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Intelligent Agent-Assisted Decision Support for Personalized Virtual Learning Environment

Caddie Shijia Gao[1)], Dongming Xu[2)]

[1)] UQ Business School, University of Queensland (c.gao@business.uq.edu.au)
[2)] UQ Business School, University of Queensland (d.xu@business.uq.edu.au)

Abstract

In the delivery of online learning, Virtual Learning Environments (VLEs) have been growing quickly and research on intelligent agent supported eLearning systems has developed rapidly in the last decade. However, some online learning programs have not been successful, and one of the main reasons could be that those online learning programs supported by VLEs have not fully considered learners' differences. VLEs developed under constructivism and embedded personalization learning functions have a potential to meet different requirements of different learners. In order to provide decision support for personalization decisions in VLEs, we formulate a conceptual model for personalization by following Simon's decision-making process model. Based on this model, in order for a more adaptive, intelligent and flexible solution for personalized virtual learning environment (PVLE), the intelligent agent technology is applied in this research. Intelligent agent technologies with features such as autonomy, pre-activity, pro-activity and co-operativity, facilitate the interaction between students and the systems. By applying intelligent agents in PVLEs, individual learners can be uniquely identified, with content specifically presented for them, and progress can be individually monitored, supported, and assessed. Several types of agents are proposed and a novel and open multi-agent architecture is presented for PVLE. A prototype system for PVLE is also developed to demonstrate the advances of the proposed system architecture.

1. Introduction

Online learning in virtual learning environments (VLEs) has grown quickly in recent years. A VLE can be defined as "computer-based environment, both mobile and stationary, as stand alone systems or Internet accessed systems" [29], that provide "any time/any place learning" for individual learners. Researchers and practitioners are making rapid improvements in the design and implementation of eLearning environments, resulting in continuous progress towards successful eLearning environments [3]. However, online learning is not always effective and sometimes fails to meet learning objectives because of insufficient flexibility and interactivity. For instance, eLearning environments, such as WebCT or Blackboard, still adopt a traditional homogenous learning model with one single set of learning materials for all learners (one-size-fits-all) although they have different backgrounds, learning styles, and cognitive capabilities. This lack of flexibility in a homogeneous model could be one reason that current VLEs supporting those online education programs have not been as successful as expected in recent years [3, 35].

VLEs are best able to achieve learning effectiveness when they can adapt the online instructions to the needs of individual learners. VLEs should be able to identify learning needs and personalize solutions that foster successful learning and performance. Therefore Personalized VLEs (PVLEs) are defined as those VLEs that provide a set of personalization functionalities, such as personalized learning plans, learning materials and tests, and initiating interactions with the learner by providing advice, necessary instant messages, etc. PVLEs are becoming more promising for achieving eLearning effectiveness due to their individual and adaptive eLearning supports.

Applying the constructivist learning theory and model [16], each individual learner has developed their own method of understanding and using learning materials, depending on an individual's ability and learning style. This implies that a VLE should personalize learning materials to match each learner's individual cognitive capability and style. Critical to the development of effective VLEs is the development of a formal personalization process model of the system's reasoning and decision making [2]. Although all good teachers understand intuitively that personalization of traditional learning environments is the best mechanism for assisting students to maximize their achievement level, it is very difficult to identify personalization functionalities in developing VLEs without a formal personalization conceptual model. The prior studies do not provide such a formal personalization process model for the development of VLEs. Therefore, it is very important to start from a personalization decision-making process model on common understandings developed in traditional learning environments. In this research, we have adopted Simon's [21] well-known model of decision-making process as a framework for a decision-based VLE personalization model.

Most recent advances in the field of eLearning environments have proposed the use of Artificial Intelligence techniques such as multi-agent or agent oriented architectures [33, 34]. Intelligent agents are a special kind of computer program that 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 often more appropriate route to the development of complex systems, especially in open and dynamic environments [16]. In the last decade research into the field of Intelligent Tutoring Systems (ITS) has been developing rapidly and forms a major part of research into VLEs. Along with the growth of computing capabilities, more and more ITS researchers have focused on VLEs to provide tailored learning materials, instructions, and instant interaction to suit individual learners or a groups of learners by using intelligent agent technology [4]. Intelligent agent technologies with features such as autonomy, pre-activity, pro-activity and co-operativity, facilitate the interaction between students and the systems. The technologies allow the generation of artificial intelligence models of learning, pattern recognition, and simulation, such as the student model, task model, pedagogical model, and repository technology [26]. These models work together in a productive way to support students' learning activities adaptively. Therefore, based on the conceptual decision-based VLE personalization model, intelligent decision-making agents are proposed to achieve the personalization in PVLEs by employing intelligent agents' autonomous, pre-active and pro-active behaviors, and a multi-agent based PVLE architecture is designed.

The remainder of the paper is organized as follows: Section 2 presents a literature review on relevant prior studies and theories. After the decision-based VLE personalization model is proposed in Section 3, the architecture, development, and operation of a multi-agent-based PVLE are presented in Section 4. The final section addresses our contribution as well as the future work.

2. Background

2.1 Personalized e-Learning

E-Learning is shifting from being instructor-centric to learner-centric, which emphasizes relevance and personalization (learning according to individual's interest, previous knowledge, and style, etc.), and learning flexibility (time and location) [1]. ELearning refers to any type of learning situation when instructional content is delivered electronically via the Internet when and where people need it [35].

Most of the work in the instructional design of current VLEs is grounded in objectivism [2]. Any mechanism that enhances the communication of knowledge should enhance the knowledge transfer, or student learning at different locations [16]. However, VLEs are best at facilitating learning effectiveness when they adapt to the needs of individual learners.

In traditional education, personalization is defined as instruction and learning effort undertaken by a school to take into account individual student characteristics and needs, and involves interactive and thoughtful instructional practices to organize the learning environment. The *personalization* in VLEs, grounded in the constructivist learning theory in a broad definition, recognizes that every online learner is an individual, with a distinct learning style, pace, and path. The knowledge is individually constructed from what learners do in their experiential worlds through PVLEs. As what is known at a certain time is particular to the individual learner and based on previously acquired knowledge, the designed instruction may need to be adapted to the individual characteristics of the learners during the learning process. Therefore, PVLEs can support individual learning styles and characteristics, provide personalized features for each individual online learner who has experience with hypothesizing and predicting, manipulating objects, posing questions, researching answers, imaging, and investigating, in order for knowledge construction to occur. Therefore, PVLEs can be viewed as learner-centred, two-way interactive and active learning process of knowledge construction [16].

The personalization process is viewed as consisting of three main stages: learning, matching, and evaluation. The learning process starts with the collection of data from learners. The data may be explicitly provided by the learners, such as demographic data or inferred from the learner's interaction during the learning process, such as learning activities evolved with VLEs. In the matching stage, each individual learner's learning situation is matched with contents to be learnt and therefore, each learner will receive personalized learning materials. The final stage is evaluation, which requires the development of appropriate metrics for investigating the learning performance and assessing the effectiveness of a personalization program.

VLEs have evolved to link pedagogical earning models to meet e-learning objectives. PVLEs provide personalized eLearning environments for online learners to amplify and extend cognitive capabilities as well as organize their own thinking processes. In addition, they help learners manage the complexity of a learning environment. In PVLEs, content presentation is modeled in terms of situations rather than in terms of knowledge structures [2]; self-evaluation testing is integrated with the task and is not a separate activity [18]; Therefore individual learners can be uniquely identified, with content specifically presented for them, and progress can be individually monitored, supported, and assessed [17]. Learners can undertake active participation and interact with one another through quiz routines designed for self testing and mastery of learning [12].

2.2 Herbert A. Simon's Model of the Decision-Making Process

In his classic work [21], Herbert A. Simon proposed a model of decision-making process comprising four distinct phases—*intelligence*, *design*, *choice*, and *review*. In the *intelligence* phase, the decision maker gathers information about the situation and recognizes the problem at hand. The *design* phase is marked by structuring the problematic situation, developing criteria, and identifying the various alternatives through which the problem can be solved. In the *choice* phase, the decision maker chooses the best alternative that meets the criteria, and makes the final decision. Following these three phases, the decision maker uses the feedback from the results of the decision to review how well the process was executed. Such reflection on past processes can form a basis of the *intelligence* phase for future decisions. Although generic and simple in nature, Simon's decision-making process model has been applied and validated in a wide array of situations [9, 11, 24].

Based on Simon's model, we formulated the decision-making process model for PVLE, which includes gathering learner information and assessing learner profile according to learner personal information (demographic and preference information) and learning activities (e.g., browsing path, learning time for each session, exercises, and examinations) (*intelligence*); building and refining the learner model (*design*); determining appropriate instructional actions and execution, such as presenting personalizing contents, initiating interaction, etc. (*choice*); and evaluating and revising the learning plans (*review*) (see Section 3 for more detail).

It is clear that Simon's model of the decision-making process matches the personalization process in VLEs very well. However, there is a lack of research in adopting classic theories of decision-making in modeling personalization process. In this research, we attempt to fill this gap by formulating a conceptual model of personalization decision-making process in VLEs according to Simon's model. Furthermore, we propose a PVLE whose design and implementation architectures are organized by the phases of Simon's model.

2.3 Intelligent Agent-Assisted Decision Support Systems

The development of intelligent agents (IAs) and multi-agent systems (MASs) has recently gained popularity among IS researchers [15]. Although there is no universally accepted definition of the term “agent,” and indeed there is a good deal of ongoing debate and controversy on this very subject, the central point of agents is that they are autonomous: capable of acting independently, exhibiting control over their internal state. Wooldridge and Jennings [30] suggest a precise description of agents; one that may be widely adopted in artificial intelligence communities as well as general computing areas. An *agent* is defined as a computer system that is situated in some environment, and is capable of autonomous action in that environment in order to meet its design objectives [30, 32]. Furthermore, agents are able to act without the intervention of humans or other systems: they have control both over their own internal state, and over their behavior [31]. An *intelligent agent* (IA) is one that is capable of flexible autonomous action in order to meet its design objectives, where flexibility includes properties such as autonomy, social capability, reactivity, and proactivity [30, 32]. A generic agent has a set of goals, certain capabilities to perform tasks, and some knowledge about its environment. To achieve its goals, an agent needs to use its knowledge to reason about its environment and the behaviors of other agents, to generate plans and to execute these plans.

Various definitions from different disciplines have been proposed for the term MAS. The study of MAS originates from research in distributed artificial intelligence [8], where the activities of the system are distributed among multiple nodes for cooperative problem solving. More recently, the term MAS has been given a more general meaning: A *MAS* consists of a group of agents, interacting with one another to collectively achieve their goals. By absorbing other agents’ knowledge and capabilities, agents can overcome their inherent bounds of intelligence [13, 14]. One of the current factors (and arguably one of the more important ones) fostering MAS development is the increasing popularity of the Internet, which provides the basis for an open environment where agents interact with each other to reach their individual or shared goals.

The principles of multi-agent systems have shown adequate potential in the development of eLearning environments with intelligent behavior. In the early application of multi-agents in educational systems, intelligent agents were mostly designed as personal assistants, user guides, alternative help systems, dynamic distributed system architectures, human-system mediators, and so forth [4]. The interest for an explicit representation of tutorial knowledge has been continuously growing: concepts like student models, pedagogical diagnosis and tutoring expertise have been widely discussed since their introduction into educational systems research. The information repository and student profiling system provide facilities and services to support the knowledge communication within a multiple agent system, and address several co-operative ITS for distance learning and online learning. With repository support, ITSs are able to provide collaboration and cooperation services to both students and teachers that demonstrate that the repository technology is an appropriate technical solution to support multi-user co-operation and collaboration in complex ITS [26]. The most recent research has been focused on the implementation of multi-agent based online education systems where the individual function has been specified, such as content management systems, selfregulated systems, self-assessment systems [7], etc. However, most of the previous research is, in fact, based on the objectivist pedagogical approach that intelligent eLearning systems enable some components reflecting the values of the particular view among the nature of knowledge, learning and teaching. Those approaches have led to architectures that focus on representing the knowledge to be learned (domain knowledge), inferring the learner’s knowledge (learner model), and planning instructional steps to learning (teaching model) [2]. This reveals a challenge of using intelligent agents to provide more flexibility and cooperativity in dealing with the dynamic interaction and eLearning situation.

The potential contributions of intelligent agents to decision support systems (DSSs) have been described as enormous [28]. This has been reemphasized in the special issue of the DSS journal on the future directions of DSS [6, 20, 27]. Intelligent agents appear in an increasing number of DSS applications and intelligent agents’ properties can facilitate active decision making.

Intelligent DSSs (IDSSs), incorporating knowledge-based methodology, are designed to aid the decision-making process through a set of recommendations reflecting domain expertise [25]. IDSSs are able to provide services to users and they try to satisfy the user’s requirements through interaction, cooperation, and negotiation. IDSSs also offer tremendous potential in support of well-defined tasks [5] such as data conversion, information filtering, and data mining, as well as supporting ill-structured tasks in dynamic cooperation [10, 19, 25].

3. Decision-Making Process Model for Personalized Virtual Learning Environment

The design purpose of our research is to propose a framework for an intelligent agent–assisted decision support system that targets achieving learning effectiveness and supports the major phases of personalization decision making. To achieve learning and decision support effectiveness, an ideal system should be built with reference to the adoption of learning and decision-making theories. The personalization model developed in this research is grounded on the constructivist pedagogical principle. The constructivist pedagogical principle views effective learning as a learner-centered and active process of knowledge construction. Learners can learn more effectively and meaningfully in a favorable environment where their ideas are explored, compared, criticized, and reinforced through talking with and listening to others [23]. Herbert A. Simon [21] proposed the most famous model of the decision-making process, which identifies four different phases—*intelligence, design, choice,* and *review*. We have developed a conceptual process model based on the well-known Simon framework. However, the forth phase, the *review* activity, is to assess the past decisions, which may evaluate any of first three phases and restart the decision-making process again. Therefore, only first three phases are formulated in our conceptual model. Fig. 1 below shows the personalization decision-making process conceptual model with specific activities contained within each decision-making phase.

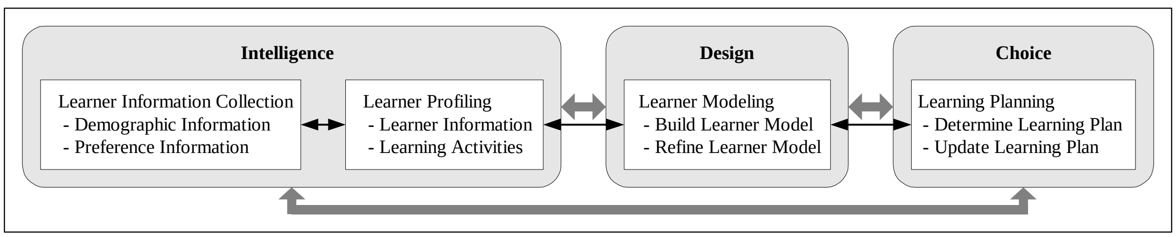

Fig. 1 Personalization Decision-Making Process Model for VLE

There are two automated supports in the *intelligence* phase for personalization in VLE. According to Simon [21], the *intelligence* phase involves searching the environment for conditions calling for decisions. Therefore, as this phase relates to personalization, it is to articulate the general reasoning process leading up to a decision-making situation (i.e., personalization in VLE). The most common form of computer "support" for this initial phase in designing a PVLE is to provide convenient access to a variety of information sources, such as the learner's demographic information, preference information, learning activity history, and previous learning result, and to detect developing problems and opportunities [9, 24]. Use of agents for this task has been widely advocated. For example, Teo and Choo [22] stress the importance of automated gathering of relevant information for competitive intelligence. As long as the system collects all necessary information, it needs to create the learner profile based on learner's personal information and learning activities (both current and historical). When a leaner profile is built, a call for decision-making regarding personalization will be launched and passed to the next phase.

In the *design* phase, the learner model will be abstracted based on the learner profile. To achieve this, it is necessary to first analyze the learner profile generated from the *intelligence* phase. It is very important at this stage to assemble the information in order to calculate the overall knowledge level and time spent on the current topics. It is also important to take the learner's demographic (e.g., intelligence level) and preference into account. After building or refining the learner model, it is passed to the next phase.

In the *choice* phase, after each individual eLearning activity is specified, the corresponding instruction will be provided. In conjunction with the content database, the individual learner plan that determines the appropriate instructional action based on the individual learner model is updated. These instructional actions are executed including the personalization of reading materials for each individual learner to match the individual's learner model; a self-evaluation quiz is personalized according to a diagnosis of the online learner's learning problems; and individual learning advice that is distributed to a learner to increase interactions.

Many research studies show that personalization is a complex decision situation in which decision makers attempt to gather a good deal of information before making their final choice. However, for different decision-making phases the required information differs, thus, it is not efficient to collect all the data at the very beginning and pass it throughout the entire decision-making process. Therefore, in our proposed framework, with the *design* and *choice* phases, information corresponding to their tasks would be requested from the *intelligence* phase when required (bidirectional arrow means information requesting and providing). For the same reason, for the *choice* phase, information from previous *design* phase would also be requested when required.

This personalization decision-making process model provides guidance on identifying personalization functionalities and processes from an educational point of view. In this study, we employ intelligent agent techniques to achieve personalization in PVLEs based on this conceptual model. In each step of the personalization process, intelligent agents work correspondingly to play a crucial role in providing the intelligent behavior of the system. A number of intelligent agents can work together to achieve the personalization tasks. The detailed system architecture design, development, and operation are in the next section.

4. Design and Development of Intelligent Personalized Virtual Learning Environment

Our intelligent personalized virtual learning environment (IPVLE) is a personalized computer-based online learning environment that provides a set of personalized functionalities, such as personalized eLearning plans, learning materials, self-evaluations, and initiates the interaction in terms of advice, necessary instant messages, etc., to online learners. Our IPVLE has the capability of reaching learners in remote areas around the country or across country boundaries at very low cost, provide the opportunities for online learners to learn at the time and location of their choosing, to communicate with other online learners, as well as to access to a wide range of resources. The analysis and design of a novel agent-based IPVLE is described in this section, based on the proposed personalization decision-making process model.

4.1 System Design Architecture

Personalization was designed as *personalized content, personalized self-evaluation, and personalized tutoring* in the IPVLE. Based on previously acquired knowledge, the newly-designed instruction needs to be adapted to the individual characteristics of the learners during the learning process. In the IPVLE, online learners receive personalized instructions that meet their particular conditions and needs. The design architecture of the IPVLE is portrayed in Fig. 2, which describes the internal interactions among agents and the external relationship between the IPVLE and learner.

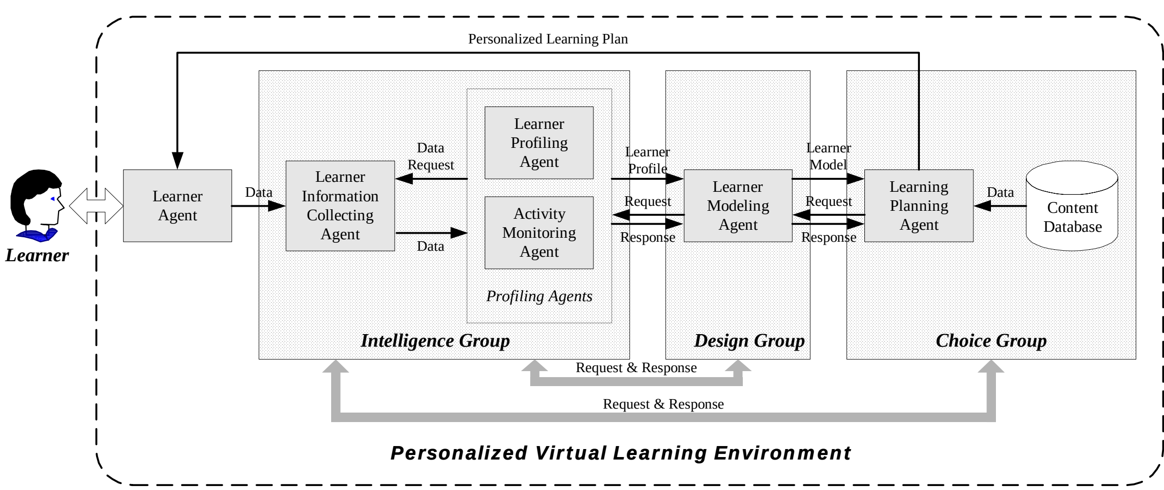

Fig. 2 Intelligent Personalized Virtual Learning Environment Architecture

The personalized functions of the IPVLE are achieved by a set of intelligent decision-making agents. The agents communicate with each other through the Internet. As related before, all these agents work autonomously and collaboratively in the multi-agent environment. Each agent focuses on its particular task without inventions from outside. And by drawing on other agents' knowledge and capabilities, agents can overcome their inherent bounds of intelligence and work collaboratively to pursue their goals.

As discussed before, the *Intelligence Group* contains *Learner Information Collecting Agent* and two *Profiling Agents*. The following *Design* and *Choice Groups* may request information relating to their task from the *Intelligence Group*, if required. The *Learner Information Collecting Agent* enables the system to collect information from the learner through the *Learner Agent*, such as the personal demographic data, previous learning experience and results, etc. It also records eLearning activities, such as mouse action (time and target), learning duration on a particular task, test score, documents load/unload, etc.

Two kinds of *Profiling Agents* include *Learner Profiling Agent* and *Activity Monitoring Agent*, are proposed in our system to build and refine the learner profile.

- The *Learner Profiling Agent* is to assess a wide variety of detailed information relating to the learner, typically collected at the time that the learner first uses the system. The agent determines the learner's intelligence level, previous learning performance, learning preference, etc.
- The *Activity Monitoring Agent* is to analyze the learning activities, such as learning time for each session, the quiz results, time spent on completing the quizzes, etc. The agent assesses the learner's learning path and knowledge level.

The two *Profiling Agents* (*Intelligence Group*) will work corporately to produce a learner profile, and pass to the *Learner Modeling Agent* (*Design Group*) for further process. When receiving the learner profile, the *Learner Modeling Agent* will start its modeling process to build or modify the learner model. This agent may conduct analysis on learner profile and request any additional information if necessary to model the learner.

When the *Learner Modeling Agent* built or refined the learner model, it will be automatically sent to the *Learning Planning Agent*, which is of *Choice Group*. The agent analyzes the current learning plan of the particular online learner based on the learner model and the content model, and then updates the learning plan. As an example, the topic sequence may be updated. Meanwhile, the *Learning Planning Agent* is also able to exhibit goal-directed behaviors by using the pro-activity. For example, when the planning agent determines that the online learner may fail a topic, the agent may update his/her learning plan to prevent this unexpected problem happening.

Finally, the personalized learning plan is sent to the *Learner Agent*. The agent dynamically assembles personalized instructional materials in terms of reading contents, quizzes and feedback for a particular online learner based on the learning plan. Such an assembling process includes the generation of the learning materials, the generation of quizzes, quizzes summary and instant messages. For example, because a particular online learner, Tony, has a current learning plan that requires him to study the topic "Constraints after DFD Diagrams," the materials for the topic "DFD Diagrams" will be displayed on the webpage. When Tony clicks on the "next" button, the material of the topic "Constraints" will appear. There is a set of fuzzy rules has been implemented to determine the suitable level of topic for the learner, based on the learner's previous efforts, previous learning performance, and the intelligence level. For example, IF the student has the prior knowledge of the concept *well,* AND the time the student spent on the prior knowledge is *short*, AND the intelligence level of the student is *high,* THEN the displaying level of the concept should be *abstract*.

4.2 System Operation

In order to evaluate our architectural design, a prototype has been implemented (details refer to Xu and Wang, 2006). To demonstrate the effectiveness of our approach and illustrate how multiple intelligent agents work together to reach the learning effective goal, the operation process of their collaboration is illustrated in the following case. It is assumed that Tony is an online learner. After he enrolls in the online course provided in IPVLE, the operation process unfolds as follows in Fig. 3:

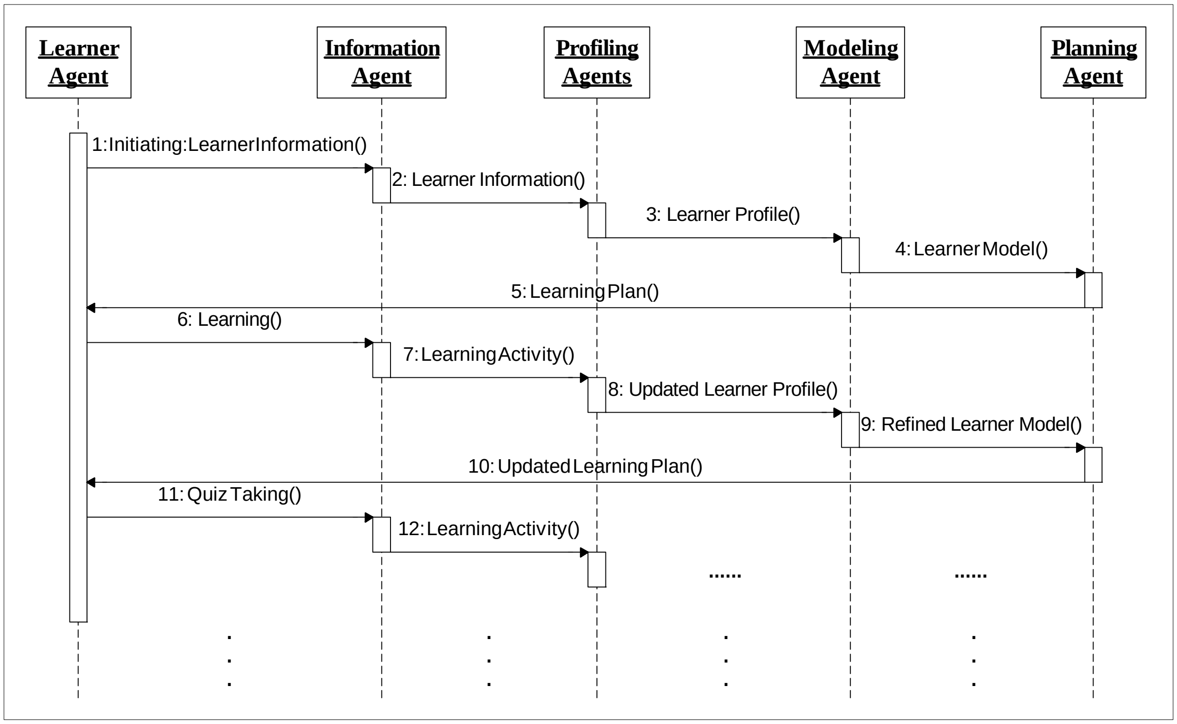

Fig. 3 Learning Operation Sequence in IPVLE

1. After Tony enrolls in the online course, IPVLE will create the Profile_Tony with initial value; Tony's initial Learner Model, Model_Tony; and Tony's initial Learning Plan, the LearningPlan_Tony. The creation of such initial models is similar to the creation of a number of instances from some pre-defined classes. For instance, the "Learner_Model" is a pre-defined class with a number of attributes, such as the initial_knowledge and learning_behaviour. When the object "Model_Tony" is created, his pre_test results will be put in the initial_knowledge and his learning_behaviour is an empty set. Similarly, the object "LearningPlan_Tony" is created. However, the initial value of the Learning Plan_Tony is set based on the Model_Tony. When Tony logs in to the IPVLE, the *Learner Agent* will be generated by IPVLE on the server side. The *Learner Agent* will manage the communication between IPVLE and Tony. If *Learner Agent* finds that Tony has logged in for the first time, it will show the pretest Web-page to Tony. After Tony completes the pre-test and submits it, *Learner Agent* will pass it to the *Information Agent*.
2. The *Information Agent* will pass Tony's personal information collected during his enrolment and the pretest results to the *Profiling Agents*.
3. The *Profiling Agents* will analyze Tony's personal information and pre-test results and save the results to the Profile_Tony. The *Profiling Agents* will also pass Tony's profile to the *Modeling Agent*.
4. The *Modeling Agent* will modify Tony's learner model, Model_Tony, based on Tony's pre-test results and a set of modification rules, and send to the *Planning Agent*.
5. Based on the new version of Model_Tony, the *Planning Agent* will update the LearningPlan_Tony, and send to the *Learner Agent*.
6. Different types of learning materials are provided to Tony by the *Learner Agent*, based on the LearningPlan_Tony. Tony's learning activities, such as mouse action (time and target), learning duration on a particular task, test score, documents load/unload, etc, are captured and passed to the *Information Agent*.
7. The *Information Agent* will pass Tony's learning activities to the *Profiling Agents*.
8. The *Profiling Agents* will analyze Tony's learning behaviors and update the results to the Profile_Tony. The *Profiling Agents* will also pass Tony's updated profile to the *Modeling Agent*.
9. The *Modeling Agent* will modify Tony's learner model, Model_Tony, based on Tony's learning behaviors and a set of modification rules, and send to the *Planning Agent*.
10. Based on the new version of Model_Tony, the *Planning Agent* will update the LearningPlan_Tony, and send to the *Learner Agent*.

11. The quiz is generated dynamically by the *Learner Agent*, based on LearningPlan_Tony. The behaviors during the quiz and the quiz results will be captured and passed to the *Information Agent*.
12. The *Information Agent* will pass Tony's quiz activities to the *Profiling Agents.* The *Profiling Agents* will analyze the answers to the quiz. Such analysis is based on the match between the correctness of the quiz and the LearningPlan_Tony. The outputs are the achievement degree of the LearningPlan_Tony, which is a portion of the Profile_Tony.

5. Conclusions

This paper explores the approach of intelligent agents supported PVLEs to overcome the limitations of one-fits-all instructional VLEs. Learning material is structured and delivered to online learners with consideration of the learner's capacities, prior learning and the learning process. In this study, we proposed a decision-making process model for personalization in VLEs by applying Simon's [21] classical model of a decision process. Based on this conceptual model, a novel and open multi-agent-based PVLE is designed and implemented, in which various classes of intelligent agents are proposed to provide a set of functionalities for PVLE. In sum, the main contribution of this study to the research literature can be summarized as follows:

- The personalization decision-making process model of VLEs: This is a conceptual model that identifies the specific activities involved in each decision-making phase for personalization in VLEs. The application of this model can lead to an unambiguous understanding of the concepts of personalization, and provide a uniform framework with which different approaches can be integrated together to provide more sophisticated functions and facilities. Therefore, by creating a rich conceptual model, the study provides a solid framework for PVLEs practice. This model provides the basis for formal study and leads to analysis, design, and development of PVLEs.
- System design innovation: A novel and open architecture for PVLE has been designed. The personalization can be achieved by intelligent agents' decision-making capability, through recognizing individual eLearning pace and reacting correspondingly. Based on the personalization model, a number of decision-making agents in IPVLE were designed and developed. Prototype of multi-agent supported PVLE was designed and developed. In IPVLE, online learners can be uniquely identified, course contents are specifically presented, learning progress is individually monitored, supported, and assessed, and a learning situation is afforded.

By following the architecture, we will conduct further task analysis and knowledge acquisition on the prototype. In the future, the conceptual model, system architecture, and development will be improved. The further development of the IPVLE for real-world application will also be explored.

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