Understanding the Impact of the Tempo of Distractions on Cognitive Ability

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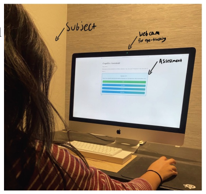
Objective

The objective of this research project is to utilize an online assessment and its associated eye-tracking data to understand whether distractions, and more particularly their tempo, has an impact on an individual's concentration while completing a task. In this phase of the project, the goal is to develop and apply an assessment which features questions from a computer science technical question database and where audio stimuli are introduced as distractions for the user. This assessment was administered through an online portal that utilizes a webcam to include eye-tracking capabilities. Data from subjects' performance on this assessment and the eye-tracking data was used to create Linear Regression, Polynomial Regression, and k-means clustering models that reflects the behavior of test subjects based on the collected data (performance, time spent per question (seconds), and eye movements). These models are meant to clarify the effect of patterned versus randomly timed audio distractions as they will provide more information regarding the impact on the test subjects performance through factors like overall scores and time spent per question (seconds).

Approach

An exploratory study was defined. The study includes the completion of an online assessment through the React framework using questions from a computer science technical question database while eye-tracker data and performance on the assessment are collected. In order to collect eye-tracking data, the user was asked to turn on the 'recording' feature on the GazeRecorder application before they begin their assessment. The assessment will feature three tests; one without auditory stimuli (auditory distraction) and two where a soundtrack is played as the auditory stimuli (auditory distraction) In order to remove any bias regarding the order of the tests, each participant was given a randomized order in which to take the assessments.

Set-up:
Figure 1



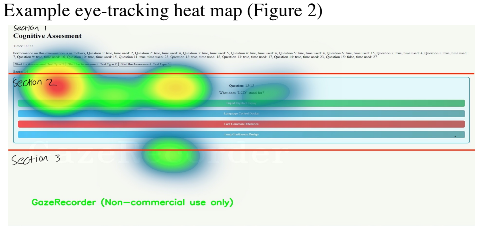
In order to limit any visual distractors, testing environment is cleared.

The webcam is turned on for the GazeRecorder software to collect eye-tracking data.

Subject is a college student in a STEM field.

There are 3 types of assessments; each assessment has 15 technical questions, and records time spent on each question in addition to performance.

Example eye-tracking heat map (Figure 2)



Research Question

What is the effect of patterned versus randomly timed audio distractions on a student's cognitive ability?

Method

The study was completed though an online assessment tool, React framework, with the GazeRecorder eye-tracking software.

1. Data Collection
12 subjects (F = 42%, M = 58%, age m = 19.33 years, age SD = 1.07 years) completed the assessment through the GazeRecorder software. Each subject completed the three tests' conditions: control (no audio stimuli), randomly-timed audio distractions, and patterned-time audio distractions. The data collected included performance in the tests (scores), time spent on each test, and eye-tracking data.

2. Data Pre-Processing
It is vital to pre-process the data so that the formatting and quality is appropriate for use in the regression and prediction models. A python data cleaning script was used to either remove or reformat the results from the online assessment.

3. Processing of Data
Linear regression and k-means clustering to analyze the data were performed. The insight from this model allows for a better understanding of the distraction's effect on the user's cognitive abilities.

Read in data file and clean data sets using Pandas Data Frames → Use one-way ANOVA test to determine if the audio distractions had an effect on the participants test scores → Create Linear Regression Models to analyze the time subjects spent on every question over the 15 question assessment → Create polynomial Regression models that can better represent how the time users spent on every question increased during the duration of the assessment → Create a k-means clustering model to predict subject eye-tracking focus for each assessment

Results and Findings

Effect of Distractions on Assessment Scores
To determine if the audio stimuli had any effect on the subjects' scores, a one-way Anova was performed with an alpha level of 0.05. The null hypothesis was that the audio stimuli had no effect on the subject's scores, while the alternative hypothesis was that the audio stimuli does influence the subjects' scores. The determined p-value was 0.18. Since $p > 0.05$, we fail to reject the null hypothesis. Based on this evidence, it is reasonable to suspect that the score was not affected by the presence or the tempo of the audio distractions. Also completed a multiple comparison one-way Anova test to determine if there was any significant difference between any of the three tests. Similar null and alternative hypotheses were assumed; however, the p-value for each comparison was above 0.05 which indicated there was not a significant difference between the scores of each test.

SUMMARY

Groups	Count	Sum	Average	Variance
Column 1	12	114	9.5	2.45454545
Column 2	12	98	8.16666667	4.15151515
Column 3	12	102	8.5	3

ANOVA

ırce of Variat.	SS	df	MS	F	P-value	F crit
Between Grc	11.5555556	2	5.77777778	1.8044164	0.18043174	3.28491765
Within Grou	105.666667	33	3.2020202			
Total	117.222222	35				

Time Used per Question
Participants had up to sixty seconds to complete each question on the assessment. To determine whether there was a linear relationship between the progression of questions in the test and the time spent per question (seconds) a linear regression was performed using the NumPy Python library for all three assessment conditions. For all three assessments, there was a weak linear correlation, with an average approximate r-squared value of 0.476. Therefore, polynomial regression was performed with degree of 2. The graphs for the control, patterned, and random audio distraction assessment is as follows, Figure 4 shows that there was a trend between the growth of the time spent (seconds) on the control assessment compared to time spent on the assessments with an audio distraction. The Control assessment had a smaller average time spent per question than both the Patterned Stimuli Assessment and the Randomly-timed Stimuli Assessment. However, the difference between the growth of the time spent between the Patterned Assessment and Random Assessment was marginal as evidenced in Figure 4.

Eye-tracking Data
Using the GazeRecorder software, a heatmap was provided for every question. The screen was split into three sections: section 1, instructions/score; section 2, question and answer choices; section 3, white space, and through the use of this heat map it was apparent which section had the highest focus. To determine if there was a relationship between the time subjects spent per question and the highest focus point in their heatmap, K-means clustering was used. For the control assessment, with no audio distractions, the clustering model was able to predict the region with highest focus based on time spent per question (seconds) with 50% accuracy for section 1, and 63% for section 2. The predictions for section 3 were inaccurate due to the lack of data. For the patterned audio distraction assessment, the clustering model was able to predict the region with highest focus based on time spent per question (seconds) with 43% accuracy for section 1, and 58% for section 2. The predictions for section 3 were inaccurate due to the lack of data. For the randomly-timed audio distraction assessment, the clustering model was able to predict the region with highest focus based on time spent per question (seconds) with 71% accuracy for section 1, and 51% for section 2. The predictions for section 3 were inaccurate due to the lack of data.

Polynomial and Linear Regression model analysis of processed data set

Figure 3

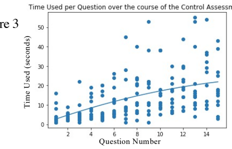


Figure 4

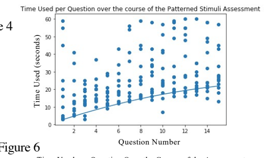


Figure 5

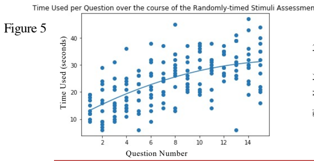
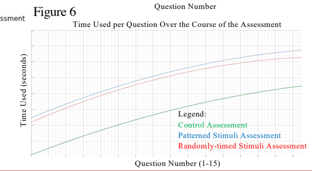


Figure 6



Conclusion

The objective of this experiment was to investigate the effects of different tempos of auditory stimuli on the user's cognitive ability. This phase of the research focused on completing testing and analysis on this data to draw a conclusion on the effects of this audio stimuli on a subject's performance. The data analysis was successful in determining how much more time users spent per question under the three given conditions. Based on the results of the polynomial regression, it was observed that there was a clear increase of time between the control and other assessments that featured patterned and randomly-timed audio distractions. However, there was not a significant difference between the increase in time spent per question (seconds) between the assessments that featured patterned and randomly-timed audio distractions (refer to graph). The one-way ANOVA test determined that there was no effect on the subject's score on the assessments despite the different audio stimuli. Finally, using k-means clustering to predict user focus based on the time they spent per question yielded promising results as the model hovered around 50-60% accuracy. Given the limited data used for training, this model hints at a correlation between the time users spend per question and the section of the screen that they most focus on. All k-means clustering models used for the three assessments suggested a correlation between the most time used per question and users focusing on section 2 (question and answer choices), and the least amount of time used per question and the users focusing on section 1 (instructions/score). There was not enough data to find a correlation between time used per question (seconds) and users focusing on section 3 (white space). Based on this data, this study can suggest that there is no significant difference between impact of the patterned and randomly-timed auditory distraction on a subject's performance measured through multiple categories. One limitation of this study that must be considered is the small sample size. Future work could include to perform a similar study with a bigger sample size as well as considering collecting more eye-tracking data such as the actual gaze and the pupil dilation to better identify the focus of the subject.

Acknowledgements and References

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