Education Tech Research Dev
https://doi.org/10.1007/s11423-018-9634-6

DEVELOPMENT ARTICLE

Use of Felder and Silverman learning style model for online course design

Moushir M. El-Bishouty[1,7] · Ahmed Aldraiweesh[2] · Uthman Alturki[2] · Richard Tortorella[3] · Junfeng Yang[4] · Ting-Wen Chang[5] · Sabine Graf[1] · Kinshuk[6]

Abstract
Learning Management Systems are used in millions of higher education courses, across various countries and disciplines. Teachers build courses reflecting their individual teaching methods, which may not always fit students' different learning styles. However, limited information is known about how well these courses support the learners. The study aims to explore the use of Felder and Silverman learning style for online course design. The study has used linear transfer function system models to develop fundamentals of feedback by a course analyzer tool. This interactive tool allows teachers to determine a course's support level for specific learning styles, based on the Felder and Silverman learning style model. The Felder and Silverman learning style model in this study is used to visualize the fit between course and learning style to help teachers improve their course's support for diverse learning styles. The results of a pilot study successfully validated the course analyzer tool, as it has potential to improve the design of the course in future and allow more insight into overall student performance. The findings suggest that a course designed with certain learning styles in mind can improve learning of the students with those specific learning styles.

Keywords Course analysis · Course design · Learning management system · Learning style · Online education

Introduction

Online courses have been growing tremendously in the past especially; since the initiation of massive open online courses (MOOCs) decade (Collins et al. 2013; De la Varre et al. 2014). Few of the researches have revealed that the higher dropout rates are due to insufficient engagement, motivation, and presence, which challenges MOOCs and traditional online courses (Kennedy 2014; Gasevic et al. 2014). The learning styles of students are reflected into online courses to make learning easier and increase students' learning efficiency (Lee and Choi 2011). Different students learn most effectively in different ways. A

✉ Uthman Alturki
ualturki@ksu.edu.sa

Extended author information available on the last page of the article

Published online: 02 November 2018

difference in the teaching methodology of instructor and the learning capability of students result in an inefficient learning and teaching process (Felder and Silverman 1988).

A learning task has a structure that is responsive to experiences and the demands of the situation (process), allows for changes, and enables adaptive behavior (Cassidy 2004). Various learning style models have been presented in the past by researchers such as Mayer and Myers (1995), Kolb (1984), and Felder and Silverman (1988). The model presented by Felder and Silverman (1988) has been adopted and validated by various studies (Hwang et al. 2013). According to Felder and Silverman (1988), there are various components involved in the learning process; such as visual/verbal, sensing/intuitive, sequential/global and active/reflective. The study also proposed various teaching styles, which can be adopted in an online teaching environment. The essential teaching components or elements include visual/verbal, active/passive, sequential/global and concrete/abstract.

Over the years, researchers have developed mechanisms and tools for the automatic detection of traces of learning styles that are reflected in Learning Management Systems (LMSs) based on the Felder–Silverman model (Chang et al. 2009; Ozpolat and Akar 2009; Graf and Liu 2009; Dorca et al. 2013; Ahmad et al. 2013; Mamat and Yusof 2013). Ozpolat and Akar (2009) presented a method for automatic detection of learning styles based on Felder–Silverman using NB Tree classification algorithm in conjunction with the Binary Relevance classifier. Graf et al. (2010) presented an approach to automatic student modeling and a tool for identifying and showing students' learning styles in LMSs. Dorca et al. (2013) presented an automatic, dynamic, and probabilistic approach for modeling students' learning styles based on reinforcement learning.

Few of the studies have discussed the mechanisms for generating an adaptive course based on detected leaning styles, which are based on learning objects and material already provided by teachers (Graf 2007; Sangineto et al. 2008). However, limited attention has been paid on how to support teachers, who wish to adapt their courses to specific learning styles. Thus, this study has presented an interactive tool designed for the analysis of existing course content in LMSs. Moreover, the effectiveness of a tool or methodology can be measured based on the feedback of the students. Additionally, the teaching methodology or tool must align with the needs of the students. Moreover, pilot study has been conducted to validate the efficacy of the tool and investigate ways of improvement.

The research work, done in this area, have focused on identifying students' learning styles and adapting courses. Past literature has mostly focused on examining the course curriculum and the teaching tools, adopted by educational institutions. The main focus is on analyzing the effectiveness of the various teaching tools. It would help teachers to improve the support level of each course, accordingly.

Related works

Learning styles are referred to the ways individual learners prefer to learn (Truong 2016; Shannon and David 2012). The concept of learning style has been widely accepted in the perception of public; however, its efficacy is still questioned. Learning styles provide the knowledge related to the different ways the students prefer to learn, to this end, they provide significant information regarding the preference of students. Thus, this knowledge can be utilized by optimizing the learning process of students. As compared to traditional learning styles, new learning styles models have emerged that incorporate computer and internet-based instructional approaches to facilitate students. According to Truong (2016), the new learning style models have effectively addressed the issues related to the traditional detection methods.

Despite the numerous advantages provided by online learning, the approach imposes serious risk to the privacy and security of students (Mayes et al. 2015). The technological advances, the expanding internet, powerful mobile devices, etc. are introducing new formal and informal challenges associated with the learning process. On the contrary, ethical issues, such as, equal access to the enriched resources also become a crucial factor being faced by the students in the online learning process (Mayes et al. 2015). Although, online learning serves as a potential approach to teaching; educators need to design the future online courses with adequate scope and sequence, interaction facilitation and well-timed delivery (Bower 2006).

The development of adaptive learning systems is a subject of long-standing scientific interest, which can adjust to reflect learner profiles. In this context, adaptation means the customization of content and presentation to match the profiles of given learners to best satisfy their needs and ensure fast and efficient learning (Al-Azawei and Badii 2013). Previous studies have shown the importance of integrating learning styles into online course design. Graf et al. (2010) analyzed the association between the learners' navigational behavior and Felder–Silverman learning style. The findings of this study showed that some of the teaching styles and tools are only suitable for a particular class environment. Therefore, it is imperative for the teachers to adopt different teaching styles based on the capability and specific needs of the students. The mental aptitude of the student should be considered in selecting a teaching style or methodology.

Rogers (2011) explored the relationship between four core-learning styles under Myers–Briggs model and performance outcomes in online courses. The results showed that "Sensing/Thinking" (ST) and "Intuitive/Thinking" (NT) learners appeared to have more success in online courses, cognitively. Rogers and McNeil (2009) further suggested that greater use of collaboration, discussion boards, and teamwork could make the online course environment more conducive for the success of both Sensing/Feeling (SF) and Intuitive/Feeling (NF) learners. Hwang et al. (2013) investigated the ability of students to choose the best-fit e-learning course for their own learning styles. The results showed that preference for one course over another does not necessarily mean that the student in question will learn better in that course. Moreover, this was taken to reveal the importance and necessity of developing adaptive learning courses explicitly based on learning styles. Moreover, Gogus and Ertek (2016) conducted a study to evaluate the learning and personal attributes of university students in predicting and classifying the learning styles, using Kolb's nine-region versus four-region learning styles. Furthermore, findings of the study predicted that the following learning style is essential for the evaluation of the perceptions of students regarding learning and studying, as well as, students' personal attitudes. To this end, learning style can be considered as a more robust learning style which takes into account the aspect of teachers, as well. Such that, the following learning style can help teachers to improve the support for their course in diverse learning styles by visualizing the fit between learning style and course.

Previous studies have reported several challenges faced by the students in their day to day activities. For instance, as reported by Dorça et al. (2016), students engage more in educational content when it is according to their preference; therefore, it is difficult for teachers to develop communication with each student individually. The learning style as preferred by students is equally important; therefore, personalization of the teaching process based on learning styles can help in improving the current teaching practices. On the contrary, Adkins and Guerreiro (2018) also emphasized on the importance of classifying students according to their preference of learning style. The study reported that a gap exists between the assessment of students and earning styles. Moreover, Li (2015) also reported that the preference of learning style of students also plays a critical role in enhancing teaching practices. To this end, it can be concluded that students' perception plays a critical role in improving the learning styles. However, previous studies have emphasized on the student-centric approach, the current study proposes a course analyzer tool, utilizing learning styles, that emphasizes on a teacher-centered approach.

Methodology

The aim of the study was to explore the use of the Felder and Silverman learning style for online course design, through a course analyzer tool. The effectiveness of the course analyzer tool can be assessed for the overall efficiency of the teaching methodologies used in the tool. This tool is used by teachers to examine whether the students are comfortable with the tool or not. Furthermore, the instructors are able to design the curriculum in an effective manner, so that the students can easily understand the teaching material. The linear transfer function system models are used for developing fundamentals of feedback by the course analyzer.

Figure 1 displays the tool's system architecture. The data extraction component connects to the LMS's database keep the tool generic (that is, usable with any LMS schema), and feeds raw data to the proposed mechanism. To this end, few research questions were developed;

Question 1 Will the current course analyzer tool helps teachers to develop more robust teaching strategies based on learning styles?

Question 2 How can the proposed tool be implemented in class lectures and group discussions?

Question 3 Is the proposed course analyzer tool reliable in terms of the challenges faced by teachers in their teaching methods?

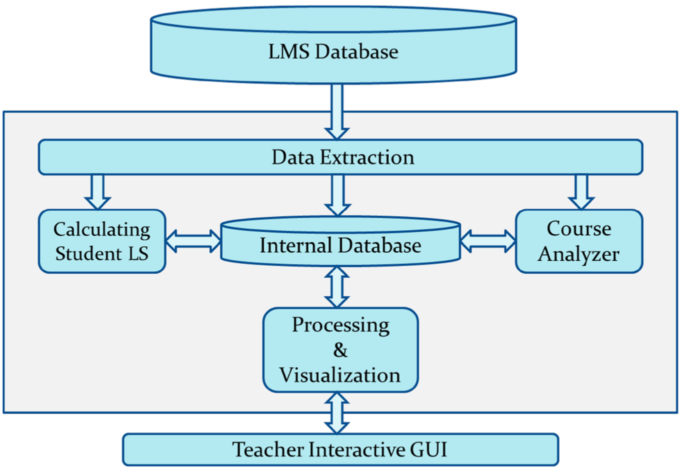

Fig. 1 System architecture

Data collection tool

The data collection tools used in this study include MySQL and PHP. The results have been analyzed based on the linear transfer function system models that are used to develop fundamentals of feedback by the course analyzer. The data is stored and exchanged through internal database among different structural components. The processing and visualization component retrieve available information and visualizes it as an interactive Graphical User Interface (GUI). Moreover, the tool supports the integration of other components to calculate students' learning styles.

The analysis mechanism

The analysis mechanism has been designed to analyze the structure and content of an existing course in LMS to measure the level of support, provided by the course for diverse learning styles. From a technical point of view, the learning objects (LO) can be added easily if required; however, the current mechanism considers eleven types of LOs, as listed below;

- *Commentaries*—gives concise summary of course unit to the learners
- *Content Objects*—represent the topics, which will be covered in the entire course.
- *Reflection Quizzes*—have multiple open-ended questions and exercises regarding the material, which are covered in the entire section. The exercises at the end of the section help learners in judging their overall understanding about the taught material.
- *Self-Assessment Tests*—judge the knowledge of the learners based on closed-ended questions. The self-assessment tests include multiple questions. The learners are able to judge themselves immediately after reviewing the answers.
- *Discussion Forum Activities*—encourage the learners to analyze the various aspects of a topic. In case of any difficulty in understanding the questions, the learners feel free to ask questions without any hesitation.
- *Additional Reading Materials*—are a valuable resource for learners and provide learners information related to the topic of the section or supplements of its content that include more elaboration.
- *Animations*—represents the information and theories in a visually more appealing form.
- *Exercises*—are a useful form of providing practice to the students. Through exercises the learners are able to execute the theories that have been taught by the instructor
- *Examples*—represents the material in a more concise and clear manner
- *Real-Life Applications*—enable the learners to directly connect the taught material in a real-time environment
- *Conclusions*—provide an overall view about the whole section. It represents summary of the section.

The course curriculum usually consists of various modules, units and sections. Therefore, multiple learning objects can be used in every section or unit of the curriculum. Each unit or section can begin with commentary. The content is presented in the next step. Different types of LOs may be presented in the following area, i.e. the area after content (AAC). Role of the course analyzer is to examine the effectiveness of the course methodology.

The Felder and Silverman learning styles are useful in the designing of course curriculum (Felder and Silverman 1988). The learning methodologies or frameworks include sensing, verbal, active, sequential, intuitive, global, reflective and sensing poles. These poles are effective in measuring the frequency, sequence and the availability of learning styles and objects (Table 1).

Availability and frequency factors

Specific learning objects may or may not be able to support diverse learning styles (Felder and Silverman 1988). Table 1 reflects upon various learning objects, which are suitable for every type of learning technique or style. There are various factors that contribute towards enhancing the learning ability and skills of a student. The assessment tests, quizzes, assignments, group activities, practical work and forum discussion all contribute towards enhancing the confidence level and understanding of the student. These activities enable the students to understand complex concepts in a limited amount of time. An instructor can adopt different strategies and techniques in the deliverance of lecture. The effectiveness of teaching methodologies is measured during the entire duration of the course. In contrast, reflective learners learn by thinking and reflecting on the taught course units and sections. Hence, the reflective assignments, reading assignments, tasks, and quizzes provides a useful way for judging the capability and competence level of individual students. Furthermore, improvements are made in the teaching practices based on the results of assignments and quizzes. The learners that are included in the sensing type prefer a practical and holistic approach towards teaching. Hence, the taught practical should focus on introducing the students toward the practical side of the study. It enables the students or learners to connect the taught material with their overall surroundings and industry standards. The students, which lie under the intuitive learner's domain, are mainly focused on understanding theories. These types of learners are creative in their approach. Therefore, a traditional teaching approach is not suitable for them. The instructors need to innovate and experiment with their teaching methodologies, so that the students are able to understand the complex concepts. The individuals failing under visual learner's domain rely on the visual aesthetics and animations to completely understand the taught material. Therefore, an animation-based teaching approach is more appropriate for these types of students. The next category or type includes verbal learners, which can benefit from text-based teaching approach. The reading material, forum discussion and activities can enable these types of

Table 1 Relations between learning object types and learning styles

Learning object/learning style	Active	Reflective	Sensing	Intuitive	Visual	Verbal	Sequential	Global
Reflection quizzes		x		x				
Self-assessment tests	x		x					
Discussion forum activities	x					x		
Additional reading materials		x		x		x		
Animations	x		x		x			
Exercises	x		x					
Examples		x	x					x
Real-life applications			x					x

students to express their opinions in both written and spoken form. The students or learners should be provided with proper guidance so that they are able to understand complex concepts. Global learners prefer understanding the real-time applications of the taught material. Therefore, teachers or instructors should give specific real-time examples of the theories and concepts discussed in the lecture.

Learning objects have direct impact on the selection of learning style. The efficiency and effectiveness of education process is improved because of adaptive learning and teaching strategies. The significance of learning objects is considerably reported in the selection of learning style, which allows teachers or instructors to understand the real-time applications and examples of the taught material. There is need of a novel approach for incorporating the learning style theory to assess appropriate learning object classification (Sun et al. 2007). Availability factor is used to analyze and examine the effectiveness of learning objects and how these learning objects contribute towards supporting learning styles (Singh 2003). The availability factor is calculated using formula described in Eq. (1). On the other hand, frequency factor helps in determining the learning objects, which are supporting learning style. Frequency threshold should be able to support any specific learning style. Frequency threshold is set to a particular level by the instructor. The frequency threshold can be varied or altered as per the requirement of teaching style. The Eq. (2) is used for calculating the frequency factor. The results or values calculated using the formula lie within 0–1 range (Hwang et al. 2013).

$$Ava_{ls} = \frac{(\#\, of\ existing\ LO\ types\ that\ support\ ls)}{(\#\, of\ LO\ types\ that\ support\ ls)} \tag{1}$$

$$Freq_{ls} = \frac{(\#\, of\ existing\ LOs\ that\ support\ ls)}{(frequency\ threshold)} \tag{2}$$

Sequence factor

Position, order and type of learning objects have a direct impact in the selection of suitable learning styles. This is because students get encouraged to listen, retain the sounds, and compare them with the familiar sounds. These students provide a spoken version for computer generated written tasks along with the multisensory approach that significantly facilitates the revision process. Sequence factor is used for assessing and measuring the effectiveness of teaching methods. The effectiveness of teaching begins with each teacher's ability to apply the instructional strategies and cover the appropriate material as outlined in the scope and sequence of the selected curriculum. Teachers need to make the connection between the underlying story behind student data and how the data is used for instructional strategies to implement effective teaching methods. The interactive learning methodology or style is supported through exercises, visual presentations or animations and assessment quizzes and tests. These practices are helpful in developing the students' interest towards the taught material. A reflective learning style can be supported by locating the conclusion right after the content and following it with additional learning material, examples, and reflection quizzes. This is because reflective learners prefer to read the content first before thinking about visiting other LOs. The use of animations, visual presentations and real-time implementation and applications of theoretical concepts maintain the interest of the learners in the course. The students are able to actively participate in group based and individual activities. Sensing learning methodology is supported through introducing children to the real-time application of theoretical concepts. The students can be introduced to real-time applications of theories just after the deliverance of lecture. Taking quizzes at the end of particular lecture are helpful in assessing the skill level of students. It is a useful method for judging the involvement of students in class activities and assignments. Locating exercises at the beginning fits with the learning style of intuitive learners. The visual learners are presented or introduced to animations and visual presentations during the deliverance of a lecture. The induction of visual elements in the teaching practices enables the students to gain in depth understanding of the complex concepts. The reading assignments, group discussions, and forum activities are suitable for verbal learners. The visual learners learn a lot through different interactive activities. The sequential learners benefit from reflective assignments and quizzes, animations, online exercises and activities. Global learners are interested in gaining holistic view of the complex theoretical concepts. Therefore, it is essential for the instructors to introduce these types of learners with practical approach in solving various real-time problems. An effective approach is to directly jump to the conclusion after deliverance of the lecture. Summarizing the theoretical concepts in a clear and concise manner helps in enhancing the overall understanding of the learners. The assessments tests, quizzes and assignments help in measuring the overall performance level of each individual.

Sequence factor is measured and calculated based on the type of learning objects. The Eq. (3) is used for calculating the sequence factor. The results obtained through Eq. (3) forms the basis for developing an effective teaching methodology or style (Agarwal et al. 2004). The f_{ls} represents the relative earn in Eq. (3), n represents total number of learning objects and w is for weights. The w in the formula shows or represents LO position.

$$Seq_{ls} = \frac{\sum_{i=1}^{n} f_{ls}(LO_i) \times w_i}{\sum_{i=1}^{n} w_i}, 0 < w \leq 1 \tag{3}$$

Visualization component

The visualization component of the analyzer has presented the results; it reflects the effectiveness of teaching methodologies. The visualization component also reflects whether the course adopts well to the diversified learning styles of the students. Visualization modes are divided into two categories i.e. cohort mode and general mode. The general mode provides high level of support for different learning techniques or styles. The general mode adopts the Felder–Silverman learning styles model (FSLSM) approach. Figure 2 represents the visualization of general mode. Furthermore, Fig. 2 illustrates the support level for diversified learning styles. The harmony of the course with learning styles is represented in Fig. 2. These learning styles are depicted as a percentage, which is calculated by the average of the three factors. A 0% score demonstrate no support for a particular learning style; whereas, a one 100% would indicate complete support. The higher level of the bar represents that the students are satisfied with the support level. The green bar represented in Fig. 2 represents the overall support level. This support level includes different learning styles of the students. It is measured by calculating average of different support levels.

The Cohort Mode visualizes the course's support level. The support level of the course is examined in relation to learning techniques or styles of students (Fig. 3). Comparison and critical examination of visualization elements and learning styles is dependent on

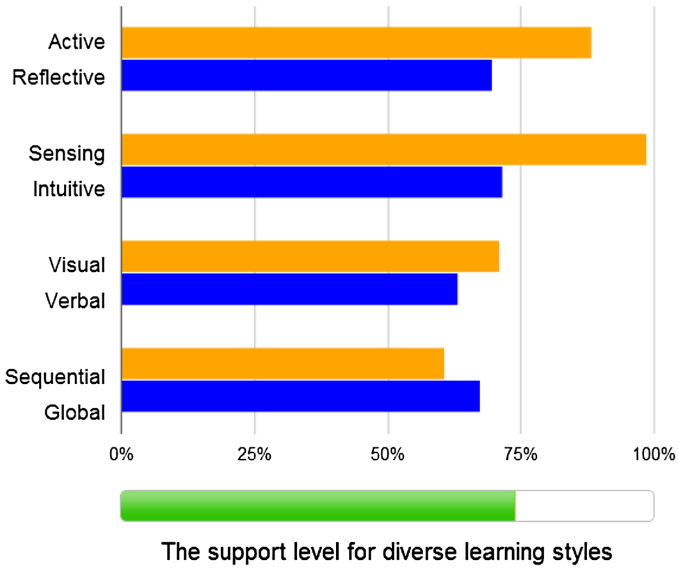

Fig. 2 Visualization of general mode

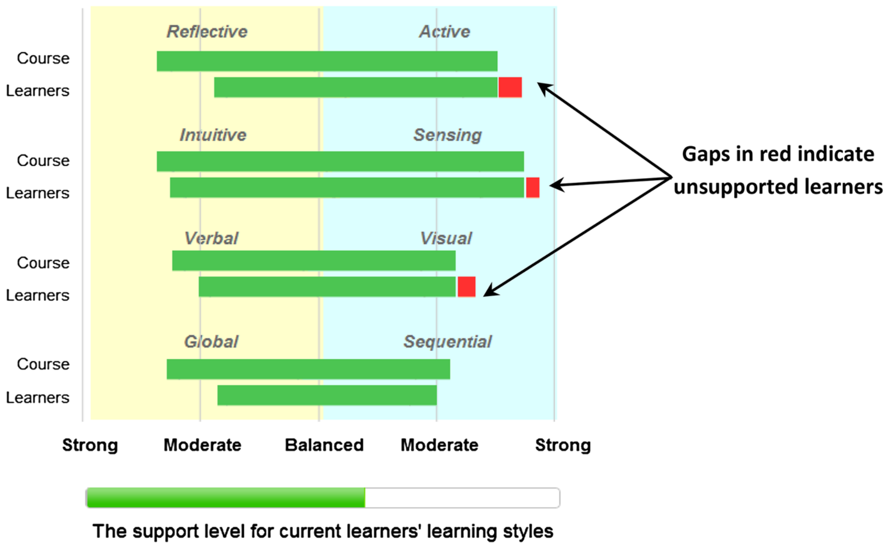

Fig. 3 Visualization of cohort mode

multiple factors. The support level of the course is measured by calculating average of all the factors involved. The 100% green bar represents that all the students are satisfied with the support level. The gap in the support level has been represented by red bar in Fig. 3. The red bar also represents the total number of unsupported learners or students.

Pilot study

An 8-week pilot study was conducted to verify the efficiency of the tool for the provision of online courses that fit students' learning styles. The course "Using Computers in Education WSL 506," using the Moodle LMS, was selected for the pilot study. It was a required course in the "Master of Educational Technology program" in the College of Education, at a Saudi Arabian university. At the outset, 25 students were registered in the course. They were asked to enroll in Moodle and were required to complete the Index of Learning Styles (ILS) form or questionnaire developed by Felder and Soloman (2012) to measure their learning styles, before they were given access to the course in Moodle. During the course, two students withdrew for personal reasons, leaving 23 students who completed the course. All the students were female, aged predominately between 18 and 35 years. All the students were from the field of computer science, with around 50% having no prior teaching experience.

The first step in launching the pilot study was the collection of course material, which was then classified based on the course syllabus. The course material was divided into 8 units in the syllabus, allowing students to access new content on a weekly basis. The learning objects and the incorporated learning strategies varied in each unit. The former included course content, examples, animation, additional reading, and exercises. Class discussions were conducted over the course of the pilot study the after lectures, following which students were required to access course material in Moodle. They were also encouraged to debate and discuss course material via LMS. The course analyzer identified the learning strategies, which best corresponded to the student's preferences. Student's preferences help in the analysis of cohort learning styles by bringing significant improvement in the implemented strategies. This was done by calculating and analyzing the course support level for the cohort learning styles. The data was collected from a whole cohort, alumni or any other subgroup of students. This led to the creation of a tool for exploring large amounts of student and course related data. Based on the course analyzer feedback, the lecturer focused on the identified learning styles to build future units. The goal was to verify whether the tool could assist the lecturer in improving the course to support students' learning styles. For this purpose, the study evaluated benefits for offering recommendations about the relative utility of proposed techniques. Criterion tasks are associated with different outcome measures that are relevant to student achievement.

Results and discussion

The pilot study provided data on the effectiveness of the course analyzer for both general and cohort modes.

Analysis of general support level

The general support analysis for the course showed how well the course matches the students' different learning styles. Figure 4 has shown that the overall average support level for the course material was 31%.

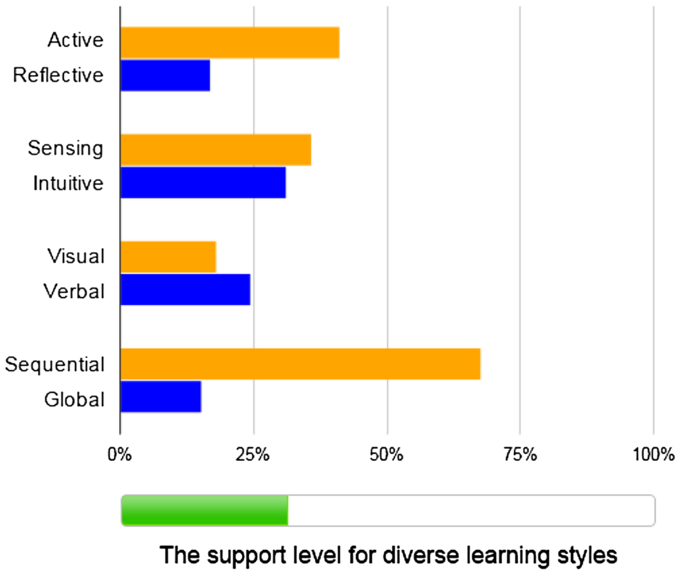

Fig. 4 General support for pilot study

Table 2 Average support per learning style

Learning type	Average support (%)
Active	41
Reflective	17
Sensing	36
Intuitive	31
Visual	18
Verbal	24
Sequential	68
Global	15
Average	31

Table 2 has shown that the reviewed course over its eight sections supported the sequential learning style the most, at 68%. The course did not support the global learning style, which had a 15% overall average as expected by the binary opposition of sequential and global styles.

Analysis of cohort support level

Once the abstract support characteristics of the course, the next step was to see how the course supported the cohort of students actually taking it. In Fig. 5, the top bar and labeled course represented the course value from Fig. 4 for each of the Felder–Silverman scales; while, the learners' bar represents the average value for the students. Both bars are taken as

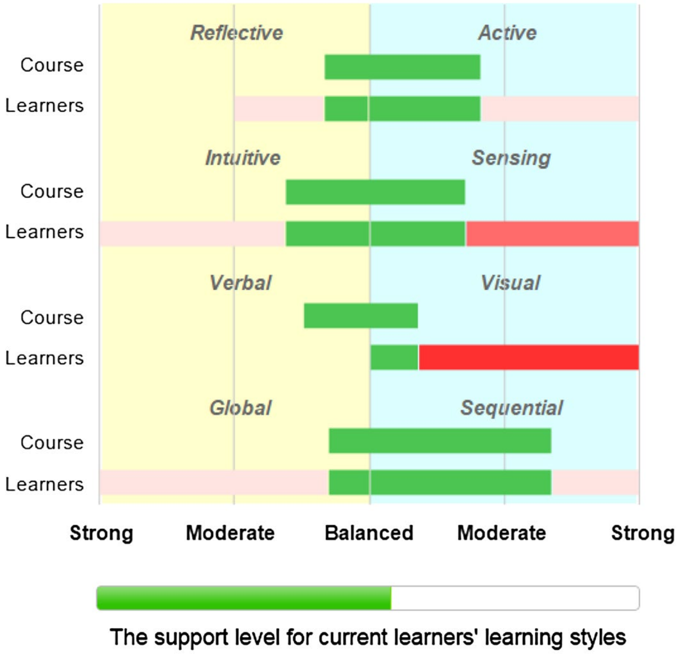

Fig. 5 Cohort support level for pilot study

equally weighted averages over the eight sections of the pilot study course. The course and students' requirements do not match as observed by the red sections found on the learners' bars for intuitive/sensing and verbal/visual styles. This divergence is of great importance to the effectiveness of the course.

The independent and dependent cognitive styles tend to result in successful models that try to understand their learners. Online instructors need to remember that students are strongly dominated by focusing on the overall structure of the organization (British Council 2016). To match the field dependency of students, teachers need to adopt the field dependent styles and behaviors (Pithers 2002). These results show consistency with the results proposed in the present study. In terms of reducing learning time and increased satisfaction, students have a better learning experience and improved learning outcomes, when their learning styles match the styles of the material presented in online courses (Buch and Sena 2001; Tseng et al. 2008; Popescu 2010; Surjono 2015).

The students in an online course, who received content that matched their multimedia preferences and learning styles scored higher, as compared to the students whose preferences and styles did not match (Surjono 2015). Similarly, Lo et al. (2012) provided evidence for the effectiveness of an adaptive web-based learning system that dynamically identifies students' cognitive styles as they browse through a multi-layer feed-forward neural network. Another study conducted by Yang et al. (2013) found that students, who learned through online courses were able to develop an effective learning style model that helped them to achieve better in a traditional online course.

Similar to the results of present study, another study conducted by Garland and Martin (2005) revealed that there is no similarity between the learning styles of a student learning through online classes and another student learning by attending grace to face course. This specified the significance of implications for online course designers. The results concluded that learning style and gender of all the students need to be considered, while designing the online learning courses. Another study showed that reflective learners have proved to be successful in learning through online courses (Battalio 2009). Moreover, global learners are out-performed by the sequential learners. It has also been shown that students are likely to gain knowledge and learn in different ways for using different teaching resources. Proper understanding of the learning styles can be utilized for identifying and implementing better teaching and learning strategies that would allow students to acquire efficient knowledge in an efficient and effective way (Franzoni-Velázquez et al. 2012).

Conclusion

The study has demonstrated the validity of the course analyzer tool at the cohort level and shed light on how the course can be improved. The tool can be helpful for teachers in evaluating the preference of students regarding a particular course, to this end, the teaching methodology can be significantly improved leading to better students' assessment outcomes. Moreover, the tool will also help instructors to develop good communication level with students by also considering their choices. The tool can be used by instructors at all education levels. The instructor can use the tool by providing course material on a specific tool. Thus, through this technique, students will gain knowledge regarding the course without any mishap. Moreover, discussions between teacher and student will be improved, as the tool helps teachers to analyze the perceptions of students, effectively. Moreover, the intensity of feedback and the criteria of assignments can also be significantly improved. Although, the pilot course was not able to provide a suitable learning environment for either sensing or visual learners; however, it demonstrated the real-world feasibility of the interactive tool. The independent and dependent cognitive styles resulted in successful models that try to understand their learners. In the present study, the course analyzer tool based on learning styles has mainly focused on the teacher's attention regarding the potential modifications in the course structure (e.g., adding learning objects) and improve the support the course provided for students with different learning styles. It has potential to not only improve the design of the course in future but also allow more insight into overall student performance and address problems mentioned in previous studies. The implications of having such a tool are numerous, with the ability to determine specific strengths and weaknesses of a course from the pedagogical standpoint. It is also believed that teachers will be able to use this tool to make changes not only post hoc but also during the course itself.

Acknowledgements The authors would like to extend their sincere appreciation to the Deanship of Scientific search at King Saud University for its funding this Research group No. RG #-1436-033.

Funding This research is not funded by any resource.

Compliance with ethical standards

Conflict of interest The research has no conflict of interest.

References

Adkins, D., & Guerreiro, M. (2018). Learning styles: Considerations for technology enhanced item design. *British Journal of Educational Technology, 49*(3), 574–583. https://doi.org/10.1111/bjet.12556.

Agarwal, S., Awan, A., & Roth, D. (2004). Learning to detect objects in images via a sparse, part-based representation. *IEEE Transactions on Pattern Analysis and Machine Intelligence, 26*(11), 1475–1490.

Ahmad, N., Tasir, Z., Kasim, J., & Sahat, H. (2013). Automatic detection of learning styles in learning management systems by using literature-based method. *Procedia-Social and Behavioral Sciences, 103,* 181–189. https://doi.org/10.1016/j.sbspro.2013.10.324.

Al-azawei, A., & Badii, A. (2013). A probabilistic approach for the generation of learning sessions tailored to the learning styles of learners. *International Journal of Emerging Technologies in Learning, 8*(6), 42–49. https://doi.org/10.3991/ijet.v8i6.3084.

Battalio, J. (2009). Success in distance education: Do learning styles and multiple formats matter? *The American Journal of Distance Education, 23*(2), 71–87.

Bower, M. (2006). Virtual classroom pedagogy. *ACM Sigcse Bulletin, 38,* 148–152. https://doi.org/10.1145/1124706.1121390.

British Council. (2016). Teaching English: Field independent learners. Retrieved from http://www.teachingenglish.org.uk/article/field-independent-learners.

Buch, K., & Sena, C. (2001). Accommodating diverse learning styles in the design and delivery of on-line learning experiences. *Journal of Workplace Learning, 17*(1), 93–98.

Cassidy, S. (2004). Learning styles: An overview of theories, models and measures. *Educational Psychology, 24*(4), 419–444. https://doi.org/10.1080/0144341042000228834.

Chang, Y. C., Kao, W. Y., Chu, C. P., & Chiu, C. H. (2009). A learning style classification mechanism for e-learning. *Computers & Education, 53*(2), 273–285. https://doi.org/10.1016/j.compedu.2009.02.008.

Collins, D., Weber, J., & Zambrano, R. (2013). Teaching business ethics online: Perspectives on course design, delivery, student engagement, and assessment. *Journal of Business Ethics, 125,* 1–17. https://doi.org/10.1007/s10551-013-1932-7.

De la Varre, C., Irvin, M. J., Jordan, A. W., Hannum, H., & Farmer, T. W. (2014). Reasons for student dropout in an online course in a rural K–12 setting. *Distance Education, 35*(3), 324–344. https://doi.org/10.1080/01587919.2015.955259.

Dorça, F. A., Araújo, R. D., De Carvalho, V. C., Resende, D. T., & Cattelan, R. G. (2016). An automatic and dynamic approach for personalized recommendation of learning objects considering students learning styles: An experimental analysis. *Informatics in education, 15*(1), 45.

Dorca, F. A., Lima, L. V., Fernandes, M. A., & Lopes, C. R. (2013). Comparing strategies for modeling students learning styles through reinforcement learning in adaptive and intelligent educational systems: An experimental analysis. *Expert Systems with Applications, 40,* 2092–2101. https://doi.org/10.1016/j.eswa.2012.10.014.

Felder, R., & Silverman, L. (1988). Learning and teaching styles in engineering education. *Engineering Education, 78*(7), 674–681. https://doi.org/10.1109/FIE.2008.4720326.

Felder, R. M., Soloman, B. A. (2012). Index of learning styles questionnaire. North Carolina State University. Retrieved from http://www.engr.ncsu.edu/learningstyles/ilsweb.html.

Franzoni-Velázquez, A. L., Cervantes-Pérez, F., & Assar, S. (2012). A quantitative analysis of student learning styles and teacher teachings strategies in a mexican higher education institution. *Journal of applied research and technology, 10*(3), 289–308.

Garland, D., & Martin, B. N. (2005). Do gender and learning style play a role in how online courses should be designed. *Journal of Interactive Online Learning, 4*(2), 67–81.

Gasevic, D., Kovanovic, V., Joksimovic, S., & Siemens, G. (2014). Where is research on massive open online courses headed? A data analysis of the MOOC research initiative. *International Review of Research in Open and Distance Learning, 15*(5), 134–176. https://doi.org/10.19173/irrodl.v15i5.1954.

Gogus, A., & Ertek, G. (2016). Learning and personal attributes of university students in predicting and classifying the learning styles: Kolb's nine-region versus four-region learning styles. *Procedia-Social and Behavioral Sciences, 217,* 779–789. https://doi.org/10.1016/j.sbspro.2016.02.145.

Graf, S. (2007). Advanced adaptivity in learning management systems by considering learning styles. Retrieved from http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=5284970\nhttp://dl.acm.org/citation.cfm?id=1632300.

Graf, S., & Liu, T. (2009). Supporting teachers in identifying students' learning styles in learning management systems: An automatic student modelling approach. *Educational Technology and Society, 12,* 3–14. https://doi.org/10.1016/j.lindif.2010.11.016.

Graf, S., Liu, T. C., & Kinshuk, (2010). Analysis of learners' navigational behaviour and their learning styles in an online course. *Journal of Computer Assisted Learning, 26,* 116–131. https://doi.org/10.1111/j.1365-2729.2009.00336.x.

Hwang, G. J., Sung, H. Y., Hung, C. M., & Huang, I. (2013). A learning style perspective to investigate the necessity of developing adaptive learning systems. *Educational Technology and Society, 16*(2), 188–197.

Kennedy, J. (2014). Characteristics of massive open online courses (MOOCs). *Journal of Interactive Online Learning, 13*(1), 1–16.

Kolb, D. D. (1984). *Experiential learning: Experience as the source of learning and development*. Englewood Cliffs, NJ: Prentice-Hall.

Lee, Y., & Choi, J. (2011). A review of online course dropout research: Implications for practice and future research. *Educational Technology Research and Development, 59,* 593–618. https://doi.org/10.1007/s11423-010-9177-y.

Li, K. M. (2015). Learning styles and perceptions of student teachers of computer-supported collaborative learning strategy using wikis. *Australasian Journal of Educational Technology, 31*(1), 32. https://doi.org/10.14742/ajet.521.

Lo, J. J., Chan, Y. C., & Yeh, S. W. (2012). Designing an adaptive web-based learning system based on students' cognitive styles identified online. *Computers & Education, 58*(1), 209–222. https://doi.org/10.1016/j.compedu.2011.08.018.

Mamat, N., & Yusof, N. (2013). Learning style in a personalized collaborative learning framework. *Procedia-Social and Behavioral Sciences, 103,* 586–594. https://doi.org/10.1016/j.sbspro.2013.10.376.

Mayer, I. B., & Myers, P. B. (1995). *Gifts differing: Understanding personality type*. Mountain View, CA: Davies-Black Publishing.

Mayes, R., Natividad, G., & Spector, J. M. (2015). Challenges for educational technologists in the 21st century. *Education Sciences, 5*(3), 221–237. https://doi.org/10.3390/educsci5030221.

Ozpolat, E., & Akar, G. B. (2009). Automatic detection of learning styles for an e-learning system. *Computers & Education, 53*(2), 355–367. https://doi.org/10.1016/j.compedu.2009.02.018.

Pithers, R. T. (2002). Cognitive learning style: A review of the field dependent field independent approach. *Journal of Vocational Education and Training, 54*(1), 117–132. https://doi.org/10.1080/13636820200200191.

Popescu, E. (2010). Adaptation provisioning with respect to learning styles in a Web-based educational system: An experimental study. *Journal of Computer Assisted Learning, 26,* 243–257. https://doi.org/10.1111/j.1365-2729.2010.00364.x.

Rogers, P. (2011). Student online course performance: Does learning style matter? *Journal of the Academy of Business Education, 12,* 28–43.

Rogers, P. R., & McNeil, K. (2009). Student learning styles and online course performance: An empirical examination of student success in web-based management courses. *Business Education Digest, 18,* 1–15.

Sangineto, E., Capuano, N., Gaeta, M., & Micarelli, A. (2008). Adaptive course generation through learning styles representation. *Universal Access in the Information Society, 7,* 1–23. https://doi.org/10.1007/s10209-007-0101-0.

Shannon, E., & David, S. B. (2012). Learning style and its importance in Education.

Singh, H. (2003). Building effective blended learning programs. *Educational Technology-Saddle Brook Then Englewood Cliffs NJ, 43*(6), 51–54.

Sun, S., Joy, M., & Griffiths, N. (2007). The use of learning objects and learning styles in a multi-agent education system. *Journal of Interactive Learning Research, 18*(3), 381.

Surjono, H. D. (2015). The effects of multimedia and learning style on student achievement in online electronics course. *The Turkish Online Journal of Educational Technology, 14*(1), 116–123.

Truong, H. M. (2016). Integrating learning styles and adaptive e-learning system: Current developments, problems and opportunities. *Computers in Human Behavior, 55,* 1185–1193. https://doi.org/10.1016/j.chb.2015.02.014.

Tseng, J. C. R., Chu, H. C., Hwang, G. J., & Tsai, C. C. (2008). Development of an adaptive learning system with two sources of personalization information. *Computers & Education, 51,* 776–786. https://doi.org/10.1016/j.compedu.2007.08.002.

Yang, T., Hwang, G., & Yang, S. J. (2013). Development of an adaptive learning system with multiple perspectives based on students' learning styles and cognitive styles. *Educational Technology and Society, 16,* 185–200.

Moushir M. El-Bishouty is Academic Expert at Athabasca University and Senior Consultant - Research, Innovation and Analytics at Alberta Health Services, Canada. Since April 2011, he works as Assistant Professor at City for Scientific Research and Technological Applications, Egypt. He received his Ph.D. from the Department of Information Science and Intelligent Systems, the University of Tokushima, Japan. His research interests include technology enhanced learning, ubiquitous and mobile learning, adaptivity and personalization, knowledge awareness, and artificial intelligence. He has published more than 40 refereed journal papers, book chapters, and international conference papers. Besides, he received many recognized international awards.

Ahmed Aldraiweesh is an Associate professor at educational technology department—College of Education—King Saud University in Saudi Arabia; he works as a vice dean of scientific research for Development and Quality. He worked as the head of educational technology department at teachers' college for 2 years, before that he worked as the head of Quality Unit at teachers' college for 2 years. He is interested in employing educational technology for student with special needs.

Uthman Alturki is a full professor at educational technology department—College of Education—King Saud University in Saudi Arabia. Before that he worked as a full time consultant for 3 years at (NCEL) National center for e-learning and distance learning, before that he worked as the head of computer department at teachers' college for 2 years, before that he worked as the dean and deputy dean of training and community service for 4 years in (MoE) Ministry of education.

Richard Tortorella received his M.Sc. degree from Athabasca University, Canada in 2013. He is currently a Ph.D. candidate at the University of Eastern Finland. He is a member of the IEEE Society and an Assistant Editor for the Smart Learning Environments journal. His current research interests include context-aware learning systems, m-Learning, and artificial intelligence.

Junfeng Yang is distinguished professor in Hangzhou Normal University, and he is the dean of department of Educational Technology in Hangzhou Normal University. He received his Ph.D. from Beijing Normal University in 2014. His research interests include smart learning environments, blended synchronous cyber classroom, and the digital generation of learners.

Ting-Wen Chang is the associate research fellow and the director of international cooperation center in Smart Learning Institute of Beijing Normal University (SLIBNU) for doing the research on Smart Learning as well as making many international cooperation projects since March 2014. As the director of international cooperation center, he has made more than 50 international scholars/experts as well as several oversea institutions for SLIBNU in order to create lots of international cooperation about innovative and the cutting-edge technologies of smart learning. He was the workshop coordinator for some key workshops of SLIBNU, such as in 2017, the 1st Workshop on VR and Immersive Learning in Harvard University, The 4th Annual International Conference "Education & Global Cities: Smart Learning for World Universities" in St. Petersburg, Russia, and The 12th edition of the eLearning Africa Conference in Republic of Mauritius. On September 2017, he has also been responsible for the ME310 Global Project with d.School of Stanford University.

Sabine Graf is an Associate Professor at Athabasca University, School of Computing and Information Systems, in Canada. Her research aims at making information systems, especially learning systems, more personalized, intelligent and adaptive. Her research expertise and interests include adaptivity and personalization, student modeling, ubiquitous and mobile learning, artificial intelligence, and learning analytics. She has published more than 130 peer-reviewed journal papers, book chapters, and conference papers in these areas, which have been cited over 3500 times, and four conference papers were awarded with a best paper award. She is Executive Board Member of the IEEE Technical Committee on Learning Technologies, Editor of the Bulletin of the IEEE Technical Committee on Learning Technology, and Associate Editor of the International Journal of Interaction Design and Architectures.

Kinshuk is the Dean of the College of Information at the University of North Texas. Prior to that, he held the NSERC/CNRL/Xerox/McGraw Hill Research Chair for Adaptivity and Personalization in Informatics. He was also Full Professor in the School of Computing and Information Systems and Associate Dean of Faculty of Science and Technology, at Athabasca University, Canada. His work has been dedicated to advancing research on the innovative paradigms, architectures and implementations of online and distance learning systems for individualized and adaptive learning in increasingly global environments.

Affiliations

Moushir M. El-Bishouty[1,7] · Ahmed Aldraiweesh[2] · Uthman Alturki[2] · Richard Tortorella[3] · Junfeng Yang[4] · Ting-Wen Chang[5] · Sabine Graf[1] · Kinshuk[6]

Moushir M. El-Bishouty
moushir.elbishouty@gmail.com

Ahmed Aldraiweesh
aaldriwish@ksu.edu.sa

Richard Tortorella
tortorella@ieee.org

Junfeng Yang
yangjunfengphd@gmail.com

Ting-Wen Chang
tingwenchang@bnu.edu.cn

Sabine Graf
sabineg@athabascau.ca

Kinshuk
kinshuk@ieee.org

1 Athabasca University, Athabasca, Canada

2 King Saud University, Riyadh, Saudi Arabia

3 University of Eastern Finland, Kuopio, Finland

4 Hangzhou Normal University, Hangzhou, China

5 Beijing Normal University, Beijing, China

6 University of North Texas, Denton, USA

7 City for Scientific Research & Technological Applications, Alexandria, Egypt