



Research article

Identifying learning styles and cognitive traits in a learning management system

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ABSTRACT

Investigating learner behavior is an increasingly important research topic in online learning. Learning styles and cognitive traits have been the subjects of research in this area. Although learning institutions use Learning Management Systems such as Moodle, Claroline, and Blackboard to facilitate teaching, the platforms do not have features for analyzing data and identifying behavior such as learning styles and cognitive traits. Instead, they only produce certain statistical reports from the daily access records. Even though complex models have been proposed in the literature, most studies are based on a single behavior such as learning styles or cognitive traits but not both. Only a few have investigated a combination of cognition-based theories such as working memory capacity and psychology-based ones such as learning styles. Thus, this study sought to answer the research question of whether it was possible to establish a methodology for the estimation of learning styles and cognitive traits from a learning management system. The study combined the Felder-Silverman Learning Style Model and Cognitive Trait Model as theoretical frameworks to identify behavior in a Learning Management System. This study designed a model for extracting records from Learning Management Systems access records to estimate learning style and cognitive traits. From this, a prototype was developed to estimate the learning style and cognitive traits for each student. The model was evaluated by administering manual tools to students in a classroom environment then comparing the results gathered against those estimated by the model. The results analyzed using Kappa statistics demonstrated the interrater reliability results were moderately in agreement. Taken together, these results suggest that it is possible to estimate the learning styles and cognitive traits of a learner in a Learning Management System. The information generated by the model can be used by tutors to provide a conducive online learning environment where learners with similar behavior ask each other for help. This can reduce the teaching load for online tutors because learners themselves act as a teaching resource. Information on learning styles and cognitive styles can also facilitate online group formation by isolating the individual factors that contribute to team success.

1. Introduction

Learner behavior modeling has received much attention over the last two decades (Chrysafiadi and Virvou, 2013; Abyaa et al., 2019). Learner characteristics such as Learning styles (LS) and cognitive traits (CT) are the most prevalent topic in educational psychology texts (Wininger et al., 2019). These characteristics measure learners' psychological attitude towards learning (Drachsler and Kirschner, 2012). A learner model is a system that collects and processes information on student behavior such as LS and CT. Knowledge of learner characteristics enables instruction designers to create relevant instructions for a target group. Although institutions use Learning Management Systems (LMS) such as Moodle, Claroline, and Blackboard (Don, 2014) to facilitate teaching, the

platforms do not have features for analyzing data and identifying behavior such as LS and CT. Most LMS have Sharable Content Object Reference Model (SCORM) specifications. SCORM format allows the creation of the learning contents that can be managed, re-used, and assembled in different learning platforms (Varlamis and Apostolakis, 2006).

Recent developments in online learning renewed the interest in learner behavior modeling in an LMS. According to Blakemore et al. (1984), learning style indicates the way a learner observes, interacts with, and answer back to learning content. Several examples of learning style models exist in the literature. Felder-Silverman Learning Style Model classifies learners as sensing or intuitive, verbal or visual, active or reflective, and sequential or global (Felder, 1988); Myers Briggs Type

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Indicator classifies learners as extraversion or introversion, sensing or intuition, thinking or feeling, judging or perceiving (Myers, 1995); Honey and Mumford model groups learners as an activist, reflector, theorist, and pragmatist (Honey and Mumford, 1982); Kolb learning model groups learners as concrete experience or abstract conceptualization, active experimentation or reflective observation (Kolb, 2015); VARK learning styles groups learners as visual, aural, read/write, and kinesthetic (Fleming, 2014).

According to Zhong-Lin and Barbara (2007) cognitive style is a variation in an individual's manners of perceiving, remembering, and thinking. Kellogg (2012) identifies the main cognitive processes as sensation, attention, memory, learning, remembering, and forgetting. The studies in learner behavior modeling have used both manual and automatic methods to identify learner characteristics. In manual detection, a questionnaire corresponding to a learning style model, in which individuals fill their answers to identify their learning styles, is used. Cognitive assessment tests are also administered to identify different types of behavior such as memory, concentration, reasoning, and planning based. However, it is almost certain that manual measurements have psychometric flaws. They are prone to errors, require resources to administer and consume a lot of time to fill.

Concerning the automatic modeling method, the actual actions of students when accessing an online course are analyzed to infer students' behavior. Several studies investigating learner behavior in LMS have been carried out. More recently, Şahin et al. (2020) utilized the ELECTRE TRI method to classify the learners based on the interaction data gathered from LMS and concluded that there was a correlation between the categories investigated and the real-life classification. In another related study, Ferreira et al. (2019) used machine learning algorithms to analyze data from the Moodle LMS and characterized the learning profiles of students according to the Felder-Silverman Learning Style Model (FSLSM). Troussas, Chrysafiadi, and Virvou (2020) combined the Visual, Auditory, Reading/Writing, and Kinesthetic (VARK) learning style model and the Herrmann Brain Dominance Instrument (HBDD) to model the sensory modalities of learning and the way of thinking. Even though complex models have been proposed in the literature, most studies are based on a single behavior such as learning style or cognitive traits but not both. Only a few such as Nakić et al. (2015) investigated a combination of cognition-based theories such as working memory capacity and psychology-based ones such as learning styles. Thus, the studies highlight the need for further research in learner behavior modeling.

It is worth noting that LS models have been criticized by some authors. For instance, Pashler et al. (2009) argued that many versions of learning styles models had not been tested at all. Kirschner (2017) further questioned the existence of students with diverse learning preferences. In contrast, Felder and Spurlin (2005) reported that the ILS was a reliable and valid tool for measuring learning styles. FSLSM has been used to date in several studies involving learner behavior modeling in LMS such as Aissaoui et al. (2018), Abdelhadi et al. (2019), and Ferreira et al. (2019).

This study adopted a hybrid of the Felder-Silverman Learning Styles Model (FSLSM) and Cognitive Traits Model (CTM) as theoretical frameworks. Analysis from the literature shows the two are the most researched and validated with LMS to model CT (Kinshuk, Lin and McNab, 2004, 2006; Lin et al., 2007; Lin and Kao, 2018) and LS (Graf et al., 2009; Graf et al., 2013; Aissaoui et al., 2018) thus acceptable.

The study sought to answer the research question: is it possible to establish a methodology for the estimation of learning styles and cognitive traits from LMS records? The study combined the Felder-Silverman Learning Style Model (FSLSM) and Cognitive Trait Model (CTM) to identify behavior in an LMS. FSLSM profiles a learner as active or reflective, sensing or intuitive, sequential or global, and visual or verbal (Felder, 1988). The model uses a 44 - questions Index of Learning Styles Questionnaire (ILS) with 11 for each dimension as a manual measurement tool. A student selects choice a or b. The questionnaire score sheet classifies a respondent as 1–3 mild, 5–7 moderate, 9–11 strong preference for either dimension. The cognitive Trait Model (CTM) on the other hand profiles a learner based on associative learning ability, working memory capacity, inductive reasoning ability, and Information processing speed (Graf et al., 2009).

The first objective of this study was to design a model based on LS and CT. The second objective was to develop a prototype implementing the model. The third objective was to evaluate the developed model using a case study and analyze the results. This paper presents a model for extracting records from LMS access records to estimate LS and CT based on FSLSM and CTM dimensions. A prototype was developed to estimate LS and CT for each student. The results evaluated using the Kappa statistic demonstrated the interrater reliability results were moderately in agreement.

The rest of the paper has been organized as follows. Section 2 discusses the proposed model. Section 3 discusses the implementation and evaluation. Section 4 discusses the results. Section 5 discusses the conclusions and suggests future work. Throughout this paper, the acronym LS will refer to learning styles. CT will refer to cognitive traits. CTM will refer to Cognitive Trait Model. FSLSM will refer to the Felder-Silverman Learning Style Model. SCORM will refer to the Sharable Content Object Reference Model. LMS will refer to learning management systems.

2. Proposed model

The initial objective of this study was to design a learner behavior model complementing LS with psychology-based ones such as CT. In this section, we present a model based on the FSLSM and CTM that analyses student access records generated by LMS to estimate LS and CT. As stated in the previous section, the two theories are well researched and validated with promising evaluation results in many similar studies such as Bernard et al. (2017), Lin (2007). Figure 1 illustrates the working mechanism of the model. First, the model extracts records of students' access from learning content hosted in LMS. Second, it maps access patterns to relevant LS and CT dimensions described in FSLSM and CTM respectively. Third, it estimates and displays LS and CT for each student.

To understand the model implementation process, it is important to explain the log data used to implement the prototype. As indicated in Figure 1 above, the learning resources hosted in an LMS are the source of data for implementing and testing the model. These are electronic books prepared in SCORM format and hosted in an LMS. The first component of each book section contains introductions, objectives, and outlines of the topics covered. The second part of the book section covers the definition of concepts. The third section has topics and subtopics. These are pages with concepts and facts discussed in detail. Activity questions appear at the end of each topic. Finally, each section ends with a summary of the topics discussed. Some content pages consist of illustrations and pictures.

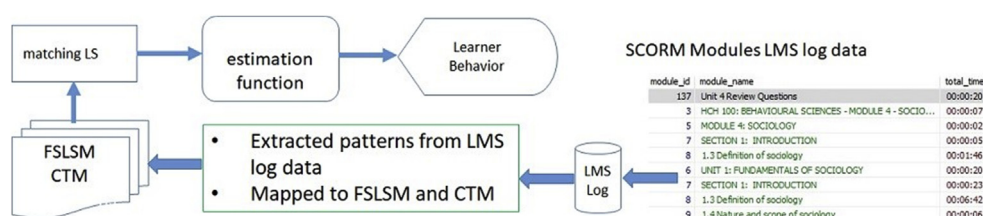


Figure 1. LS and CT detection process.

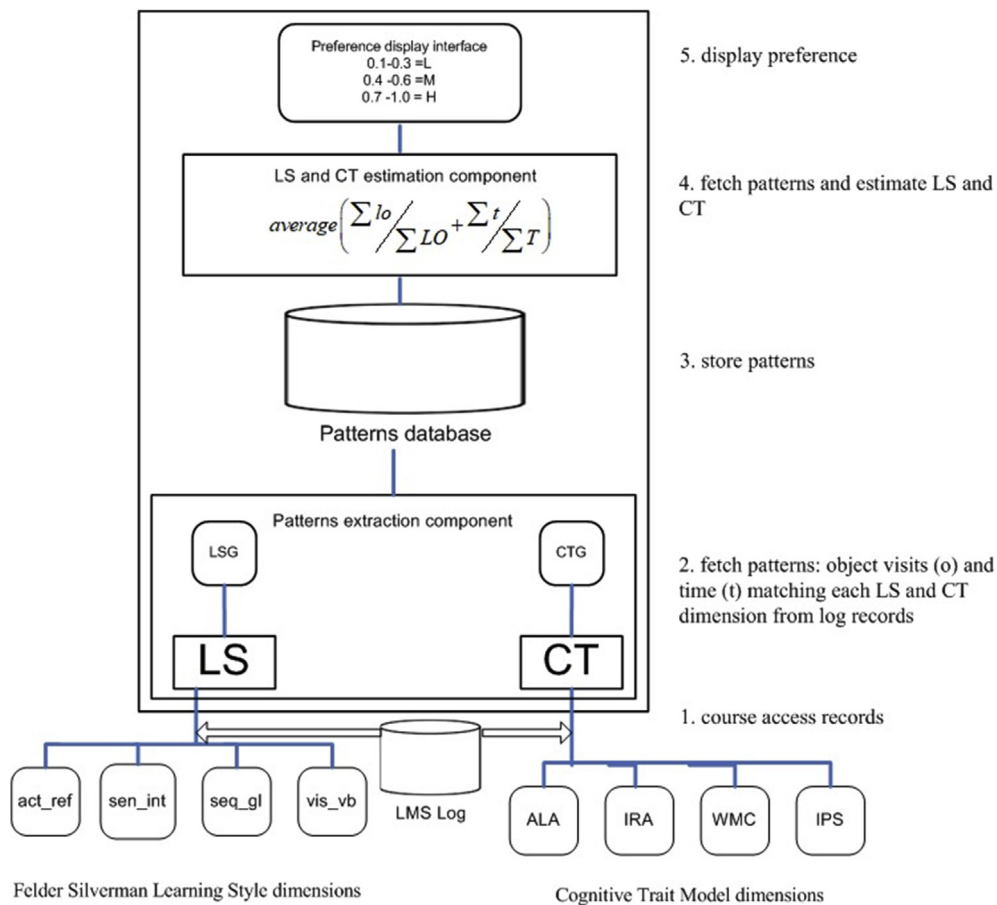


Figure 2. Model architecture.

Figure 2 illustrates the layout of an electronic learning module hosted on a Learning Management System. The navigation window displaying a list of book pages appears to the left. Learning content is displayed on the right when a user selects the page. The sample log data extracted from LMS records appear in table 12 in the appendices. The table shows the number of relevant content pages viewed and the times spent. These are introductions and overviews, definitions, topics, activities, summaries, and illustration pages viewed. The average grade a student scored in online tests and attempts was recorded. The table also indicates the average grade scored in online tests and the overall number of content pages in percentage viewed by a student. Table 13 in the appendices shows sample log data on content navigation. The table shows the ratio of pages that are viewed once or revisited by a student out of the total. These formed the dataset for identifying and estimating LS and CT as explained in section 3.

Figure 2 above shows the components of the model. LS and CT pattern extraction engines fetch relevant LS and CT from the LMS log database. Learning Style Generator (LSG) and Cognitive Trait Generator (CTG) engine receive data from pattern extraction component, calculate then map results to 3 item scale: 0.1–0.3 low, 0.4–0.6 moderate, and 0.7–1.0

high and 0.0 – no preference. The behavior for both LS and CT is combined and displayed for each student.

3. Implementation

The second objective was to develop a prototype implementing the above model. First, the study participants were identified. The participants accessed an online course hosted on an LMS for a 15-week semester. Records of the participant's interaction with the LMS were analyzed and used to implement the model. The following sections describe participants, course information, and the model development process.

3.1. Participants and course information

The study was conducted on the 600 first-year students taking Bachelor of medicine and bachelor of surgery degrees in the academic year 2017/2018 at the University of Nairobi. Usually, the students taking a degree in Bachelor of Medicine and Bachelor of Surgery at the University of Nairobi study a common medical psychiatry unit in behavioral

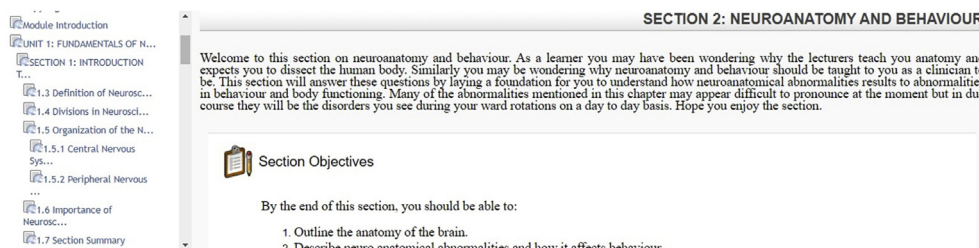


Figure 3. A course interface in SCORM format.

• Name :
 • First name : SADIK
 • Email : aashna.mithwani@gmail.com

Module	Last session time	Total time	Module status	Progress
HCH100: BEHAVIOURAL SCIENCES - : NEUROSCIENCES	00:00:09	00:00:09	completed	100%
Copy Right	0000:00:00	0000:00:00	not attempted	0%
Module Introduction	00:01:28	00:01:28	completed	100%
UNIT 1: FUNDAMENTALS OF NEUROSCIENCES AND BEHAVIOUR	00:02:38	00:02:38	completed	100%
SECTION 1: INTRODUCTION TO NEUROSCIENCES	00:00:34	00:00:34	completed	100%
1.3 Definition of Neurosciences	00:00:35	00:00:35	completed	100%
1.4 Divisions in Neurosciences	00:00:37	00:00:37	completed	100%
1.5 Organization of the Nervous System	00:00:10	00:00:10	completed	100%
1.5.1 Central Nervous System	00:00:14	00:00:14	completed	100%
1.5.2 Peripheral Nervous System	00:01:26	00:01:26	completed	100%
1.6 Importance of Neuroscience in Medicine	00:00:45	00:00:45	completed	100%
1.7 Section Summary	0000:00:00	0000:00:00	not attempted	0%
SECTION 2: NEUROANATOMY AND BEHAVIOUR	00:01:01	00:01:01	completed	100%
2.3 Anatomy of the Brain	0000:00:00	0000:00:00	not attempted	0%
2.3.1 Basal Ganglia	00:00:13	00:00:13	completed	100%
2.3.2 Meninges	00:00:35	00:00:35	completed	100%
2.3.3 Neurons and Glia	00:00:56	00:00:56	completed	100%
2.3.4 Thalamus, Hypothalamus and Pineal Body	00:05:15	00:07:55	completed	100%

Figure 4. The content navigation statistics.

science. The course unit is divided into 10 learning modules taken over one year. The learning modules are psychology, social processes, foundations of human behavior, social processes, sociology, social psychology, anthropology, physical illness causing the behavior, neurosciences, and healthcare systems. The learning modules are converted to SCORM format and hosted on a university LMS running on the Claroline open-source platform (Claroline, 2017).

Figure 3 below shows an example of the course page interface in the LMS used in the study.

In Figure 3 above, the contents of the online learning modules are systematically arranged by instruction designers to enable easy navigation. Each learning module is divided into sections, topics, and subtopics. Activity questions are provided after each topic to test learners' understanding. The course contents have both textual and visual information. Figure 4 below shows content navigation statistics. The LMS tracking tool records the time taken on each page and the status as complete or incomplete. A single page viewed by a student is marked as complete or incomplete. The page that is viewed is assigned a numerical value of 100%. Any page which is not visited is assigned status 0.

3.2. Data collection procedures

Once the online learning modules were hosted on the university LMS, the students accessed the psychology and sociology modules for a period of 15 – week semester. Two online tests in multiple-choice questions (MCQ) formats were administered to students on the LMS in the mid-semester and at the end. Each test had 100 questions and students were instructed to answer all. The tests were scheduled to last for two hours. The LMS was programmed to automatically submit answers entered by

each student when allocated time elapsed. The MCQs were preferred because the LMS could automatically mark and generate the mark sheet upon submission of the answers. Figure 5 a below shows sample questions.

As indicated in the sample mark sheet in Figure 5 b below, the LMS records the minimum, maximum, and average grades for each student. The time spent is also recorded for each student by the LMS.

Data was collected from the LMS and analyzed to identify learner behavior. Only students who viewed the online resources by visiting revision pages, outlines, summaries, and attempted quizzes were considered for the study. Approximately 200,000 log records of 311 students who satisfactorily accessed the learning modules for a 15-week semester were extracted from the system to create a dataset. Access records of instructional materials and tests were analyzed to identify patterns. The patterns were used as hints matching descriptions of FLSM and CTM.

To evaluate the model, Index of Learning Styles (ILS) Questionnaires and Online Cognitive Multiple Choice Questions were also administered. The evaluation process is discussed in section 3.6 of this paper.

3.3. Extracting data patterns from log

The study analyzed navigation records on learning contents and online assessment tests to identify patterns from the LMS database. The annotations were done on the records to match the descriptions of FLSM and CTM. Table 1 and Table 2 show how each of the patterns was mapped to FLSM and CTM dimensions.

Table 1 above shows each dimension of FLSM, description, learning object investigated and pattern extracted. According to FLSM, an active

► Exercise : BEHAVIOURAL SCIENCES MID SEMESTER 1 TEST (MCQS)1

- Maximum allowed time : 2 h.
- Attempt 1 on 2
- Available from November 24, 2017 at 12:58 PM until November 24, 2017 at 06:00 PM

Question 1

82. A 12 year old boy repeatedly wakes up in the middle of the night screaming, but could recall only fragments of any mental images. He appears to be disoriented for several minutes on waking.

1. A 12 year old boy repeatedly wakes up in the middle of the night screaming, but could recall only fragments of any mental images. He appears to be disoriented for several minutes on waking. Which of the following diagnosis is the most appropriate?

Nightmares
 Night terrors
 Sleep apnoea
 Narcolepsy
 REM sleep behavioural disorder

Multiple choice (Unique answer)

Question 2

59. The highest need in Maslow's hierarchy is:

Safety
 Biological
 Attachment
 Self actualization

Figure 5. a. sample MCQ.

Table 1. Investigated patterns for LS. Visits indicate the number of times a relevant page is viewed. Time indicates how long the page was viewed.

FSLSM	Description of LS	Learning objects considered	Pattern extracted
active	Likes trying out things with what is learned	activities, exercise	Visits and time
reflective	revisits materials learned	summaries, conclusion, revisions	Visits and time
sensing	Uncomfortable with challenges but likes details	Topics and subtopics	Visits and time
intuitive	Comfortable with challenges, but dislikes details	Definitions, meanings	Visits and time
verbal	Likes reading written text	Textual contents	Visits and time
visual	Likes viewing images	Images, illustrations	Visits and time
global	Reads by skipping content; wants to see the full picture of the content	Introductions, overviews, outline	Navigation order, visits, and time
Sequential	Reads the content section by section skipping	introductions, content, summary pages	Navigation order, visits, and time

Table 2. Investigated patterns for CT. Visits indicate the number of times a relevant page is viewed. Time indicates how long the page was viewed.

CTM dimension	Description of CT	Learning objects considered	Pattern extracted
Associative learning ability	ability to link new to existing knowledge	Revisited pages, pages visited once	Visits and time
Working memory capacity	ability to briefly concentrate and keep information read	Forward navigation, backward navigation	Visits and time
Inductive reasoning ability	ability to understand and create concepts from examples	Examples	Visits, time
Information processing speed	How fast a learner retrieves information from the memory and makes the correct decision with it	Exercises	Attempts, time, score

learner likes trying out things; a reflective learner thinks about materials read. A student who spent time viewing content with activities was considered an active learner; a student who spent time on content with summaries, conclusions, and revisions was considered a reflective learner.

A sensing learner dislikes challenging tasks but is patient with details; an intuitive learner likes challenges but is impatient with details. A student who spent time viewing content with topics and subtopics was considered a sensing learner; a student who spends time on content with definitions and meanings was considered an intuitive learner.

A verbal learner likes text-based content; a visual learner likes illustrations and pictures. A student who spent time viewing content with text-based pages only was considered a verbal learner; a student who spends time on content with illustrations was considered a visual learner.

A global learner likes getting the full picture of the content; a sequential learner likes navigating content step by step. A student who spent time viewing content with introductions, overviews, and content outlines was considered a global learner; a student who followed the content pages systematically by accessing overviews, followed by topics then summary pages was considered a sequential learner.

Table 2 above shows each dimension of CTM, description, learning object investigated and pattern extracted.

According to CTM, an associative learner likes linking new to existing knowledge. The number of visits and time spent viewing already visited content pages was considered a sign of associative learning. A student who spent time viewing already read content was assumed to have a high associative learning ability.

Working memory capacity tests the ability to keep a limited amount of information for a brief period. The number and time spent navigating content page forward was considered signs of high working memory capacity. Such a student was able to concentrate on a reading task. A student who viewed the content without revisiting previously read pages was assumed to have a high working memory capacity.

Inductive reasoning is the ability to construct concepts from examples. The number of visits and time spent viewing content with examples was considered a sign of inductive reasoning. A student who spent time viewing content with examples was assumed to have inductive reasoning ability.

Information processing speed checks how fast the learner acquires and uses the information to make the correct decision. The number of attempts marks scored, and time spent on online tests was considered an indication of information processing speed. A student who took a short time on online tests with few attempts but scored high marks was assumed to have high information processing speed.

Table 3. LS estimation functions.

FSLSM	Relevant Learning Object	Pattern extracted	Estimation function for average ratio.
Active (a)	Activities, exercises	object visits (o) and time (t)	$average\left(\frac{ta}{ta + tr} \cdot \frac{oa}{oa + or}\right)$
Reflective(r)	summaries, conclusion, revisions	object visits (o) and time (t)	$average\left(\frac{tr}{ta + tr} \cdot \frac{or}{oa + or}\right)$
Sensing (s)	Topics and subtopics topics	object visits (o) and time (t)	$average\left(\frac{ts}{ts + ti} \cdot \frac{os}{os + oi}\right)$
Intuitive(i)	Definitions, meanings	object visits (o) and time (t)	$average\left(\frac{ti}{ts + ti} \cdot \frac{oi}{os + oi}\right)$
Verbal(v)	Textual content	object visits (o) and time (t)	$average\left(\frac{tv}{tv + tv_i} \cdot \frac{ov}{ov + ovi}\right)$
Visual(vi)	Images, illustrations	object visits (o) and time (t)	$average\left(\frac{tvi}{tv + tv_i} \cdot \frac{ovi}{ov + ovi}\right)$
Global(g)	Introductions, overviews, outline	object visits (o) and time (t)	$average\left(\frac{tg}{tg + tsq} \cdot \frac{og}{og + osq}\right)$
Sequential(sq)	Introductions, topics, summary	object visits (o) and time (t)	$average\left(\frac{tsq}{tg + tsq} \cdot \frac{osq}{og + osq}\right)$

Table 4. CT estimation functions.

CTM dimension	Relevant Learning Object	Pattern extracted	Estimation function
Associative learning	Revisited pages, pages visited once	Visits and time	$average\left(\frac{trp}{trp + ts}, \frac{orp}{orp + os}\right)$
Working memory capacity	Forward navigation, reverse navigation	Visits and time	$average\left(\frac{tr}{tr + tf}, \frac{or}{or + of}\right)$
Inductive reasoning ability	Examples, revision, and exercises	Visits, time	$average\left(\frac{ti}{T}, \frac{o}{O}\right)$
Information processing speed	Exercises	Attempts, time, score	$average\left(\frac{t}{T}, \frac{a}{A}, \frac{s}{S}\right)$

3.4. Behavior estimating from patterns

Using the automatic behavior estimation method proposed by Pham and Florea (2013) patterns above were used to estimate LS and CT by computing the average ratio of total learning objects accessed and time spent by each student. The following steps describe the estimation procedure.

3.4.1. Estimating LS

For matching pairs of learning preferences such as active-reflective, sensing-intuitive, sequential-global, and visual-verbal, the LS was computed based on the following steps:

- i. Time on learning objects relevant to an LS dimension (t) (e.g. active or reflective) out of total time spent in all objects (T) $\frac{\sum t}{\sum T}$ (e.g. active + reflective)
- ii. Number of visits on a learning object relevant to an LS (lo) (e.g. active or reflective) dimension out of total objects accessed (LO) $\frac{\sum lo}{\sum LO}$ (e.g. active + reflective)
- iii. Compute average ratio from step 2 $average\left(\frac{\sum lo}{\sum LO} + \frac{\sum t}{\sum T}\right)$
- iv. Map to 3 item scale: 0.1–0.3 -low, 0.4–0.6 moderate and 0.7–1.0 high to get appropriate preference

Table 3 below shows the estimation procedure for each CT dimension.

3.4.2. Estimating CT

For matching pair of CT patterns such as pages revisited vs visited once for associative learning or forward vs backward navigation for working memory, the CT was estimated based on the following steps:

- i. Time on learning objects relevant to a CT dimension (t) (e.g. revisited vs visited once for associative learning or forward vs backward navigation) out of total time spent in all objects (T) $\frac{\sum t}{\sum T}$

(e.g. revisited + visited once for associative learning or forward + backward navigation)

- ii. Number of visits on a learning object relevant to CT (lo) (e.g. revisited vs visited once for associative learning or forward vs backward navigation) dimension out of total objects accessed (LO) $\frac{\sum lo}{\sum LO}$ e.g. revisited + visited once for associative learning or forward + backward navigation)
- iii. Compute average ratio from step 2 $average\left(\frac{\sum lo}{\sum LO} + \frac{\sum t}{\sum T}\right)$
- iv. Map to 3 item scale: 0.1–0.3 -low, 0.4–0.6 moderate and 0.7–1.0 high to get appropriate preference

For inductive reasoning ability, summation $average\left(\frac{ti}{T} + \frac{o}{O}\right)$ time spent on relevant objects (ti) and total objects accessed (o) out of the total time (T) and total objects (O) were considered. For information processing speed, summation $average\left(\frac{t}{T}, \frac{a}{A}, \frac{s}{S}\right)$ time spent (t), attempts (a), and score (s) out of the total time (T), total attempts (T), and the total score (T) for relevant objects were considered.

Table 4 shows the estimation procedure for each CT dimension.

3.5. Prototype development

A web-based system was developed based on the above estimation functions. The prototype was developed using the MYSQL database and the PHP scripting language. The model initiates the connection to the MYSQL database, fetches data, and computes LS and CT then displays preference. The MYSQL database and the PHP scripting language are open-source tools thus available for use free of charge. Figure 6 below shows the model's interface functionality.

From Figure 6 above, a user can initiate a search by entering the identification or registration number. As shown in Figure 6 above, a student with user id 224043, for instance, is strongly reflective 0.74 than active 0.26, sensing 0.74 than intuitive 0.31, visual 0.78 than verbal 0.15, sequential 0.85 than global 0.15, with strong associative learning

user_id	Worst score	Best score	Average score	Attempts	Average Time
280780	22	22	22	2	11 min. 12 sec.
280916	22	26	24	2	16 min. 46 sec.
285803	26	26	26	1	21 min. 3 sec.
280765	29	29	29	1	6 min. 52 sec.
289275	30	33	31.5	2	11 min. 58 sec.
285582	15	15	15	1	25 min. 47 sec.
267075	11	27	19	2	11 min. 34 sec.

Figure 5. b. The sample mark sheet.

Know Your Learning Behavior

userid	active	reflective	sensing	intuitive	verbal	visual	sequential	global	LS CT	ALA	WMC	IPS	IRA
224043	0.26	0.74	0.69	0.31	0.22	0.78	0.15	0.85	**	1.00	0.99	0.54	0.33

Figure 6. Model interface functionality.

1.00, strong working memory capacity 0.99, moderate information processing speed 0.54 and weak inductive reasoning 0.33. A lecturer can use such information to provide appropriate learning materials, apply appropriate tutoring methods, and provide individualized attention matching learner behavior. A student on the other hand uses the above information for self-awareness to apply appropriate study methods and choose appropriate learning materials.

3.6. Evaluation

As mentioned in the introduction section, the third objective was to evaluate the developed model using a case study and analyze the results. The evaluation was done by administering manual tools to students then comparing the results gathered against those estimated by the model. The performance of the prototype was evaluated using experiments done with students in a classroom environment. A total of 200 students taking bachelor of medicine and bachelor of surgery participated. The group was part of the 311 students who had actively accessed the psychology and sociology learning modules and did online tests during course work. Only 200 students were available and readily accessible through the course lecturer. The first experiment was done to evaluate the learning style results generated by the prototype. Index of Learning Styles Questionnaires (ILS), a standard measurement tool for FLSM were administered to students which they filled and returned. Learning styles for each student were calculated and analyzed. The second experiment was done to evaluate the cognitive traits generated by the system. Online Cognitive Multiple Choice Questions based on a method adapted from Cambridge Brain Sciences (Cambridge Brain Sciences, 1998) were created and hosted in the university LMS. Four categories of tests were administered. Paired associate tests, spatial span tests, abstract reasoning tests, and mental speed tests were created on university learning management systems to evaluate associative learning ability, working memory capacity, inductive reasoning ability, and information processing speed respectively. Cognitive traits were determined in terms of marks scored in the test classified as low, moderate, and high. These were compared to CTM results predicted for the same students by the model.

The interrater reliability test was done to measure the agreement between the behavior gathered through the Index of Learning Styles Questionnaires (ILS), Online Cognitive Multiple Choice Questions, and those estimated by the model. The test was conducted to determine how well the implementation of the model was in agreement with the traditional methods. The reliability analysis was done using the Kappa statistic to determine consistency among raters. Kappa statistic as a method was selected because it is the metric frequently used to assess the agreement between two raters (Cohen, 1960). The study opted for the kappa coefficient as the most suitable method for the assessment of the model because the extent of agreement between predictions made by the psychometric tools and the model could be established.

The analysis was performed using the Statistical Package for the Social Sciences (SPSS) software (version 1.1.463). According to Landis and Koch (1977) values of Kappa between less than 0 indicates there is no agreement. Values 0.0 and 0.20 indicates slight agreement. Values between 0.21 and 0.40 indicate fair agreement. Values between 0.41 and 0.60 indicate moderate agreement. Values between 0.61 and 0.80

indicate substantial agreement. Values between 0.81 and 1.00 indicate almost perfect agreement.

4. Results and discussions

As indicated in the previous section, the study was designed to compare the LS and CT estimated by the model against those gathered by the ILS and online cognitive tests.

Tables 5–11 in the appendices section show the interrater reliability analysis results for LS and CT. As shown in table 5, the results of the interrater reliability for the active-reflective raters were found to be Kappa = 0.260 ($p < .018$). This indicates a fair agreement between the students predicted by the model as active-reflective compared to the data collected through the ILS questionnaire. The results of the interrater reliability for the sensing-intuitive raters were found to be Kappa = 0.595 ($p < .002$) as shown in table 6. This indicates a moderate agreement between the students' LS predicted by the model as sensing-intuitive compared to the data gathered through the ILS questionnaire. The results of the interrater reliability for the sequential - global raters were found to be Kappa = 0.326 ($p < .004$) as shown in table 7. This indicates a fair agreement between the LS for students predicted by the model as sequential - global compared to the data gathered through the ILS questionnaire. The study did not do the interrater reliability test on the visual-verbal learning style since all students indicated a preference for visual content.

Concerning CT evaluation, the results of the interrater analysis of Kappa = 0.012 with $p < 0.640$ were recorded for associative learning ability as shown in table 8. This indicates a slight agreement between the behavior of students predicted by the model compared to the data gathered through the online cognitive multiple-choice questions. The results of the interrater analysis of Kappa = 0.455 with $p < 0.067$ were recorded for information processing speed as shown in table 9. This indicates a moderate agreement between the behavior of students predicted by the model compared to the data gathered through the online cognitive multiple-choice questions. The results of the interrater analysis of Kappa = 0.224 with $p < 0.052$ were recorded for inductive reasoning ability shown in table 10. This indicates a fair agreement between the behavior of students predicted by the model compared to the data gathered through the online cognitive multiple-choice questions. The results of the interrater analysis of Kappa = 0.455 with $p < 0.067$ were recorded for working memory capacity as shown in table 11. This indicates a moderate agreement between the behaviors of students predicted by the model compared to the data gathered through the online cognitive multiple-choice questions.

Interestingly, results based on LS are more statistically significant than CT. However, the results for associative learning ability and information processing speed were not statistically significant. A possible explanation for this could be the psychometric flaws associated with the measurement tools. It seems possible that some students experienced challenges when attempting the online cognitive tests used to access CT. Since the study was conducted on first-year students who were new to the university, it may be that some students were unable to use the computer well and this affected the response to the online tests.

The findings in this study support the previous research in this area which links LMS records to learner behavior such as LS and CT. The method validates the ideas of Şahin et al. (2020) who classified the

learners based on the interaction data gathered from an LMS. The author analyzed the relationship between the classification based on the ELECTRE TRI method and the classification in real life. The ELECTRE TRI method is a multi-criteria decision-making technique designed to classify the learners based on the interaction data in different units. The classification results in the ELECTRE TRI method were compared to the real-life classification, which showed a medium-level correlation. This also supports our findings which showed that there was a moderate agreement between the behavior of students predicted by the proposed model compared to the data gathered through the online cognitive multiple-choice questions.

The results are also in agreement with Aissaoui et al. (2018) who extracted learning sequences from learners' log files and classified the extracted records according to FLSM using clustering algorithms. The study reported 88.61 % 89.93 % 92.35 % 88.97 % accuracy, precision, recall, f-measure. One difference between this study and that of Aissaoui et al. (2018) is that the reliability analysis was done using the Kappa statistic while their study used precision, recall, and f-score. The prediction success rates in our study are, slightly lower than the previous studies cited above. This study proposed a mathematical method for estimating the learners' behavior based on the time spent on the content and the number of objects visited while the previous studies used machine learning models. The results are expected to improve after further data cleaning to remove impurities from LMS records.

5. Conclusion

This study set out to determine a methodology for estimating learning styles and cognitive traits from LMS access records. In this paper, we presented a model for the automatic identification of learner behavior in LMS records. The model takes advantage of data collected from the LMS log, education theories, and literature-based methods to automatically estimate learning styles and cognitive traits. This brings forth a generic modeling architecture that developers can integrate with existing learning management system platforms to improve learner characterization. The interrater reliability test was done to compare the agreement between the behavior gathered through the Index of Learning Styles Questionnaires (ILS), Online Cognitive Multiple Choice Questions, and those estimated by the model. Taken together, these results suggest that it is possible to estimate the LS and CT an LMS. Whilst the study did not confirm a perfect match between behavior gathered through the Index of Learning Styles Questionnaires (ILS), Online Cognitive Multiple Choice Questions, and those estimated by the model, it did partially substantiate that the interrater reliability results were moderately in agreement. The results can be improved with more data cleaning and refinement.

The results of this study have implications for online instructional design and teaching. An online instructor can use the information generated to design and develop appropriate instructional materials matching appropriate LS and CT preferences. According to Churngchow et al. (2020), learners from different disciplines have different learning styles. Such learners need the instructional materials matching their learning preferences. Malacapay (2019) reported that both visual and auditory learners learned best when subjected to audio-visual contents while kinesthetic learned best when exposed to actual objects. On the same note, an online instructor can use the information generated by the model to form online learning groups for students with similar LS and CT to improve learning outcomes. According to Mutrofin et al. (2017), the group learning approach results in a better learning outcome than the lecture-discussion method. Thus an instructor can form online learning groups according to the respective preferences and prepare the learning materials relevant for each group. Research also reports that students find it easy to understand difficult concepts when they learn in groups (Wikle and West, 2018). On the same note, an online instructor can use the information generated by the model to improve the social interaction among online learners. A recent study carried out by Mahmoud Hawa and Tilfarloğlu (2019) reported that

the learners' preferred learning styles had a relationship with their self-efficacy and social interactions.

The study has some limitations. First, data used in the study was collected from log records of 311 students who satisfactorily accessed learning modules for a 15 – week semester. Second, the study evaluation was conducted only on 200 preclinical students. Further studies might be carried out with more students from other disciplines to further validate the findings. Another important issue to resolve for future studies is developing a real-time model integrated with an LMS to estimate LS and CT.

Future work involves automatically mapping e-Learning course content to respective learning styles and cognitive traits. Additional evaluations may also be carried out to properly validate the model.

Declarations

Author contribution statement

C. Lwande, L. Muchemi, R. Oboko: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Wrote the paper.

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The authors declare no conflict of interest.

Additional information

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