Decision Support System Framework for Personalized Adaptive Learning based on Behavioral Modelling

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Abstract - Learning style (LS) is a method of how students receive and process information. It describe how they collect, sift through, organize and interpret the information. Each student has a different LS, thus teachers are now prioritizing identifying the LS of students. An appropriate learning method can engage and sustain students' interest and further enhance their academic achievement. The conventional method using questionnaires to identify LS is ineffective where students may have differences in understanding and interpretation while it is hard to convey feelings and emotions on paper. To overcome the limitations of questionnaires, this study proposed an automated approach to identify LS based on student's behavior. A Decision Support System (DSS) is experimented on user behavior demonstrating their unique LS. The framework of the LS detection is based on student behavioral modeling and employs the parameters of student behavior under the visual-auditory-kinesthetic (VAK) model. The proposed framework considers three main phases: identifying the behavior of each learning style, determine the learning style of the behavior, and predicting the learning style. The framework is implemented on an application which was developed with three modules: the interface, process, and decision modules, which serve as a DSS tool to automatically predict the LS of students as the users. This paper presents the framework of VAK and the architectural model of DSS to automatically identify student's LS as a tool to assist teachers in providing correct guidance to students based on their unique LS. The experimental results will be presented in future publication.

Keywords: Adaptive learning, behavioral modeling, decision support system, learning style detection, visual-auditory-kinesthetic (VAK) model.

1. Introduction

Decision Support System (DSS) is able to assist decision makings for which predetermined solutions are unknown by using certain models and data analysis. It is very crucial to get the right models for accurate results. In addition, the pattern mapping of system usage behavior also affects the final decision (Deborah, Sathiyaseelan, Audithan, & Vijayakumar, 2015; El Guabassi, Bousalem, Al Achhab, & EL Mohajir, 2019; Khademolqorani & Hamadani, 2013; Nihad, Mohamed, & El Mokhtar, 2020). Thus, analyzing consumer behavior is important to help decision-makers select alternatives and more accurately predict future decisions. Examples of techniques used in behavioral modeling are the decision tree, neural network, fuzzy set, the bayesian network, and rule-based techniques (Ahmad, Tasir, Kasim, & Sahat, 2013; El Mokhtar & Abdelhamid, 2019; Graf, Kinshuk, & Liu, 2009; Graf, Kinshuk, & Liu, 2008; Maylawati, Priatna, Sugilar, & Ramdhani, 2020). The Rule-based technique (RBT) is one of the techniques to form knowledge rules from user behavior without involving user set data. The effectiveness in improving decision quality has also been proven in individual preferences detection as shown in a previous research (Jonassen & Grabowski, 1993; Rathore & Arjaria, 2020). In learning style detection, RBT is a commonly used and appears to be more practical when the focus is more on the content of the activities. The calculation of learning styles is also based on the simple rules and does not involve the design of the system.

Behavioral patterns can be applied in the decision-making process to determine learning styles. This is because learning styles are a way that people focus and act to process and acquire new information, knowledge, or experiences. According to a previous studies (Dunn & Dunn, 1978; Good & Lavigne, 2017; Manning, Baruth, & Lee, 2017; Slavin, 2019), each student has his or her own needs and traits including different learning styles. This difference causes the students to have different ways of acquiring knowledge. In this context, students have different ways of learning based on the learning theory, learning styles, and their psychological state. Indirectly, the relationship between learning styles in the learning environment facilitates the learning process and enhances academic achievement (El Mokhtar & Abdelhamid, 2019; Graf et al., 2008; Jonassen & Grabowski, 1993; Rathore & Arjaria, 2020).

Large class sizes, high workloads, and time constraints are the challenges in the traditional classroom setting that provides difficulties for teachers to provide different guidance or teaching style to students with different LS. An appropriate learning techniques to students' learning styles can motivate the students and improve academic achievement (Estriegana, Medina-Merodio, & Barchino, 2019; Graf et al., 2008; Zainuddin, 2018). Therefore, this paper introduces an automatic learning style detection system to solve the issue. The student can use this system independently at any time according to his or her needs to help the teacher identify his or her learning style. In specific, this study focused on an automated approach that identifies the student learning styles based on student behavior in the learning process. The main objective of this study is to propose a framework for learning style detection based on the leaners' behavioral pattern. The architectural system for the detection of Visual, Audio, and Kinesthetic (VAK) learning styles was based on learner behavioral patterns and Rule- based techniques.

The paper is structured into five sections. A related study of the main concept, such as the learning style models, behavioral modeling, and Rule-based techniques, are presented in Section 2. The proposed framework is discussed in detail in Section 3, while Section 4 demonstrates the proposed architecture. The conclusion is presented in Section 5.

2. Related Works

This section presents the previous studies related to the basic theory of learning styles. The scope of discussion also includes the basic process, automatic detection, and the importance of detecting student learning styles.

2.1 Learning Style

Studies in cognitive and psychological sciences indicate that individuals have different capabilities that determine the way and the tendencies they receive and process information (Graf et al., 2008; Khandaghi & Farasat, 2011; Maylawati et al., 2020; Surjono, 2014). In the learning environment, this tendency is known as learning style, which is the way an individual concentrate on, processes, and retains new information and difficult information (Chetty et al., 2019; Dunn & Dunn, 1978; Yassin & Almasri, 2015). Learning style is also said to be the strategy that an individual use in dealing with the environment and learning materials. This strategy is designed to elicit the individual's respective learning style (Azzi, Jeghal, Radouane, Yahyaouy, & Tairi, 2020; Liyanage, KS, & Hirakawa, 2016; Surjono, 2014).

The interaction between the learning style with the structure of the teaching material and the type of content affects learning achievement. Teaching methods that match a student's learning style have led to better academic achievement (Dincol, Temel, Oskay, Erdoğan, & Yılmaz., 2011; Övez & Uyangör, 2016; Riding & Rayner, 2013). According to a study (Graf et al., 2009), learning styles indicate the way people begin to concentrate, process, and remember any difficult or new information. Commonly, most students have a unique learning style, it is important for teachers to recognize and understand the differences in student learning styles (Felder & Silverman, 1988; Jonassen & Grabowski, 1993; Khandaghi & Farasat, 2011; Rathore & Arjaria, 2020). There are more than 71 types of learning style models that have been identified from previous studies (Khan, Weippl, & Tjoa, 2009; Kolb, 2014; Liyanage et al., 2016; Surjono, 2014). Among them include the Kolb, Dun and Dun, Felder Silverman, and Visual, Auditory, and Kinesthetic (VAK) learning styles. This study focuses on the VAK learning style.

2.2 Visual, Auditory and Kinesthetic (VAK) Learning Style Model

The VAK learning style model was introduced in a previous studies included three types of learning styles that are often used by students in the learning process, which are the learning style based on visual, auditory, and kinesthetic senses (Benmarrakchi, El Kafi, Elhore, & Haie, 2017; Ibrahim & Hussein, 2016; Mohd, Ismail, Jalil, & Noor, 2019). Visual style often involves visual-verbal and visual-nonverbal. Visual-verbal students are more interested in information presented in visual and written form. Meanwhile, visual-nonverbal students are more likely to be interested in information presented in the form of pictures or design formats (Chen, 2019).

Additionally, students that prefer the auditory learning style will focus more on information from oral learning sessions (Leasa & Corebima, 2017). In the learning session, the learning process will be more effective when students focus on hearing the presentation and engage in group discussions. This student learns better when interacting with others in the form of listening or speaking activities (Ibrahim &

Hussein, 2016). Students with a kinesthetic learning style love physical activity that uses body, hands and sense of touch. These students are more interested in challenging learning sessions and thrive in activities that require them to experiment with something new such as in laboratories that allow them to touch and manipulate material (Ibrahim & Hussein, 2016; Leasa & Corebima, 2017).

2.3 Learning Style Detection

There are two approaches that can be used to identify learning styles: collaborative and automated (Hasibuan & Nugroho, 2016; Hmedna, El Mezouary, Baz, & Mammass, 2016; Klašnja-Milićević, Ivanović, Vesin, & Budimac, 2018; Pham & Florea, 2013). Collaborative approaches are based on a questionnaire, while the automated approach is based on behavioral patterns during online learning. Collaborative approaches are said to be inaccurate because users are not sincere when answering the questionnaire. Emotions such as anger, sadness, disappointment, and joy could alter the results of questionnaires into different values and will influence the validity of the respondents' decision (Ahmad et al., 2013; Fasihuddin, Skinner, & Athauda, 2015; Jonassen & Grabowski, 1993).

Unlike the collaborative approach, automatic approaches are considered better in terms of data accuracy, as they are based on actual student behavior (Ateia & Hamtini, 2016; Jonassen & Grabowski, 1993). However, the automatic approach has its own disadvantages. For instance, it takes a lot of time to acquire the behavioral pattern of students participating in online learning. In addition, the habitual behavioral patterns obtained from the data are sometimes not strong enough (Ahmad et al., 2013; El- Bishouty et al., 2019). Nevertheless, previous works recommend using an automated approach to study learning styles because it is believed to be able to identify the learning styles more accurately (Ateia & Hamtini, 2016; Estacio & Raga Jr, 2017; Khan, Graf, Weippl, & Tjoa, 2010).

2.4 Behavioural Modelling

Many studies have been done on behavioural modelling in various applications and domains. The user behaviours considered in online application are the time spent completing an activity, the number of occurrences of the activity, and the number of completed activities. Even the number or page frequencies visited and the mouse clicks through the interface are collected as the user behavioural pattern (Togou, Lorenzo, Lorenzo, Cornetta, & Muntean, 2018; Zou et al., 2017). Other studies that have evaluated user behaviour assessed the click or purchase behaviour, consumer rate item value, criticism, value setting to item attributes, and user-specific requirements to generate recommendations based on user needs. The finding supported the user to make better and more accurate selections (Amato, Moscato, Picariello, & Piccialli, 2019; Jugovac & Jannach, 2017). Behavioural modelling has also been applied to predict customer purchasing (Jaini, Quoquab, Mohammad, & Hussin, 2019) and future trends (Gangurde, Kumar, & Gore, 2017). Past customer behaviour was taken and analysed to predict future customer behaviour. The study suggested a pattern search to predict changes in customer behaviour. This assisted mobile phone service providers to predict the type of service or brand that a customer will likely select (Banerjee, El-Bendary, Hassanien, & Tolba, 2013). In addition, many researchers have focused on modelling behaviour in education to automatically identify learning styles based on student behaviour (Bernard, Chang, Popescu, & Graf, 2016; Moharm, 2019; Mohd et al., 2019; Truong, 2016).

Most of these studies applied decision tree, neural network, fuzzy set, bayesian network, and rule-based techniques to develop the behavioral models (Azzi et al., 2020; Bernard, Chang, Popescu, & Graf, 2017; Feldman, Monteserin, & Amandi, 2015; Premlatha, Dharani, & Geetha, 2016; Sheeba & Krishnan, 2019). The Rule-based is considered as a suitable technique because the ability to form knowledge rules from the corresponding number of indicators based on user behavior without involving set user data (Kolekar, Pai, & MM, 2019). Other studies have applied rules in constructing the decision, are found that this technique gives better results and precision in detecting learning styles in comparison to the data-driven approach (Estacio & Raga Jr, 2017; Sheeba & Krishnan, 2019).

3. Learning Style Detection Framework

This section describes in detail the proposed framework for learning style detection based on user behavioral patterns. The discussion begins with the main phases of the framework. The proposed framework helps decision-makers, the teachers to collect and analyze important information in the process of detecting the learning style. The learning style detection system framework is then proposed (see Figure 1). Three main phases are involved in the proposed framework. The first phase is the identification of the behavior for each learning style, the second phase is the learning style determination of the behavior, and the last phase is the prediction of the learning style.

3.1 Identifying User Behaviour for Every Learning Style

Three processes were conducted to identify the relevant behaviors for each learning style. The first process was the selection of the characteristics and behavioral patterns of the relationship. The second process classified the behavioral events. The third process determined the behavioral parameters for each dimension of learning style. Four parameters of behavioral patterns that were commonly used were identified (Bousbia, Labat, Rebai, & Balla, 2009; Normadhi et al., 2019). In this study, four parameters were used to determine the student learning styles, namely the time used, the number of visits, the visit frequency, and the depth of the visit as presented in Table 1. The parameter of the time-consuming behavioral pattern was the time used (T) to use the learning object of each learning style element. The number of visits (V) is defined as the number of visits to the learning object of each learning style element. The parameters for frequencies (F) are the visit frequencies of the learning object of each learning style element. The last parameter is the depth (D) of the visit for the learning object path used in each learning style element.

Table 1: Parameters of behavioral patterns

Parameter	Description
Time used (T)	The time used for each learning object
Number of visit (V)	Number of visits for each learning object
Visit frequency (F)	The frequency of visits for each learning object
Depth of visit or path (D)	Depth of visits for each learning object

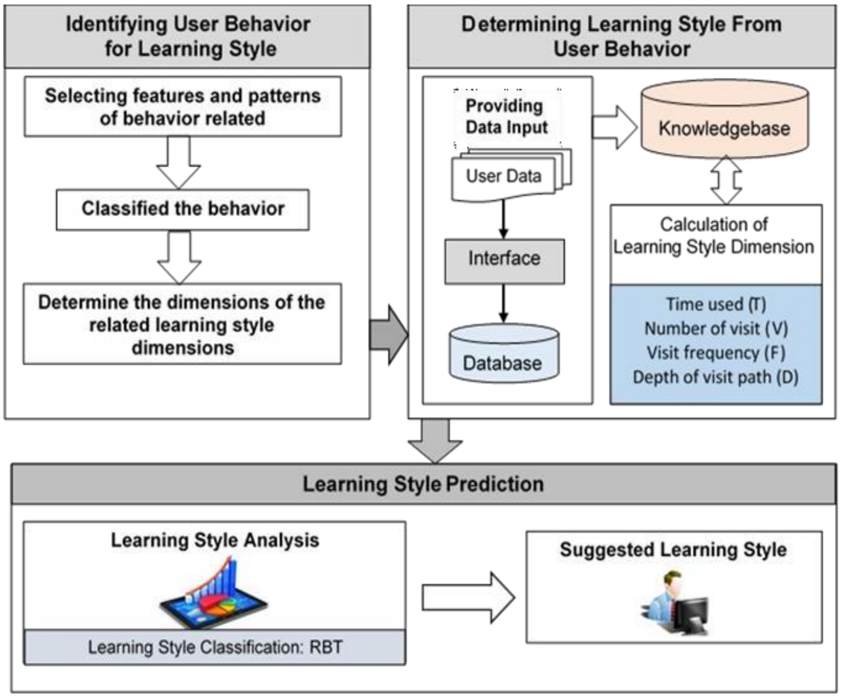

Figure 1: Framework for VAK Learning Style Detection

3.2 Determining Learning Style from User Behaviour

There are two processes in this phase. The first process is providing the data input and calculation methods. Input data was collected from the extracted and formulated information corresponding to each learning style. Then, the behavioral pattern parameters for learning styles were calculated. The formulae for calculating the ratio of each parameter for the selected patterns of behavior are listed below:

- The ratio of time used (T) was calculated using Eq. 1:

$$RT_{LS\_e} = \frac{\sum T_{LS\_e}}{\sum T} \quad (1)$$

Where RT_{LS_e} is the time ratio used for each learning object, $\sum T_{LS\_e}$ is the total amount of time each learning object is used, and $\sum T$ is the total time the learning object is used.

- The ratio number of visit (V) was calculated using Eq. 2:

$$RV_{LS\_e} = \frac{\sum V_{LS\_e}}{\sum V} \quad (2)$$

Where RV_{LS_e} is the ratio of the number of visits to each learning object, $\sum V_{LS\_e}$ is the amount of time each learning object is used, and $\sum V$ is the total number of learning objects used.

- The ratio of visit frequency (F) was calculated using Eq. 3,

$$RF_{LS\_e} = \frac{\sum F_{LS\_e}}{\sum F} \tag{3}$$

Where RF_{LS_e} is the frequency ratio of learning objects used, $\sum V_{LS\_e}$ is the number of learning object frequencies used, and $\sum F$ is the total number of learning object frequencies used.

- The depth of visit path (D) was calculated using Eq. 4:

$$RD_{LS\_e} = \frac{\sum D_{LS\_e}}{\sum D} \tag{4}$$

Where RD_{LS_e} is the depth of the visit path for each learning object ratio, $\sum D_{LS\_e}$ is the number of depth of visit path for each learning object, and $\sum D$ is the total number of depths of the visit path for each learning object.

3.3 Predict Learning Style

This phase is divided into two processes, namely the analysis of learning styles and learning style suggestions. The first process of learning style analysis was calculated based on the average ratio of the learning style element which is adapted from past study (Xiao & Rahman, 2017). Then, it this study that ratio was presented as Eq. 1, which shows the average calculation of the ratio of each element of the learning style (Ratio_{e_GP}), and it can be calculated using Eq. 5:

$$NP_{e\_GP} = \frac{\sum P_{e\_GP}}{\sum P} \tag{5}$$

Where NP_{e_GP} is the average ratio of learning style elements, $\sum P_{e\_GP}$ is the total behavior parameter ratio, and $\sum P$ is the total number of behavioral pattern parameters.

The second process is the learning style suggestion. The suggested learning styles were determined using a rule-based technique (Kolekar et al., 2019; Liyanage et al., 2016; Okoye, Tawil, Naeem, Bashroush, & Lamine, 2014). The development of rules was based on an average of the learning style elements. The suggested learning styles were used by the decision-makers to determine the VAK learning styles. The rule production of the LS element determination was based on the average ratio (N) of the LS element, which was constructed from previous studies: $0 \leq N < 0.3$ means that the element of LS is weak, $0.3 \leq N < 0.7$ means that the element of LS is moderate, and $0.7 \leq N \leq 1.0$ means that the element of LS is strong (Gaikwad & Potey, 2013; Zhang, Huang, Lv, Liu, & Zhou, 2018). The third step is the LS recommendation, which was produced based on the ranking of the average ratios.

4. Learning Style Application Architecture

This section elaborates the design of the learning style system based on the proposed framework. The Visual, Auditory, and Kinesthetic (VAK) learning style was the chosen domain for the proposed learning style framework in this study. The architecture of the VAK learning style application (VAKLes) is illustrated in Figure 2, which contains three modules: the interface module, process module, and decision module.

The interface module is a module that manages the interaction between the decision-makers, students, and the VAKLeS application. This module is important for determining the usability of a system. There are two types of user interfaces that are designed to control the flow of information: the interface style learning modules and decision support module interfaces. The learning style user interface connects learning style tracking functions based on student behavior using a Rule-based technique. Meanwhile, the decision support interface is a function that supports decision-makers during the analysis of learning styles. The database serves as storage for keeping student information and student behavioral information. The detection process begins once a student logs in to the system. The user information obtained is the visit time, the number of visits, visit frequency, and depth of the path used for each learning object. These were recorded and stored in the database. The process module suggests the learning styles according to the student behavior from the time spent, the number of visits, visit frequency, and depth of the path visit to each learning object. The data obtained from the activities were stored in a learning style knowledge database. Meanwhile, the decision module composed the learning style data and learning style analysis.

Generally, the flow for determining the learning styles based on student behavior was divided into three steps. The first step is the collection of a record of user behavioral parameter information from the learning object usage activity. Each activity represents the VAK learning style object. All the information collected was then stored in a database. The second step is the welding of the learning style dimensions. This step contains two processes, namely the calculation of learning style behavior parameters and decision-making process using the RBT, which is the input for the decision obtained from the previous step. The third step is the decision-making process of the learning styles using the production rules. The rules are based on the average of the learning style element ratio. The results obtained determine the choice of learning style of the student based on the suggestion of the learning style according to the position in the average ratio order.

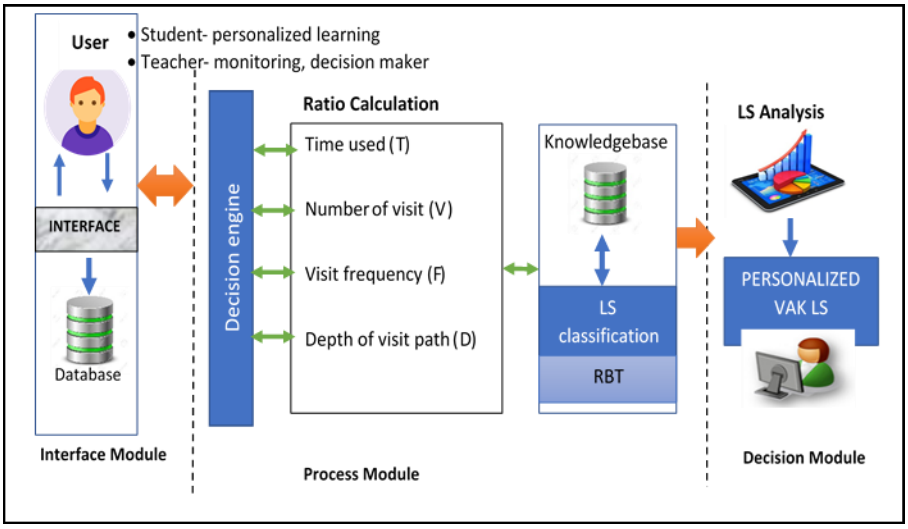

Figure 2: Architecture of VAKLeS

5. Conclusion

This study comprehensively explained the phases involved in a framework for the Visual, Auditory, and Kinesthetic learning style detection based on student behavior. The proposed framework contained three main phases: (1) identification of the behavior for each learning style, (2) the learning style determination of the behavior, and (3) the prediction of the learning style. Four parameters of behavioral patterns have been identified and used in the determination of student learning styles: (i) the time spent, (ii) the number of visits, (iii) the visit frequency, and (iv) the depth of the visit for each learning style object. In addition, the architecture of the VAK learning style (VAKLeS) Decision-Support System is presented with detailed illustration. The development of the architecture was based on three modules of the Decision Support System: the interface, process, and decision modules. The flow of architecture was demonstrated by applying a learning style detection domain focusing on the VAK learning style models. In future, the framework and DSS will be evaluated to measure the effectiveness of the overall system in multiple domains. This study recommends a generic framework for learning style detection be developed for other applications by applying different methods and models according to the relevant domain.

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