of current VLEs is grounded in objectivism. The instructor is the centre of control of the learning material, with the assumption that the instructional process is predictable (implying a preconceived structure and sequence for instruction). VLEs developed under objectivism support knowledge transfer from instructors to students. However, VLEs facilitate learning effectiveness when they adapt to the needs of individual learners.

Personalization is grounded in the constructivist learning theory. In traditional education it assumes that instruction and learning in a classroom occur *via* interactive and thoughtful instructional practices that organize the learning environment [16]. In VLEs, , personalization assumes that every online learner is an individual with a distinct learning style, pace, and path,: its PVLE. These can be viewed as learner-centered, two-way interactive, and active learning process of knowledge construction. They provide contextually appropriate toolsets by enabling individual's learning, resulting in a model where learner needs drive the learning process.

PVLEs provide personalized e-learning environments for online learners to amplify and extend cognitive capabilities as well as organize their own thinking processes. Table 2 presents a comparison of PVLE components under both constructivism and objectivism and their corresponding systems implementation considerations.

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Table 2. Comparison of e-learning Models and their system implementation considerations				
Learning Process	Constructivism (learner –centered)		Objectivism (instructor-entered)	
	Pedagogical Model	System Implementation	Pedagogical Model	System Implementation
Stage 1: Learning	<ul style="list-style-type: none"> • Content modeled via situations rather than knowledge structures¹ • Concern with processes whose perspective and interpretation can be constructed • Should be in realistic settings² • Allows for individual differences: takes account of learners' knowledge 	<ul style="list-style-type: none"> • Learning materials are structured. Each concept linked by keywords, consequence and related issues • Each student receives material based on learning progress and patterns • System initiated personalized learning 	<ul style="list-style-type: none"> • Content presentation modeled in terms of structures The goal of teaching is to transfer knowledge, thus presentation is critical • Instructor controls learning material assuming that the process is predictable 	<ul style="list-style-type: none"> • Learning materials are predefined by instructor via electronic documents. • Learning materials controlled by instructor • All receive the same material • Instructor initiated approach
Stage 2: Interaction	<ul style="list-style-type: none"> • Instructors provide feedback on process • Feedback mediates understanding and mastery of topic 	<ul style="list-style-type: none"> • Two-way interaction • System provides analytical feedback on student's performance • Student issues questions along with his/her study • Dynamic approach 	<ul style="list-style-type: none"> • Interaction occurs via electronic communication • Students evaluate learning progress and needs, complementing the high degree of learning control³ 	<ul style="list-style-type: none"> • One-way interaction • System provides static feedback on performance based on pre-defined answer, narrow approach
Stage 3: Self Evaluation	<ul style="list-style-type: none"> • Self-evaluation test integrated with the task and not separate activity • Students actively participate and interact through quiz routines: self testing and mastery of learning • Routines include diagnostic feedback 	<ul style="list-style-type: none"> • Self test integrated with learning • Test generated dynamically based on student's progress • System diagnoses self-test results and provide feedback on reasons for wrong answers • Diagnostic feedback based on link between test and learning materials. • Individualized approach 	<ul style="list-style-type: none"> • Self-evaluation is student's reflection on the results of testing of what has been learned • Individual tasks designed to evaluate learning performance 	<ul style="list-style-type: none"> • Self-evaluation test integrated with learning • Test pre-defined for all students • System provides simple right/wrong answers without analytical analysis • All-in-one static approach

¹ Akhras, F. N. , and Self, J. A., "Beyond Intelligent Tutoring Systems: Situations, Interactions, Processes and Affordances," Instructional Science, Volume 30, Number 1, 2002, pp. 1-30.

² Leidner, D. E., and Jarvenpaa, S. L., "The Use of Information Technology to Enhance Management School Education: A Theoretical View," MIS Quarterly, Volume 19, Number 3, 1995, pp. 265-291

³ Piccoli, G; Ahmad, R.; and Ives, B., "Web-Based Virtual Learning Environments: A Research Framework and a Preliminary Assessment of Effectiveness in Basic IT Skills Training," MIS Quarterly, Volume 25, Number 4, 2001, pp. 401-425

4. Research Model and Proposition Development

Mayer's Model of Understanding describes the relevant components in the teaching/learning process. Learning outcome is defined as the knowledge that the students acquire as a result of the learning process. Self-efficacy and satisfaction are included as part of the measures of learning effectiveness, which also includes learners' achievement (test scores), satisfaction, and historical self-efficacy. Performance of learning has two parts: academic and affective. Academic outcomes refer to the mastering and perceived mastering of materials, while affective outcomes are the subjective assessment of satisfaction with the learning process. Self-efficacy is a measure of an individual's confidence in his/her ability to use IT to undertake tasks. Individuals who have high self-efficacy are more likely to make an effort to be effective, thus achieving better learning outcomes [4, 19].

Our research model extends the Piccoli et al. model by using the Mayer model (as shown in Figure 1). The study focuses on personalized VLE e-learning effectiveness, human attributes, and the design dimension. The human attributes include learners' previous knowledge and attitude towards online learning. The design dimension includes the four major personalization components, content management, self-evaluation management, adaptive interaction, and learning process. It was assumed that PVLE provided a complete self-learning virtual learning environment, with Instructors playing a role in the course design rather than teaching/tutoring during the learning process.

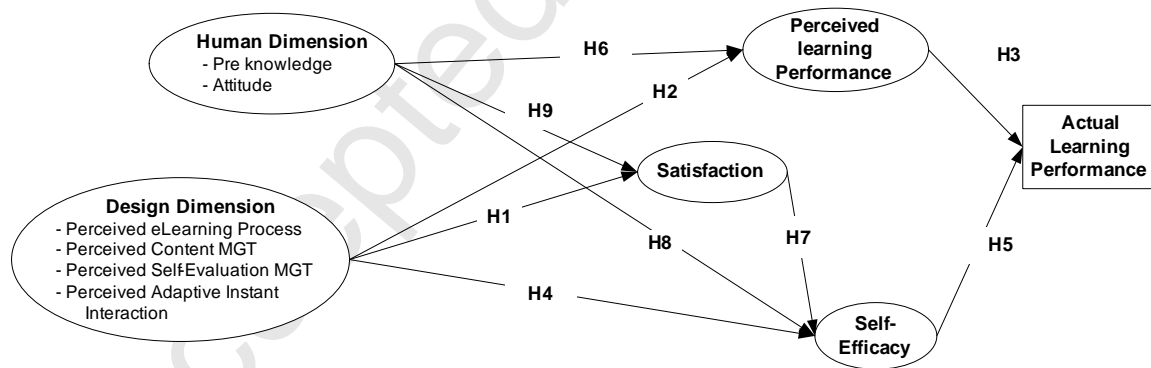


Figure 1. Model of Personalized e-learning Effectiveness

5. Hypotheses

The learning process includes the way that students encode new information, while effectiveness implies “doing the right things.” A primary goal in studying any medium of communication for educational delivery is the identification of its effectiveness. Therefore :

In personalized VLEs, both the Design and the Human Dimensions are associated with levels of e-learning effectiveness, including Satisfaction, Learning Performance, and Self-Efficacy.

E-learning effectiveness can be decomposed into three individual sub-variables (Learning Performance, Satisfaction, and Self Efficacy). We developed our propositions from the determinants that influence learning outcomes in an e-learning environment (Design and Human Dimensions).

5.1 Personalization Process in the Design Dimension

Earlier research indicated that students' learning under the constructivist learning model with personalized material and resources had higher learning effectiveness. Self-evaluation was defined as the student's reflection on, and evaluation of his or her, learning. Furthermore, instructors were available for individual tutoring and guidance and were accessible by students on an individual basis.

The concept of user satisfaction has been used to represent the degree to which users believe their IS conforms to their requirements. Wang and Liao showed that user satisfaction was often seen as a key antecedent to predict the success of a particular IS [3, 14, 30], or to anticipate a user's use of the IS [10, 11].

Satisfaction has also been widely used as an indicator of the effectiveness of the learning environment. Student satisfaction, combined with student performance, has been added as a learning effectiveness measure. Satisfaction can be measured through observation of variables such as anxiety and/or frustration during the learning process. Wang [22] examined the direct quality-satisfaction relationship. It is claimed that learner interface, learning community, content, and personalization are the core criteria that impact student satisfaction. Student satisfaction can also be seen as the result of good learning. Students who contributed to their knowledge formulation achieved better learning outcomes. So allowing online learners to engage in the learning activity when and where they prefer, allowing them to learn at their own pace, and to focus on the material they deem important results in a positive response and increases subjective satisfaction with the learning process and its outcomes. Therefore, we proposed:

Hypothesis 1: Students in a PVLE will be more satisfied with the learning experience than students in a VLE.

Knowledge of subject matter may be split into two parts: domain knowledge (the subject-matter that forms the individual's understanding of a specified field) and topic knowledge (the individual's depth of understanding of particular concepts or topics in the domain). The *learning outcome* cannot be measured directly, but may be assessed by the learning performance. *Effectiveness* has historically been measured in terms of learners' achievement. A higher student achievement involves fewer errors on an achievement test following the instruction. However a student's performance in a test will be moderated by their perception of their learning outcome. Self-evaluation allows students to evaluate their learning performance, and determine their learning weaknesses. Students using this feature are likely to perform better

than those who do not. Thus we assumed that students' measured learning performance would be directly associated with their perception of how well they have learned, leading to:

Hypothesis 2: Students in a PVLE will exhibit higher Perceived Learning Performance scores than students in a VLE.

Learning outcome is the addition to a student's ability as a result of learning. It follows that Actual Learning Performance may be mediated by the learner's perception that learning occurred (otherwise the learner would continue before parts of the course had been well learned); i.e., perceived mastery of learning material is likely to lead to better performance. So we proposed:

Hypothesis 3: Students' Actual Learning Performance will be positively associated with their Perceived Learning Performance.

Self-efficacy is the belief that one is able to perform a particular task. It has been found to influence the actual performance. Wan et al. [18] noted students with high self-efficacy would make more effort to be effective. Relying on social cognitive theory, Wu et al. [25] demonstrated that self-efficacy influenced performance expectations, and Hasan and Ali [32] posited that Computer Self-Efficacy had a positive influence on computer learning. Thus we proposed:

Hypothesis 4: Students in a personalized e-learning environment will exhibit higher self-efficacy scores than students in a traditional e-learning environment.

Hypothesis 5: High levels of Self-Efficacy are positively associated with high levels of Actual Learning Performance.

5.2 Attitudes towards Computer Usage and Previous Knowledge

The Human Dimension is derived from both a model of understanding and a model of preliminary e-learning effectiveness. In our study, it was assumed that PVLEs provide a complete self-learning virtual learning environment. Instructors played no role in the course design other than teaching/tutoring during the learning process. Therefore only student characteristics were considered in the Human Dimension. Constructivism assumes that the educational situation should be modified to take account of prior knowledge and the understanding and attitude of the learner.

TAM posited that people form intentions to behave in a way that they believe will have a positive effect. When students use computers to help them complete tasks, they are likely to have a positive attitude towards the use of computers, and are likely to look for additional tasks that can be completed using a computer. If students do not know how to use a computer or do not like using computers, they will avoid using them. A positive attitude toward using computers is likely to be associated with increased usage. Previous knowledge also plays a very important positive role in learning performance. Synthesizing:

Hypothesis 6: Students' with high Human Dimension scores, positive attitudes towards computers and more previous knowledge, learning in a PVLE will exhibit higher Perceived Learning Performance scores than students in a VLE.

Performing a task successfully strengthens one's sense of self-efficacy. Muretta and Wollan [13] summarized the phenomenon of Mastery experience as the most powerful source of self-efficacy, because, enactive mastery is based on experiences that are direct and personal, and mastery is usually attributed to one's own effort and skill. This lead to:

Hypothesis 7: Students' high levels of Satisfaction are positively associated with students' high Self-Efficacy scores.

Social cognitive theory suggests that individuals expend more effort on behaviors and tasks they believe help them to perform successfully. It has been applied to IS to predict and explain individual behavior, particularly IS acceptance and use. Thus:

Hypothesis 8: Students' with high Human Dimension scores, positive attitudes towards computers, and more prior knowledge, will exhibit higher levels of Self-Efficacy when learning in a PVLE than students who learn in a VLE.

Jonassen showed that high human dimension characteristics are likely to contribute to greater satisfaction. This lead to:

Hypothesis 9: Students' with high Human Dimension scores using a PVLE will exhibit greater Satisfaction than students in a VLE.

6. Research Methodology

To investigate the impact of intelligent agents supported personalized VLEs on learning performance, we conducted a field experiment to contrast the learning effectiveness between a treatment and a control group. A prototype of a PVLE and a prototype of a non-personalized VLE were implemented simultaneously. Time series data were obtained by collection from pre- and post-questionnaires, and data obtained from the system database.

Because of the personalization process, learning, matching, and evaluation functions are specified to distinguish the PVLE from the VLE. First, an ideal PVLE should provide online learners with the personal relevance of subject matter and give them guidance in developing their strategic repositories; by matching an individual learner's situation to the learning content, a personalized content management component will be derived to provide personally relevant subject matter. Second, personalized tutoring can provide instant feedback to match individual differences and take into account learners' current knowledge and attitude toward education. Third, self-evaluation can foster effective learning and implement effective learning control.

6.1 The Experimental Systems Implementation

The PVLE prototype, Intelligent e-learning System (IeLS), was implemented as an experimental system with personalized functions, while the prototype of a traditional, non-personalized VLE, e-learning System (eLS), was implemented as the control system. Their designs were such that, when the personalized functions in IeLS were disabled, the system

became an eLS. Thus we knew that the only variable being tested was a personalization element. The details are shown in Table 3.

Personalization was designed as *personalized content, personalized self-evaluation, and personalized tutoring* in the IeLS. Based on previously acquired knowledge, IeLS needed to be adapted to the characteristics of each learner during the learning process. In the IeLS, online learners received personalized instructions that met their particular needs. In contrast, the control group received one-size-fits-all instruction (that fitted the needs of most of the class).

e-learning	IeLS (Experimental system)	eLS (Control system)
Learning Process	<ul style="list-style-type: none"> • abstract, regular, and detailed levels • Content selected by system after each quiz • Suggested reading material after quiz 	<ul style="list-style-type: none"> • One-size-fits-all content presentation, regular (R) • Students read course materials freely
Self - Evaluation	<ul style="list-style-type: none"> • quiz questions generated dynamically for each individual • questions generated and presented one after another based on performance to test students' learning problems 	<ul style="list-style-type: none"> • All students receive same quiz questions with the same level of difficulty and number of questions • All questions presented at the start of each quiz; one-size-fits-all
Tutoring Interaction	<ul style="list-style-type: none"> • Instant instruction: students receive messages of learning performance, such as time spent, achievements, and class comparison. • Feedback on quizzes with corrections for each error, with explanation and suggestions 	<ul style="list-style-type: none"> • No instant instructions, including warning/greeting messages • Feedback on quizzes with corrections for each error • Quiz performance with grading

The architecture of the IeLS is shown in Figure 2 of Appendix 2. The personalized functions of the IeLS were implemented as a set of intelligent agents [20, 31]. When a student starts to learn, a personalized learning plan is generated by the *Modeling agent*, based on the learner and the curriculum model. During the learning process this plan is adjusted by the *Modeling agent*, based on the learning profile, which is generated by the *Activity agent*, based on the learning activities. Personalized contents are generated by the *Learner agent* dynamically using the learning plan and the curriculum model.

“Introduction to the Oracle Database” was a four-chapter online course that we designed and implemented in both IeLS and eLS. The course included an introduction to the foundations of databases and advanced features of the Oracle Database, together with quizzes, one following each chapter. The quizzes were designed for students' self-evaluation, helping them evaluate their performance in terms of their strengths and weaknesses. This course was targeted at the students who had little or no knowledge of the Oracle Database. The contents of the course were developed in early 2000 and have been validated and used for several research experiments [26]. Therefore, we continued to use the course with the further development of personalization components.

6.2 Data Collection

Two hundred and twenty-eight students were recruited through campus advertisements in a public university in Hong Kong. Participation in the study was voluntary. All participants were undergraduates familiar with computers and using them regularly; they were offered three major incentives: Awards of HK\$50 were given for participation in and completion of the study;

certificates were issued by the University Department of Information Systems to those who passed the final exam; and an additional HK\$150 and HK\$100 were offered to the top 10% and top 30% of performers, respectively.

The experiment lasted for one week. It included three stages, as shown in Figure 4.

Registration. Prior to the experiment, participants were told to register using the system. During this stage, participants provided their demographic data and to took a pre-test. They were also asked to agree that they would follow the Experimental Rules. After registration, participants were randomly assigned to one of two e-learning systems, and then received a training program on how to use that system. The pre-test was used to confirm homogeneity of the two groups.

e-learning Process. Next, participants received instruction directly from either IeLS or eLS, with no study time or space constraints. The two e-learning systems were accessible 24 hours per day until the experiment was completed. Participants took a quiz after each chapter. Once the quiz answers were submitted, participants received a quiz summary from their e-learning system.

Final Evaluation. All participants from both groups took the final exam at the same time. After submission of this exam, they were told to complete a post-experiment questionnaire about the learning effectiveness of the system (learning satisfaction, self-efficacy, and perceptions of the personalized functions). At the end of this, participants signed that they had not broken any of the Rules.

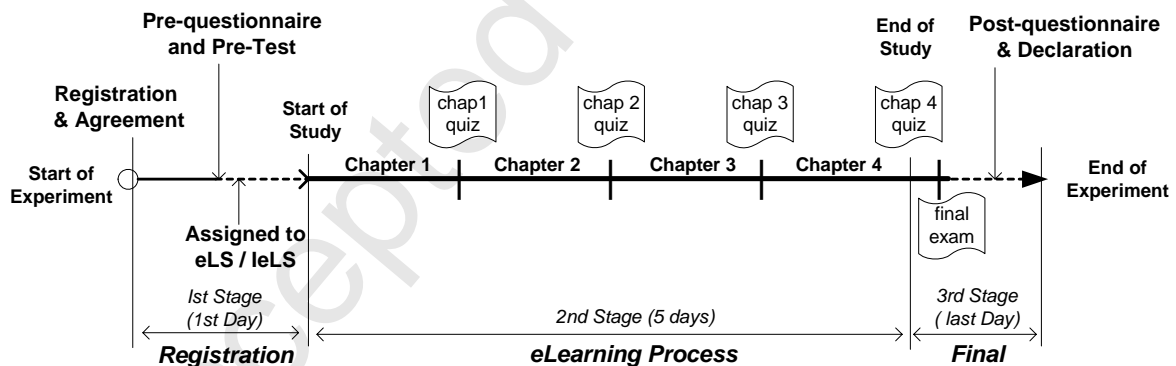


Figure 4. The Experimental Procedure

A total of 228 responses were collected at the beginning and 220 after the experiment. The students' average age was 22. The gender distribution was balanced (55.7% males, 44.3% females). They were randomly assigned to the two groups, 117 using IeLS and 111 using eLS. In total, 183 participants completed the entire experiment, 92 from IeLS and 91 from eLS. The completion rate was therefore 80%.

6.3 Experimental Controls

Instructor effects in the Human Dimension and Learner Control in the Design Dimension were controlled. The results from the Independent Samples T-tests revealed that there were no

significant differences between the participants in the two groups in terms of age, past experience, or self-reported computer skills.

There was no obvious communication between the two groups during the experiment. Our Experimental Rules prohibited direct communication with other students during the experiment and all participants reported that they had obeyed these rules. This agreed with our random checks of students after the experiment. No violations were reported.

6.4 Measurements

Table 4 in Appendix 3 lists the measures used in this research. **Human Dimension** was measured by **Attitudes** (*towards computer usage*) in the pre-experiment questionnaire and **Previous Knowledge** was obtained from a pre- test. For the measurement of Personalized E-learning Environment (**Design Dimension**) we asked participants to evaluate their perceptions to learning experiences (**Learning Process, Content Management, Self-Evaluation Management and Instant Interaction**) in the post questionnaire, completed after the experiment. Human and Design Dimension constructs were measured using a 5-point Likert scale where 1 represented Strongly Disagree, 3 was the neutral point, and 5 represented Strongly Agree.

For learning effectiveness, the measures of **Self-Efficacy** and **Satisfaction** had been validated in prior research, but the wording was modified in order to fit our context of personalized learning. **Self-efficacy** was measured by asking participants to indicate their ability to perform computer-based learning. The instruments were copied from previous research⁴. **Satisfaction** with the learning environment was measured in the post-questionnaire. This instrument was developed by Green and Taber.⁵ Learning Performance was measured by two constructs, **Perceived learning Performance** and **Actual Learning Performance** were measured by the final examination score.

6.5 Data Analysis

Data were analyzed using SEM (Amos 4.0). Appendix 3 presents the loadings, composite reliability and average variance extracted. All items have significant path loadings at the 0.01 level. All the values of composite reliability and AVE were satisfactory, with composite reliability greater than 0.80 and AVE greater than 0.50.

Discriminant validity was determined by checking whether the items measure that construct or other (related) constructs. Discriminant validity was verified by making sure that the square root of the average variance extracted for each construct was higher than the correlations between it and all other constructs

⁴ Compeau, D. R., and Higgins, C. A., "Computer Self-Efficacy: Development of a Measure and Initial Test," MIS Quarterly, Volume 19, Number 2, 1995, pp. 189-211.

⁵ Green, S., and Taber, T., "The Effects of Three Social Decision Schemes on Decision Group Process," Organizational Behavior and Human Performance, Volume 25, Number 1, 1980, pp. 97-106.

7. Experimental Results

Table 5 in Appendix 4 shows the means, standard deviations, and correlations for all variables in this study. As shown in Table 5, each construct shares greater variance with its own block of measures than with the constructs representing a different block of measures.

7.1 Comparison between Experimental Group and Control Group

As indicated in Table 6 (see Appendix 5), results from the independent sample t-test implied that participants from both groups had no significant differences in online course learning motivation, attitudes towards computer, and self-efficacy (pre-experiment). As hypothesized, participants from the experimental group (using personalized e-learning system) perceived their system to be better in their evaluation of the e-learning process, content management, and self-evaluation management, than did their counterparts in the control group. In particular, the students from both groups had no significant differences in pretest, quiz1 and quiz 2. However, as the experiment evolved, the students in the experimental group achieved significantly better scores on Quiz 3, Quiz 4, and the final exam. Lastly, there were no significant differences between the groups in their satisfaction, perceived learning performance, and self-efficacy (post-experiment). Also, while both groups were satisfied, the experimental group showed a higher degree of Self-Efficacy (post-experiment), and improvement in Perceived Learning Performance. The control group actually showed poorer Self-Efficacy than the experimental group. Post experiment, Self-Efficacy scores in the experimental group increased, while the score decreased for the control group.

7.2 The Structural Model

Figure 5 shows the results of the SEM analysis with its overall explanatory power and estimated path coefficients. We modeled Human Dimension theoretically as a composite (formative) construct, it is affected by Attitude and Previous Knowledge, both of which change independently of one another. Similarly, the Design Dimension is also a composite (formative) construct that results from the combination of four independent measures. A change in the score or value of any one of the four measures may not result in a change in the score or value of any of the other measures.

Significant paths are presented with an asterisk. The model shows an RMSEA of 0.049. The statistically significant loadings are at the 95 percent significance level. The model meets generally accepted criteria for acceptable fit ($X^2 = 362.$, $df = 240$, $X^2 / df = 1.5$, $GFI = 0.874$, $RMR = 0.083$, $NFI = 0.877$, $TLI = 0.947$, $IFT = 0.955$, $CFI = 0.954$).

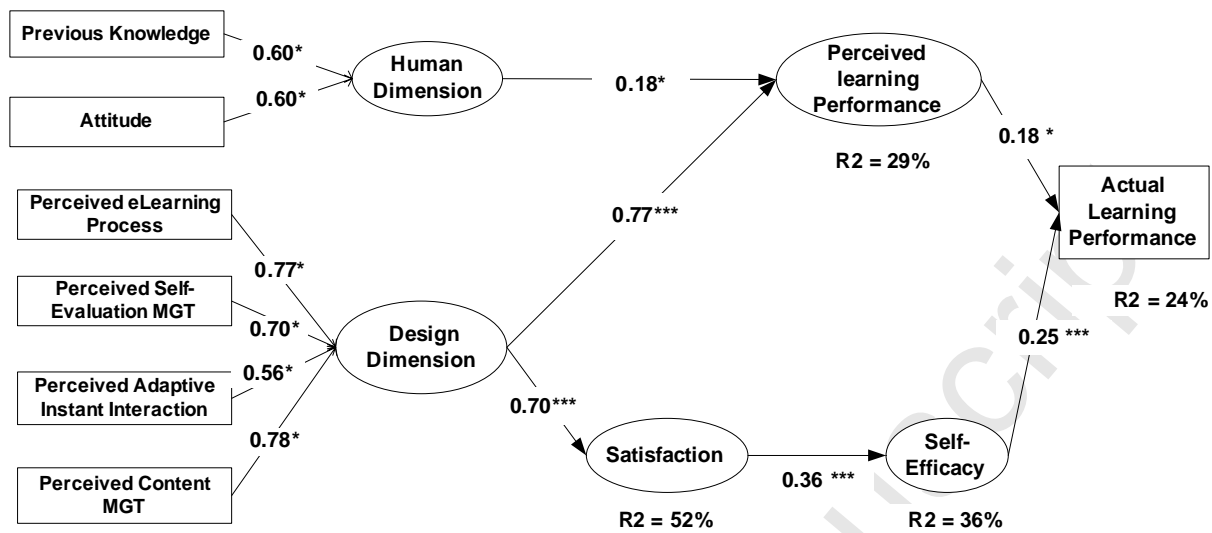


Figure 5. Results of hypothesized relationships

Human Dimension scores were derived from Attitude and Previous Knowledge with loadings of 0.60 and 0.60 respectively. Design Dimension scores were derived from Perceived e-learning Process, Perceived Content Management, Perceived Self-Evaluation Management and Perceived Adaptive Instant Interaction with loadings of 0.77, 0.78, 0.70, and 0.56 respectively. For online learners Satisfaction, only Design Dimension was found to impact Satisfaction significantly, with a path coefficient of 0.70, explaining 52 percent of its variance. Both Design and Human Dimensions had a significant impact on Perceived Learning Performance. The two constructs account for 29 percent of the variance in Perceived Learning Performance. Finally Actual Learning Performance was found to be significantly affected by Perceived Learning Performance and post Self-Efficacy with path coefficients of 0.18 and 0.25 respectively, accounting for 24 percent of the variance in Actual Learning Performance.

8. Discussion and Conclusion

By using intelligent agents to simulate instructors, agent-based VLEs can serve as powerful tools that dynamically personalize online instruction to meet online learner's preferences, learning pace, goals and desires;). We added to the body of knowledge of VLE's under constructivism by extending their domain to include PVLE's implemented by intelligent agents. The constructivist learning model is the root of the PVLEs design and the intelligent agent is the fundamental technology for their implementation. Content Management, Self-Evaluation Management and Adaptive Instant Interaction are features shown to enhance Personalization functions under the constructivist learning model.

8.1 Conclusions

The results from our empirical studies show that the personalized functions in VLEs can significantly improve e-learning effectiveness through actual learning achievement. VLEs are best for achieving e-learning effectiveness when they integrate personalization into the needs of

individual learners. Therefore, we conclude that PVLEs allow online learners to amplify and extend their capabilities as well as to organize the thinking processes by altering the tasks using individualized instruction.

8.2 Implications for Research and Practice

To the best of our knowledge our study was the first to investigate e-learning effectiveness in intelligent agent supported Personalized Virtual Learning Environments. We decomposed the preliminary e-learning effectiveness model to investigate the effectiveness of individual factors in e-learning. We believe that our theoretical development provided a step toward a better understanding of e-learning effectiveness. Moreover, according to the constructivist learning model, learners are active participants in knowledge acquisition and engage in restructuring, manipulating, reinventing, and experimenting with knowledge to make it meaningful, organized, and permanent.

Results of our study also provide initial recommendations to the VLE community on the characteristics of successful VLEs. The findings suggest that VLE should be based on constructivism rather than on objectivism. By using intelligent agents to simulate instructors, agent-based PVLEs can serve as powerful tools to personalize online instruction to meet online learner's preferences, learning pace, goals, and desires.

8.3 Limitations

Our study focused on the personalization of learning as a whole. It lacks an in-depth investigation of the different dimensions of learning personalization on e-learning effectiveness.

The differences of learning effectiveness between different technologies that support personalized VLEs are beyond this research scope. However, it would be interesting to know if there is any difference in a PVLE implemented by intelligent agent technology versus other technologies, such as machine learning. One limitation of this study is that the experimental course length was short. A one-week course duration may not be sufficient to test the students' learning effectiveness in general, especially for self-efficacy and satisfaction.

The spectrum of formalized learning ranges from school students through undergraduates, post-graduates and practitioners. Our sample comes from undergraduates who lie well within those extremes. The traditional methods of learning are similar in all groups, as are assessment methods. We consider that the implications of our work would be similar, but if those implications only applied to undergraduates, the contribution from a practice perspective is still substantial

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Appendix 1:

Table 1. Learning Theories Paradigms					
	Objectivism	Constructivism	Cognitive Information Processing	Collaborativism / Cooperative Model	Socioculturism
Definition	<i>Learning</i> is uncritical absorption of objective knowledge. Reality is abstracted and generalized by the instructor who is the source.	<i>Learning</i> is process of constructing / creating knowledge. The goal of learning is to format the abstract concepts to represent reality, to assign meaning to events and information.	Extension of Constructivism. <i>Learning</i> is the processing and transfer of new knowledge into long-term memory. It focuses on learners and the effectiveness of their information processing style	Extension of Constructivism. <i>Learning</i> through shared understanding of more than one learner. Promotes group skills – communication, listening, and participation.	Extension of collaborativism and cognitive information processing. <i>Learning</i> is subjective and individualistic. Learning occurs when person is well known.
Instruction Method	Instructor-Centred	Learner-Centred	Individualized	Teamwork-oriented	Action-Oriented
Knowledge Creation	transferred from instructor to students	constructed by individual learner's views of reality	created by improving cognitive processing abilities	Created through knowledge sharing among individuals	from historical and cultural background of learner
Role of Instructor	Knowledge source, controlling learning process and learning materials	serve as a creative mediator of learning process	Match an individual's learning style to effect learning	Serve as leader/questioner of communication and provide feedback	should have no culturally biased interpretation
Role of Learner	Passive, receives knowledge from experts/instructors	Controls pace of instruction.	Supports the existing knowledge construction and selection of learner's information processing style.	Generates high-level reasoning strategy through sharing; individual contributes to group knowledge sharing.	Socially conscious learners with a view to change society; Learning is individual behavior.
Learning Effectiveness	Pace of students learning designed for the majority of the class on their learning progress	Individuals learn better when directed to discover things rather than told or constructed.	Each individual mental model is important determinant of how the learner will process new information.	Knowledge sharing increases what is learned; greater diversity of ideas, when actively learned in groups	The more meaningful and situated in context, and the more rooted in cultural background, an event, the more reality it is learned.

Appendix 2:

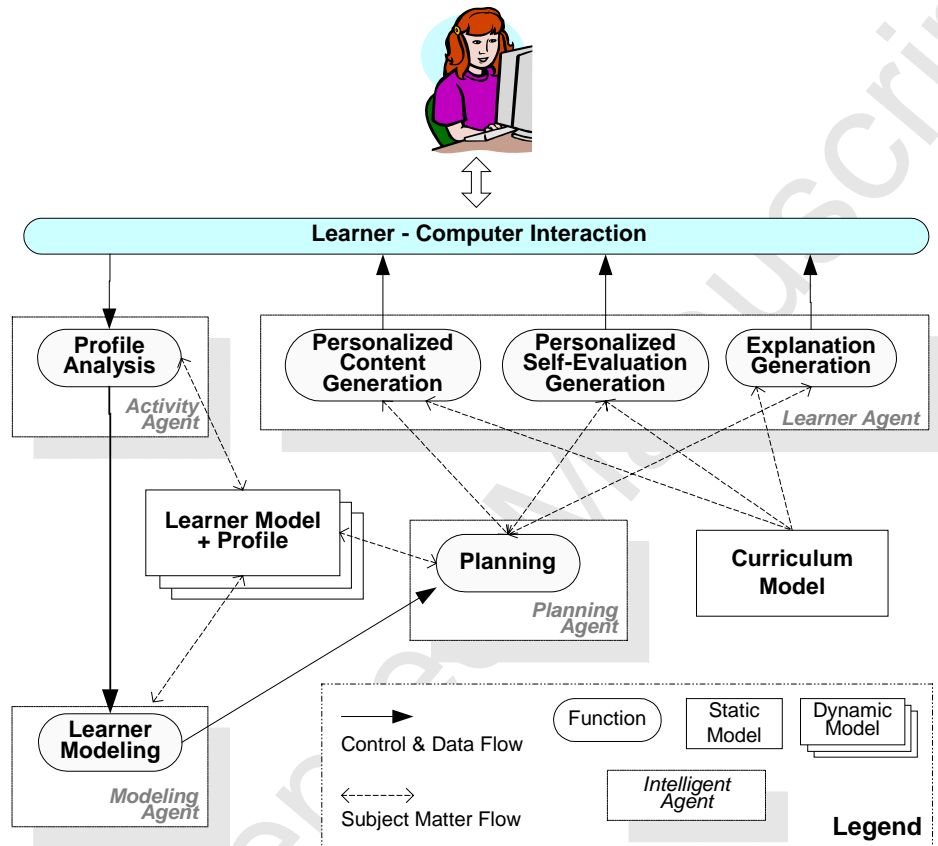


Figure 2. Personalized eLearning System Functions and Architecture

Appendix 3:

Table 4. Psychometric Properties of Measures			
Construct	Measures	Loading	t-value
Attitude towards computer usage CR=0.85, AVE=0.59	<i>Please indicate your feelings towards using computer:</i>		
	FPC: Un-useful – useful	0.94	
	Hindering – helpful	0.90	15.5
	Boring – fun	0.58	9.2
	Dull – stimulating	0.58	9.2
Self-Efficacy (pre-exp.) CR=0.945, AVE=0.68	<i>I could complete the job using the database software ...</i>		
	if I had used similar packages before this one to job the same job	0.71	
	if someone showed me how to do it first	0.80	14.9
	if I had a lot of time to complete the job for which the database was provided	0.77	12.4
	if someone else had helped me get started	0.91	12.5
	if I could call someone for help if I got stuck	0.89	12.3
	if I had seen someone else using it before trying it myself	0.71	9.8
Perceived E-learning Process CR=0.81, AVE=0.52	<i>To what extent, do you agree with the following statements about the e-learning process?</i>		
	The reading materials in the prototype e-learning system nicely fit my learning capability in terms of difficulty level	0.71	
	The quiz questions fit well with my understanding of the course materials.	0.76	9.6
	I feel comfortable with the learning pace/schedule on the prototype e-learning system	0.77	9.7
	The interaction with the prototype e-learning system makes my learning easy.	0.66	8.5
Perceived Content Management CR=0.87, AVE=0.57	<i>To what extent, do you agree with the following statements about the course content?</i>		
	I feel comfortable with the reading materials on the prototype e-learning system.	0.72	
	The materials in the prototype e-learning system help me understand course concepts better	0.77	10.5
	The materials in the prototype e-learning system make me feel learning this subject is not so difficult as I thought	0.74	10.1
	The materials in the prototype eLearning system make learning enjoyable	0.76	10.4
	The overall organization of the course contents is excellent	0.80	10.9
Perceived Self-Evaluation Management CR=0.84, AVE=0.56	<i>To what extent, do you agree with the following statements about the quiz?</i>		
	The quiz questions make me feel enjoyable to learn chapters of the course	0.78	
	The quiz increases my confidence in learning subsequent chapters of the course	0.72	10.2
	The quiz makes the learning process more enjoyable	0.82	11.7
	The quiz's difficulty level is appropriate.	0.68	9.6

Perceived Adaptive Instant Interaction CR=0.81, AVE=0.52	<i>To what extent, do you agree with the following statements about the adaptive instant feedback?</i> The system's feedback to my questions is prompt.	0.64	
	The system's feedback to my questions is accurate.	0.66	10.1
	The system's feedback to my quizzes is helpful.	0.73	8.3
	The system's feedback makes my learning easy.	0.85	8.8
Satisfaction CR=0.86, AVE=0.55	<i>How would you describe the learning process in this course?</i> very inefficient – very efficient	0.77	
	Very uncoordinated – very coordinated	0.73	10.2
	very confusing – easily understandable	0.71	9.9
	Very dissatisfying – very satisfying	0.75	10.3
	Very un-enjoyable – very enjoyable	0.74	10.2
Perceived Learning Performance CR=0.87, AVE=0.56	<i>To what extent, do you agree with the following statements about their learning outcomes?</i> I became more interested in the subject.	0.78	
	I gained a good understanding of the basic concepts.	0.83	12.2
	I developed the ability to communicate clearly about this subject.	0.74	10.8
	I was motivated to do my best.	0.64	9.2
	I increased my competence with Oracle Database.	0.75	11.1
Self-Efficacy (post-exp.) CR=0.95, AVE=0.76	<i>I could complete the job using the database software ...</i> if I had seen someone else using it before trying it myself	0.79	
	if I could call someone for help if I got stuck	0.87	16.7
	if someone else had helped me get started	0.91	15.3
	if I had a lot of time to complete the job for which the database was provided	0.82	13.32
	if someone showed me how to do it first	0.85	13.9
	if I had used similar packages before this one to job the same job	0.82	13.2

Appendix 4:

Table 5. Means, Standard Deviations, and Correlations

	Mean	S.D.	1	2	3	4	5	6	7	8	9
1. Attitude	3.79	0.82									
2. Pre-test	3.40	1.48	-0.050								
3. Perceived E-learning process	3.42	0.69	0.157 (*)	0.186 (**)							
4. Perceived Content MGT	3.32	0.73	0.099	0.138 (*)	0.616 (**)						
5. Perceived Self-Evaluation MGT	3.34	0.66	0.138 (*)	0.186 (**)	0.526 (**)	0.560 (**)					
6. Inst. Interactions	3.56	0.70	0.213 (**)	0.119	0.417 (**)	0.420 (**)	0.557 (**)				
7. Satisfaction	3.37	0.79	0.190 (**)	0.200 (**)	0.492 (**)	0.560 (**)	0.424 (**)	0.365 (**)			
8. Perceived learning outcome	3.43	0.69	0.276 (**)	0.277 (**)	0.610 (**)	0.553 (**)	0.580 (**)	0.482 (**)	0.481 (**)		
9. Self Efficacy	4.21	1.22	0.133	0.194 (**)	0.175 (*)	0.181 (**)	0.322 (**)	0.237 (**)	0.336 (**)	0.269 (**)	
10. Actual Performance	7.17	1.98	0.059	0.209 (**)	0.196 (**)	0.117	0.222 (**)	0.205 (**)	0.181 (**)	0.252 (**)	0.302 (**)

Note: Final exam: 10 is the maximum value
 Diagonal Elements are Square Roots of the Average Variance Extracted
 N= 220; * $p < 0.05$; ** $p < 0.01$

Appendix 5:

Table 6. Comparison between ELS group and IELS group					
	ELS group (n=92)		IeLS group (n=91)		t value
	Mean	S.D.	Mean	S.D.	
1. Attitude	3.84	0.79	3.73	0.86	-0.96
2. Self-Efficacy (pre-exp.)	4.38	1.11	4.18	1.12	-1.24
3. Perceived Learning Process	3.28	0.68	3.60	0.67	3.39**
4. Perceived Content Management	3.18	0.67	3.52	0.76	3.46**
5. Perceived Self-Evaluation Management	3.27	0.58	3.44	0.73	1.87+
6. Perceived Adaptive Instant Interaction	3.53	0.68	3.58	0.73	0.51
7. Pre-test	3.40	1.45	3.41	1.52	0.03
8. Quiz 1	2.39	0.96	2.25	0.92	-1.10
9. Quiz 2	5.95	1.95	6.27	1.98	1.17
10. Quiz 3	6.09	2.11	6.64	1.77	2.04*
11. Quiz 4	5.98	2.42	6.63	1.80	2.26*
12. Actual Learning Performance	6.90	2.06	7.53	1.83	2.28*
13. Satisfaction	3.32	0.81	3.45	.77	1.16
14. Self-Efficacy (post-exp.)	4.10	1.26	4.36	1.17	1.54
15. Perceived learning Performance	3.38	0.68	3.50	0.71	1.28

Note: + $p < 0.10$; * $p < 0.05$; ** $p < 0.01$