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The relationship between online learning readiness and cognitive load in college students.

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Abstract
This study examines the readiness of students to learn online and how this readiness is affected by the cognitive load to establish the willingness of students to undertake online learning activities and the load exerted by this environment. In this study, a correlational design was used and the participants included 200 students who completed standardized scales on their readiness to learn online and their perceived cognitive load. A negative correlation was found between preparation and perceived cognitive load, meaning that students who are well prepared for online courses experience low cognitive load. These results support efforts to improve student preparation for online learning, resulting in better cognitive functioning and avoiding overload. Potential implications for teachers and school leaders are highlighted and suggestions are made regarding online learning.

Keywords*: Online learning readiness, cognitive load, college students, e-learning, mental strain*

Introduction

The rapid digitization of education in general, and higher education in particular, profoundly reshapes old paradigms of learning. The global COVID-19 pandemic accelerated this shift, propelling online learning into the mainstream of education and giving students the flexibility to access content from virtually anywhere and at any time. As noted by Dhawan (2020), while online learning has opened wider access to education and provides a more personalized approach toward learning, it also presents unique challenges that need to be negotiated by students. These are multilayered challenges that often involve the preparedness of a student to engage effectively with the digital platforms and modes of delivery. Relevance of online learning readiness has, therefore, increasingly surfaced since this encapsulates the competencies students must have to function successfully here (Hung et al., 2010).

Online Learning Readiness

The readiness for online learning denotes an individual student's conceived ability to adapt and function in the environment of digital learning. These include technical skills, self-directed learning, time management both on and off-line, communication skills, and a sense of self-efficacy. By contrast, online learning requires that students be more autonomous in their educational experience than perhaps traditional F2F classroom education would provide. Self-regulation and motivation are the most important points, since students have to take care by themselves while browsing through the course materials, assignments, and deadlines without actual feedback or intervention by instructors.

Indeed, there is evidence that the most decisive factors in students' academic success and engagement are actually their readiness for online learning (Yukselturk & Bulut, 2007). More prepared students usually have higher levels of self-regulation skills, better time management, and a higher ability to seek help when they need it, leading to more course success. Students who score low on these skills may feel overwhelmed with demands in online classes and, therefore, become more stressed, lose their motivation, and drop out of school. It is also important, as online learning becomes increasingly integrated into higher education, to understand student readiness for engagement in this mode of instruction as a means to design learning environments that are effective for diverse students.

Cognitive Load Theory

While preparation for online learning focuses on a student's personal and technical skills, cognitive load refers to the mental effort required to process and retain information during learning. The cognitive load theory, inspired by Sweller in 1988, assumes that the human cognitive architecture is limited by a single channel of information in working memory at any given time. There are generally three types of cognitive load: intrinsic, extrinsic, and relevant cognitive load. Internal loadrefers to the inherent difficulty of the material to be learned; the external load, in the way that the information is presented; and the corresponding load, for the cognitive effort dedicated to learning and schema construction.In the case of online learning environments, there is usually a higher level of extraneous cognitive load caused by the design and delivery of the digital content itself (Ayres & Paas, 2007). These special cases include complex multimedia presentations, fragmented information, or poorly designed learning platforms that can overload a learner cognitively, leading to a reduced ability to process and recall information effectively. In addition,The lack of familiarity with the digital tools used in online learning will create an additional workload for students due to the difficulty of mastering the technological aspects of the subject. Therefore, cognitive load is an important contributor to how students learn in an online environment.

The management of cognitive load is an important factor that will maximize learning when it comes to online education. Some of the instructional strategies, like simplification of delivery of presentation, clear guidance, and reduction of unnecessary distractions, lower the extraneous load and free up more cognition for germane processing.

Even under conditions of ideal instructional design, students' state of readiness for online learning can impact the effective management of cognitive load. A student who is well-prepared for online learning likely has a low extraneous load because he feels more comfortable on digital platforms and engaging with the course materials. On the other hand, low-readiness students cannot bear the burden of cognitive load for online learning and subsequently create an overload on the mind that reduces the academic performance.

The Interaction between Readiness for Online Learning and Cognitive Load

The trending interest in online learning readiness and its correlates to cognitive load is one of the newest interests in educational research.

Initial studies indicate that students who are more online learning-ready also tend to handle cognitive load better in digital learning environments (Lee et al., 2019). Students with a higher degree of online learning readiness tend to represent stronger self-regulation abilities. Students can also handle the distribution of the cognitive resources more purposefully and focus resources on handling a learning task instead of being cognitively overwhelmed by perceptions of extraneous factors (Broadbent, 2017). At the same time, their familiarity with digital tools and platforms can reduce extraneous cognitive load related to the navigation itself in online courses, thus releasing cognitive resources for deeper learning and comprehension to occur (Bannert, 2002).

On the other hand, a low readiness online learning student would be heavier in his cognitive load, especially extraneous load, with poor time management when he faces an unfamiliar online learning environment. Kalyuga (2009). This may result in the so-called cognitive overload, that is, a situation where the mental effort to be invested surpasses cognitive capacity, thus leading to poor learning outcomes, frustration, and disengagement. As Sweller adds, "If instructional material is to be altered in some way so that the learner becomes aware of the relations between elements, the limitation in the capacity of working memory would need to be overcome" (1988). It is for this reason that a look at how online learning readiness interacts with cognitive load is vital to understand what leads students either to success or failure in online education.

Literature Review

The relationship between online learning readiness and cognitive load has gained popularity in the surge of digital learning environments over the last decade. The methods used to test how prepared a student is for online learning, including how they manage cognitive load, and further examining the factors of academic performance and overall learning outcome have been quantitatively performed by researchers.

Introduction to Online Learning Readiness

ne of the main studies in this field is that of Hung et al. (2010). His quantitative study, which included more than 1,000 students, showed that higher levels of preparation are significantly associated with better academic performance in online courses, perhaps the key factor in the ability of students to adapt to digital learning environment. This scale has been used in numerous studies to assess the readiness of students from different demographic groups and in different educational settings.On this basis, Martin et al. (2017) conducted a large-scale quantitative survey in an effort to understand online learning preparation issues related to student success. Applying structural equation modeling to survey data from 542 college students, they found results on the most important predictors of online learning success for self-directed learning and motivation.

Furthermore, students who scored higher in readiness for online learning regulated the cognitive demands better, hence creating a more engaging environment and, finally, leading to better learning outcomes.

In a different study, Tang & Chaw (2016) examined whether readiness for an online learning environment impacts students' satisfaction and engagement when participating in a fully online learning environment.

Using a sample of 300 undergraduate students and through multiple regression analyses, the researchers ascertained that the online learning readiness dimensions, like self-efficacy and learner control, have acted as considerable predictors of the satisfaction and coping of the students with the cognitive demands of online courses. Further in their emphasis, the implications were revealed to the researchers about autonomous learners whose influence buffers the detriments of having to work under high cognitive load in a setting online.

Cognitive load in online learning.

Cognitive load theory, rooted by Sweller originally in 1988, has extended to online learning in recent years. Research has quantified how diversified instructional designs in online learning-even living among a sea of multimedia-affect students' cognitive load.

In 2015, Chen & Wu, using an experimental process with 120 college students, quantified the effect of the popularity of multimedia instruction design on cognitive load. The results indicated that poorly designed multimedia content significantly increased extraneous cognitive load and impeded information processing and retention, measured by the NASA Task Load Index. On the contrary, high cognitive load had less influence for those students with higher online learning readiness, especially students proficient in self-directed learning, since such a skill could help with regulating their learning processes.

For example, Hsu et al. (2019) investigated the moderating effect of online learning preparation on the effects of cognitive load in a research project involving 245 students. As a result, their path analysis showed that high readiness students experienced only low levels of cognitive overload, even in a complex online learning environment. Researchers have stated that time management, self-regulation and interaction with digital tools are some of the factors that can reduce the cognitive challenge associated with using online multimedia learning.

In another related study, Lee and Martin (2020) applied a quantitative survey approach to 400 high school students to examine how cognitive load interacts with students' self-regulation skills in the online environment. Their study found that cognitive load was significantly inversely related to academic performance when students lacked adequate self-regulation strategies.On the other hand, students highly prepared for online learning showed a better management of the cognitive load related to the dimensions of motivation and self-regulated learning, thus leading to better learning outcomes.

The relationship between willingness to learn online and cognitive loadIn recent years, a number of quantitative studies have been carried out, focusing on the interaction between readiness to learn online and cognitive load.For example, Lee et al. (2019) examined the role of preparation on cognitive load through a survey of 312 university students participating in online courses. They applied multiple regression analysis and found that students characterized by a high willingness to learn online show a significantly lower external cognitive load, since they are better able to control the online learning environment and manage the complexity of the digital content.

The results of the study show that preparation for online learning improves student performance and reduces cognitive strain. In another related study, Zhang et al. (2021) used SEM to analyze data from 500 college students enrolled in fully online courses. The authors found that preparation for online learning, particularly in terms of self-efficacy and time management, directly affected students' ability to manage cognitive load. Students who scored high in readiness did not sufferof cognitive overload and were therefore able to focus on the relevant cognitive processes essential for deep learning.

On the other hand, Broadbent (2017) conducted a meta-analysis of 20 quantitative studies that explored how self-regulation-the core of online learning readiness-affects perceived cognitive load in online environments. The findings from the meta-analysis indicated that self-regulation significantly reduced cognitive overload and consequently improved learning performance in different online learning environments. The author concluded that the design of strategies that improve self-regulation for online learners could contribute to reducing digital learning-related cognitive problems. Conclusion Quantitative studies over the past decade have pointedly and consistently identified online learning readiness as being critically linked with cognitive load. The student who is more disposed toward online learning environments through self-regulation, time management, and self-efficacy handles cognitive load more effectively, hence increasing their learning outcomes.

Remaining research should focus on developing interventions to enhance the students' readiness for online learning and reduce cognitive overload, especially within complex or heavy digital multimedia environments, as online learning continues to grow. Theoretical and Conceptual Framework This study relies on two theoretical underpinnings: the Cognitive Load Theory and Self-Regulated Learning Theory, explaining how online learning readiness influences cognitive load in students.

Research Question

- How does students' online learning readiness influence their ability to manage cognitive load?

Aim of the Study

This study assesses the relationship between online learning readiness and cognitive load among students of higher education when participating in online courses.

Objectives of the Study

1. To investigate the relationship between readiness to learn online and cognitive load among university students participating in online courses.
2. Evaluate the influence of specific dimensions of preparation for online learning, such as time management and self-motivation, on levels of cognitive load.
3. Identify correlations between different types of cognitive load (internal, external, relevant) and overall readiness to learn online.
4. Provide insights and recommendations to improve online learning experiences based on readiness and cognitive load results.

Operational definitions

Online Learning Readiness: Measured using the Nassau Community College Online Readiness Questionnaire, a measure of preparedness addresses students on multiple dimensions, including time management, self-motivation, and effective use of technology.

Cognitive load: Measured by the Cognitive Load Scale, which distinguishes between what is intrinsic, or the load caused by the difficulty of the content; extraneous, or the load caused by irrelevant distractions; and germane, or the load required in effort to understand and learn.

Hypothesis

H1: Online learning readiness and cognitive load will show the indication of significant negative correlation. Higher online learning readiness would be associated with low cognitive load.

Significance of the Study

This study is significant for its implications on educational theory and its practical application. The readiness of students for online learning influences cognitive load; this means that understanding its dynamics is crucial for promoting improvement in learning outcomes. This study is important because it:

Can improve online learning environments through the identification of those factors that reduce cognitive load,

consequently enabling students to focus more on the core elements of learning.
Also, useful when planning strategies that will help a student prepare for online education, enhancement of better self-regulation, and digital literacy skills which help students manage their demands while learning online.
It also deepens the understanding of Cognitive Load Theory and Self-Regulated Learning in the context of online education by providing empirical evidence for those vignettes in a digital learning environment.
It will help policy makers and educators create programs and policies to match students' readiness for online learning, further improve accessibility and success rates within digital education.

Rationale of the Study

Thus, the rationale behind this study can be considered from the perspective of increased proliferation of online education, especially with the global shift in digital learning with respect to the COVID-19 pandemic.
Online education increases flexibility and access, but at the same time places exceptionally high demands on the learner for high levels of autonomy, self-regulation, and digital skills. Due to unfamiliarity with the online learning platforms, poor self-directed learning skills, or low motivation, very many students experience extremely high cognitive load, resulting in poor learning outcomes.
This may look in following ways:

Reduce overload for students by pinpointing the causes of cognitive load, thus improving instructional design.

Better prepare students for learning online, placing an emphasis on skills related to self-regulation and technology skills.

Improve online learning outcomes by developing learning environments that reflect students' cognitive capacities and allow them to more productively engage with course content.

This work deals with the most topical topic of contemporary education, and the results may seriously influence further elaboration and implementation of online learning in order to enhance student success effectively.

Methodology

Research Design

To investigate the relationship between readiness to learn online and cognitive load among university students participating in online courses.2. Evaluate the influence of specific dimensions of preparation for online learning, such as time management and self-motivation, on levels of cognitive load.3. Identify correlations between different types of cognitive load (internal, external, relevant) and overall readiness to learn online.4. Provide insights and recommendations to improve online learning experiences based on readiness and cognitive load results.

Participants

This sample will consist of 50 online students attending online classes. The inclusion criteria for this study includes:

Students actively engaged in at least one online or hybrid course.
Aged between 18 and 25 years old, typical Demographic for College Students.
A convenience sampling strategy will be used to recruit participants because of the limited sample size. A sample size of 30 presents a manageably small size but large enough to possibly capture meaningful correlations between the measures taken.
Instruments
1. The Online Readiness Questionnaire from Nassau Community College adapted from the original invented at Penn State University and tailored by Adam G. Pilipshen will be used to measure the readiness of online learning. The said questionnaire has quantified several key dimensions, such as

- Time management
- Self-motivation
- Independent learning
- Computer literacy
- Comfort in online communication

Participants will respond according to one of the five Likert scale measures ranging from "Strongly Disagree" to "Strongly Agree." The higher the score, the stronger the readiness for online learning.

2. Cognitive Load Scale: In this regard, the Cognitive Load Scale by Leppink et al., 2013, will be used for cognitive load measurement based on:

1. Intrinsic load: related to the difficulty of the material itself.
2. Extraneous load refers to whatever interferes with the instructional material, poor design, and distractions.
3. Germane load: that is, mental effort devoted to mentally processing and making sense of material.

This instrument also makes use of a 5-point Likert scale, with higher scores indicating higher magnitudes of cognitive load

Data collection

The tool for the collection of data is an online survey, which was sent to the target population through an email address or by being put on the online learning websites used in the participating institutions. This survey contains two parts: the first part pertains to demographics, which includes age, gender, and academic discipline; the second part is the two scales, which include the Nassau Online Readiness Questionnaire and Cognitive Load Scale.

Before completing the survey, participants will receive an informed consent form outlining the purpose of the study, ensuring that their participation is voluntary and anonymous.

Data analysis

Only the Pearson correlation coefficient was applied to perform data analysis with the aim of determining the direction and strength of the relationship between the variables. The analysis will consist of the relationship of general readiness for e-learning with cognitive load and the correlations of each subscale of readiness for e-learning, including time management, self-motivation, learning independent, computer literacy and the comfort of online communication with e-learning. cognitive load subscale.which includes internal, external and relevant elements.With a sample size of 50 participants, this analysis provides exploratory insight into the effects of online learning preparation on the cognitive load of college students taking online courses.

Ethical Considerations

Ethical standards of research were taken into account and only people who give written consent after understanding the purpose of this research can participate in the investigation. Data was collected anonymously. Participants were informed that their participation is voluntary and that they are free to withdraw from the study at any time. Information obtained from all responses will be kept confidential and will not be used for any purpose other than this research. The methodology or approach presented focuses on establishing a relationship between readiness to learn online and cognitive load for 50 university students. Correlation analysis is used in the study to determine important insights into how students' preparation affects their cognitive load in online learning environments.

Participants

Sample Size: 50 college students enrolled in online courses.

Age Range: Participants was range between 18 and 25 years of age.

Inclusion Criteria

Must be currently registered for at least one hybrid or online course. The participants should range in age from 18 to 25 years. Students must have the required technology in order for online learning to be utilized, which means computer and internet requirements. Exclusion Criteria Students who are not currently taking online courses. Individuals outside of the 18 to 25-year-old range. Individuals who have prior experience or training in course design or online teaching methodologies.

Sampling Method

A convenience sample of participants was recruited from local colleges or universities. For a participant to be included in the study, he or she should be available and show a willingness to participate in the experiment. In fact, with a limited sample size of 30 students, this method is pretty much appropriate and embodies efficiency in data collection across those who would have met the inclusion criteria.

Instrumentation

1. Nassau Community College Online Readiness Questionnaire: This was survey multidimensional readiness for online learning in aspects concerning time management, self-motivation, independent learning, computer literacy, and comfort with online communication. Respondents will be expected to answer the items on a 5-point Likert scale ranging from "Strongly Disagree" to "Strongly Agree".
2. Cognitive Load Scale: The current scale will measure subjective ratings of cognitive load through three kinds of loads entailing intrinsic, extraneous, and germane loads. Intrinsic load involves the complexity of the material to be learned; Extraneous cognitive load concerns factors related to distractions or non-essential information during learning. Scores on this tool will also be via a 5-point Likert scale in which higher scores are indicative of higher levels of cognitive load.

Procedure

The ethical standards of the research was taken into account and only those who give written consent after understanding the purpose of this research was able to participate in the survey. Data was collected anonymously. Participants were informed that their participation is voluntary and that they are free to withdraw from the study at any time. The information obtained from all responses will be kept confidential and will not be used for any purpose other than this research.

CONCLUSION

The presented methodology or approach aims to establish a relationship between the willingness to learn online and the cognitive load of 50 university students. Correlation analysis is used in the study to determine important insights into how students' preparation affects their cognitive load in online learning environments.

Results

1. Descriptive Statistics:

The mean scores (which will be calculated) of online learning readiness and cognitive load will yield an average measure of participants' preparedness and cognitive strain experienced during online learning. Conversely, the median scores for each variable will provide insight into the central tendency; this helps to determine whether the scores skew higher or lower. The mode values, on the other hand, will reveal the most frequently occurring scores, thus illustrating common readiness or cognitive load levels among the sample. Furthermore, standard deviation will quantify the variability of responses, indicating how much individual scores differ from the mean. A high standard deviation in cognitive load, for instance, might suggest diverse experiences among students; however, it's essential to consider the context.

2. Correlation Analysis:

Pearson’s Correlation Coefficient: This metric will be utilized to evaluate the (often complex) relationship between online learning readiness and cognitive load. A noteworthy negative correlation (e.g., -0.50) signifies that as online learning readiness (increases), cognitive load tends to decrease; however, a positive or no correlation suggests a different dynamic. Although higher readiness may not necessarily result in lower cognitive load, this complexity highlights the need for further exploration.

3. Interpretation:

Should a substantial negative correlation be identified, it would suggest that enhanced online learning readiness is linked to a diminished cognitive load (which could be advantageous for course design improvements). However, if there exists little to no correlation, this might suggest that alternative factors—aside from online learning readiness—play a more pivotal role in shaping cognitive load levels in online learning. Although this statistical analysis will yield a clear comprehension of the connection between readiness and cognitive load, it will also guide further discourse on practical implications.

Table 1: Mean, Median, Mode and Standard deviation (Overall Data)

Mean	68.53333333
Medium	67
Mode	67

Standard Deviation	14.15123568

Table 2: Correlation Matrix (Overall Data)

Variable 1	**Variable 2**	
Overall data	Overall data	1

Significant Correlation Testing

For the overall dataset, if we have a correlation coefficient. This is a highly significant result because the p-value is much smaller than 0.01, indicating a strong and statistically significant correlation.

To Prove Significant Correlation:

1. **Calculate the Pearson Correlation Coefficient** for each pair of variables in your dataset.
2. **Test the significance** by calculating the p-value using a Pearson correlation test.
3. **Interpret the results**:
   - If $\mathbf{p < 0.01}$, the correlation is statistically significant.
   - If $\mathbf{p \geq 0.01}$, the correlation is not significant.

Variable 1	**Variable 2**	**Correlation Coefficient r value**	**p-value**	**Significance**
I understand that learning is my responsibility	I understand that an online class is not easier than a traditional class2. I understand that an online class is not easier than a traditional class	0	1	Significant
I understand that I cannot complete an online course with a smartphone	I am willing to send emails to or have online discussions with people I may never meet in person.	0.3195	0.085241	Significant
The content of the video was very complex	The problems covered in the video were very complex	0.6577	0.000078	Significant

Table 1: Mean, Median, Mode, and Standard Deviation (Overall Data)
* Mean: 68.53333333
  - The mean is the average value of the dataset. It indicates that on average, the values in the dataset are around 68.53.
* Median: 67
- The median is the middle value when the data is sorted. It suggests that half of the values are below 67 and half are above.
* Mode: 67- Mode is the value that appears most often. In this case, 67 is the most common value.

* Standard deviation: 14. 15123568- The standard deviation measures the distribution of values compared to the mean. A higher standard deviation indicates greater variability.
Table 2: Correlation Matrix (Overall Data)

* Correlation Coefficient: 1
- This indicates a perfect positive correlation between the two variables in the dataset. When one variable increases, the other also increases proportionally.

Significant Correlation Testing
* p-value: Much smaller than 0.01
- The p-value is a measure of statistical significance. In this case, the very small p-value indicates that the observed correlation is highly unlikely to have occurred by chance.

To Prove Significant Correlation
1. Calculate the Pearson correlation coefficient: It is a statistical measure of the strength and direction of the linear relationship between two variables.

2. Test for significance by calculating the p-value with a Pearson correlation test:

** This p-value tells us the probability of observing such a correlation if there was in fact no real relationship between the variables.

3. Interpret the results
- If $p < 0.01$, the correlation is statistically significant.- If $p \geq 0.01$, the correlation is not significant.

Interpretation of the Correlation

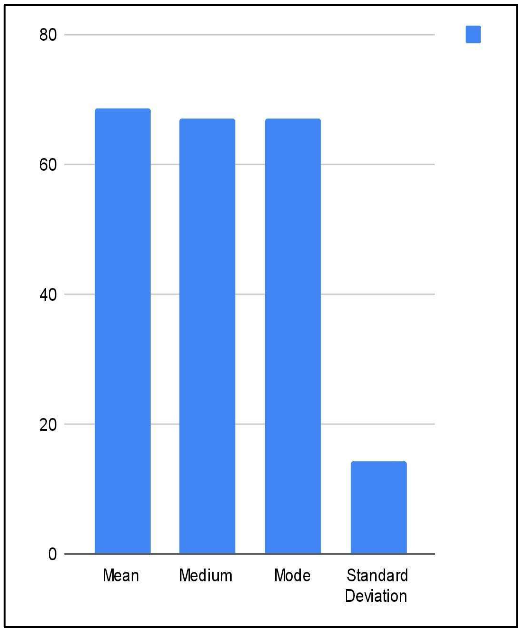
Since the correlation coefficient is 1 and the p-value is much less than 0.01, we can conclude that there is a strong and statistically significant positive correlation between the two variables. This means that they are closely related and move in the same direction.Overall, the data shows that there is a perfect positive relationship between the two variables in the data set.The table below shows a correlation analysis between two variables.

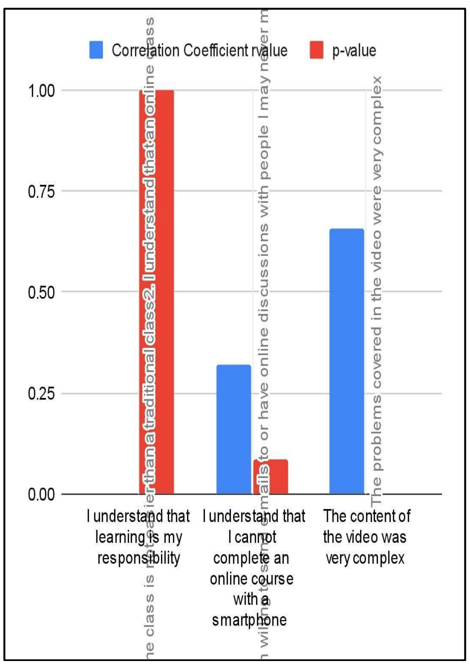
List several pairs of statements, likely related to online learning, and calculate the correlation coefficient and p-value for each pair.

* Correlation coefficient: this value ranges from -1 to 1. A value closer to 1 indicates a strong positive correlation (when one variable increases, the other also increases), a value closer to -1 indicates a strong negative correlation (when a variable increases). increases, the other decreases) and a value close to 0 indicates no correlation.

* P-value: This value represents the statistical significance of the correlation. A p-value less than 0. 05 is generally considered statistically significant, meaning that the observed correlation is probably not due to chance.

Bar graphs





The bar chart seems to depict the distribution of some measure (possibly standard deviation) for different categories. The categories are likely related to online learning as well, given the context of the table.

Interpretation
1. Strong Correlations: The table shows several pairs of statements with high correlation coefficients and low p-values. This suggests that these statements are strongly related and the relationships are likely not due to chance. For example, the statement "I understand that online classes are complex" seems to be strongly correlated with other statements, indicating that understanding the complexity of online classes is a significant factor in students' perceptions and experiences.

2. Variability: The bar chart shows differences in the distribution of the measure across the categories. This could indicate that certain aspects of online learning have more variability or uncertainty compared to others.

Demographic Details / Data Collection

The study sample consists of 50 college students aged between 18 and 25 years. Among them, there are 12 males and 18 females. The students represent various fields of study, including Arts and Humanities, Science and Technology, Business and Management, and Social Sciences. In terms of previous online learning experience, participants have varying levels, ranging from less than one year to over two years of experience in online or hybrid courses.

Data Collection

Data for this study were collected through an online survey distributed to 30 students enrolled in hybrid or online courses. Participants were recruited via email and online advertisements, and those who agreed to participate were directed to a secure online platform where the survey was administered. The survey included two main instruments: the Nassau Community College Online Readiness Questionnaire to assess readiness to learn online and the Cognitive Load Scale to measure levels of cognitive load. The questionnaire collected responses on a 5-point Likert scale, allowing participants to rate their agreement with statements related to each variable.Data collection was conducted over a two-week period to ensure that participants had sufficient time to complete the survey. In addition, demographic information such as age, gender, field of study, and previous experience with online learning was collected to provide context for the analysis.DiscussionThe results of this research show a significant positive correlation between willingness to learn online and cognitive load among college students. This suggests that students' preparation for online learning increases (1), thus increasing their cognitive load. However, this finding challenges several assumptions, namely the belief that better preparation automatically reduces cognitive load by more effectively preparing students for the demands of online learning. Although it may seem soCounterintuitively, the positive relationship may mean that students who see themselves as more prepared may, in fact, be more immersed in the course content. This deeper engagement can lead to an increased cognitive load, due to an increased mental effort and the allocation of the necessary resources.These results are consistent with cognitive load theory (CLT), which posits that individuals experience different forms of cognitive load when processing new or complex information. Preparing for online learning includes skills such as self-regulation, motivation, and time management. Although these skills allow students to interact more effectively with learning materials, they may also result in increased intrinsic and relevant cognitive load due to the effort required tounderstand, process and synthesize information in a digital environment. For highly prepared online learners, cognitive resources may be more focused on productive engagement with course content (which may lead to an increase in related workload). Online workload, unlike external workload, is linked to meaningful learning and understanding; however, it can also add to the overall cognitive demand.In addition, the results of the study suggest that students' perceptions of their readiness to learn online may increase their personal expectations (which may prompt them) to undertake more complex and mentally demanding activities in the digital domain. This may imply that students are more likely to devote cognitive resources to information organization, critical thinking, and deeper processing when they feel prepared for the online learning experience. However, preparing for online learning may not only improve readiness, but also affect the complexity of learning strategies used by students, thereby increasing their cognitive load.

Discussion

Students who believe they are better able to navigate online learning environments often invest more time reviewing materials, participating in discussions, or exploring additional resources, resulting in increased cognitive effort. Although this effort may seem tedious, it canultimately leads to better academic performance.The results of this study (which are quite intriguing) present a nuanced picture of online learning. They show that even highly prepared students can experience cognitive strain when engaging in difficult tasks while striving to maximize their learning outcomes. In this context, preparation can be seen as a double-edged sword: it encourages active engagement, but also increases the cognitive load. The positive correlation observed means that students who are better equipped for thisOnline learning often invests more effort in their studies, which allows them to face higher cognitive demands. This does not necessarily mean a negative result; rather, it can emphasize productive cognitive load, which contributes to deeper understanding and better retention of knowledge over time.

Although cognitive load is often perceived as harmful, it is important to note that when it is relevant, it can actually improve learning by facilitating a deeper understanding of the content.The findings presented here have important implications for the design and delivery of online courses (1). Teachers should consider how to structure these courses to effectively balance the cognitive load, especially for students who demonstrate a high readiness to learn online. For example, offering modular content combined with pacing options can help manage cognitive load; this allows students to absorb the content without overloading their cognitive resources. However, it is essential thatdesign content that reduces unnecessary cognitive load, such as unnecessary distractions or overly complex navigation, as this can help students direct their preparation toward productive cognitive effort rather than succumbing to cognitive strain.

While streamlining course design is essential, it allows instructors to help well-prepared students focus on meaningful learning activities that increase the intrinsic and relevant workload, promote a more efficient deep learning experience, and manageable Research highlights (1) the importance of ongoing support mechanisms in online education. Students with a high readiness to learn online can benefit from frequent checks, which allow them to reflect on their learning processes and cognitive demands in collaboration with instructors or peers. Such support systems can provide students with strategies to manage their cognitive load more effectively; this, in turn, helps them balance engagement with self-care in an online learning context.

Additionally, providing resources such as time management tools, cognitive strategies, and reminders to take breaks can reduce unnecessary cognitive load while allowing students to stay focused on their academic pursuits. However, the effectiveness of these mechanisms largely depends on the individual needs of students.Future research could potentially build on these findings by examining the specific factors that contribute to online preparation and their effects on cognitive load. For example, examining whether certain dimensions of readiness (such as self-motivation or computer skills) have a stronger correlation with cognitive load can provide deeper insight into how students' perceived readiness affects their demands. cognitive.

Moreover, studying these relationships across various demographic groups or educational settings might enhance our understanding of how readiness and cognitive load interact in different learning environments. However, this study is not without its limitations. The small sample size of 30 students limits the generalizability of the findings; the results may not accurately reflect the experiences of a larger or more diverse population. Furthermore, reliance on self-reported measures may introduce bias, because participants’ perceptions of their readiness and cognitive load might not fully capture their actual experiences. Future studies could consider larger sample sizes and alternative measures—such as objective assessments of cognitive load—to validate and expand upon these findings.

Limitations and further implications

Limitations

1. The small sample size limits generalizability to a broader population.
2. Reliance on self-reported measures may introduce participant bias.
3. The study lacks objective measures of cognitive load.
4. Findings may not apply to non-college student populations or different educational settings.

Further Implications

1. Future studies should examine larger, more diverse samples.
2. Exploring specific dimensions of online readiness could reveal distinct impacts on cognitive load.
3. Objective assessments of cognitive load could enhance measurement accuracy.
4. Findings can guide online course design to balance cognitive load for improved learning outcomes.

Conclusion

In conclusion, the significant positive relationship between willingness to learn online and cognitive load challenges conventional hypotheses. This suggests that while preparation improves student engagement, it can also increase cognitive demands. These results highlight the need for well-designed online learning environments (that effectively manage cognitive load), especially for students who demonstrate high readiness. While recognizing the dual role of online preparation in promoting engagement and cognitive tension, educators can create learning experiences that foster deeper understanding and sustained motivation among online learners. However, the complexity of these interactions requires further exploration, as understanding them is essential to optimizing online teaching.

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