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Measuring Cognitive Load and Motivation in e-learning: The Case of two Kenyan Universities

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ABSTRACT

E-learning is an emerging trend in most universities. Due to COVID-19, many universities adopted e-learning. With the sudden adoption and implementation of e-learning, learners had to undergo learning on how to learn and take examinations electronically, which could have increased cognitive load in their learning experience. Without regular, face to face interactions with their peers, lecturers and tutors, learners could have also experienced challenges in keeping themselves motivated to study, carry out their course projects and prepare for examinations. Though cognitive load and motivation are essential elements in ensuring effective e-learning, there are not many studies that have looked at the impact of e-learning implementations on these elements for learners. This study therefore aimed to measure the cognitive load and motivation of e-learners and see the relationship between support provided to learners and cognitive load and motivation. The study was carried out in two Kenyan universities. A total of 314 learners participated in the study. The study revealed that e-learners experienced average cognitive load and above average motivation levels. Learners who received support reported lower intrinsic and extraneous cognitive load and higher germane and motivation levels. The study concludes that, learners in e-learning environment are experiencing average cognitive loads and above average motivation and therefore require instructional designers to implement strategies to reduce the cognitive load and improve motivation.

Keywords: *Cognitive load, motivation, e-learning, learner support, distance learning*

INTRODUCTION

With the onset of COVID-19 in the world, learning in universities was disrupted by closure of institutions. Students and lecturers were both forced to stay at home because of the need for social distancing. In order to cover learning for that period, most universities were forced to implement e-learning. E-learning provided the universities with an opportunity to reach their students who were spread out in different parts of the world. The use of e-learning in these institutions continues as an established mode of teaching and learning even after the Covid-19 pandemic.

In Kenya, most universities were closed and learning was halted during the Covid-19 period, but a few institutions moved to e-learning and students were able to continue with their studies. Those who adopted e-learning experimented with different e-learning platforms that were made available. The platforms used ranged from web conferencing tools such as Zoom, Google Meet, Microsoft Teams, Cisco Webex and BigBlueButton for synchronous learning. For asynchronous learning, learning management systems such as Moodle, Blackboard, Google Classroom and Canvas were used. Those institutions which had existing platforms utilized them. The implementation of e-learning took different approaches, such as fully online with varying degrees of synchronous and asynchronous learning, and blended which consisted of online classes with a few physical classes.

Though the use of e-learning was catalyzed during the COVID-19 pandemic, e-learning continues to be used in most learning institutions even after the end of the pandemic. Institutions are still using e-learning either to offer fully online courses or to offer blended learning. There are many benefits that can be drawn from the use of e-learning such as flexibility in terms of access, availability of learning opportunities anytime and anywhere.

Studies have been carried out to investigate the challenges of e-learning during Covid-19 period to both students and teachers' (Abidah et al., 2020; Aboagye et al., 2020). The challenges identified can be categorized as social, academic or generic. Though the impact of e-learning is being investigated, few studies have looked at what effect e-learning has on the learner's cognitive load and learner motivation. It is important to look at these aspects because the effort put into learning is not only determined by the learners' intellectual capacity, but is majorly determined by their motivational levels (Abeysekera & Dawson, 2015) and the amount of free working memory for processing the new information (van Merriënboer & Ayres, 2005; Oboko, 2012).

Cognitive overload is one of the factors known to impair learning. Cognitive load is the load imposed on the learner's memory when they are trying to process information (Morrison et al., 2014). According to cognitive load theory, the brain is divided into two: working and long-term memory. The information that learners receive is first processed in the working memory which has limited capacity. The cognitive load the learner experiences varies, depending on whether the information is new or already learnt. High cognitive load leads to learning impairment (Sweller et al., 2019). Depending on the design of the learning experience, learners are known to experience different cognitive loads (Sweller, 2011).

Motivation is another aspect that has an effect on learner performance (Wu et al., 2020). In their analysis of key determinants of performance of students in e-learning, Castillo-Merino & Serradell-López (2014), found that motivation was one of the key factors that determine the performance of e-learners. Other studies have shown that highly motivated students perform better than those who are not motivated (Chiu & Li, 2015). In order to ensure that students are motivated in e-learning, motivational strategies need to be employed. Literature on motivation has outlined principles of motivating students in e-learning such as learner's curiosity arousal and sustenance, providing learning relevant to learners' personal needs and goals, arousing conviction to succeed and the alignment of learning with the learner's motivation (Keller, 2008).

LITERATURE REVIEW

Cognitive Load Theory

Cognitive load theory was developed in the 1980's. The basis of the cognitive load theory is the architecture of human cognition (Sweller, 2011). The theory builds on the premise that our memory is divided into two: working memory and long-term memory. When learning new concepts, the information is first processed in our working memory, before it is transferred to the long-term memory. According to cognitive load theory, our working memory is limited in terms of the number of information elements it can process at a time. If the information being learnt is already present in the long term memory, the limitations of the working memory are eliminated. Cognitive load therefore can be defined as the load experienced by learners when processing information. Cognitive load is increased when the working memory is used to process demands that are not necessary, hence gets filled with information that is not required for learning at a particular point in time. Higher cognitive loads hinder learning (Sweller et al., 2019). If the load that prevents learning is reduced and the memory resources are used by the load that enhances learning, then learners will experience optimal learning (Choi & Kim, 2021).

Cognitive load is divided into three categories: intrinsic, extraneous and germane cognitive load. The intrinsic cognitive load is as a result of complex information processing brought about by the concept of how elements interact. The amount of intrinsic cognitive load that learners experience is majorly determined by the complexity of the information and the learners' prior knowledge (Sweller et al., 2019). Extraneous cognitive load is as a result of processing information that is not relevant to learning, imposed majorly by poor instructional designs. Extraneous cognitive load can therefore be reduced by proper instructional design (Sweller et al., 1998). Germane cognitive load is the load imposed to the learners' memory that is necessary for learning such as problem solving or engaging in discussion. Germane load is basically the amount of effort the learner uses to be able to deal with the intrinsic load. There is therefore a direct relationship between germane load and the intrinsic load. The higher the germane load, the lower the intrinsic load (Sweller et al., 2019).

Cognitive load and e-learning

There are some studies that have been carried out to evaluate the learners cognitive load in e-learning environments. This section discusses some of those studies.

The length of an interactive video has been found to have an effect on the cognitive load of the learner. In his study on the impact of the length of the video on cognitive load and academic achievement in e-learning environment (Afify, 2020), found that the students who studied using the short interactive videos had better academic achievement and had reduced cognitive load as compared to those who studied longer videos. This result was attributed to the fact that watching shorter videos does not put an extra cognitive load to the learner. Furthermore, shorter videos are known to focus on only relevant information as compared to long videos which might contain unnecessary information hence leading to higher extraneous cognitive load.

E-learning personalization is another aspect that has been found to affect the cognitive load of learners. The increase in personalization has been established to lead to decreased levels of cognitive load in a study done by Lange (2023). Another study by Sun & Yu (2019), found that personalization leads to the reduction of the intrinsic and extraneous load and an increase in the germane load. Though literature has majorly shown that personalization leads to management of cognitive load, one study has found contradictory results, where the results show that personalization did not have an impact to the learners' cognitive load (Van de Weijer-Bergsma & Van der Ven, 2021). This result was attributed to the fact that, personalization might not be effective if the problems provided were easy for the learners. In the case of the study by Van de Weijer-Bergsma & Van der Ven (2021), they noted that the problems provided to the learners might have been too easy for the learners for it to provide the desired effect of personalization.

Another technique in e-learning that affects cognitive load is use of leads. Leads are basically information that is provided to guide the learner on what a hypertext link is about. In their study on investigating the impact of hypertext leads on the cognitive load, Antonenko & Niederhauser (2010) found that leads have an influence on the germane cognitive load.

Even though studies have been done that evaluate the impact of certain e-learning aspects to cognitive load, there is still a gap in terms of studies that generally evaluate the impact of learning using e-learning platforms on learners' cognitive load.

The Attention, Relevance, Confidence, and Satisfaction model (ARCS)

Motivation is an important factor that contributes to effective learning (Orhan Özen, 2017). Research has indicated that motivated learners perform better than those who are not motivated. According to the Attention, Relevance, Confidence, Satisfaction (ARCS) model, motivation to learn can be categorized into four aspects; attention, relevance, confidence and satisfaction (Keller, 2008). Keller argued that learners will be motivated if their attention is aroused and maintained, that relevant content is provided to them to keep them motivated, they have self confidence that they will succeed in their learning endeavors and that they are engaged in learning activities that bring them satisfaction. Some of the strategies that have been used for motivating learners in e-learning include, the use of videos to provide rich content, cues, metaphorical interfaces, hypertext and sequencing (Ochukut & Oboko, 2021).

The relationship between e-learning and motivation was studied by Harandi (2015) where he found a significant relationship between e-learning and motivation, supporting the idea that the use of e-learning improves learner's motivation. In some studies, e-learning has been found to lead to higher motivation in learners as compared to traditional face to face learning (Lin et al., 2014). In a study carried out by Law et al. (2010), reward, recognition, clear direction, attitudes of the individuals and their expectations were found to increase motivation.

Learner support

Learner support is an import aspect of any e-learning initiative that has been established to affect both the cognitive load and motivation of learners. According to (Baruah, 2018), learner support includes all the services provided to those learners engaged in distance learning so that they do not feel isolated. There are several forms of learner support offered in e-learning platform. This may include support given by teachers facilitated by technology such as messaging the lecturer or emailing the lecturer, scaffolding support such as link hiding, annotation and sequencing.

It has been proved that learner support can enhance student motivation and engagement. In his study Chiu, (2021) found that the different types of support (teacher support and digital support) contributed positively to learners' engagement. In other studies learner support has been found to play a mediating role on the impact of the cognitive load in learning using e-portfolios (Lin et al., 2013). In addition, learner support has also been noted to influence performance outcomes.

In order to make learning successful, it is important for e-learning designers to think about the various ways they can support learners in e-learning platforms.

Even though there is a shift by universities to e-learning, the impact that e-learning has on student learning is not known (wei bao, 2020). In addition, there are not many studies that have looked at the impact of providing support to both cognitive load and motivation. This study was therefore carried out to contribute to filling this gap by measuring the cognitive load and motivation of e-learners in Kenyan Universities.

RESEARCH METHODS

Objective of the study

This study was carried out to measure the learners' cognitive load and motivation in e-learning environments and to establish the effect of support on learners' cognitive load and motivation.

Research questions

The study sought to answer the following questions:

1. What levels of cognitive load and motivation are experienced by learners who use e-learning?
2. What is the relationship between learners' cognitive load and motivation?
3. What is the effect of the mode of study on learners' cognitive load and motivation?

This research was based on the cognitive load theory developed by Sweller (2011) and the Attention, Relevance, Confidence and Satisfaction (ARCS) model by Li & Keller (2018). The study employed the survey methodology.

The questions were measured on a 11-point Likert scale with 0 indicating not the case at all and 10 indicating completely true. This scale has been commonly used in other studies for measuring cognitive load (Morrison et al., 2014; Leppink et al.,2013). The questions for intrinsic and the extraneous load were phrased negatively and the questions for germane load were phrased positively. A rating of 10 indicated that the learner experienced the highest load.

The motivation questionnaire was measured on a 5-point Linkert scale with a 1 indicating not true and 5 indicating very true. The motivation questionnaire had twelve questions. Each of the ARCS model component was measured using three questions. The ratings of the three questions were averaged to get the overall rating for a component.

Sampling technique:

Purposive sampling was used to select the two institutions of higher learning for the study; University of Nairobi (UON) a public university and United States International University (USIU) which is a private university. The two institutions were selected based on the fact that they were offering their courses online. The students who were taking e-learning courses at the selected Universities were asked to respond to the questionnaire.

Sample size

The sample size was calculated using the Cochran formulae with a 95% confidence level, a maximum variability of 0.5 and the error rate of 0.05. This gave the sample size of 314.

Data collection instruments

A questionnaire was developed based on existing questionnaires. The cognitive load questionnaire was adapted from Leppink et al., (2013) while the one for measuring motivation, was adapted from Loorbach et al. (2015). The adapted questionnaires were modified to fit the study. The wordings of the questionnaire were particularly changed to reflect the e-learning aspects such as the learning platform and the instructions and explanations provided in the learning platform. The Cronbach alpha values for the items used in this study as reported in the study by Leppink et al. (2013) are 0.85, 0.80 and 0.89 for the intrinsic load, extraneous load and germane load items respectively. For the motivation aspects, the Cronbach alpha values as reported by Loorbach (2015) were; 0.90, 0.82, 0.89, 0.85 for attention, relevance, confidence and satisfaction respectively. The questionnaire contained four sections: demographic data section, the cognitive load measurement section, and the motivation measurement section.

Data analysis

Data were analysed using Microsoft Excel 2013. The analysis was done in form of descriptive statistics using the mean and the standard deviation and inferential statistics using correlation and Mann-Whitney U Test which is a non-parametric test.

Research study approvals

The researchers received a permit to carry out the research provided by NACOSTI a research body in Kenya that licenses all researchers.

RESULTS

Demographic data

The sample used in this study consisted of 314 undergraduate students from UON (85.8%) and USIU (14.2%). 35% of the participants were female and 65% were male. The participants were aged 17 to 35 years old. The participants were either learning full time or part time, with a great majority of them, 93.9%, studying full time. The participants were drawn from the 4 levels of study, which is First year to fourth year, with the first year and the third-year students being the majority and constituting 30% of the participants each. The students were studying either in a blended mode or fully online synchronous mode. The learning management platform used by the participants were; Moodle, blackboard and Google classroom. The mode of study used were blended and synchronous.

Types of support provided

Out of the 314 participants, 76% reported that they had received support while 24% reported not having received support. The support received by the participants were in various forms, as shown in Table 1. Email was reported to be the most common channel for providing support to the learners at 68.4%, followed by chats to the instructors at 56.3%. Only 12.1% of the participants reported having received personalized suggestions as a form of support. For support in form of worked examples, only 2% of the participants reported having received it.

Table 1: *Types of support provided*

Forms of support	Number of learners and percentage
Emails	175 (68.4%)
Chats with instructors	144 (56.3%)
Tasks with solutions in the material	76 (29.7%)
Prompts while solving problems	53 (20.7 %)
Prompt feedback on assignment	104 (40.6%)
Prompts while solving problems	53(20.7%)
Guided Navigation	50 (19.5%)
Sequencing of materials	44(17.2%)
Personalized suggestions	31 (12.1%)
Worked examples in the materials	2 (0.8%)

Cognitive load and motivation levels

To determine the cognitive load and motivation levels of the participants, the mean scores of the various aspects of cognitive load as shown in Table 2. The participants recorded higher germane load as compared to other forms of cognitive load, with extraneous load being the lowest.

Table 2: *Cognitive load measurements*

Type of cognitive load	Mean	Standard deviation
Intrinsic load	5.4	2.54
Extraneous load	3.9	1.97
Germane load	6.5	2.51

For motivation, the relevance aspect had the highest score at an average of 3.5 out of 5, followed by confidence. Satisfaction had the lowest score at an average of 3.0 out of 5 as indicated in Table 3.

Table 3: *Motivation measurement*

Motivation aspect	Mean	Standard deviation
Attention	3.1	1.06
Relevance	3.5	0.98
Confidence	3.4	1.09
Satisfaction	3.0	1.20

Difference in cognitive load and motivation between learners who reported having received support and those who did not

In order to determine whether there was a significant difference in cognitive load and motivation among the learners who reported having received support and those who did not, Mann-Whitney test was carried out. The Mann-Whitney test was selected because the data was not normally distributed. The data showed that participants who received support experienced a statistically significant higher germane load than those who did not receive the support, with a p-value of 0.00 and effect size of 0.408. There was, however, no statistically significant difference between the learners who received and those who did not receive support in the cases of extraneous load and intrinsic. The results are shown in table 4.

Table 4: *Cognitive load difference between participants who received and did not receive support*

	MEAN		U	p-value	Effect size
Cognitive load	**Yes**	**No**			
Intrinsic	5.3	5.8	7807.0	0.09	0.129
Extraneous	3.8	4.3	7916.5	0.13	0.117
Germane	6.9	5.1	12643.0	0.00	0.408

For motivation, results shown in table 5 indicate that there was a statistically significant difference between the participants who reported as having received support and the participants who reported that they did not receive support, in the relevance, confidence and satisfaction aspects of motivation. Participants who received support recorded higher motivation levels than participants who did not receive support. The results indicate that, there is a statistically significant difference in all motivation aspects between learners who received support and those who reported not having received support.

Table 5: *Motivation difference between participants with support and those without support*

			U1	**p-value**	**Effect size**
Motivation	**Yes**	**No**			
Attention	3.3	2.7	6303.0	0.00	0.292
Relevance	3.6	3.1	6118.5	0.00	0.317
Confidence	3.6	3.1	6571.0	0.00	0.267
Satisfaction	3.1	2.5	6270.0	0.00	0.300

Differences in cognitive loads and motivation between the learners who used different modes of study

There was a statistically significant difference in extraneous load between the participants that were using blended learning and those who were using purely synchronous mode. The learners using blended learning reported higher extraneous cognitive load. Though there was a difference in the means of the intrinsic and germane load between the participants in blended learning and those in synchronous learning, they were found to be not statistically significant according to the Mann-Whitney test as shown in Table 6.

Table 6: *Difference in cognitive loads between participants who were on blended learning and those on Synchronous learning*

	Blended(mean)	**Synchronous(mean)**	**U1**	**P**
Intrinsic	5.51	5.31	10540.0	0.63
Extraneous	4.36	3.72	11850.0	0.02
Germane	6.52	6.55	10178.0	0.99

For motivation, even though there was a difference in the means of the two groups, that is blended learning and synchronous learning, all the aspects had no statistically significant differences between the two groups, as shown in Table 7.

Table 7: *Difference in motivation levels between participants who were on blended learning and those on Synchronous learning*

	Blended (Mean)	**Synchronous (Mean)**	**U1**	**P**
Attention	3.13	3.13	10128.0	0.93
Relevance	3.13	3.13	1015.5	0.91
Confidence	3.42	3.49	9947.0	0.74
Satisfaction	3.06	3.00	10579.5	0.59

Correlation between cognitive load and motivation

In order to find out if there was a correlation between the cognitive load levels with the levels of the various aspects of motivation of the participants, correlation analysis was carried out. The data showed that, intrinsic and extraneous load ware positively correlated with each other while being negatively correlated with germane load and all the motivation aspects. Germane load on the other hand, was positively correlated with all the aspects of motivation. All the motivation aspects were positively correlated with each other. Figure 1 shows the correlation between the various aspects of cognitive load and motivation.

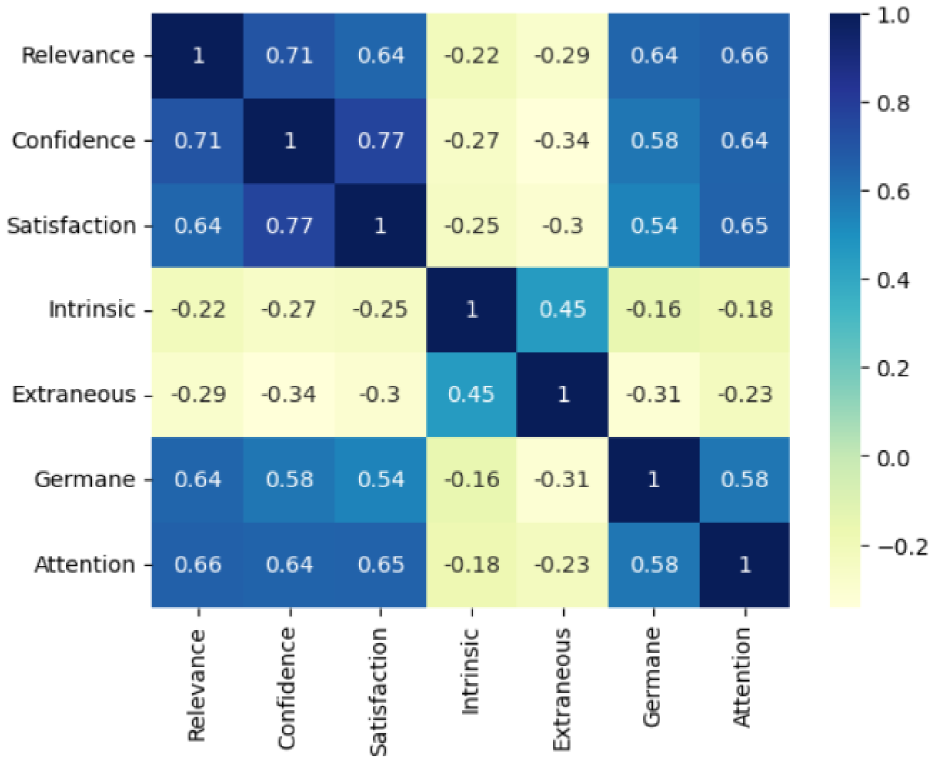

Figure 1: Correlation between the various aspects of cognitive load and motivation

DISCUSSION

The main aim of the study was to measure the cognitive load and motivation of learners in e-learning. The results indicate that the participants experienced average cognitive load. Participants who reported having received support had slightly lower intrinsic 5.3 and extraneous load 3.8 and slightly higher germane load 6.9 as compared those learners who reported not having support. This can be explained by the fact that providing support in terms email explanations simplifies the tasks for learner hence the less intrinsic load. In addition, support provided to learners removes the need for the learners to look for solutions in other places, hence the lower extraneous load. Those who reported not having received support had 5.8, 4.3, 5.1 Intrinsic, extraneous and germane load respectively. This shows the importance of providing support to e-learners. Providing support to learners tends to reduce their extraneous and intrinsic cognitive loads therefore providing more memory for the germane load which is necessary for learning (Van Merriënboer et al., 2006). This is indicated by the significant difference in the germane load between the participants who received support and those who reported not having received support. Previous research has shown that managing cognitive load leads to optimal learning. Higher intrinsic and extraneous load have also been shown to affect learning negatively (Choi & Lee, 2022). Providing support to online learners will therefore help in contributing towards effective learning in e-learning environments.

In terms of motivation, the participants experienced above average motivation levels in all the aspects of motivation based on the ARCS model. This means that learners believed that the e-learning courses captured their attention, made them confident, were relevant and they were satisfied with the learning. Learners who reported having some form of support had statistically significant (0.00<0.05) higher motivation levels as compared to those who did not receive support. This indicates that providing support to learners makes them more motivated. Learner motivation is considered as one of the factors that influence learners' success. The results of this study support similar finding from studies from Berestova et al. (2022), who found out that support from instructors was one of the factors that influenced learner motivation. (Fryer & Bovee, 2016), also found out that teacher support had a significant influence on learners' motivation. In a study done to evaluate the impact of learning support provided through nudges, it was found that nudges had a positive effect on learner satisfaction, a component of motivation (Rodriguez et al., 2022).

This study also revealed a correlation between motivation and the germane load. It found out that germane load was positively correlated with all the aspects of motivation. Meaning motivation makes learners want to spend more effort in learning. Negative correlation was found between the intrinsic and the motivation aspects and between extraneous load and the motivation aspects This indicate that if learners experience higher intrinsic and extraneous cognitive load, they are likely to be demotivated to learn. Other studies have shown that high motivation level leads to lower intrinsic load as learners who are highly motivated perceive tasks to be less difficult (Feldon et al., 2019). Xu et al. (2021). This is consistent with the results of this study that indicate that an increase in motivation leads to a decrease in extraneous and intrinsic cognitive load.

One limitation of this study is that it did not consider one form of support rather all the forms that the learners had indicated they were using, because of this, it may be difficult to know which form of support is effective in reducing the cognitive load and enhancing the motivation of the learners. Future studies could consider looking at the different forms of support and their individual impact on cognitive load and motivation.

CONCLUSION

This study has shown that e-learners who participated in this study experienced average cognitive load and above average motivation. It has also shown that learners who receive support have lower cognitive load and higher motivation levels as compared to those who did not receive support. This indicates the importance of providing support to e-learners. Support leads to lower intrinsic and extraneous load, and higher germane load and motivation. It is therefore important for learning designers to consider providing support to e-learners for effective learning.

The study also revealed a negative correlation between intrinsic and extraneous cognitive load with the aspects of motivation and a positive correlation between germane load and the aspects of motivation. This shows that highly motivated learners will have more effective learning since motivation is associated with lower levels of the undesirable extraneous and intrinsic cognitive load while it is associated with higher levels of the desirable germane cognitive load. It is important for the e-learning designers to include motivational aspects in their course designs.

The study recommends the provision of learner support to e-learners in order to help in the management of cognitive load and enhancement of learner motivation. The study also recommends exploring the most effective ways to support e-learners.

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