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Matching Learning Styles with Digital Media Preference for Recommending SQL Instruction in a Database Management Course

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Abstract: With the benefits of online learning environment, digital media related to personalized information of individual students have been rapidly developed. For learning Structured Query Language (SQL) in a database management system, although, there were various online learning systems, which were developed based only on single-source of personalization information, such as learning style, cognitive style or learning achievement. In this study, an innovative approach has been proposed by basing upon two main sources of personalization information that is, learning styles and digital media preference. This paper, a pilot study was conducted to explore the relation between learning styles and preferred digital media for arranging the sequence of digital media to each student learning on SQL topic.

Keywords: Online learning, SQL, learning style, digital media, personalized learning

1. Introduction

In the past decade, Structured Query Language (SQL) has been one of necessary programming languages to retrieve and manipulate database systems (Mitrovic, 2003). Teaching and learning SQL has been normally need in part of computing/IT courses (Connolly, 2006; Soflano, 2015). Previous research showed several digital media types for supporting learning SQL, such as computer-aided instruction, web-based learning, and computer game-based learning (Piyayodilokchai, Panjaburee, Laosinchai, Ketpichainarong, and Ruenwongsa, 2013; Latham, 2012; Soflano, 2015).

In recent years, learning style models has been recognized as a different way of learning and processing in personalized information, such as Felder and Silverman's index of learning style, Kolb, Rancourt's, hemispheric, and VAK. As mentioned in previous study, individual students have different learning experience based on their background, learning goal, and learning style (Kolb, 1984). With the reason, we have considered that the learning style could be applied to serve proper instruction for each student. Although, several researchers combined four of learning style models, such as Kolb's, Rancourt's, hemispheric and VAK to find the relation of learning styles and different multimedia types, such as animations and video materials, document with color discrimination, well-structured learning materials, audio learning materials to present learning material for each student (Ocepek, Bosnić, Šerbec, and Rugelj, 2013). However, it still was not considered in any specific learning content.

With the benefits of online learning environment, learning materials related to personalized information of students have been rapidly developed. The recommend system that provides appropriate learning materials by considering personalized information aims to increase learning performance; in other hand fixed digital learning material without consideration technology preference reduced learning performance (Vogel-Walcutt, Gebrim, Bowers, Carper, and Nicholson, 2011). Consequently, it was implied that the low level of learning performance might be affected by digital media types that did not fit with the students' learning style. Therefore, for supporting SQL learning, we have faced with the research question as follows: what is the method for recommending SQL digital instruction by matching learning styles with digital media preference?

In this pilot study, we focused on Kolb's and Felder–Silverman's learning style models, which are frequently used in adaptive E-learning system (Truong, 2016). To cope with the research question, this paper revealed the method and relation between two learning style model and preferred digital media for arranging the sequence of digital instruction to individual students for learning SQL.

2. Related Research

2.1 Learning styles

Learning style is the way individuals prefer to learn, which students perceived, and processing information that are reflected in their learning behavior; how students learn, how students like to learn, how teacher teach, and how students interaction with the learning environment (Felder and Brent, 2005; Kolb, 1984; Keefe, 1991; Reiff, 1992; Filippidis ,and Tsoukalas, 2009).

In the past decade, there are various researchers proposed learning style model such as Kolb (1984), Keefe (1979) and Felder and Silverman (1988). Previous studies have represented the use learning styles as a one factor for recommending personalized learning content (Graf, Viola, Kinshuk and Leo, 2007; Papanikolaou, Mabbott, Bull and Grigoriadou, 2006; Tseng, Chu, Hwang, and Tsai, 2008). Among learning style models, Felder and Soloman (1997) created Index of Learning Styles (ILS) questionnaire and developed Felder–Silverman Learning Style Model (FSLSM) which is the most appropriate model for developing e-learning systems (Hwang, Sung, Hung and Huang, 2012; Akbulut ,and Cardk, 2012; Kuljis and Lui ,2005).

The four main dimensions of the learning styles in Felder–Silverman Learning Style Model (FSLSM) with subsequent updates (Felder and Spurlin, 2005) contain two sub-styles: perception dimension (sensitive-intuitive), input dimension (visual-verbal), processing dimension (active-reflective), and understanding dimension (sequential-global). Particularly, the perception dimension is the most important learning style considered in (Felder, Felder, and Dietz, 2002; McCaulley, 1990). According, Kolb's learning theory set four experience type of learner, he believes that learning styles are not fixed personality traits, but relatively stable patterns of behavior depend on their background and their experiences. The four stage are concrete experience (CE) that being involved in a new experience, reflective observation (RO) which watching others or developing observations about own experience, abstract conceptualization (AC) that creating theories to explain observations and active experimentation (AE) that using theories to solve problems and make decisions. Kolb's model differs from others because it offers both a way to understand individual learning styles, which he named the "Learning Styles Inventory-LSI", and an explanation of a cycle of experiential learning that applies to all learners.

In adaptive learning systems, learning style information has been used to provide opportunity for students to learn in preferred way. Many researchers interested in different parts of online learning such as e-learning environment, predict of learning style and application for automatic classification of learning style type (Truong, 2016). Truong (2016) had reviewed 51 articles and grouping themes of integration of learning styles theories applied in adaptive e-learning system. The results showed that used theories of Felder-Silverman Model was 70.6%, Honey and Mumford Model and Kolb Model was 3.9%, VAK Model was 9.8% and 11.8% for others. Consequently, it is challenge to use Felder-Silverman Model synergy with Kolb Model in SQL learning for university students in Thailand context.

2.2 Digital Media in SQL Learning

Several researchers studied many types of digital media used in various subjects. Piyayodilokchai, Panjaburee, Laosinchai, Ketpichainarong, and Ruenwongsa (2013) developed CAI multimedia based on the 5E learning cycle model for teaching second-year undergraduate students. The results showed that using the CAI could help students' learning achievement better than other instructions. For the web-based learning environment, Lister (2014) suggested that development of E-Learning and Online Learning has been rapidly growth of learning. Some web-based learning was developed for teaching SQL content, such as Latham (2012), Mitrovic (2003), and Allen (2000) developed tutoring system. Moreover, based on the content in database course, the game-based learning focusing on supporting learner's skills was proposed (Connolly, 2006). In recent years, SQL topic has popularity development in computer game-based learning based on learning styles, which helped students to complete task faster than the other instructions (Soflano, 2015). It is clearly that E-learning systems has been included various types of digital material to delivery SQL content, in this pilot study, we have reviewed from articles published from 2000 to 2015; and then categorized the similar attributed into three groups, such as Computer-assisted instruction, Web-based learning, and Game-based learning.

3. The Proposing Matching Learning Styles with Digital Media Preference Approach

In this study, we have developed a web page embed questionnaires in order to explore students' learning styles and their frequencies to use digital learning. This phase was conducted by randomly selected undergraduate students from universities in Thailand (North, South, East, and Northeast parts of Thailand). Totally, there were 190 students who registered in database course or course related to SQL. We collected data with three tools are Index of Learning Styles developed by Felder and Soloman (1997), Learning Style Inventory developed by Kolb's Learning Style (KLS) (1995), and the Digital Media Preference Questionnaires.

Based on literatures of the digital material delivering SQL content, in this pilot study, we have employed three types of digital material for presenting SQL content such as M1: CAI; M2: Web-based learning; and M3: Game-based learning. Therefore, the framework of exploring relation between learning styles and digital material preference for recommending SQL instruction was shown in Figure 1.

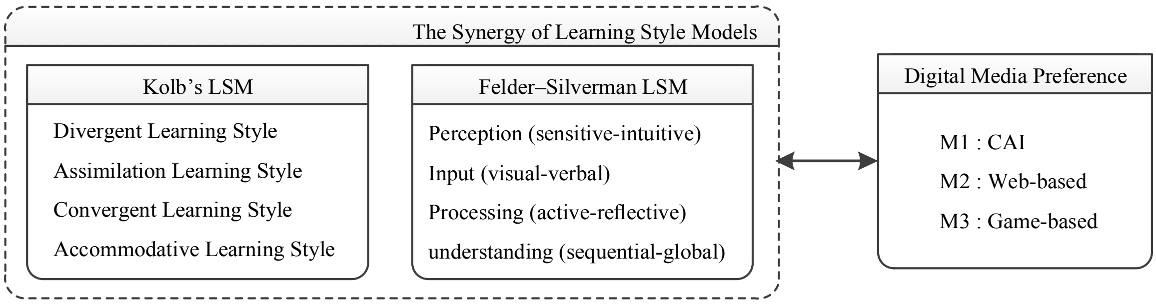

Figure 1. The synergy of learning style models and digital media preference

The participating students were asked to login to the web page to complete all questionnaires. After submitting learning style questionnaires, we exported data from the web page to excel format and then imported into Microsoft SQL Server for analyzing those data. We categorized student's learning style preference as shown in Figure 2.

Figure 2. Demographic of participants

The core of this pilot study is to combine two learning style models and find relation between learning style group and digital material preferences with Pearson's Correlation. Moreover, we analyzed by using Regression to find coefficient of determination (R square) and minimize the sum of squared errors of prediction (β) from equation $Y = a + \beta_1X_1 + \beta_2X_2 + \ldots + \beta_kX_k$ in which Y represents digital media types in four of Kolb Learning Style value from M1 to M3; "M1" represents CAI, "M2" represents Web-based learning and "M3" represents Game-based learning. For predictor variable X_i

represents Felder's learning styles as act, ref, sen, int, vis, vrb, seq and glo. If other X_1, X_2,.. and X_k are fixed, then for each change of 1 unit in X_i, Y changes β_i value. We observe a value of β_i, which Felder's learning styles (X_i) is most influence to digital material (Y). From this analysis, we can sort the sequence of digital learning which is suitable for each learning style group. In this phase, we proposed a mechanism to recommend the sequences of digital material for each student to learn SQL. The proposed idea to identify the sequential of Digital Media Mechanism Pseudocode following.

```
Declare an array of string type variable called Ki
Declare an array of string type variable called F1
Declare an array of string type variable called F2
Declare an array of string type variable called F3
Declare an array of string type variable called F4
    For all Kolb learning type Ki = 1 to 4; Ki = [DIV  ASS  CON  ACC]do
    For all Felder learning type F1 = 1 to 2; F1 = [act; ref] do
    For all Felder learning type F2 = 1 to 2; F2 = [sen; int] do
    For all Felder learning type F3 = 1 to 2; F3 = [vis; vrb] do
    For all Felder learning type F4 = 1 to 2; F4 = [seq; glo] do
        For i = 1 to 3 do //all Digital Learning Types M ϵ {M1, M2, M3}
            PMi = Min (PMiF1, PMiF2, PMiF3, PMiF4)
            Read β Mi Value from PMi
        End for
        For i = 1 to 3 do //Find Each Sequence of Digital Learning Type
        If PMi is minimum and β Mi >0 then
            SMi =1st
            Next PMi
            If PMi is minimum and β Mi >0 then
                SMi =2nd
                Next PMi
                SMi = 3rd
            Else
                SMi = 3rd
                Next PMi
                SMi = 2nd
            End if
        Else
            SMi = 3rd
            Next PMi
            If PMi is minimum and BMi >0 then
                SMi = 1st
                Next PMi
                SMi = 2nd
        Else
            SMi = 2 nd
            Next PMi
            SMi = 1st
        End if
    End if
    End for  //Sequence of  Digital Learning Type
End for  // Felder learning type F1
End for  // Felder learning type F2
End for  // Felder learning type F3
End for  // Felder learning type F4
End for  // Kolb
End for
```

4. Example of Results and Discussions

By using the proposed algorithm, we could categorize students learning style synergy group and sequence of digital material preference. The results of relation between Kolb's and Felder–Silverman's Learning Style models affected to Digital Material as shown in Figure 3.

Learning Style Cluster		Sequence of Digital Learning								
Kolb	Felder	M1			M2			M3		
		Seq.	Beta	sig	Seq.	Beta	sig	Seq.	Beta	sig
Diverger	INT	1st	0.123	0.200	2nd	0.024	0.803	3rd	-0.172	0.062
Diverger	VRB		0.094	0.320		0.026	0.786		-0.140	0.123
Assimilator	ACT		0.730	0.037*		-0.057	0.841		-0.457	0.119
Assimilator	GLO		0.426	0.194		0.120	0.717		-0.442	0.171
Assimilator	VRB		1.084	0.057		-0.379	0.456		-0.340	0.440
Converger	VRB		0.046	0.807		0.031	0.942		-0.113	0.852
Converger	GLO		0.370	0.163		-0.109	0.830		-0.247	0.732
Accomodator	SEQ		0.220	0.129		-0.078	0.588		-0.184	0.210
Accomodator	INT		0.183	0.210		-0.222	0.129		-0.010	0.946
Assimilator	INT	1st	-0.647	0.210	3rd	-0.559	0.317	2nd	1.107	0.059
Converger	ACT		0.678	0.045*		-0.394	0.466		-0.089	0.903
Converger	INT		0.497	0.074		-0.562	0.279		0.443	0.515
Accomodator	REF		0.074	0.596		-0.132	0.346		0.034	0.809
Accomodator	VRB		0.079	0.566		0.043	0.756		-0.131	0.353
Diverger	ACT	2nd	0.018	0.852	1st	0.095	0.332	3rd	-0.128	0.174
Diverger	GLO		0.026	0.791		0.203	0.035*		-0.257	0.006*
Assimilator	SEN		0.647	0.210		0.559	0.317		-1.107	0.059
Converger	SEN	3rd	-0.497	0.074	1st	0.562	0.279	2nd	-0.443	0.515
Converger	REF		-0.678	0.045*		0.394	0.466		0.089	0.903
Accomodator	ACT		-0.074	0.596		0.132	0.346		-0.034	0.809
Accomodator	SEN		-0.183	0.210		0.222	0.129		0.010	0.946
Diverger	SEQ	2nd	-0.026	0.791	3rd	-0.203	0.035*	1st	0.257	0.006*
Diverger	REF		-0.018	0.852		-0.095	0.332		0.128	0.174
Diverger	SEN	3rd	-0.123	0.200	2nd	-0.024	0.803	1st	0.172	0.062
Diverger	VIS		-0.094	0.320		-0.026	0.786		0.140	0.123
Assimilator	VIS		-1.084	0.057		0.379	0.456		0.340	0.440
Assimilator	SEQ		-0.426	0.194		-0.120	0.717		0.442	0.171
Assimilator	REF		-0.730	0.037*		0.057	0.841		0.457	0.119
Converger	VIS		-0.046	0.807		-0.031	0.942		0.113	0.852
Converger	SEQ		-0.370	0.163		0.109	0.830		0.247	0.732
Accomodator	VIS		-0.079	0.566		-0.043	0.756		0.131	0.353
Accomodator	GLO		-0.220	0.129		0.078	0.588		0.184	0.210

Figure 3. The results of relation between Kolb and Felder affected to Digital Learning

The results were analyzed by Liner Regression and using mechanism to arrange sequence of digital media. The results show that *p*-values and Coefficients (β) between each Kolb's Learning Style and one dimension of Felder–Silverman's Learning Style affecting to the first priority for arrangement. We had explained only a statistic significant (*p*-value < .05).

For discussion of significant data, the result of Assimilator mode and Active learner is M1 for being the first sequence. The group of students who had Assimilator mode learning based on experience related to Abstract Conceptualization (AC) and Reflective Observation (RO). They learn by readings, learning with lectures, need more time to think, and individual learning. For Active leaner of Felder learning style, they prefer to learn in-group and need the experimental practice. Because of CAI (M1) have properties to aim learning activities for this group such as drill and practice exercises, reading content, and individual interactive with system. But the reflective students with Assimilator group is need more time for process information before doing, then practice which is M1 is the last sequence.

For students who have Converging learning style with Active preference, the first sequence is M1. The Converger mode on experience related to Abstract Conceptualization (AC) and Active Experimentation (AE). They learn by a practical of idea, problem-solving approach, and do better in situation applications such as simulations that mostly exist in properties of CAI. Moreover, active leaner is experimentalist, which learns by doing. The opposite *p*-value of reflective with Assimilator group prefers to think more than doing, that is to say M1 is the last selected digital learning.

For students who have a Diverger mode with Global preference, the sequence are M2. This Diverger mode related to Concrete Experience (CE) and Reflective Observation (RO). Students had situated in Social, they learn by working in groups and need response their feedback such as Brainstorming. The students can chat or conference in their group, learning of web-based learning (M2) provided those properties. With the Global preference, the students can understand information by overview and when understand they jump to next step or next interested content, which include in web-based learning type. The *p*-value of Sequential contrast the global group, students prefer the understand information with increase each step-by-step and hard to grasp over picture. The reason of the game-based learning that created story line to students learns by increase small knowledge in each higher level is better media for Sequential group.

Each Kolb's Learning Styles and each of Felder's Learning Style had sequential results in Table 1, but it could not justify some conflict sequential like student who have Converger Mode with four Felder's learning style in ACT, INT, VRB, and SEQ. The Converger Mode with Active, Intuitive, and Verbal preferences provided M1 to be the first learning media, but the Sequential preference selected M3. Therefore, we proposed the mechanism for decision sequence of media, which using minimum *p*-value of four dimensions in each media type would most influence of selected sequence of digital learning.

In additions, we can categorize students learning style synergy group (Kolb's learning style model and Felder–Silverman's Learning Style Model) and sequence of digital learning preference. The correlations between three digital learning types are represented by circle and four of learning style synergy group represented by rectangles, and significant correlations represented by the arrows as shown in Figure 4. The solid line represents positive relation; the other dash line represents negative relation.

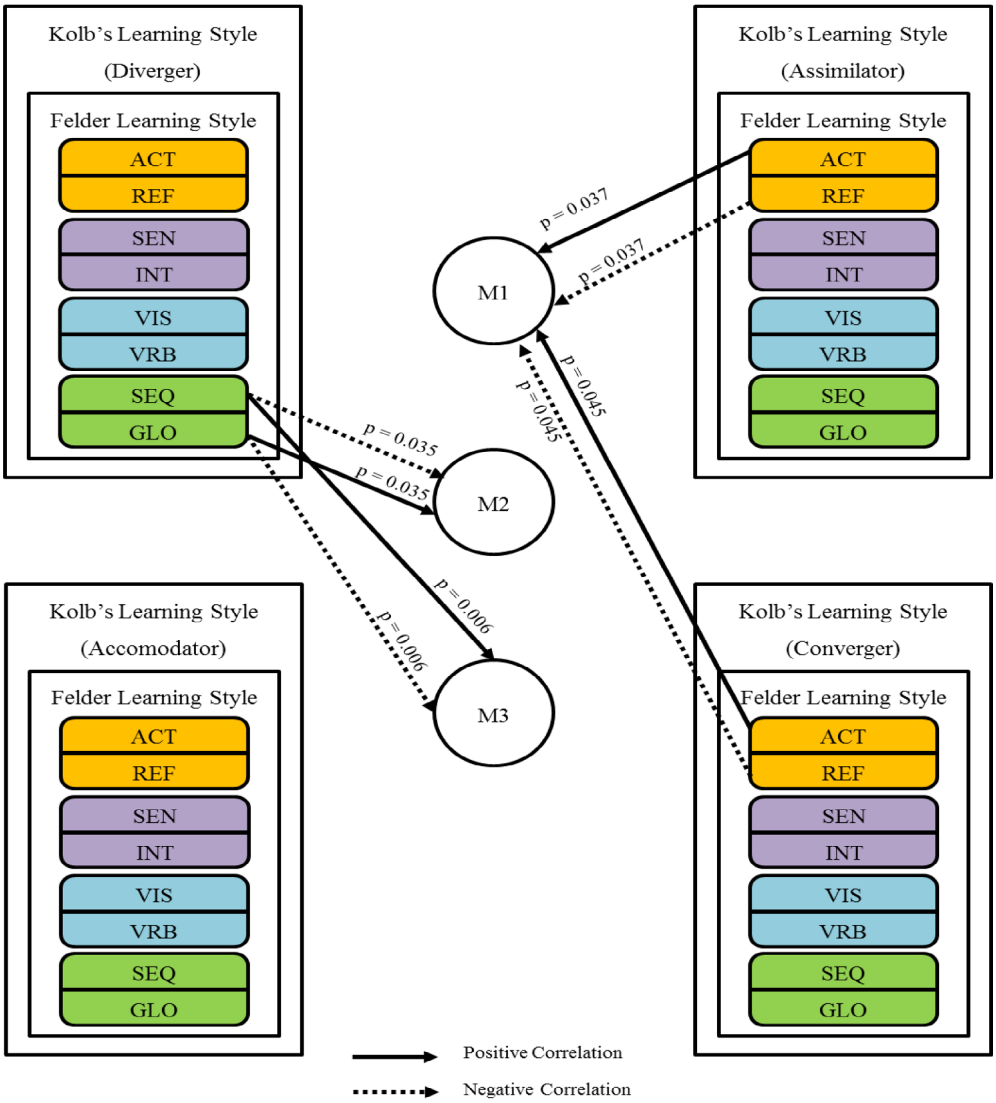

Figure 4. Relations of Synergy Learning Style Models and Digital Media Preference

To sum up, we could synergy the different learning style models in order to get information about student's learning preference. The results in Figure 4 show positive and negative correlation only significant values. For example, students who have the mode of Diverger experimentation (Kolb's learning style model) and a sequential preference (Felder–Silverman's Learning Style Model) seem to use Game-based learning (M3) as the positive correlation, but they avoid to using Web-based learning as the negative correlation. The reason is mode of Diverger like to gather information and need new experience that have properties matching in Games-based learning attribute normally created for challenge and gather data environment during playing a game. Otherwise, the reason is students who have a sequential preference learn in material step-by-step and increases small step when they understand, it similar to student playing in game each level will increase harder when they pass the level.

5. Conclusions

This paper presents an innovative approach for recommending sequence of digital material for learning SQL in university level by matching the Kolb's learning style model and the Felder–Silverman's Learning Style Model with the Digital Media preference to each student. Based on the proposed approach, an adaptive learning support system has been developing and implementing. To evaluate the performance of this innovative approach, an experiment on SQL in database management course of a university student will be conducted. 200 first year students will be recruited to compare the performance of the conventional web-based learning systems and our enhanced approach.

Figure 5 proposes the system architecture of the adaptive learning support system based on the proposed approach. We shall summarize the proposing system that the Registration of Learner module will provide opportunity for students to create their own profile for log into the system to complete questionnaires and learning activities. The students' data will be stored in Learner's Profile database. The system will calculate students' information in order to create digital learning sequences by using proposed mechanism and this information will be stored in Learning Sequence database. Recommendation Sequence of Digital Media module will provide sequence of digital media for each student. The students can select to confirm the recommended sequence or change digital learning sequence based on their preference before starting to learn in each unit of SQL in Confirm Recommendation module. If the students select the sequence of digital media by their own preference, the system will change sequence in Learning Sequence database. The Learning Content module connected with Learning Material database will provide SQL content for each student.

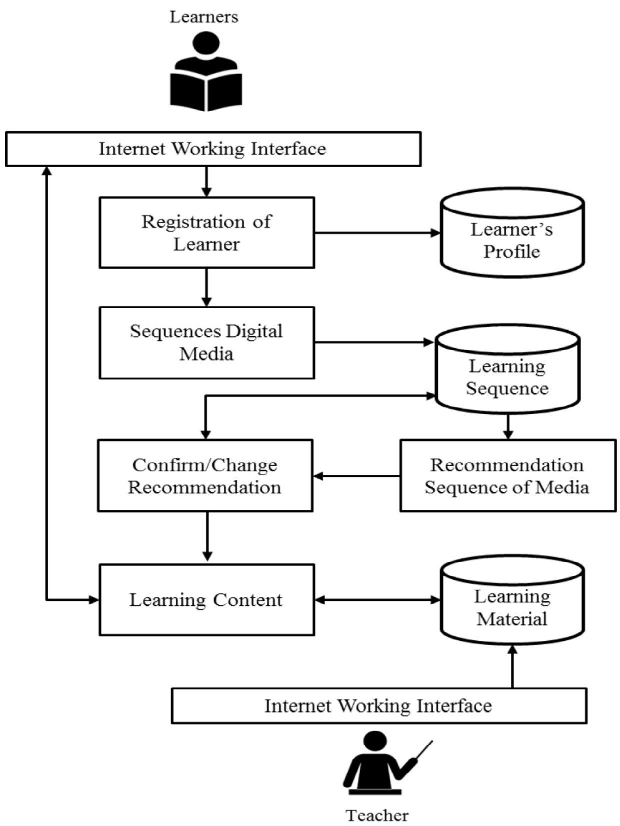

Figure 5. System Architecture of the Adaptive Learning Support System

The success of this study will plays an important role in enhancing the effectiveness of the entire adaptive web-based learning environment in SQL learning.

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