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Exploring The Effect of Online Course Design on Preservice Teachers' Knowledge Transfer and Retention Through Learning Analytics

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ABSTRACT
There is a vast amount of data collected on e-learning platforms that can provide insight and guidance to both learners and educators. However, this data is rarely used for evaluation and understanding the learning process. Hence, to fill this gap in the literature this study explored the effect of online course design on students' transfer and retention of knowledge through learning analytics. The aim was to reveal study behaviors of participants over a short time while exploring their academic performance. Using a mixed method approach, this research is conducted in two different countries in a limited time. The results showed that the more times students visited the learning module and the longer these visits, the higher the students' transfer knowledge scores in this module. Most importantly, the only variable found to be a significant predictor of students' transfer learning outcome was the number of sessions in the module website.

Keywords: online course design, knowledge transfer, retention, learning analytics

Introduction

Demand for online programs and courses has increased dramatically during the last two decades due to the convenience of online learning, the flexibility of scheduling and the opportunity for students to adapt online learning to their lifestyles (e.g., Ifenthaler & Widanapathirana, 2014; Law et al., 2018; Loh et al., 2015). The ease of access to continuously changing and emerging technologies coupled with the ability to reach a widening range of open multimedia learning resources has allowed many online students to benefit from the media-rich learning content and to explore enormous relevant information (Low & Sweller, 2005; McGuinness, 1990).

Furthermore, students' engagement in their learning process can be monitored through learning management systems and analytics tools which track a variety of information about the students' progress and performance. Learning systems can also provide educators feedback and analyses of students' data to make formative evaluation and future learning decisions (Gašević et al., 2016). Although, educators can use this data to reflect on the teaching process, there is little information provided on how to interpret these data regarding students' learning outcomes and their online habits (Viberg et al., 2018).

Literature Review

Prior research in the field of learning analytics (LA) is mainly focused on gaining insights into learners' behaviors and academic performance in online learning environments (Greller & Drachsler, 2012; Peña-Ayala, 2018; Saarela & Kärkkäinen, 2017). Other LA research was conducted to provide automated feedback about students' patterns in online learning environments (Er et al., 2021; Huang et al., 2019). The overarching theme of these studies was to review and analyze students' activities collected data to support learning and teaching (Nguyen et al., 2017, 2018; Nistor & Hernández-Garcíac, 2018). However, few studies have explored students' behaviors to predict their academic performance. Some of the early studies have used learning interaction data to evaluate and predict the students' academic performance in online learning environments and found that students' access behaviors of learning content, books, forums, and course activities can significantly affect their learning outcomes (e.g., Kokoç & Altun, 2021). Other studies found a significant correlation between students' online activities and their academic performance (e.g., Rubio-Fernández et al., 2019). Similarly, researchers found that there is a positive correlation between the number of logins, homework completion and video completion rate and the final grades of students (e.g., Qureshi et al., 2021; Shen et al., 2020; Zheng et al., 2020).

Another aspect of LA research is the investigation of the design and implementation of online learning content on students' academic outcomes. The main finding of this research is that ignoring the guidelines of online course design could prevent meaningful learning experiences and result in undesirable learning outcomes (Gašević et al., 2015; Lockyer & Dawson, 2012; Lockyer et al., 2013; Redmond & Macfadyen, 2020). Therefore, using LA in conjunction with properly designed online learning content can reveal students' learning difficulties, distractors as well as personal learning preferences while providing them with effective and timely feedback to assist and support their learning process (Muljana & Luo, 2020). For instructors, identifying best practices, characteristics of high achievers and milestones for increasing achievement help improve course design and teaching. Instructors' improvement of the learning environment complements the students increased understanding of their own strengths and weaknesses in the learning process (West et al., 2016; West et al., 2015). Although there is a vast amount of data collected on many e-learning platforms that can provide insight and provide guidance to both learners and educators, the data collected is rarely organized and provided to students and/or instructors (Mah et al., 2019; Schumacher & Ifenthaler, 2018).

Most of the prior research has shown that LA has a promising impact on teaching and learning. However, there are only a few studies that investigate the effect of online course design on students' transfer and retention of knowledge through learning analytics (Martin & Ndoye, 2016; Schmitz et al., 2017). Additionally, prior research showed that preservice teachers prefer to see personalized recommendation based on their feedback and learning analytics (Yilmaz & Yilmaz, 2020). Therefore, this study will explore the effect of online course design on students' learning outcomes through learning analytics.

Research design

When students interact with the content in the learning management system (LMS), they leave massive digital footprints. As a result of this big data, a new area in educational research has emerged, learning analytics. The main purpose of learning analytics is to collect static and dynamic information about the learning environments, and the learners' activities and assessments. Web analytics programs such as Google Analytics track students' usage of LMS and other digital learning objects to gauge learner engagement. Additionally, learning analytics programs collect and process various data such as learner characteristics, library catalogue searches, online frequency and times, interactions, downloads and anticipated learning outcomes (Ifenthaler & Widanapathirana, 2014; Wong, 2017). This data has presented great prospects to discover useful insights of students' online learning hapits and can result in highly adaptable and personalized learning environments through analyzing, predicting, and optimizing students' learning processes, learning environments and educational decision-making (Loh et al., 2015). Additionally, embedding the LA interface within the online course environments offers different features such as visualizations, learning recommendations, prompts, rating possibilities, and self-assessments (Ifenthaler & Widanapathirana, 2014).

Students' knowledge transfer

Knowledge transfer is a major goal of higher education (Brennenraedts et al., 2006; O'Reilly et al., 2019; Sharifi et al., 2014). According to Bloom's Taxonomy, students' creation of new knowledge is a result of their ability to retain, understand, apply, analyze, and evaluate the new concept (Bloom, 1956). The transfer of knowledge is an indication of students' deeper understanding of the learning content rather than basic rote learning (Barnett & Ceci, 2002; Schunk, 2012). Therefore, many college instructors test newly acquired skills as evaluation criteria for students' mastery of the learning content.

Background of the Study

There are many studies conducted about learning analytics, which focus on a wide range of variables and tries to reach meaningful interpretations of data for students and instructors. However, few studies attempt to discuss the effect of online course design on students' learning outcomes through findings gathered through Google Analytics (Strang, 2017).
Therefore, the purpose of this study was to explore the effect of online course design on students' transfer and retention of knowledge through learning analytics. This research study was designed to reveal study behaviors of participants over a short time while exploring their academic performance. This study was guided by the following quantitative research questions:

1. Do students' final scores in an online module correlate with their number of session views and the duration of these visits?
2. Do students' retention knowledge scores in an online module correlate with the number of the website visits and the duration of these visits?
3. Do students' transfer knowledge scores in an online module correlate with the number of the website visits and the duration of these visits?
4. What factors best predict students' transfer knowledge scores in an online course?

Additionally, the following qualitative research questions were postulated:

5. How did the participants define and what examples could they provide for "Universal Design for Learning?"

6. How did participants perceive the use of multiple representations, multiple actions, and expressions in their lessons?
7. How did the participants design instruction to address the given scenarios?

Method

Research design

This study employed a mixed method to examine the effect of online course design through learning analytics on students' transfer and retention of knowledge.
The quantitative method used correlation and multiple linear regressions analyses to examine the effect of the learning module design on students' knowledge transfer and retention. The qualitative method used students understanding of the learning concept (Universal Design for learning), and the learning analytics data during completion of the learning module. Google and YouTube Learning Analytics were used to collect data on the students' learning activities and video watching patterns while they completed the online learning module.

Sample and participants

The investigators used a convenient sample to recruit participants in the current study.
The participants in the present study were 81 preservice teachers enrolled in instructional technology course. Participants were 49 students from a state university from the USA (4 male and 45 females, age between 18-40 years) and 32 students from a state university in Turkey (all female, age 18-22 years). Participations consisted of freshmen, sophomores, juniors, and seniors in education major. Majority of participants were familiar with using technology and fluent in English and completed all module activities online as part of their class activities.

The Learning Module

The investigators developed a website with online video, online presentations, and web pages for reading and assessment. The materials used in this module focused on teachers' use of universal design for learning (UDL). The UDL is an educational framework based on research in the learning sciences, including cognitive neuroscience, that guides the development of flexible learning environments that can accommodate individual learning differences. In this learning module, students learn about how to design curriculum to be universal, the use of multiple representations in a lesson, the meaning of using multiple actions and expressions in a lesson, the use of instructional methods to present information, assess students, and maintain their engagement. The webpages used in this study included: introduction, applications, engagement, representation, and action and expression. The objective of the learning task was for students to understand the UDL concept and its applications for teaching and learning. The learning content included interactive multimodal learning content in both verbal and visual representation. The design of the learning content allowed students to have full control to navigate the website pages and review the content without limitations. The following URL represent the learning content: (https://sites.google.com/view/udl2019/home).

Measures

Quantitative Data

The investigators developed two assessments: (1) Retention knowledge was measured with a quiz that included four open-ended questions. The retention quiz was to show how much learners recalled from the information about the UDL framework, thus confirming that students really learned the information. (2) Transfer knowledge was measured by a quiz that included two open-ended questions. The Transfer knowledge quiz demonstrated the students' ability to apply this information in teaching. To ensure that the instrument is reliable and valid, the investigators computed the interrater reliability of the instrument using the correlation between the results from different classes and semesters and found that it has strong correlation (.870). The investigators checked further the internal consistency of the instrument (using Cronbach's Alpha) and found that it was .895. Taken together, these results demonstrate that the instrument is robust and ready to be used in this study. Other measures were collected through student's module activities from Google Learning Analytics: Students' effort (measured by the average learning session duration on the online learning content), motivational factors (measured by the number of sessions they conducted on the online learning module) and metacognitive factors (measured by the time spent watching video, viewing presentation and navigate the online reading).

Validity and Reliability of the Instrument

To establish the content validity for the measure, the investigators used a scale that was tested over several semesters with preservice teachers. For the construct validity, the investigators conducted Pearson correlation coefficient analyses between all items and found positive significant correlations. For reliability, the researcher used Cronbach's alpha internal consistency reliability ranging from 0.495 to 0.818.

Qualitative Data

The investigators looked for patterns and trends in students' responses to identify the main themes in their answers. The process of the data analyses includes reading through students' responses, categorizing the responses, labeling each comment with one or several categories, examine the focus of responses, identifying the patterns and trends of all responses and then writing up the analysis.

Procedure

Preservice teachers in the Turkish and the American universities completed the assigned module about the use of Universal Design for Learning (UDL) in teaching and learning. Students in both universities had one week to complete the UDL activities. At the end of the week, students completed retention and transfer knowledge tests. Students' quantitative data, such as their behaviors and activities in the online module, was collected through Google Analytics. Students' qualitative data was gathered through open-ended questions offered on the course site. In the first section of the module, students started the UDL module by viewing the introductory video about the UDL framework and then answered four open-ended questions structured at the lowest levels of Bloom's Taxonomy to solicit about the level of remembering and understanding of the UDL concept. In the second section, students explored examples of the UDL applications in teaching and learning. At the end of the second section, students were presented by two teaching scenarios and challenged to address the four higher levels of Bloom's Taxonomy, namely, applying, analyzing, evaluating, and creating.

Data Collection and Analysis

To reveal student behaviors, Google Analytics was used to collect quantitative data, while qualitative data was gathered through open-ended questions on the course site.

After viewing the introductory video on Universal Design for Learning (UDL), students answered four open-ended questions structured at the lowest levels of Bloom's Taxonomy – remembering and understanding. After the presentation of the UDL applications, students faced two teaching scenarios, challenged to address the four higher levels of Bloom's Taxonomy – applying, analyzing, evaluating, and creating.

Results

Quantitative Results

First question: Do students' final scores in an online module correlate with their number of sessions views and the duration of these visits?

To answer the first question, the investigators conducted a Pearson product-moment correlation coefficient to assess the relationship between students' module final grade (retention & transfer test scores) and their number of the websites visits and the duration of these visits to the module. The analysis shows that there was a strong and positive correlation between students' module final grade (M = 8.3 SD = 2.8), n = 76, the number of their session views in the module (M = 5.41, SD = 6.34), r = .56, p = < .001, n = 71, and the duration of the website visits in seconds (M = 334.44, SD = 520.89) r = .53, p = < .001, n = 76. Overall, there was a strong and positive correlation between all three variables. In summary, the more times students visited the learning module and the longer these visits, the higher students' grades in this module. Table 1 summarizes the correlation analysis.

Table 1. Correlations between three variables: students' scores of the module (retention and transfer), number of sessions views in the module and the duration of the website visits in seconds

		Total grade of retention and transfer	The number of sessions views in the module	Site session duration in seconds
Total grade of the module (retention and transfer)	Pearson Correlation	1	.563**	.526**
	Sig. (2-tailed)		.000	.000
	Sum of Squares and Cross-products	592.039	693.296	59364.065
	Covariance	7.894	9.904	791.521
	N	76	71	76

Note: *Three variables were included **. Correlation is significant at the 0.01 level (2-tailed).*

Second question: Do students' retention knowledge scores in an online module correlate with the number of the websites visits and the duration of these visits?

To answer the second question, the investigators conducted a Pearson product-moment correlation coefficient to assess the relationship between students' retention knowledge scores and the duration and the number of visits to the module. The analysis shows that there was a positive correlation between students' retention knowledge scores (M = 5.82, SD = 1.831), number of sessions in the module (M = 5.41, SD = 6.337), r = .28, p = < .02, n = 71. However, the results showed that there was no relationship between students' retention knowledge scores and the duration of their module visits (M = 123.97, SD = 221.39), r = .50, p = < .001, n = 84.
In summary, the more times students visited the learning module the higher students' retention knowledge scores in this module. Table 2 summarizes the correlation analysis.

Table 2. Correlations between three variables: students' retention test scores, number of sessions in the module and the duration of the website visits

		Total of retention questions	Number of sessions	Session duration in seconds
Total of retention questions	Pearson Correlation	1	.276*	.064
	Sig. (2-tailed)		.020	.608
	Sum of Squares and Cross-products	251.421	228.493	1694.848
	Covariance	3.352	3.264	26.075
	N	76	71	66

Note: *Three variables were included **. Correlation is significant at the 0.05 level (2-tailed).*

Third question: Do students' transfer knowledge scores in an online module correlate with the number of the websites visits and the duration of these visits?

To answer the third question, the investigators conducted a Pearson product-moment correlation coefficient to assess the relationship between students' transfer knowledge scores and the duration and the number of visits to the module. The analysis shows that there was a strong and positive correlation between students' transfer knowledge scores in the module (M = 2.91, SD = 1.792), the number of their sessions in the module (M = 5.41, SD = 6.337), r = .54, p = < .001, n = 71 and the duration of the website visits in seconds (M = 334.44, SD = 520.885), r = .50, p = < .001, n = 84.
In summary, the more times students visited the learning module and the longer these visits, the higher students' transfer knowledge scores in this module. Table 3 summarizes the correlation analysis.

Table 3. Correlations between three variables: students' transfer test scores, number of sessions in the module and the duration of the website visits

		Transfer test scores	The number of sessions views in the module	Duration of the website visits in seconds
Total of transfer questions	Pearson Correlation	1	.544**	.495**
	Sig. (2-tailed)		.000	.000
	Sum of Squares and Cross-products	205.446	408.246	32048.803
	Covariance	3.210	6.379	500.763
	N	65	65	65

Note: *Three variables were included **. Correlation is significant at the 0.01 level (2-tailed).*

Fourth question: What factors best predict students' transfer knowledge scores in an online course?

To answer the fourth question, the investigators conducted multiple regression analysis to identify the unique variance predicted by independent variables.
The investigators screened students' data to remove any incomplete responses (17 records were removed). The multicollinearity assumption was checked and found that the correlations between variables were less than 0.7; therefore, the multicollinearity assumption was met. Further, the probability and the scatter plots were checked and found that all points were following a straight line and the regression standardized predicted value on the x-axis within negative 3 to 3. Finally, the investigators checked the residuals statistics and found that standard residual was with minimum of -1.74 and maximum 1.86.

Multiple linear regression analysis was conducted to develop a model to predict students' transfer knowledge scores in an online course through their number of sessions in the module and their session duration. The predictor model was able to account for 27% of the variance in the dependent variable and was statistically significant at p < .01. Individual predictors were examined further, and the result indicated that out of the two independent variables, the only variable found to be a significant predictor of students' transfer learning outcome was the number of sessions in the module website (t = 4.532, p = .01). Model Summary and regression coefficients are summarized in Tables 4 and 5.

Table 4. Regression analysis model summary predictors

	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.521a	0.272	0.246	1.528	0.272	10.635	2	57	0

Note: *a. Predictors: (Constant), the number of sessions in the module, and the session duration. Dependent Variable: Module transfer tests scores.*

Table 5. Unstandardized coefficients, standardized coefficients and significance of all independent variables included in the model

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Correlations Zero-order	Correlations Partial	Correlations Part	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	2.178	.284		7.658	.000					
	The number of sessions in the module	.136	.030	.515	4.532	.000	.519	.515	.512	.990	1.010
	Session duration	.021	.052	.046	.403	.688	.097	.053	.046	.990	1.010

Note: *a. Dependent Variable: The transfer test scores*

Quantitative Results

Fifth question: How did the participants define and what examples could they provide for "Universal Design for Learning?"

In defining universal design for learning, most participants mentioned the importance of addressing individual differences of learners in terms of various dimensions such as learning styles, backgrounds, and interests. Additionally, most participants also cited the importance of providing equal learning opportunities or alternative learning options for all students. As one participant stated "UDL is all about adapting your teaching style to your individual students so that the students do not have to struggle to learn the concepts". However, when participants were asked to provide different examples not mentioned in the video, only one-third were able to provide realistic examples. More than half of the participants explained the three important concepts by either defining or providing justification for importance while a few specifically focused on addressing individual differences.
The most frequent examples focused on providing alternative learning and assessment methods. Flexible work and study space, learning preferences (audio, visual, kinaesthetic) interest and abilities, tools & software, and providing feedback were also mentioned by several students.
One of the students mentioned that "If I had a student that was in a wheelchair and couldn't move around good, they would do a virtual reality lesson instead of physically exploring something. If we were learning about plants the virtual reality game would allow the student to look at all the different plants in their natural settings, but virtually." While another mentioned that "If a teacher has a student with dyslexia, maybe they could read instructions out loud or use more assignments and assessments that are performance-based rather than on paper".

Sixth Question: How did participants perceive the use of multiple representations, multiple actions, and expressions in their lessons?

When participants are asked the meaning of using multiple representations in their lessons, the most frequent answer mentioned multiple media and/or materials and tools that would help students in the learning process. Some of the students suggested accommodating several types of learning and/or learning styles to reach all types of learners. One participant stated, "A mixture of representation for each lesson is a good way to make sure every student gets the proper educational attention" while another participant proposed "Allowing the content to be displayed in various forms can help bridge the gap between teaching style and learning type". Most of the participants were in favour of using multimedia resources to promote both audio and visual support. Hands on learning activities to address the needs of kinaesthetic learners was also frequently mentioned.

When participants are asked what it meant to use multiple actions and expressions in their lessons, the most frequent responses were giving students opportunities to display what they know and have learned through multiple means, using more than one way to test your students, or allow them to demonstrate their skills and their knowledge. One of the participants stated “Students should be given multiple outlets to show what they know. To account for varying levels of proficiency, each should be presented with varying levels of models, feedback, and support. Ongoing tasks can be scaffolded for support with the offer of graphic organizers or guided notes. Teachers should create tasks that could, for example, be completed through written assignments, technology-based presentation tools, or a recorded video. Feedback can be provided in verbal form, written form, or even using a screencast to combine the two” whereas another student added “Authentic materials prepared by the teacher can be used to get students' attention during teaching or practice sessions. I think the most important thing is to get your students' ideas while designing your lesson, so teachers should pay attention to their students' advice to meet their needs”.

Participants mentioned the importance of providing alternative learning and assessment activities, allowing students to choose how to present their information to the class. The participants also noted the value of providing regular feedback, support and providing models and/or examples to help students set goals based on their own levels and interests.
In terms of examples of learning activities, participants’ responses split into providing different alternatives to be chosen by the student or providing a project where the students would decide their own roles and the products they would produce.

Seventh Question: How did the participants design instruction to address the given scenarios?

a) Suggested Instructional Methods to Representation, Assessment and Engagement

Participants were presented a scenario of teaching a second-grade class a unit on plants. After reading the scenario, the participants were asked what instructional methods they would use to present the information, maintain student engagement, and assess student learning. Most participants focused on learning activities and instructional media rather than on instructional methods. Some students referenced the importance of the three concepts but did not mention any specific method.
Regarding the presentation of information, approximately one-fifth of the participants mentioned assessing students’ prior knowledge. Lecture, discussion, and questions and answers were the most noted instructional methods. Learning stations, guest speakers, virtual reality and self-discovery were also suggested.

Multimedia, visuals, and hands-on activities were the learning activities most preferred by the participants. Some also suggested the use of online tutorials, 3d models, experimenting with plants on the Internet and listening to audiobooks.
No two participants suggested the same approach to the scenario, even the purpose and content of videos were different. While one participant suggested showing how plants grow, another planned to demonstrate the life cycle of a bean from seed stage to a full-grown plant. Even those who agreed on observing plant growth differed as to location – plantings at home or at school. Still others recommended dissecting plants to learn about the parts. For assessment purposes, most of the participants favoured group work but approached the activity in various ways – such as growing plants in groups or preparing a class leaf identification book. Also mentioned were quizzes and tests, interactive online applications, and discussions.

The creation of posters, presentations, written reports, songs, stories, video clips or animations were also suggested as activities reflecting the students’ level of understanding. Some participants provided alternative assessments. One suggested: “answering questions out of a textbook for visual learners, playing a plant simulation on computer for kinaesthetic learners, or listening to text to speech and answering questions on computer for auditory learners”.

Challenged with maintaining students' engagement, participants favoured hands-on activities and group projects. Others suggested that discussions, interactive educational games, field trips, or student visual reports would help in maintaining engagement. Guest speakers and learning through apps were also recommended for increasing and maintaining engagement.

b) Suggested Lesson Design for a Specific Learning Goal

Participants were also given a scenario of a classroom having a total of 29 students in a tenth-grade biology class. The proposed class included 12 visual learners, 10 verbal learners, and 7 kinaesthetic learners. Additionally, two of the students struggle with reading and several have difficulty with the planning and organizing of writing assignments. Participants were tasked to design a lesson on DNA. They were to identify materials, instructional methods, and assessment techniques. The specified learning goal was Students will learn about and present information on their understanding of DNA.
Most participants favoured lectures accompanied by either videos or visually rich presentations to address visual and audio learners. Hands on activities were mentioned for kinaesthetic learners. Videos and visually rich presentations (graphics, animation, or simulation) were mentioned by almost all participants whereas the use of DNA models and printed materials was referred to by approximately one-third of the participants. Additionally, some participants listed audio support, graphic organizers and tests and rubrics as instructional materials for their courses. The least cited instructional materials included microscopes, arts and crafts, games, and online learning tools.

In parallel with the preference of instructional materials, most participants stated their preference as lecturing assisted by visuals and further supported by hands on activities such as building a DNA model. Group work, discussion, self-guided research, learning stations, online learning games and using analogies were also mentioned by some participants. Hence, participants noted the integration of both cognitive and constructivist learning approaches in their planning. One of the participants said "Students will be given guided notes to fill in as they watch a video on DNA (pausing to recap important ideas) and participate in a class discussion. They will pair off and review their answers to make sure their notes are accurate. Students will travel to stations to learn about each part of DNA and how it functions through a short video or activity or website and a 3D model". Most participants mentioned individual or group presentations of the final student products while providing various alternative choices. Less than 10% of participants preferred summative assessment using quizzes and tests.

Many project ideas also focused on constructing a DNA model composed of different materials or even online. One of the participants stated, "For final assessment, students may complete a 3D model of a DNA structure in the media of their choice (online, using craft supplies, etc.), make a movie, or create a song/rap/poem/skit that explains the different parts of the DNA structure and their purpose". Whereas another participant mentioned alternatives including "a story board, build a model of DNA structure, or write an essay on DNA". One of participants mentioned that "collaborative groups to create a presentation they can share with the class, create illustrations and posters to demonstrate their understanding. They could create a drama in which the characters are the different components that make up DNA". Thus, participants proposed a wide range of alternatives for students to demonstrate understanding.

Discussion

This research study was designed to reveal study behaviours of participants over a short time while exploring their academic performance. For this purpose, the effect of online course design on students' transfer and retention of knowledge was analysed using learning analytics. Based on a mixed method approach, both qualitative and quantitative evidence is used to understand the phenomenon.

Evidence on Performance of Students

The first question addressed the possible correlation of the students' final scores in an online module correlate with their number of session views and the duration of these visits. There was a strong and positive correlation between all three variables. Thus, the more times students visited the learning module and the longer these visits, the higher students' grades in this module. This finding is similar with many findings in the literature (Webber et al., 2013; Yukselturk & Bulut, 2007). One conclusion that can be drawn from this correlation is the material was either new to the students or considered difficult. If the material had not been novel and or difficult, students would have considered it prior knowledge and not have repeatedly viewed the material. Although this is not causal, the correlation does demonstrate that students with higher final scores valued the material and repeatedly accessed the online module.

Next, the students' retention knowledge scores were examined for a possible correlation with the number of the website visits and the duration of these visits. As with the students' final scores, the more times students visited the learning module the higher students' retention knowledge scores in this module. This finding is parallel with the literature where Wolff et. al. (2013) also stated that "it is possible to predict student failure by looking for changes in user's activity in the VLE, when compared against their own previous behaviour, or that of students who can be categorised as having similar learning behaviour" (p. 145).

The third research question examined the relationship of students' transfer knowledge scores in an online module with the number of the website visits and the duration of these visits. Again, there was a strong and positive correlation between all three variables. The more times students visited the learning module and the longer these visits, the higher students' transfer knowledge scores in this module. Thus, the students found value in the online module and returned to the online module. This is a fact that learning design activities strongly influence how students engage online (Rienties et al., 2015).
This correlation of transfer knowledge to the number and duration of website visits leads to the question of what factors would best predict students' transfer knowledge scores in an online course. A multiple linear regression analysis was conducted to develop a model to predict students' transfer knowledge scores in an online course through their number of sessions in the module and their session duration. Individual predictors were examined further and indicated that the only variable found to be a significant predictor of students' transfer learning outcome was the number of sessions in the module website.

Engagement Analytics of Participants

Participants were presented with a four-and-a-half-minute video. In comparing video interactivity, Turkish participants spent an average of just over six minutes engaged with the video compared to the U.S. participants who ended the video at four minutes. Even though all Turkish participants were fluent in English, new and unfamiliar phrases might account for the increased time, perhaps re-watching sections of the video again to fortify the definition of the new terms or clarify the contextual meaning. Most U.S. participants opted not to view the last 30 seconds of the video. In reviewing the video, this may be due to the presenter declaring, "…and that's it." at the four-minute mark followed by the words "in summary…". Thus, U.S. participants may have recognized from these verbal clues that the last 30 seconds had no new information and chose to opt out.

Definition and Examples of Universal Design for Learning

After viewing the video and other websites, participants answered four open-ended questions. Most participants were able to cite the importance of addressing individual differences in defining Universal Design for Learning (UDL) and providing equal learning opportunities for all students. However, while the participants grasp the definition and basic concept of UDL, they struggled with providing meaningful examples. Approximately one-third of the participants were able to provide a realistic example of UDL other than those presented in the video. Thus, the online module provided information at the lowest level of Bloom's Taxonomy (Remember) while providing a path to move up to the next levels of Bloom's Taxonomy (Understand and Apply).

Meaning of Using Multiple Representations, Multiple Actions and Expressions

The most common definition of multiple representations involved multiple media and/or materials and tools that would help students in the learning process. Some of the participants suggested accommodating different learning styles to reach all students. This would confirm that the participants understood that one approach is not ideal for all students.

Understanding of Instructional Design

a) Suggested Instructional Methods to Representation, Assessment and Engagement

After reading a scenario in which they would be teaching a second-grade class a unit on plants, the participants were asked to identify the instructional methods they would use to present the information, maintain student engagement, and assess student learning. Approximately 20% of the participants mentioned assessing students' prior knowledge. While lecture, discussion, and questions and answers were the most noted instructional methods, most participants focused on learning activities and instructional media rather than on instructional methods. Thus, the majority did not delineate between teacher instructional methods and student learning activities. One possible explanation for this confusion of terms is that many participants are early in their teacher education program and have limited background knowledge in instructional methods. Yet, in analysing the participants' assessment preferences, assessment approaches were not only in line with constructivist approaches but also addressed individual differences. This further supports the believe that the students could easily recognize constructivist learning activities and constructivist evaluation techniques but lacked the knowledge to integrate the three concepts of instructional methods, learning activities, and evaluation from a constructivist viewpoint. It is also important to note that this scenario provided no specific information on student needs. Thus, the scenario encouraged participants to focus on the lesson topic, not the students.

b) Suggested Lesson Design for a Specific Learning Goal

While the description in the first scenario was limited to "…teaching a second-grade class a unit on plants," the second scenario included learning styles of the students and learning challenges for certain individual students. The participants were tasked with having "students learn about and present information on their understanding of DNA." As in the prior scenario, participants favoured lecture as the primary form of instruction. Videos and visually rich presentations (i.e., graphics, animation, or simulation) were cited by almost all participants to address the needs of visual and audio learners. About one-third of the participants mentioned using DNA models for kinaesthetic learners. Most participants stated a preference for individual and/or group presentations for the final student products. Many included a variety of choices to allow students to personalize their presentations. Summative assessments found little support, with less than 10% of participants opting for quizzes and/or tests. The variety of final project ideas illustrated the participants' strong belief in constructivism. Creativity and alternative assessments were numerous, including creating songs, skits, movies, and 3D models. It was obvious that the participants felt that providing alternatives for learning and demonstration of gained knowledge and skills is important and should be supported by continuous feedback.

Conclusion

The quantitative and qualitative results of this study may appear at first to be at odds. With only one-third of participants able to cite a realistic example of Universal Design for Learning (UDL) one might assume that the module had little effect on the participants. However, it is important to remember that none of the participants had any prior knowledge of UDL before accessing the learning module. Additionally, this module was only available for one week. Thus, most participants would be considered on the "Remember" level of Bloom's Cognitive Theory, moving up from no knowledge. Having a third of participants be able to offer a unique example (Bloom's Understand level) of UDL is a significant

improvement in a short period of time. Scaffolding takes time and is tied to prior knowledge. It is anticipated that knowledge gained in the module will lay the foundation for growth in other courses.
In addressing the needs of the students in the second scenario, participants overwhelmingly targeted student learning styles and individualized needs. Valuing learning styles and individual needs are cornerstones to properly using UDL concepts. It is anticipated that as these preservice teachers learn more about teaching methods, they will improve their ability to incorporate UDL into their lesson plans. Additionally, the pretest/posttest indicates a possible cumulative effect – final grades, retention knowledge scores, and transfer knowledge scores were highly correlated to the number of times the students visited the learning module. The more times students visited the learning module and the longer these visits, the higher participants' grades in this module. Although this is not causal, the correlation does demonstrate that students with higher final scores valued the material and repeatedly accessed the online module. As with the students' final scores, the more times students visited the learning module the higher students' retention knowledge scores in this module. In line with these findings, the more times students visited the learning module and the longer these visits, the higher the students' transfer knowledge scores in this module. Most importantly, the only variable found to be a significant predictor of students' transfer learning outcome was the number of sessions in the module website (Chen et al., 2020; Ibrahim et al., 2019).

Implications and recommendations

This study presented the results of the effect of online course design on students' transfer and retention of knowledge using LA. A major implication of these findings is that students' engagement in online learning environment and grade improvement appear to be the result of applying the online design principles to the learning content. Although many online platforms use LA to monitor students' learning patterns and the design of these online platforms are improving over time, some platforms ignore the role of theory-based and the best practices design principles to guide their design. Therefore, we recommend developing learning platforms based on best practices in the field of online learning and monitoring students' learning patterns using LA. Furthermore, online course developers should use design elements to encourage students to engage more often with the learning content to enhance students learning outcomes. It is also recommended to embed online course elements to encourage students to spend more times and pay frequent visits to the online learning modules to enhance their learning and engagement with the learning content.

Limitations of the study

The invistigators recognize in the present study that there is possible limitation related to the sampling technique. First, this study utilized a convenience sample. As such, this type of sampling has its limitation because it centers around one specific population of students and in one domain of study. Furthermore, the fact that the content used in this study was relatively low in difficulty (i.e., "remember" level of Bloom's Cognitive Theory), suggests that it is possible that researchers working with more complex topics, and other populations will produce entirely different results. This limitation has been consistently reported in another research. For example, it was reported that cognitive support through instructional design is particularly effective when used with novice learners and complex topics (e.g., Shapiro, 1999). Finally, while the investigators attempted to control for as many differences as possible between groups, any two groups, especially from two different countries, always runs the risk that prior differences exist between them on variables not measured, and these differences may cause differences in the outcome variables. However, we had no reason to suspect that the two groups of students participated in this study would differ, as all students were non-science majors and generally in their junior or senior year of college.

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Appendix

Students answered four questions after the introductory video:

1. What is Universal Design for Learning approach?
2. How can you design curriculum to be universal? Give three examples of designing universal learning different from the examples in the video?
3. What does it mean to use multiple representations in your lessons? Give three examples.
4. What does it mean to use multiple actions and expressions in your lesson? Give three examples.

Students answered two questions after the presentation of the UDL applications:

1. Imagine that you are a second-grade teacher beginning a unit on plants. You wish to make certain that you address the three principles of UDL. Describe the instructional methods you would use to present the information, assess your students, and maintain their engagement in the subject.
2. At the beginning of the year, Ms. Hamilton, a tenth-grade biology teacher, collected information about her students' learning preferences and learning needs. Of her twenty-nine students, twelve prefer to learn new information through visual means, ten prefer to hear the information, and seven prefer to learn it using a hands-on-approach. Additionally, two students struggle with reading, and several have difficulty planning and organizing writing assignments. Help Ms. Hamilton to design a lesson about DNA. Make sure to state the learning goal and to identify materials, instructional methods, and assessment techniques. Learning goal- Students will learn about and present information on their understanding of DNA.

Ethics Approval: All procedures performed in the current study were in accordance with the ethical standards of the institutional and national research committee and with the 1964 Helsinki declaration and its later amendments and the comparable ethical standards.

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