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USING CONTINGENT PRAISE TO INCREASE VISUAL ENGAGEMENT IN AN ASYNCHRONOUS ONLINE LEARNING ENVIRONMENT: AN EYE TRACKING STUDY

by

Andrew J. Rozsa III

A Dissertation Submitted to the Graduate School, the College of Education and Human Sciences and the School of Psychology at The University of Southern Mississippi in Partial Fulfillment of the Requirements for the Degree of Doctor of Philosophy

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ABSTRACT

As more students move to online learning, this results in not only new barriers but new opportunities in academia. The purpose of this study was to examine how behaviorcontingent praise affects visual engagement with an online video lecture when using WebGazer, a publicly available eye tracking software, with a user's integrated webcam. A second aim of this study was to examine if using WebGazer with an integrated webcam was a valid alternative to hand scoring when collecting visual engagement data. Results of WebGazer measurement indicated a moderate effect size for three participants in the presence of contingent praise, and a large effect size was observed for one participant when provided contingent praise. Based on visual analysis and simple linear regression, level, shape of data paths, trend, and overall range of data were similar for three participants. One participant's WebGazer and hand scoring data demonstrated a notable discrepancy in range, level, and shape for the Demand and Praise conditions. These results indicate that contingent praise may result in an increase in visual engagement in online learning environments and that using WebGazer and an integrated webcam may be a valid tool for measuring visual engagement in online learning environments. Discrepancies in WebGazer and hand scoring data are discussed.

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CHAPTER I - INTRODUCTION

Over the last three decades, the number of students enrolled in postsecondary education online courses has been growing at a phenomenal rate (Hu, Arnesen, Barbour, & Leary, 2019; Schwirzke, Vashaw, & Watson, 2018). Since 2012, the percentage of students taking at least one online class has increased by no less than .7% and as much as 1.8% per year for the period 2012-2019. By 2019, 37% of undergraduate students were taking at least one online course (U.S. Department of Education, 2021). With the movement toward online learning, education is presented with an unprecedented opportunity to assess effectiveness more efficiently and student behavior with less effort and more precision. When the public was introduced to the coronavirus disease (COVID-19) in 2019, the education system faced many struggles to ensure appropriate translation of instruction to an online environment. By Fall 2020, 74.7% of students were taking at least one online course, and 44.7% were taking only online courses. It was unknown whether many of the classroom-based strategies that had been employed for decades would be effective in this new remote environment. As the world continues to move toward online learning, it is imperative that researchers explore novel strategies to assess effectiveness. For over a century, students have sought alternative means of accessing education outside the traditional classroom setting. COVID-19 has fast-tracked the necessity to address whether this delivery format is meeting the needs of today's learners.

Evolution of Online Learning

While most publications use the terms *online learning* and *distance learning* interchangeably, there is a distinct difference between the two. A brief review of their history will serve to guide the reader to a better understanding (Singh & Thurman, 2019).

Distance Learning

According to Bates (2004), distance learning is defined as a method of education in which students have full control over when and where they study, typically without direct contact with the teacher. The defining feature of distance learning is the presence of a technology enabling the learning process. Distance learning has been evolving for decades, as can be seen in Figure 1. The first generation being characterized by using a single technology, with no direct interaction between the student and institution.



Figure 1. Generations of Distance Education

The second generation of distance learning moved from a single technology to multiple media. Lastly, the third generated incorporated the ability to teach multiple students at once and engage in live discussion. This was fueled largely by the introduction of the World Wide Web in 1989 and the subsequent introduction of the Internet for to the public in 1993 (Couldry, 2012). The third generation of distance learning has allowed easier access for otherwise isolated learners to higher education and more cost-effective means of providing education for different institutions. When both instructors and students are present during remote instruction, this is defined as synchronous learning. When instruction materials are recorded and accessed at different times, this is asynchronous learning. Many institutions have adopted more asynchronous teaching models, placing greater value on the flexibility it allows instructors to record and even re-use previous recordings (Bos, Groeneveld, van Bruggen, & Brand-Gruwel, 2015; Evans, 2008; Morris, Swinnerton, & Coop, 2019). For a more extensive review and comparison of the effectiveness of types of online learning, refer to the meta-analysis by Means and colleagues (2010), as this is outside the scope of this study. As the number of students enrolled in some form of online learning continues to increase, more research must be conducted to identify how best to increase not only effective instruction delivery, but student outcomes in these settings.

Student Engagement in the Classroom

When evaluating the effectiveness of instruction methodologies, one of the most examined variables is student engagement (Driscoll et al., 2012; Francescucci & Rohani, 2018; Watts, 2016). Although a multidimensional concept, for purposes of this study, it is defined as student involvement in academic learning, including behaviors such as attending (making eye contact) without engaging in disruptive behavior (Sinatra, Heddy, & Lombardi, 2015), asking questions in class, or engaging in class discussion (Birch & Ladd, 1997; Finn et al., 1995; Heddy, Sinatra, Seli, & Mukhopadhyay, 2014; Skinner & Belmont, 1993). This form of engagement, sometimes referred to as on-task behavior or academically engaged behavior, has decades of evidence supporting its positive correlation with academic achievement (Cobb, 1972; Greenwood, Terry, & Walker, 1994; Hecht, 1978; Lahaderne, 1968) more than any other observable behavior across all school subjects. While much of the current literature has measured behavioral engagement as a primary dependent variable to determine effectiveness of interventions, few have examined it in online environments. As recent research has indicated, measuring behavioral engagement in online environments is feasible (e.g., Rozsa, 2021). *Praise in the Classroom*

Suffice it to say that this literature review is not intended to provide the reader with an extensive review of praise. For that information, the reader is encouraged to examine the review article by Floress and colleagues (2017). Briefly stated, providing praise for engagement has consistently been found to be a reliable means of increasing student engagement. Despite an extensive history investigating praise in classrooms, the overwhelming majority of studies have been with elementary school classrooms, with only a handful of studies with high school-aged students (e.g., Blaze et al., 2014; Duchaine, Jolivette, & Fredrick, 2011; Taber, 2014), and even fewer with undergraduate students (e.g., Lessard, Grossman, & Syme, 2015).

Engagement in the Online Learning Environment

As individuals continue to move to online learning environments, the increased reliance on computers will continue to increase as well. However, computer and computer-related technology is becoming cheaper and more widely available every year. Recent research has investigated the extent to which student engagement differs between synchronous online learning environments in comparison with asynchronous online learning environments (e.g., Giesbers et al., 2013), but these studies typically measure engagement in different manners. such as number and type of messages sent by students, as measuring engagement in asynchronous online learning environments may prove more problematic. Identifying a reliable method of measuring engagement that is usable across

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different online learning environments would allow for more accurate comparisons of interventions targeting engagement in online learning environments.

At the time, several new technologies have also become available to the public, including eye tracking. Eye tracking is a technology that measures an individual's eye gaze toward a specific stimulus, typically on a computer screen. Such technological advancements also allow for more continuous, automated observation and recording of behavior that was not previously feasible due to the need for human observers which can introduce error (Charlesworth & Spiker, 1975). By contrast, computers are bound by algorithms which dictate consistent data collection methodologies, thereby alleviating observation error.

Eye Tracking to Measure Attention

One of the most important components in assessing the effectiveness of teaching strategies is being able to measure the target behaviors, such as academic engagement or student performance (Driscoll et al., 2012). Measuring behavior in classrooms has traditionally relied upon either the observer being present in the same room as the participant or taping the individual for later coding behavior. The behaviors of interest are typically related to those expected in the classroom such as taking notes, looking toward the instructor during lectures, and staying in the assigned area. How these behaviors may appear in the classroom may be similar in an online learning environment, such as looking at the instructor or taking notes, but other barriers may be present such as other programs being open or being unable to identify if the student is taking notes or doing something else off-screen. In asynchronous classes, lectures and tasks may be completed online at a different time from when they were first recorded or uploaded, similar to what

was seen in the second generation of distance learning. As more people gain access to faster internet connections and faster computers become more readily available, live lessons are more feasible for classes than ever.

Eye gaze and attention have been repeatedly shown to share a close relationship (e.g., Klein, 1980; Rafal, Calabresi, Brennan, & Sciolto, 1989; Rayner, 1998; Rayner, 2009), while research into eye movements and their relationship with academic behaviors goes as far back as 1879 (Huey, 1908). Until the advent of current technologies, most eye tracking methodologies required expensive, research-grade hardware. As a result, few groups outside research labs and universities had access to examining eye tracking applications that could be used to investigate more basic, yet important, research questions.

While some studies have successfully incorporated unique eye tracking media, such as using eye tracking glasses in face-to-face classrooms (Rosengrant et al., 2011), this type of technology is often very expensive or impractical. Most of the more recent eye tracking studies have been implemented in combination with computer screens. Some studies have examined the effect of on-screen elements such as the lecturer's video representation (e.g., Wang & Antonenko, 2017; Wang, Pi, & Hu, 2018) or monetary imbursement effects on performance and attending (Anderson, Laurent, & Yantis, 2011; Bucker & Theeuwes, 2014; Chelazzi et al., 2014; Engelmann & Pessoa, 2007; Failing & Theeuwes, 2014; Shomstein & Johnson, 2013). However, limited research has investigated the effect of praise on engagement in online learning settings.

In a recent study, Rozsa (2021) examined the effect of noncontingent praise on undergraduates' visual engagement, as measured by eye tracking software, and more formally defined as the participant looking toward the video during the lecture. Prior to this study, no other research had been conducted using live praise. All four participants experienced the baseline condition, during which no verbal interaction occurred between the researcher and participants. Each participant then experienced either the praise or neutral verbalizations condition, with half experiencing praise first, and the other half experiencing neutral verbalizations first followed by the second condition. During the neutral verbalizations condition, the researcher delivered a neutral verbalization every two mins. Neutral verbalizations were defined as verbal statements provided by the researcher that were related to video content, such as "This video is about a war," but neither indicated approval or disapproval. During the praise condition, the researcher provided a verbal statement that indicated approval, such as "I love how you are watching the screen," every two mins.

The researcher found that the presence of praise resulted in an overall increase in visual engagement for three out of four participants. The researcher also found that the presence of neutral verbalizations increased visual engagement for two out of four participants, though not to the same extent as praise. Because the experimental design was a counterbalanced ABC design, it was difficult to compare the neutral verbalizations condition data to baseline data for all participants. Furthermore, due to potential ceiling effects present during baseline, potential changes in visual engagement may have been masked, and the treatment may have been unnecessary for the chosen participants. The use of neutral verbalizations was also questionable, as these types of statements are unlikely to be made during a lecture. Lastly, praise was noncontingent, which, unless there are individual data to indicate otherwise, is less preferred to contingent praise

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(Cooper, Heron, & Heward, 2019). As a result, more precise contingencies for praise, a more accurate experimental design, better recruitment selection, and a comparison condition that better represents what may be heard in online learning environments may provide better insight into efficacious teaching strategies for increasing visual engagement.

What Works Clearinghouse

To improve the dissemination of products, programs, policies, and education practices, the U.S. Department of Education's Institute of Education Sciences developed the What Works Clearinghouse (WWC). The primary mission of the WWC is "to be a central and trusted source of scientific evidence for what works in education" (What Works Clearinghouse, 2020). Depending on the degree of adherence to the WWC's standards, studies are rated as Meets WWC Design Standards Without Reservations, Meets WWC Design Standards With Reservations, or Does Not Meet WWC Design Standards. If a study Meets WWC Design Standards Without Reservations, the outcome variable must be measured repeatedly, the independent variable must be systematically manipulated, a second observer must also measure the outcome variable for at least 20 percent of data points per condition across all participants. In the case of alternating treatment designs (ATDs), baseline must have at least five data points, each comparison condition should have at least four data points, and each condition iteration should have no more than two data points before changing conditions. This study adhered to these guidelines.

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Summary

Since the mid-twentieth century, behavioral studies and interventions have been based on classroom instruction. As more students move to online learning environments (Queens & Lewis, 2011; Taie & Goldring, 2017; Taie & Goldring, 2019; Taie & Goldring, 2020; U.S. Department of Education, 2004, 2008, 2012), more research is required to evaluate how instruction delivery may be better implemented in these environments.

The positive influence of contingent praise on student engagement has been extensively researched for decades for increasing student engagement in K-12 classrooms (Moore et al., 2018; Royer, Lane, Dunlap, & Ennis, 2019). While some research has been conducted on the effect of noncontingent praise on undergraduate student engagement in online learning environments (Rozsa, 2021), none has been conducted on the effect of contingent praise on undergraduate student engagement in online learning environments.

Classroom-based studies have traditionally used similar behavioral definitions for behavioral engagement, but there is not a consensus on defining behavioral engagement in online learning environments. As more people move to online learning as an alternative to traditional classroom-based instruction, the need for accurate online-based measures is also increasing. One of the most promising technologies in in-lab settings has been eye gaze tracking. As software is developed that may implement eye gaze tracking without the aid of additional hardware beyond what would typically be needed to access online learning, engagement data may now be accurately collected both in synchronous and asynchronous environments.

Purpose

The purpose of this study was to examine how remotely delivered contingent praise affects learners' visual engagement to video lectures, as measured by using readily available eye tracking technology. Subsequently, the research questions are: **Research Question 1**: Does providing praise contingent on percent time visual engagement (as indicated by eye tracking measurement of gaze direction) affect overall percent visual engagement compared to no praise?

Research Question 2: How closely do the eye tracking program measurements of eye gaze correspond with hand-scored measurements?

CHAPTER II - METHODS

Participants and Setting

Before beginning the study, the primary investigator received approval from the University of Southern Mississippi Institutional Review Board (Appendix A). Participants were recruited from The University of Southern Mississippi during the Spring 2022 academic semester using flyers (Appendix B). Participants were paid \$15 per hour of participation to be provided upon the discontinuation of their participation. To participate in the study, participants were required to be able to work at a computer screen without the aid of eyeglasses, for at least an hour. This was to increase the likelihood of the eye tracker correctly identifying the participant's pupil. Those who met the first criterion completed a questionnaire (Appendix C) that listed all the video topics. Potential participants rated each item on the questionnaire according to their perceived familiarity with the topic. Ratings were "not at all familiar," "a little familiar," "somewhat familiar," or "very familiar." To be considered for the study, a participant was required to be "somewhat familiar" or lower with 30 or more of the topics. These participants provided consent (Appendix D). Each participant was required to watch at least four videos lasting 10-15 mins. In a prior study using WebGazer with 10-15 min videos (Rozsa, 2021), the average visual engagement (weighted according to video duration) during baseline was calculated to be 79.25%. Participants continued to attend sessions until their average visual engagement was above 80% for two consecutive sessions. At that point, the participant was dismissed from the study. If visual engagement remained consistently below 80% average during baseline, individuals completed the rest of the study. Of eighteen screened participants, four met these criteria

and completed the study. Relevant participant demographics for those who completed the study are presented in Table 1.

Table 1

Participant Demographics

Participants	Gender	Age	Major	Race
Annie	Female	20	Medical Laboratory Science	African American
Britta	Female	17	Public Relations in Advertising	Hispanic
Jeff	Male	19	Medical Laboratory Science	Caucasian
Shirley	Female	21	Psychology	African American

During sessions, the participant was in a 200 sq ft room in the School Psychology Program area of the School of Psychology. The researcher was placed in a nonadjacent room in the same building, about 100 ft away. All verbal interaction between participants and the researcher occurred over Zoom. The room in which the participant was located was made up of two tables, 5 chairs, an unused monitor, two shelves, and two lamps. Only the lamps were visible to the participant, who was seated at a table against the wall. Various potentially distracting stimuli were placed on the table with the participant, including a tablet with a continuously moving visual that changed colors, building blocks, magnetic letters, a puzzle ball, and a book. The two lamps were located behind the participant's laptop screen. The overhead lights remained off during trials, with motion sensors taped to prevent motion detection. The laptop was seated on 3 to 5 books, adjusted based on the participant's height so that the participant could view the screen without tilting his or her head. The laptop screen was two to three feet from the participant. Sessions lasted an average of 59.9 mins (*SD*=11.82).

Materials

Computer Hardware

A Dell Latitude 5580 and an N930AF 1080p webcam were used during the study. The Dell Latitude 5580 ran on an i7-7820HQ processor at 2.9 GHz, had 16GB of RAM, and used the Microsoft Windows 10 Pro Education operating system. The screen's diagonal length was 15 inches. The researcher used an HP Envy x360, which ran on an AMD Ryzen 7 5700U processor at 1.8 GHz, had 8GB of RAM, and used Microsoft Windows 10 Home. Both laptops had an integrated webcam and microphone. *Video Stimuli*

All videos were obtained from Khan Academy (<u>http://www.khanacademy.com</u>), a site that provides academic instruction through videos that cover academic content for kindergarten to college level students. To be considered for use in the study, a video needed to cover some topic in the history of human civilizations between 5000 BCE and 2000 AD. The video also was required to be between 10 and 15 mins long. The lecturer had to be the same across all videos and not appear on-screen. The lecturer had to use a cursor or draw on the screen to emphasize text, timelines, or pictures. Thirty-seven videos were used, with an overall average of duration of 12.59 mins (*SD*=1.86). Appendix E contains a list of the links and topics of videos that were used.

WebGazer

Eye gaze data were recorded using the *WebGazer* eye tracking library which is written in JavaScript (Papoutsaki, 2016). Whereas other eye tracking studies and

applications typically require the installation of additional software or the use of additional equipment, WebGazer may be implemented with any website. WebGazer requires only permission to access the participant's webcam in order to identify the location of eyes, and subsequently to detect pupils and facial features. In order to calibrate the software, WebGazer uses cursor-gaze relationships to identify the position of eyes. When clicking on the computer screen, the user is typically focusing on the respective stimulus. For this study, multiple clickable dots appeared on the screen in random locations. Whenever the participant clicks a dot, the software identifies the location of the participant's eyes by using tracking.js (Lundgren et al., 2015), a facial feature detection library. The software first identifies the upper half of the face, then creates rectangular bounding boxes on the eyes. Next, the program sweeps the upper half of the face with a small-scale eye detection to approximate where the eyes are in order to minimize the likelihood of the program incorrectly identifying eye-like stimuli in the environment, such as a mole or a dot behind the participant. If the face is not immediately identifiable using the small-scale eye detection, full-image (large-scale) eye detection is used instead.

The pupil is the primary feature tracked when identifying where the participant is looking. First, the iris is identified, then the pupil. The program operates on three assumptions. First, the iris is darker than the rest of the eye. Second, the iris is circular. Third, the pupil is centrally located in the eye. With each click, each detected eye region is converted to 6x10 pixel images. Next, each image is grayscaled, retaining the intensity of each color. As a result, the lightest areas are whiter, while the darkest regions are black. This makes the parts of the eye easier to identify. This results in a 120D vector.

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The vector and the coordinates of the clicked square are paired and fed into the linear regression algorithm is then updated.

Each subsequent click on a square increases the accuracy of the model, with the most recent data being more heavily weighted. It should be noted that in the original Papoutsaki (2016) study, the researchers used a 24-inch monitor. The researchers also required participants to engage in at least 40 mouse clicks during the task. The researchers estimated that gaze predictions had a mean error of about 175 pixels, or around 3 cm. This was the version used in the present study.

Current WebGazer Application

In the current study, the author created a script that incorporated the *WebGazer* script. Prior to each video, the participant clicked on 35 randomly placed squares to create the eye gaze prediction model to be used for that trial. The video for each trial appeared slightly skewed toward the lower right edge of the screen. The right edge and bottom edge of the video was about 2 inches and 1 inch from the edge of the screen, respectively. The researcher created a programming code that placed a transparent dot that corresponds with where the participant is looking on screen. The dot's position was continuously updated on average 35.29 (*SD*=5.60) times per second. A transparent box was also created around the video. As the dot's position was updated, the program checked if the dot was within the box. If the dot was within the bounds of the box, a running tally of total visual engagement was increased by one and the total number of checks was increased by one. If the dot was not in the box, only the total number of checks were increased by one. During Praise and Demand conditions, intervals were 2 mins long. During these conditions, current interval checks and current interval visual

engagement tallies were also recorded. Every 2 mins, the current interval's visual engagement tallies were divided by the current interval's number of checks. This percentage was compared against the average of the participant's visual engagement during baseline. A 1 cm x 1 cm transparent square (Square A) (See Figure 2) was placed behind the video on the participant's screen with about 2.5 mm outside the border of the video. A second transparent square (Square B) (Figure 2) was placed behind the video, slightly above Square A. The right side of Square B also protruded the video border by 2.5 mm. Both squares were always transparent except at the end of the 2-min intervals. Every 2 mins during the Demand condition, Square B appeared white for 3 s to signal the researcher to speak. During the Praise condition, every 2 mins the participant's baseline average visual engagement was compared to the current interval's average visual engagement. If the current visual engagement was above the baseline, Square A's protruding corner appeared white for 3 s, signaling the researcher to speak. The current interval's visual engagement tallies and current interval checks were reset for the next interval, while total checks and the total visual engagement continued to be recorded. At the end of each video, the total percent visual engagement was recorded.

Pavlovia

Because *WebGazer* required a website to run, a secure server to host the website was required. Pavlovia (<u>https://pavlovia.org/docs/home/about</u>) is a web server that was specifically designed to host online behavioral studies. Pavlovia provides a Health Insurance Portability and Accountability Act (HIPAA)-compliant web service that does not store personally identifiable information. The webpage was run on Google Chrome, a web browser that is readily available to the public.



Figure 2. Example of researcher's screen with Square A and Square B showing. *Zoom*

The researcher and participant used Zoom (Zoom Video Communications Inc.,

2016), a third-party video conferencing software. This software allowed the researcher to see and record the participant's screen and face throughout the study.

Data Sheet

A data sheet with 90 blank boxes (Appendix F) was used for identifying whether the participant was visually engaged and during which 10-s interval the researcher delivered verbal feedback. as well as what type of verbal feedback was delivered to the participant.

Procedures

Sessions lasted for two to four trials each (M = 2.97, SD=.529). Trials began from when the researcher delivered the initial instructions until the video ended or 15 mins after the video had begun, elapsed, whichever occurred first. At the beginning of each trial, the researcher ensured that the equipment was working properly, distractions were present, the researcher's portrait was not visible to the participant, and that the participant's screen was visible on the researcher's screen. The study's website was onscreen at the start of each trial. The researcher instructed the participant to keep their speakers on, not to mute themselves, to take no notes, to stay at the computer, and to read aloud all directions on the screen. The participant input their assigned participant number and the current session number as indicated by the researcher. After reading through all directions, the participant calibrated the program by clicking on thirty-five squares that appeared on-screen in random locations. The participant then read the directions that appeared on-screen, then began the trial-specific video.

Baseline

Each participant initially experienced the baseline condition, in which the participant watched videos while the eye tracker assessed VE in the absence of verbal feedback from the researcher. This condition was conducted using the above procedure. *Praise Condition*

This condition followed the same procedure as the baseline condition, except the researcher provided contingent praise to the participant. Upon the participant beginning the video, the researcher delivered a praise statement. Praise was defined as a verbal statement by the researcher indicating approval of the participant's engagement (e.g., "I

love that you're watching the video," "Excellent job looking at the screen."). Recent literature indicates that praise delivered at a rate of as little as once per 2 mins can have a positive effect on academically-engaged behavior (e.g., Blaze, Olmi, Mercer, Dufrene, & Tingstrom, 2014). Based on these recent findings, contingent praise determined on a 2min basis. Every 2 mins the researcher identified the outer edge of a white square (Square A) near the lower right corner of the video. If it appeared, this indicated that the participant was visually engaged at or above their average baseline level of percent visually engaged. The researcher then delivered praise within 10 s of the appearance of the white square.

Demand Condition

This condition was similar to the Praise condition, except the researcher noncontingently delivered demands instead of praise every 2 mins. Demands were defined as verbal statements instructing the participant to engage in an expected behavior, specifically looking at the video (e.g., "Watch the video," "Look at the screen."). Upon the participant beginning the video, the researcher delivered the first demand statement. Subsequently, every 2 mins a white square (Square B) appeared in the lower right corner of the video, just above the location of Square A. This signaled the researcher to deliver a demand. The researcher delivered a demand within 10 s of the square appearing throughout the video.

Design, Data Analysis, and Dependent Variable

During the study, participants were exposed to different conditions: Baseline, Demand, and Praise. All participants initially experienced the Baseline condition. Subsequent conditions were administered to each participant in a staggered multiple baseline with Randomized Block Design (RBD) (Edgington, 1967, 1980a; Onghena & Edgington, 1994, 2005). Each block was comprised of a Praise and Demand condition. Three blocks of Demand-Praise and three blocks of Praise-Demand were randomly ordered following the Baseline phase. Two participants experienced Demand-Praise first and two participants experienced Praise-Demand first. Ordering of the videos were randomized for each participant. This design *meets evidence standards* according to What Works Clearinghouse Design Standards (What Works Clearinghouse, 2020).

The first condition change occurred after a participant's five sequential data points in baseline exhibited low variability around the median. Low variability was determined using a "stability envelope" (Barton et al., 2018; Lane & Gast, 2013), which was defined by a creating a range of +/- 20% of the median. If at least 80% of the data points are within that envelope, the data are considered to have low variability. Subsequent condition changes for other participants occurred once the participant experienced at least three more baseline data points than the previous condition change, and five sequential baseline data points demonstrated low variability, also using a stability envelope.

Data were also visually analyzed for trend, level, immediacy of change, stability of data, and percent of non-overlapping data (PND; Scruggs et al., 1987). Percent of nonoverlapping data was chosen for evaluating effect due to likelihood of ceiling effects encountered in past studies. Because one of the main research questions was regarding the extent to which *WebGazer* data and hand-scored data agreed, comparison of effect sizes may be masked by false negatives due to ceiling effects from other visual analysis techniques such as percent of all non-overlapping data (PAND; Parker et al., 2007). In accordance with analysis guidelines (Scruggs & Mastropieri, 1998), the independent variable was classified as being very effective if 90% or more data points fell higher than the highest data in baseline. If 70% to 90% of data fell higher than the baseline data, the effect was classified as effective. If 50% to 70% of data fell higher than the baseline data, the effect was considered questionable. For those with less than 50% of data falling above baseline data, the effect was classified as ineffective.

Visual Engagement

The primary dependent variable for this study was percent time visually engaged (VE), defined as the participant's eye gaze being directed toward the video during the lecture. Visual engagement was measured by a variation of the *WebGazer* JavaScript (Papoutsaki et al., 2016). For hand scoring, VE was defined more explicitly by the absence of specific behaviors. A participant was scored as not being visually engaged if their eyes were closed for more than 3 s continuously, if they were looking away from the screen so that the sclera of their eyes was not discernible, if their eyes were not visible due to moving their face out of the video, or if they were looking down toward the keyboard. Hand scoring was performed using a 10-s MTS procedure.

Procedural Integrity and Interobserver Agreement

To assess for procedural integrity, the primary researcher recorded whether the above procedure was followed using Appendix G, H, or I for respective conditions. Because distractions were not in the view of the camera, the primary researcher recorded if the distractions were present at the beginning of sessions (i.e., before a participant's first trial of the day) and if they were still present at the end of sessions (i.e., after the participant's final trial of the day). A second observer was trained by the primary investigator to record the dependent variable and to record whether steps were followed, using 4 videos, one from each participant and covering all 3 conditions. During training, if the second observer had not achieved at least 90% agreement with the primary researcher, the primary researcher would have explained where the errors occurred, and another video would be run. However, average IOA was 95.45% (Range: 93.9%-100%) for the dependent variable and 100% for procedural integrity IOA. Interobserver agreement was determined using scored interval IOA. The number of intervals scored for visual engagement were compared between the observer and the primary investigator. The number of agreements were divided by total number intervals, then multiplied by 100. The second observer also coded at least 30% of videos for each condition, across all participants. The observer was required to have above 80% agreement with the primary investigator in the video. Interobserver agreement was again determined using scored interval IOA.

For Annie, IOA for the dependent variable and procedural integrity were calculated for 40% of baseline trials. For Britta, IOA was calculated for 37.5% of baseline trials. For all other conditions, including across all other participants, 33% of trials were coded for IOA.

Annie's mean IOA for the dependent variable during baseline was 93.78% (range 92.10%-95.45%), Praise IOA was 100%, and Demand IOA was 100%. Procedural integrity IOA was 100% across all conditions. Britta's mean IOA for the dependent variable during baseline was 96.02% (range 93.94%-98.88%), Praise IOA was 98.88% (range 97.75%-100%), and Demand IOA was 96.15% (range 89.45%-96.15%). Procedural integrity IOA was 100% across all conditions. Shirley's mean IOA for the

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dependent variable during baseline was 92.78% (range 88.16%-96.83%), Praise and Demand IOA were 100%. Procedural integrity IOA was 100% across all conditions. Jeff's mean IOA for the dependent variable during baseline was 95.65% (range 89.77%-100%), Praise IOA was 99.20% (range 98.39%-100%), and Demand IOA was 99.16% (range 98.31%-100%). Procedural integrity IOA was 100% across all conditions.

CHAPTER III – RESULTS

WebGazer Visual Engagement

Annie's baseline data indicated a minimal to slightly increasing trend (Figure 3). Her baseline data indicated low to moderate variability (65.71%-83.89%) with a mean visual engagement of 76.07%. Her final five data points in baseline had a median of 77.52%, with all five falling within the 20% stability envelope (65.89% to 89.14%), indicating stable data. Annie experienced the Praise condition first upon leaving baseline. Her data did not immediately increase upon the condition's introduction. Her Praise data demonstrated moderate variability (74.02% - 98.09%) and a slight upward trend. Her average visual engagement during the Praise condition (M=86.20) was higher than during baseline (M=76.07). Of her Praise data, 50% did not overlap with baseline, indicating a questionable effect. However, all her data overlapped with the Demand condition.

Annie's Demand data immediately increased upon the condition's introduction, and demonstrated moderate variability (75.81% - 99.14%) and no apparent trend. Her average visual engagement during the Demand condition (M=89.58) was higher than during baseline (M=76.07). Of her Demand data, 83.33% did not overlap with baseline, indicating overall effectiveness, and 16.67% did not overlap with her Praise data. Overall, her visual engagement during Praise and Demand did increase above baseline, with a larger effect for the Demand condition.

Britta's baseline data indicated no apparent trend (Figure 3). Her baseline data indicated low to moderate variability (67.95%-86.57%) with a mean visual engagement of 75.59%. Britta's final five data points in baseline had a median of 78.31%, with all five falling within the 20% stability envelope (62.65% to 93.98%), indicating stable data.



Figure 3. Percent visually engaged as measured by WebGazer (WG) application

Britta experienced the Demand condition first upon leaving baseline. Her data did not immediately increase upon the condition's introduction. Her Demand data demonstrated moderate to high variability (70.05% - 95.53%) and a slight upward trend. Her average visual engagement during the Demand condition (M=85.27) was higher than during baseline (M=75.59). Of her Demand data, 50% did not overlap with baseline, and 16.67% did not overlap with her Praise data.

Britta's Praise data demonstrated high variability (56.83% - 94.97%) and an upward trend. Her average visual engagement during the Praise condition (M=80.54) was higher than during baseline (M=75.59). Of her Praise data, 50% did not overlap with baseline, indicating the condition was overall ineffective. All her Praise data overlapped with the Demand condition. Overall, her visual engagement during Praise and Demand did increase above Baseline, with a similar effect for both compared to baseline, but with Demand having a slightly larger average change.

Jeff's baseline data indicated an overall decreasing trend (Figure 3). His baseline data indicated high variability (0.72%-51.63%) with a mean visual engagement of 26.08%. Jeff's final five data points in baseline had a median of 13.91%, with four of the five falling within the 20% stability envelope (11.83% to 16.70%), indicating stable data. Jeff experienced the Praise condition first upon leaving baseline. There was an immediate increase in data upon the condition's introduction. His Praise data demonstrated high variability (17.01% - 64.84%) and a slightly decreasing trend. His average visual engagement during the Praise condition (M=42.36) was higher than during baseline
(M=26.08). Of his Praise data, 50% did not overlap with baseline, indicating it was largely ineffective. However, all his data overlapped with the Demand condition.

His Demand data demonstrated high variability (21.02% - 65.87%) and no apparent trend. His average visual engagement during the Demand condition (M=43.81) was higher than during baseline (M=26.08). Of his Demand data, 50% did not overlap with baseline and 16.67% did not overlap with his Praise data. Overall, his visual engagement during Praise and Demand did increase above baseline, with a similar effect and average for both.

Shirley's baseline data indicated no apparent trend (Figure 3). Her baseline data indicated high variability (53.21%-90.24%) with a mean visual engagement of 77.09%. Shirley's final five data points in baseline had a median of 86.61%, with four of the five falling within the 20% stability envelope (69.3% to 103.93%), indicating stable data. Shirley experienced the Demand condition first upon leaving baseline. Her data immediately increased upon the condition's introduction. Her Demand data exhibited low variability (88.65% - 97.80%) and no apparent trend. Her average visual engagement during the Demand condition (M=93.01) was higher than during baseline (M=77.09). Of her Demand data, 83.33% did not overlap with Baseline, indicating it was effective in increasing visual engagement, and 16.67% did not overlap with her Praise data.

Shirley's Praise data demonstrated low variability (87.96% - 97.42%) and no apparent trend. Her average visual engagement during the Praise condition (M=93.15) was higher than during baseline (M=77.09). Of her Praise data, 83.33% did not overlap with Baseline, which indicated effectiveness in increasing visual engagement. However, all her data overlapped with the Demand condition. Overall, her visual engagement

during Praise and Demand did increase above baseline, with a similar effect for both compared to baseline.

Hand Scored Visual Engagement

Annie's hand scored baseline data indicated no apparent trend (Figure 4). Her baseline data indicated low to moderate variability (69.84%-87.67%) with a mean visual engagement of 79.05%. Annie experienced the Praise condition first upon leaving baseline. Her data immediately increased upon the condition's introduction. Her Praise data demonstrated low variability (98.50% - 100.00%) and no apparent trend. Her average visual engagement during the Praise condition (M=99.75) was higher than during baseline (M=79.05). Of her Praise data, there was no overlap with baseline, indicating it was very effective. All data overlapped with Demand condition.

Annie's Demand data demonstrated low variability (98.30 – 100.00%) and no apparent trend. Her average visual engagement during the Demand condition (M=99.72) was higher than during baseline (M=79.05). Of her Demand data, there was no overlap with baseline and all data overlapped with her Praise data. Overall, the hand scored visual engagement during Praise and Demand increased above baseline, with a similar effect.

Britta's baseline data indicated slightly decreasing trend (Figure 3). Her baseline data indicated low to moderate variability (83.13%-94.37%) with a mean visual engagement of 90.81%. Britta experienced the Demand condition first upon leaving baseline. Her data immediately increased upon the condition's introduction. Demand data demonstrated low variability (92.65% - 98.53%) and no apparent trend. Average visual engagement during the Demand condition (M=96.60) was higher than during baseline (M=90.81).



Figure 4. Percent visual engagement as measured by hand scoring (HS)

Of her Demand data, 83.33% did not overlap with baseline, indicating, but all her data overlapped with her Praise data. Britta's Praise data demonstrated low variability (89.66% - 100.00%) and no apparent trend. Her average visual engagement during the Praise condition (M=97.11) was higher than during baseline (M=90.81). Of her Praise data, 83.33% did not overlap with Baseline, indicating it was effective. Compared to her Demand condition data, 50% of her Praise data did not overlap. Overall, her visual engagement during Praise and Demand did increase above baseline, with a similar effect for both compared to baseline.

Jeff's hand scored baseline data indicated no apparent trend (Figure 3). His baseline data indicated high variability (2.94%-54.02%) with a mean visual engagement of 18.97%. Jeff experienced the Praise condition first upon leaving baseline. His data immediately increased upon the condition's introduction. His Praise data demonstrated low to moderate variability (82.26% - 100.00%) and a slight upward trend. His average visual engagement during the Praise condition (M=96.54) was higher than during baseline (M=18.97). Of his Praise data, 100% did not overlap with baseline, indicating it was very effective. However, all his data overlapped with the Demand condition.

Jeff's Demand data demonstrated low variability (95.00 – 100.00%) and no apparent trend. His average visual engagement during the Demand condition (M=98.60) was higher than during baseline (M=18.97). Of his Demand data, 100% did not overlap with baseline, and all data overlapped with his Praise data. Overall, Jeff's hand scored

visual engagement during Praise and Demand did increase above baseline, with a similar effect for both conditions.

Shirley's baseline data indicated no apparent trend (Figure 3). Her baseline data indicated high variability (94.92 %-100.00%) with a mean visual engagement of 98.89%. Shirley's final five data points in baseline had a median of 78.26%, with four of the five falling within the 20% stability envelope (62.6% to 93.91%), indicating stable data. Shirley experienced the Demand condition first upon leaving baseline. Her data did not immediately increase upon the condition's introduction. Her Demand data demonstrated low variability (94.92 – 100.00%) and no apparent trend. Her average visual engagement during the Demand condition (M=98.89) was higher than during baseline (M=94.23). Of her Demand data, all overlapped with baseline, and all overlapped with her Praise data.

Shirley's Praise data demonstrated no variability (100.00% - 100.00%) and no apparent trend. Her average visual engagement during the Praise condition (M=100.00) was higher than during baseline (M=94.23). Of her Praise data, all overlapped with baseline and all her Praise data overlapped with the Demand condition. Overall, her hand scored visual engagement during Praise and Demand indicated both were ineffective.

WebGazer versus Hand Scored visual engagement

The second research question posed for this study was to what degree did visual engagement, as measured by *WebGazer*, correspond with visual engagement measured by an observer? Differences were expected due to the differences in frequency of observations (i.e., dozens per second by *WebGazer* versus one per 10-s by observer). As a result, variability, trend, and level were examined to account for potential systematic errors. Comparisons between visual engagement in the Praise condition as measured by *WebGazer* and hand scoring are graphed in Figure 4. Comparisons between visual engagement in the Demand condition as measured by *WebGazer* and hand scoring are graphed in Figure 5. Most conditions showed similar variability between the hand scored and computer scored data. The largest discrepancies in variability between *WebGazer* and hand scoring were observed in Britta's Praise condition (Range=56.83-94.97, 89.66 – 100.00), Jeff's Demand (Range=21.02-65.87, 95.00-100.00) and Praise (Range=17.01-64.84, 82.26-100.00) conditions, and Shirley's Baseline (53.21-90.24, 82.54-100.00).

Regarding level, most conditions across all participants were similar between *WebGazer* and hand scoring measurements of visual engagement. The largest discrepancies between *WebGazer* and hand scoring were observed for Jeff's Praise condition (44.94, 99.33) and Demand condition (46.58, 100.00), Britta's Baseline (74.79, 92.24), and Shirley's Baseline (78.57, 96.06).

Among the discrepancies, Jeff's Demand and Praise conditions and Shirley's Baseline were discrepant both in their range and their level. The data paths for Shirley's Baseline comparison had similar shapes, but the trends were similar. Using a simple



Figure 5. Comparison between hand scored (HS) and WebGazer (WG) Praise data.



Figure 6. Comparison between hand scored (HS) and WebGazer (WG) Demand data.

linear regression, the slope of Shirley's baseline data was -0.03 for *WebGazer* measurement and 0.57 hand scoring. Although these slopes are in opposite directions, they are low numbers, and thus relatively close. Using a simple linear regression for Jeff's Demand condition data, the slopes for *WebGazer* and hand scoring were 0.0081 and -0.0019, respectively. These slopes indicated no apparent trend. Lastly, Jeff's Praise condition data resulted in slopes of -0.028 for *WebGazer* and 0.025 for hand scoring. Again, these were relatively close, indicating no apparent trend.

CHAPTER IV - DISCUSSION

This study was conducted to examine two questions. First, does providing contingent praise affect participants' visual engagement, as measured by eye tracking software, during video lectures? Second, how closely do the eye tracking program measurements of eye gaze correspond with hand-scored measurements?

The first research question examined the extent to which participants' percent time visually engaged, as measured by the *WebGazer* software, changed in the presence of contingent praise. All participants' visual engagement increased in the Praise condition, with three participants' data indicating questionable effectiveness and one participant's data indicating overall effectiveness. However, all data measured during Praise condition overlapped with data in the Demand condition for all participants, indicating that Praise was not discernibly better than Demand for increasing visual engagement. The level for the Praise condition also increased across all participants. The variability of *WebGazer*'s measurements means this conclusion should be interpreted with caution. However, because WebGazer measures hundreds more times in a 10-s period than the human observer, the software may have identified more incidents of disengagement. Without continual calibration during trials, WebGazer's measurement may also be affected by head movements and repositioning, even if gradual. In answer to this first question, contingent praise had a questionable effect for three participants in the presence of contingent praise, and was overall effective for one participant. These findings are consistent with results from the Rozsa (2021) study, in which three out of four participants exhibited higher visual engagement in the presence of noncontingent

praise. Like the Demand condition data in the current study, Rozsa (2021) also observed significant overlap with neutral verbalizations, finding similar effect for each.

The second research question required a comparison between the hand-scored data and data measured by WebGazer. When looking at the hand-scored data, both Shirley's and Britta's Baseline data averaged above 90%. Although a large effect was observed in Britta's Praise data, any difference in magnitude of effect size between her Demand and Praise data may have been masked due to potential ceiling effects. Shirley's Baseline data averaged in the mid-90s, with three trials being measured at 100% visual engagement. This resulted in no treatment effect being observable. It should be noted that the overall average increased across both conditions, and the variability greatly reduced, with her Praise data being at 100% across all Praise trials. This change in variability may indicate more consistent visual engagement, but due to the differences between hand score and WebGazer, this is not necessarily true. Overall, both hand-scored data and WebGazer measured data indicated a treatment effect for three participants, though not to the same magnitude. Despite the differences in magnitude of effect size between WebGazer and hand scoring, the similarity in trend, shape, level, and variability across data paths for Annie, Britta, and Shirley suggest that WebGazer's measurements were likely valid representations of the respective participants' visual engagement.

The largest discrepancies (more than 40%) were observed in Britta's 10th trial, Shirley's 8th trial, and all of Jeff's Praise and Demand data, except one Praise and one Demand trial. Videos were reviewed, the percent visual engagement was calculated for each 2-min interval to identify artifacts or confounding variables responsible for disparities in measurements. Britta's outlying session appeared to be a result of her putting up her hair halfway through the video. Prior to putting up her hair, her average percent visual engagement was between 70% and 95%. Therefore, changing the features of her face may have reduced the tracker's accuracy. When observing Shirley's outlying sessions, *WebGazer* measured most of her visual engagement occurring during the first half of the video. As the video progressed, the participant started tilting her head and leaning forcefully into her hand, pushing upward on her cheek, forcing one of her eyes closed. Similar to Britta's video, this appeared to contribute to the disparity in measurements.

Disparities in Jeff's videos were not as apparent upon review. One of the most notable differences in appearance between Jeff and other participants was the presence of a large, dark beard. During videos in which Jeff's *WebGazer* data were most discrepant with hand scored data (i.e., trials 20, 21, 22, and 24), Jeff almost immediately tilted his head at roughly a 30–45-degree angle upon the video beginning. In multiple trials (i.e., trials 18, 19, 20, 21) Jeff covered his mouth with his hand in a thinking pose for large portions of the video. During his baseline trials, Jeff typically immediately looked away from the video upon it beginning and started solving the nearby puzzle ball or using his phone. When asked about from what source he had learned of the study, Jeff said his roommate was dismissed from the study a couple days earlier after being screened as a potential participant. In order to continue to be a participant, Jeff may have engaged in aberrant behavior during baseline. This will be discussed in more depth in the limitations section.

Overall, the results of this study demonstrated similar results with that of a prior study which used this version of *WebGazer* (Rozsa, 2021). In both studies, the majority

of participants' visual engagement increased in the presence of praise. Both studies also demonstrated observed disparities in level and variability between WebGazer and handscoring. In the previous study, ceiling effects during baseline likely masked any potential treatment effects. This study attempted to address that limitation by introducing a maximum average visual engagement of 80% during baseline as an exclusionary criterion. Unlike the previous study, this study employed an alternating treatment design to enable easier comparisons between conditions and baseline data. This study also employed more potentially distracting stimuli in the participants' immediate vicinity, whereas the previous study had minimal alternative stimuli with which to engage. Whereas the previous study used noncontingent praise with neutral verbalizations by the experimenter, this study used contingent reinforcement with demands, as both interactions were expected to be more likely to be encountered in an academic environment. Despite some disparities in data between hand scoring and WebGazer measured visual engagement, the advantages of having an online software collecting and calculating data live is invaluable.

Limitations

This study had multiple limitations that should be considered. Similar to other studies using similar eye tracking software (e.g., Hutt, 2020; Papoutsaki, 2018; Rozsa, 2021), eye gaze estimation is susceptible to head movements. Many older eye tracking methodologies even incorporated headrests (See Rayner, 1998 for a more comprehensive history of these methodologies). As a result, requirements of minimal head movements and clear view of the participants' eyes may limit its validity outside the experimental setting. The combination of multiple reminders about these requirements prior to each

trial as well as the presence of two cameras may also have affected the attentiveness of participants. Multiple participants looked directly at the webcam multiple times, then often quickly overcorrected by looking around the room. As a result, this reactivity may have affected the results.

A few of the first participants, whom were dismissed for not meeting inclusion criteria, encountered motion-activated overhead lights mid-trial, which made their eyes difficult to see due to shadows cast by these lights. This was addressed by taping over the motion sensors and placing the two lamps behind the laptop to increase the visibility of the participants' eyes. This need for precise lighting has been noted in past studies (Papoutsaki, 2016; Rozsa, 2021). Typical eye tracking software requires more expensive hardware that uses infrared light to identify the cornea continuously. This results in less reliance on precise lighting (Inhoff & Radach, 1998). To offset this disadvantage, most studies that use *WebGazer* incorporate continually updating calibration through user mouse clicks (e.g., Papoutsaki et al., 2017). This can help adjust the prediction model to account for changes in lighting, as well as changes in the participant's position.

Because the study was conducted in a controlled setting, not all components of a typical online learning environment were present, and some, such as the second webcam, were extraneous to a typical online learning environment. For example, the lecturer would likely also be the person delivering praise or demands in a synchronous online learning environment. Because the researcher interrupted the lecture to provide demands or praise, this may have made such interactions stand out more, or the video audio may have made the researcher's verbalizations harder to understand. In a previous study, no discernible difference was observed when neutral verbalizations were provided versus

praise (Rozsa, 2021). That study also had a third party providing the verbal interactions apart from the lecturer and participant. This study demonstrated similar findings. Rather than the type of interaction moderating the relationship between the independent variable and visual engagement, it may have been the interaction with a separate party itself. Once participants were aware they were being actively watched, following the first verbal interaction, this may have been enough to increase visual engagement. In a typical classroom or online learning environment, other students may also receive attention, reducing reactivity due to being observed. The addition of the square as a visual cue for the researcher may also have influenced the participants' visual engagement. In contrast with Rozsa (2021), the current study's use of contingent praise resulted in fewer instances of praise. For Jeff, this may have been partially responsible for his lower scores during Praise condition, as he was not contacting reinforcement as regularly as other participants.

Another limitation is the pool of selected participants. All but one of the participants was recruited through a psychology class. Although results were not relayed to professors in the classes, participants may have engaged in behavior that is not typical, being more attentive during trials. Furthermore, because most of the participants were in psychology classes, they may have interacted with one another, either due to being in a same class or sharing a building that houses classes of that department. For the one participant, Jeff, whom was not recruited through a class, he said he volunteered after his roommate, a dismissed participant, informed him about the study. The roommate and other participants may have identified the criteria for inclusion in the study, or the aims of the study. This may have accounted for Jeff's exceptionally low baseline data, and

subsequent near 100% data during the other conditions. As a result, his data should be interpreted with caution.

Due to the small participant pool, differences between male and female participants may have also contributed to the results. Past research has indicated that when praise more consistently results in an increase in male task performance than females, for whom task performance may even decrease when praised (Carone, 1975; Deci, 1972; Deci et al., 1975; Koestner et al., 1987; Zhao & Huang, 2019; Zinser et al., 1982). Some research has also indicated a greater decrease in performance in female undergraduate participants when the researcher providing praise was female than when the researcher was a male, and a greater increase in performance for male undergraduate participants when the research in performance for male undergraduate participants when the research in visual engagement for female participants may have been less pronounced or even decreased. Relatedly, sexual orientation may have influenced results, given the difference in performance when experimenter and participant are a different or the same gender.

Another limitation was that subjects' individual interest in topics was not considered. Although reduced familiarity with the vast majority of topics was a requirement for inclusion, this did not necessarily guarantee individual interest in the subjects. Even though the individual may not have been familiar with the rise of Hitler, they may find war-related information more interesting. Similarly, though they may be familiar with Islam or Confucius, they may find religion in general interesting.

Another limitation was the praise itself. For praise to be effective, it must have certain qualities. First, it should be delivered contingent on performance of the desired

behavior. Second, the person praising should specify what behavior is being praise. Third, the praise should sound sincere (Alberto & Troutman, 2009; O'Leary & O'Leary, 1977). The contingency for praise in this study was that the participant was visually engaged above their baseline average for 2 mins. The rate at which the contingency was evaluated was chosen based on previous research that demonstrated one praise statement per 2 mins typically results an effect on academic engagement for many students, but it does not always result in an effect for every student (Blaze et al., 2014; Williamson, 2017). Though some research has explored ideal rates of praise, these studies almost exclusively examined primary and secondary education settings (e.g., Allday et al., 2012; Dufrene, Lestremau, & Zoder-Martell, 2014; Sutherland, Wehby, & Copeland, 2000). Because the 2-min intervals were evaluated as a whole, when praise was delivered it was not necessarily when the individual was visually engaged. Furthermore, if the participant was not visually engaged above their baseline average for the first couple intervals, they were not reinforced, which may have a snowball effect, meaning the person is less and less likely to be visually engage. The sincerity of praise was also not evaluated. Because the researcher had to speak quickly and above the video, as well as from out of view of the participant, the tone was often unintelligible and nonverbal signals that may suggest sincerity was not available to the participant.

The length of videos should also be considered a potential limitation. Some studies have indicated that attention during instruction may begin to decrease after about 9 mins (e.g., Davis, 1993; Guo, Kim, & Rubin, 2014; McKeachie, 1986; Wankat, 2002). Most studies commonly cite Hartley and Davies (1978) when discussing the 10-15 mins rule. The authors of that study examined the amount of note taking at different times in lectures. As previously mentioned, this type of active engagement with material is demonstrably different from more passive visual engagement. Other studies have suggested that attention may first begin to decrease after 5 mins, with a further decrease in attention after 10-18 mins into class (Johnstone & Percival, 1976). Although no consistent threshold has been established for the ideal length of a video to maintain viewer's attention, the videos in this study were typically a little longer than the above times, longer videos may be necessary to control for naturally higher sustained attention for the first 10-15 mins.

Visual engagement was also narrowly defined as the participant looking toward the video. Sustained eye contact may not always indicate attending. For example, individuals tend to fixate on fewer regions, for longer times, and on irrelevant regions during wind wandering (Reichle et al., 2010). Saccades (eye movements between fixations) also become less frequent and/or slower (Uzzaman & Joordens, 2011). What constitutes an acceptable fixation duration or saccade length also varies on an individual basis and may change based on the type of task, such as silent reading versus scene perception (Rayner, 2009).

Future Directions

Future research into other forms of contingent reinforcement may also prove beneficial. As was stated previously, in K-12 classroom settings one praise per 2-mins often results in increased academic behavior. Part of the rationale was that it was easier for teachers in classrooms to provide praise at this rate (Blaze et al., 2014). Little research exists regarding the effects of praise on young adults. Some research has indicated that behavior specific praise may have a similar effect on young adults as grade-school-aged children (Hancock, 2000; Lessard et al., 2015). Conversely, others have indicated that person- or ability-centered praise has a positive correlation with increased performance compared to those who receive behavior specific praise or no praise (e.g., Koestner et al., 1987). If praise does not have the same effect on all undergraduate students, then alternative sources of reinforcement may be needed, depending on the individual. While this study sought to use positive reinforcement, negative reinforcement may also have been effective. If finishing a lecture was important to the student, perhaps a contingency could be put in place to pause the video after detecting no visual engagement for a set amount of time. Similarly, some professional workshops or lecture series employ clickable prompts to identify if the viewer is still watching. Some pilot studies have demonstrated the utility of eye tracking in the classroom, and its use as a means of combatting mind wandering (e.g., Hutt, 2020; Hutt et al., 2019). These studies used prediction models that would intervene with a question related to the material on-screen when probable mind wandering was detected. Students reported feeling less autonomous with this approach, and these studies still used more expensive eye tracking hardware. Future applications could combine the studies' approaches so that when the individual was not engaged, a prompt may appear, which would also serve to continue calibrating the software. Similarly, with the increasing use of computers in classrooms, the use of WebGazer with an integrated webcam to identify if a child is engaged during assignments may assist teachers in identifying who is working, who may be struggling, and if students should be praised for working on their assignments.

Future studies may also benefit from fixed momentary differential reinforcement of other behavior (Cooper, Heron, & Heward, 2019), in which the participant is observed after a specified duration. If the individual is engaging in the desired behavior, they are provided reinforcement. If not, then nothing occurs. This may increase the likelihood of visual engagement being reinforced, rather than looking at the entire interval.

Implementing this software in a multi-student online learning environment would also be a logical next step. This would require some form of signal that was bigger than the small square used in this study, as multiple students' videos would be present at once. Finding other unintrusive signals for the teacher that don't interfere with the lecture would also be helpful.

Conclusion

These results provide additional evidence for use in applied settings. Just as praise has been shown to be an effective classroom management technique for decades, it appears praise may also be useful in online learning environments. As academia moves to more online options, behavioral strategies should also continue to increase. Technology may be used beyond simply serving as a medium for accessing online instruction and material. With hardware continually improving at an exponential rate, resources that were once completely unavailable to the public are becoming more accessible. This study has demonstrated how technology may be used to assist us in data collection methodologies, as well as calculating whether students are meeting expectations based on predetermined criteria, such as portion of time spent on-task. This may allow the teacher more freedom to attend to other curriculum-based duties.

This study provided one example of how eye tracking may be used to increase academically relevant behavior. With a few modifications to the methodology, this software may be used to facilitate data collection as well as intervention implementation both in the classroom and in online learning environments. The implications of this study suggest continued application would result in fruitful opportunities for future researchers and educators.

APPENDIX A – IRB Approval Letter

Office of Research Integrity



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NOTICE OF INSTITUTIONAL REVIEW BOARD ACTION

The project below has been reviewed by The University of Southern Mississippi Institutional Review Board in accordance with Federal Drug Administration regulations (21 CFR 26, 111), Department of Health and Human Services regulations (45 CFR Part 46), and University Policy to ensure:

- The risks to subjects are minimized and reasonable in relation to the anticipated benefits.
- The selection of subjects is equitable.
- Informed consent is adequate and appropriately documented.
- Where appropriate, the research plan makes adequate provisions for monitoring the data collected to ensure the safety of the subjects.
- Where appropriate, there are adequate provisions to protect the privacy of subjects and to maintain the confidentiality of all data.
- Appropriate additional safeguards have been included to protect vulnerable subjects.
- Any unanticipated, serious, or continuing problems encountered involving risks to subjects must be reported immediately. Problems should be reported to ORI via the Incident template on Cayuse IRB.
- The period of approval is twelve months. An application for renewal must be submitted for projects exceeding twelve months.

PROTOCOL NUMBER: IRB-21-292

PROJECT TITLE: Using Verbal Reinforcement to Increase Visual Attending in an Asynchronous Online Learning Environment: An Eye Tracking Study SCHOOL/PROGRAM: School of Psychology, Psychology RESEARCHER(S): Andrew Rozsa, D Olmi

IRB COMMITTEE ACTION: Approved CATEGORY: Expedited

7. Research on individual or group characteristics or behavior (including, but not limited to, research on perception, cognition, motivation, identity, language, communication, cultural beliefs or practices, and social behavior) or research employing survey, interview, oral history, focus group, program evaluation, human factors evaluation, or quality assurance methodologies.

PERIOD OF APPROVAL: July 16, 2021

Sonald Baccofr.

Donald Sacco, Ph.D. Institutional Review Board Chairperson

APPENDIX B- Recruitment Flyer



Undergraduate Students Needed for Eye Tracking Study

What?

The purpose of this study is to identify how different forms of researcher's verbal feedback may alter participant's attending.

Who?

- Must be a USM undergraduate student
- Must be able to work at a computer for an hour <u>without</u> the aid of <u>eyeglasses</u>
- You are not registered with the USM Office of Disability Accommodations.

Why?

You will be compensated \$15 per hour upon completion of participation or upon the study's completion, whichever comes first. You may stop participating at any time.

When?

Sessions will begin **February 1**st and continue until the project is completed. Each session will last about **one hour**, during which you will watch 3-4 lectures about human history. You should expect to commit **up to 8 hours** spread across **2 to 5 weeks**. To finish in a timely manner, we will meet at least twice a week, depending on your availability.

How5

Confirm you meet the above criteria by scanning this QR code with your camera and filling out the required information on the qualitics page that appears:

Alternatively, you may go directly to the site at

https://tinyurl.com/ajreyetrack

After submission, you will receive a survey by email. Please fill this out by **January 30th**. Participants who meet criteria will be contacted within one to two days of submission.

Please direct all questions to the primary researcher at andrew.rozsa@usm.edu.

This study has been approved by USM's Institutional Review Board (Protocol #: 21-381)

APPENDIX C - Pre-Study Questionnaire

Please indicate how familiar you consider yourself with each of the following topics on a scale from "Not at all familiar" to "Incredibly familiar."

	Not at all familiar	Little familiarity	Some familiarity	Very familiar
Golden Age of Athens, Pericles and Greek Culture	0	0	0	0
Paris Peace Conference and Treaty of Versailles	0	0	0	0
International Human Rights	0	0	0	0
Hinduism: Brahman, Atman, Samsara, and Moksha	0	0	0	0
Augustus of Rome	0	0	0	0
Feudal System during the Middle Ages	0	0	0	0
Ottoman, Safavid and Mughal Empires	0	0	0	0
Indus River Valley Civilizations	0	0	0	0
Golden age of Islam	0	0	0	0
Ides of March and civil war	0	0	0	0
Socrates, Plato, and Aristotle	0	0	0	0
Punic Wars between Rome and Carthage	0	0	0	0
Initial Rise of Hitler and the Nazis	0	0	0	0
Theodor Herzl and the birth of political Zionism	0	0	0	0
Alexander the Great	0	0	0	0
Protestant Reformation: Martin Luther	0	0	0	0
Arian Controversy and the Council of Nicaea	0	0	0	0
Fall of the Roman Empire	0	0	0	0
Closing Stages in World War I	0	0	0	0
Hitler and the Nazis come to power	0	0	0	0
Blockades, U-boats, Lusitania	0	0	0	0
Continuity-Sikhism connections to Hinduism and Islam	0	0	0	0
Spread of Islam	0	0	0	0
Hittite Empire and Battle of Kadesh	0	0	0	0
Napoleon and the Wars of the First and Second Coalitions	0	0	0	0
Bay of Pigs Invasion	0	0	0	0
Cyrus the Great and the Achaemenid Empire	0	0	0	0
Ancient Egypt	0	0	0	0
French Revolution	0	0	0	0
Allende and Pinochet in Chile	0	0	0	0
Confucius and the Hundred Schools of Thought	0	0	0	0
Axis in World War II	0	0	0	0

APPENDIX D - Consent Form



INSTITUTIONAL REVIEW BOARD STANDARD (SIGNED) INFORMED CONSENT

STANDARD (SIGNED) INFORMED CONSENT PROCEDURES				
 This completed document must be signed by each consenting research participant. The Project Information and Research Description sections of this form should be completed by the Principal Investigator before submitting this form for IRB approval. Signed copies of the consent form should be provided to all participants. 				
Today's date:				
PROJECT INFORMATION				
Project Title: Visual Engagement during Online Lectures				

 Project Title:
 Visual Engagement during Online Lectures

 Principal Investigator:
 Andrew Rozsa
 Phone:
 2056168787
 Email:
 andrew.rozsa@usm.edu

 College:
 Education and Human Sciences
 School and Program:
 School Psychology Doctoral

 Program at the Department of Psychology
 RESEARCH DESCRIPTION
 Research Description

1. Purpose:

The purpose of this study will be to identify how different forms of verbal feedback may alter attending during video lectures.

2. Description of Study:

Sessions will occur in February, March, April, and/or May. During the trials, you will be recorded for data verification and to assess procedural integrity. If you agree to participate in this study, you will be seated in a room on-campus with a laptop equipped with a webcam, which will be provided by the researcher. After a short calibration sequence, you will watch a randomly chosen lecture covering a historical event/period in human history. The lecture will last between 10 and 15 minutes. During the lecture, the researcher will occasionally provide you with feedback. From calibration through the end of the video, you will need to minimize head movements as much as possible. From start to finish, each trial will last about 15-20 minutes. You should expect to commit up to 8 hours spread across 2 to 5 weeks. To finish in a timely manner, we will meet at least twice a week, depending on your availability. Sessions will begin February 1st and continue until the project is completed. You may discontinue participation at any point during the study.

3. Benefits:

You will be compensated \$15 per hour upon completion of participation. If you are not chosen to continue the remainder of the study or choose to leave the study early, you will be compensated upon the study's conclusion at \$15 per hour for time attended. You may discontinue participation at any point.

4. Risks:

Due to the nature of the experiment requiring you to be seated and looking at a computer screen for prolonged periods of time, back pain and eye strain may occur. To decrease the likelihood of these problems, sessions will not last beyond one hour. To minimize likelihood of injury or discomfort, you will be allowed to stretch after each trial. Due to the current state of the pandemic, transmission of COVID-19 may also be possible while on-campus. To minimize this likelihood you will be required to wear a mask during all face-to-face interactions. The researcher will also engage in social distancing and masking in accordance with university policies.

5. Confidentiality:

During trials, your eye gaze will be tracked and recorded using numerical coordinates. These will be stored in an Excel worksheet that is stored on Pavlovia, an experiment hosting web server. This server is Health Insurance Portability and Accountability Act (HIPAA)-compliant and does not store any personally identifiable information beyond IP address for security reasons. All data will be copied from the Pavlovia server following each session and removed from the site.

Videos will also be recorded for interobserver agreement and assessment of procedural integrity. These will be recorded only on the provided laptop and stored on two encrypted thumb drives which will be stored oncampus. These thumb drives will be accessible only to volunteer observers and the primary researcher. At the conclusion of the study, all data will be stored up to a year on-campus in a locked room accessible only to faculty.

At the study's conclusion, you will be asked for demographic information regarding age, race/ethnicity, self identified gender, current major, and your undergraduate year. This information will be available only to the primary researcher for statistics reporting and will be discarded a month following the study's completion.

6. Alternative Procedures:

Due to the exploratory nature of this study, alternatives are not being offered.

7. Participant's Assurance:

This project and this consent form have been reviewed by USM's Institutional Review Board, which ensures that research projects involving human subjects follow federal regulations. Any questions or concerns about rights as a research participant should be directed to the Chair of the Institutional Review Board, The University of Southern Mississippi, 118 College Drive #5125, Hattiesburg, MS 39406-0001, 601-268-5997.

Any questions about this research project should be directed to the Principal Investigator using the contact information provided above.

CONSENT TO PARTICIPATE IN RESEARCH

Participant's Name: _

I hereby consent to participate in this research project. All research procedures and their purpose were explained to me, and I had the opportunity to ask questions about both the procedures and their purpose. I received information about all expected benefits, risks, inconveniences, or discomforts, and I had the opportunity to ask questions about them. I understand my participation in the project is completely voluntary and that I may withdraw from the project at any time without penalty, prejudice, or loss of benefits. I understand the extent to which my personal information will be kept confidential. As the research proceeds, I understand that any new information that emerges and that might be relevant to my willingness to continue my participation will be provided to me.

Research	Participant	

Person Explaining the Study

Date

Date

http://youtu.be/9AHqFKc3mKY http://youtu.be/ojSkGvxFi4M http://youtu.be/SGSLyp8mmMc http://youtu.be/0t4MF9ZoppM http://youtu.be/Um92GZLCQ_Q http://youtu.be/T8O4AcTyjHc http://youtu.be/Y33LnxG2L80 http://youtu.be/WhTpJxIJi2I http://youtu.be/OzyH-1p9nAg

http://youtu.be/QCkn5bu8GgM

http://youtu.be/p3pYuY4buIk http://youtu.be/hNpcQEGw3S4 http://youtu.be/iPQ6GB822x4 http://youtu.be/j7N-XPi5Z0 http://youtu.be/mi9sMazNPxM http://youtu.be/K5XKjk0-hCo http://youtu.be/zc_p7Mw1A7U http://youtu.be/pJQr77Vzwyk http://youtu.be/XHVty6 XTJY http://youtu.be/g8sxNa-E-H0 http://youtu.be/Sa5eqaYwQ2Q http://youtu.be/xFBK9534NI8 http://youtu.be/B_P48TakY3Y http://youtu.be/XmkbAduMD_E http://youtu.be/EqEEndY0sT8 http://youtu.be/X3bqQI7-sCg

http://youtu.be/a9QtIfPIQl4 http://youtu.be/eIfQ4GfSz3U http://youtu.be/9e9GWdT2pEQ

http://youtu.be/MEGyRgYJKEY http://youtu.be/VO40SpSBjbc http://youtu.be/CH6FQhlZn6k http://youtu.be/F_ySQvjtAxQ http://youtu.be/Qz5zFzvbib4 http://youtu.be/O3HxPDH-s7w http://youtu.be/ALJGz4r_VF0

Fall of the Roman Empire Golden Age of Athens, Pericles and Greek Culture Spread of Islam Ancient Egypt French Revolution part 2 Allende and Pinochet in Chile Arian Controversy and the Council of Nicaea Augustus becomes first Emperor of Rome hinduism introduction core ideas of brahman atman samsara and moksha Napoleon and the Wars of the First and Second Coalitions Initial Rise of Hitler and the Nazis Feudal System during the Middle Ages Ottoman, Safavid and Mughal Empires Confucius and the Hundred Schools of Thought Hittite Empire and Battle of Kadesh Indus River Valley Civilizations Golden age of Islam Ides of March and civil war Socrates Plato Aristotle Punic Wars between Rome and Carthage Theodor Herzl and the birth of political Zionism Alexander the Great takes power Closing Stages in World War I Blockades, U-boats, Lusitania Bay of Pigs Invasion Cyrus the Great establishes the Achaemenid Empire Axis Momentum Accelerates in WW2 Overview of Chinese history 1911 - 1949 Sykes-Picot Agreement and the Balfour Declaration Vietnam War Korean War Cuban Missile Crisis Napoleon forced to abdicate French Invasion of Russia Haitian Revolution Napolean and Fourth Coalition Napoleon and Peninsular Campaigns

Date

Participant

Session

Condition

Baseline

Demand Praise

	1.1	1.2	1.3	1.4	1.5	1.6	2.1	2.2	2.3	2.4	2.5	2.6
Engage												
Praise												
Demand												
	3.1	3.2	3.3	3.4	3.5	3.6	4.1	4.2	4.3	4.4	4.5	4.6
Engage												
Praise												
Demand												
	5.1	5.2	5.3	5.4	5.5	5.6	6.1	6.2	6.3	6.4	6.5	6.6
Engage												
Praise												
Demand												
	7.1	7.2	7.3	7.4	7.5	7.6	8.1	8.2	8.3	8.4	8.5	8.6
Engage												
Praise												
Demand												
	9.1	9.2	9.3	9.4	9.5	9.6	10.1	10.2	10.3	10.4	10.5	10.6
Engage	9.1	9.2	9.3	9.4	9.5	9.6	10.1	10.2	10.3	10.4	10.5	10.6
Engage Praise	9.1	9.2	9.3	9.4	9.5	9.6	10.1	10.2	10.3	10.4	10.5	10.6
Engage Praise Demand	9.1	9.2	9.3	9.4	9.5	9.6	10.1	10.2	10.3	10.4	10.5	10.6
Engage Praise Demand	9.1	9.2	9.3	9.4	9.5	9.6	10.1	10.2	10.3	10.4	10.5	10.6
Engage Praise Demand Engage	9.1	9.2	9.3	9.4	9.5	9.6	10.1	10.2	10.3	10.4	10.5	10.6
Engage Praise Demand Engage Praise	9.1	9.2	9.3	9.4	9.5	9.6	10.1	10.2	10.3	10.4	10.5	10.6
Engage Praise Demand Engage Praise Demand	9.1	9.2	9.3	9.4	9.5	9.6	10.1	10.2	10.3	10.4	10.5	10.6
Engage Praise Demand Engage Praise Demand	9.1	9.2	9.3	9.4	9.5	9.6	10.1 12.1 14.1	10.2 12.2 14.2	10.3 12.3 14.3	10.4 12.4 14.4	10.5 12.5 14.5	10.6 12.6 14.6
Engage Praise Demand Engage Praise Demand Engage	9.1	9.2	9.3	9.4	9.5	9.6	10.1	10.2	10.3 12.3 14.3	10.4	10.5 12.5 14.5	10.6 12.6 14.6
Engage Praise Demand Engage Praise Demand Engage Praise	9.1	9.2	9.3	9.4	9.5	9.6	10.1 12.1 14.1	10.2 12.2 14.2	10.3 12.3 14.3	10.4	10.5 12.5 14.5	10.6 12.6 14.6
Engage Praise Demand Engage Praise Demand Engage Praise Demand	9.1	9.2	9.3	9.4	9.5	9.6	10.1	10.2	10.3 12.3 14.3	10.4	10.5	10.6
Engage Praise Demand Engage Praise Demand Engage Praise Demand	9.1 11.1 13.1 15.1	9.2 11.2 13.2 15.2	9.3 11.3 13.3 15.3	9.4	9.5	9.6	10.1	10.2	10.3 12.3 14.3	10.4	10.5	10.6
Engage Praise Demand Engage Praise Demand Engage Praise Demand Engage	9.1	9.2	9.3	9.4	9.5	9.6	10.1	10.2	10.3	10.4	10.5	10.6
Engage Praise Demand Engage Praise Demand Engage Praise Demand Engage Praise	9.1 11.1 13.1 15.1	9.2 11.2 13.2 15.2	9.3	9.4	9.5	9.6	10.1 12.1 14.1	10.2	10.3	10.4	10.5	10.6 12.6 14.6

APPENDIX G – Baseline Procedural integrity

Baseline				
Date: Participant: Trial: Obs:				
Circle "Y" for each step each time the implementer(s) completed the step correctly. Circle "N" for each time an implementer missed or incorrectly completed a step Integrity = Yes/(Yes+No) * 100				
1. The researcher told participant to keep their speakers on, unmute themselves, to take no notes, stay at the computer, minimize head movements, and to read all directions on the screen.	Y N			
2. Researcher confirmed that their video is disabled	Y N			
3. The participant read all instructions out loud	Y N			
4. Researcher engaged in no verbal communication during the video	Y N			
5. Distractions were present, including iPad turned on, building blocks and magnetic letters, and puzzle ball.				
Total Percent Correct Implementation	%			

APPENDIX H – Demand Procedural integrity

Demand	
Date: Participant: Trial: Obs:	
Circle "Y" for each step each time the implementer(s) completed the step correctly. Circle "N" for each time an implementer missed or incorrectly completed a	a step
1. The researcher told participant to keep their speakers on, unmute themselves, to take no notes, stay at the computer, minimize head movements, and to read all directions on the screen.	Y N
2. Researcher confirmed that their video is disabled	Y N
3. The participant read all instructions out loud	Y N
4. After the participant starts the video, the researcher delivers first demand.	Y N
5. During the video, researcher only engaged in verbal communication at the designated intervals (every 2 mins)	Y N
6. All verbalizations were demands related to the video (e.g., "Watch the video," "Look at the screen.")	Y N
7. Researcher responded with demand statement within an interval of the demand indicator (Square B) appearing	Y N
8. Distractions were present, including iPad turned on, building blocks and magnetic letters, and puzzle ball.	Y N
Total Percent Correct Implementation	%

APPENDIX I – Praise Procedural integrity

Praise	
Date: Participant: Trial: Obs:	
Circle "Y" for each step each time the implementer(s) completed the st correctly.	ep ted a step
 The researcher told participant to keep their speakers on, unmute themselves, to take no notes, stay at the computer, minimize head movements, and to read all directions on the screen. 	Y N
2. Researcher confirmed that their video is disabled	Y N
3. The participant read all instructions out loud	Y N
4. After the participant starts the video, the researcher delivers first praise statement.	Y N
5. Researcher only engaged in verbal communication during trials at the designated intervals (every 2 mins)	Y N
6. All verbalizations consisted of a verbal statement that signified approval (e.g., "Nice job watching the video," "Awesome attending.")	Y N
7. Researcher responded with praise statement within an interval of the praise indicator (Square A) appearing	Y N
8. Distractions were present, including iPad turned on, building blocks and magnetic letters, and puzzle ball	Y N
Total Percent Correct Implementation	%

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