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Faces as Ambient Displays: Assessing the Attention-Demanding Characteristics of Facial Expressions

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FACES AS AMBIENT DISPLAYS: ASSESSING THE ATTENTION-DEMANDING CHARACTERISTICS OF FACIAL EXPRESSIONS

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ABSTRACT

Ambient displays are used to provide information to users in a non-distracting manner. The purpose of this research was to examine the efficacy of facial expressions as a method of conveying information to users in an unobtrusive way. Facial expression recognition requires very little if any conscious attention from the user, which makes it an excellent candidate for the ambient presentation of information. Specifically, the current study quantified the amount of attention required to decode and recognize various facial expressions. The current study assessed the attention-demanding characteristics of facial expressions using the dual-task experiment paradigm. Results from the experiment suggest that Chernoff facial expressions are decoded with the most accuracy when happy facial expressions are used. There was also an age-effect on decoding accuracy; indicating younger adults had higher facial expression decoding performance compared to older adults. The observed decoding advantages for happy facial expressions and younger adults in the single-task were maintained in the dual-task. The dual-task paradigm revealed that the decoding of Chernoff facial expressions required more attention (i.e., longer response times and more face misses) than hypothesized, and did not evoke attention-free decoding. Chernoff facial expressions do not appear to be good ambient displays due to their attention-demanding nature.

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INTRODUCTION

Ambient displays can take many forms. For example, the battery meter icon of a computer interface, or a dangling string from the ceiling to represent network traffic on a computer network (Weiser & Brown, 1995). These examples are considered “ambient” because they convey information to the user without being substantially taxing on cognitive faculties (i.e., they are in the background and do not require the user to change focus or switch attention). Several important characteristics have been identified for the design of a good ambient display. Examples of these characteristics include: providing useful and relevant information, having a sufficient information design, using consistent and intuitive mapping, and appropriate matching between the system and the real world (Mankoff, Dey, Hsieh, Kientz, Lederer, & Ames, 2003). If these characteristics are adequately fulfilled by facial expressions, then facial expressions could be considered a good form of ambient display. The purpose of this study is to determine if face stimuli can serve as ambient indicators of quantitative information.

One situation where ambient displays may be helpful is in human-automation interaction (HAI). In some HAIs, users may become unaware of the hidden decision making processes or outcomes of automation. They may also lose track of the automation’s reliability over time (i.e., forget how reliable or unreliable it has been in the past). Such information (uncertainty of current processes, past reliability) can lead to fluctuations in trust that may not be justified (un-calibrated trust); that is trust that may be unwarranted. Un-calibrated trust can manifest itself as continued use of unreliable automation (misuse) or unwarranted discontinued use of reliable automation (disuse) both of which cause non-optimal HAIs (Parasuraman, 1997).

One way in which an automated system can encourage proper calibration is by presenting as much information about its operation as possible. For example, it could present its own confidence in its recommendation, so called “system confidence”, or it could present a historical picture of its own reliability (both are information that are easily accessible by a system). This concept can be categorized in the ambient display heuristic of useful and relevant information. For example, if the system is working from faulty data, it will weight its advice as potentially unreliable. Presenting critical information, such as system confidence, is a way of diminishing the uncertainty that can exist in HAIs (Bubb-Lewis & Scerbo, 1997). Trust is a malleable variable that can be shaped through interactions with a system (Antifakos, Kern, Schiele, & Schwaninger, 2005). If a system is presenting the operator with its system confidence level, then the operator will be able to build a more appropriate trust relationship with the automation. However, this presentation needs to be salient and the automation state indicator should not add attentional demands to the user (Parasuraman, 1997). Some previous research has indicated that methods such as tactile output and auditory output may be helpful in conveying system confidence (Wisneski, 1999; Poupyrev, Maruyama, & Rekimoto, 2002; Sawhney & Schmandt, 2000). While these modalities are novel in certain capacities, a less intrusive and less attention demanding modality would be more beneficial to users. Thus, the ideal stimulus display type would be one that provides the user with meaningful information, while not becoming a distraction or a drain on the user's attention (Antifakos, Kern, Schiele, and Schwaninger, 2005). Coding information as emotional expression in human-like faces may fulfill this role.

Human Emotion Decoding

Research has shown that humans have an ability to recognize emotional facial expressions with little attention allocation. Batty and Taylor (2003) had participants complete an implicit emotional task, which involved the presentation of target stimuli (non-faces) in a sequence with emotional faces. This experimental design allowed the researchers to test the participants' event-related potentials (ERPs) while viewing emotional faces, but without explicitly instructing the participant to look at the emotional faces. Through analysis of the ERPs, it was found that participants were processing the emotional face stimuli quickly (i.e., M = 94 ms for P1 component; M = 140 ms for N170 component). The results of this analysis of the P1 and N170 components suggest that participants were processing the emotional face stimuli pre-attentively (Batty & Taylor, 2003). Other studies have supported that tasks involving affective (emotional) stimuli may be responded to without awareness (Whalen, 1998). An fMRI study showed that participants experienced increased amygdala activation even when they were unaware of the presentation of emotional facial expressions (Whalen, 1998). The amygdala is a key area of the brain for the emotional facial recognition process. Previous research on animals has provided evidence that the amygdala is the brain area where facial and emotional processing occurs. A subsequent study built off of these findings and found the amygdala was crucial for humans' decoding of facial affect, especially the emotion of fear (Adolphs, Tranel, Damasio, & Damasio, 1994). The conclusions of Whalen (1998) make a case that explicit knowledge is unnecessary for a person to process emotional facial expressions. This process occurs below the level of conscious awareness, or in other terms, automatically (Morris, 1998; Whalen, 1998). It can be inferred from these studies, that the use of facial expressions as ambient displays should not add cognitive load and would enforce the heuristic of consistent and intuitive mapping.

Neuroimaging studies have supported the notion that the emotional processing of faces is a more effective pathway than the processing of other stimuli. A previous study compared the automatic processing of emotional facial expressions versus emotional words. Rellecke (2011) hypothesized that facial expressions would be encoded more automatically than words, due to their perceptual features and humans' natural ability to encode them. This study was novel because it took two theoretically attention-free emotional processing stimuli (i.e., faces and words), and compared their efficiency and effect. The degree of encoding automaticity was being tested for each of these stimuli. Based on the results of the electroencephalogram (EEG), the event-related brain potentials (ERPs) recorded for the facial expression conditions were found to have a prolonged effect on the brain. This finding alludes to emotional facial expression processing as being automated to a higher extent than emotional word processing. Rellecke (2011) discusses the potential necessity for preconditions for the high automatic processing of emotional words. This was apparent because the two stimuli were tested in the same superficial stimulus analysis task, but only one (i.e., facial expression) led to advanced pre-attentive processing. Facial expression seems to be a stimulus that needs no prompting or preconditions to allow fast, but also meaningful processing (Rellecke, 2011). Data analysis found that happy faces were decoded earlier than other faces (i.e., 50-100 ms). This supports the theory that happy faces are advantageous in the early stages of emotional processing and may be instrumental in attention-free encoding. Also, data showed that angry faces were advantageous for later decoding (i.e., 150-450 ms). This coincides with previous research that states angry expressions, or threat-related expressions, have prolonged effects on the brain (Rellecke, 2011). These differences in emotion type on ERPs show that there may be a specific type of emotion that elicits faster decoding for humans.

Calvo and Lundqvist (2008) found the facial expression of happiness to be the stimuli best decoded by participants. Participants were presented with a happy facial expression and responded more accurately in its identification, and rarely mis-identified the expression as another emotion (i.e., neutral, angry, sad, disgusted, surprised, fearful). Response times for neutral and happy facial expressions were the fastest among all expressions. This indicates a fast, automatic form of facial expression decoding. Calvo and Lundqvist (2008) conducted a second experiment where the participants were exposed to the stimuli in a "fixed-pace mode". Participants viewed the stimuli at fixed exposures of 25, 50, 100, 250, and 500 milliseconds. The results of this experiment paralleled the original findings, showing that the expression of happiness was consistently identified at a high accuracy level (*M* = 98.4%) regardless of the exposure time. Having additional time to decode the happy expression did not result in accuracy gains. Thus, it can be inferred that humans are very quick and accurate at decoding happy facial expressions. With indications that facial expressions are an effective pathway for the decoding of emotional data, we want to investigate the limits and capabilities of this potentially new modality for communication of quantitative information.

In order for facial expression to be used as a means of relaying quantitative system/automation information, we must know if users are able to properly and consistently decode facial expression intensity into a consistent quantitative value (e.g., a specific smiling face represents 90%). Hess (1997) investigated the issue of facial expression decoding with varying degrees of intensity for different emotional categories. When participants were given an emotional facial expression stimulus, they were accurate at perceiving its physical intensity; there was a linear trend for the perceived intensity of the expression by the human versus the actual physical intensity of the emotional facial expression (Hess, 1997). Analysis showed that when a facial expression was more intense (e.g., 80% and 100% expressive) the participant had a more accurate perception of the emotional stimulus. Happy expressions were the most recognizable across all intensity levels (Hess, 1997). This finding supports happy facial expressions as one of the most familiar and perhaps easiest of facial expressions to decode for humans. Bartneck and Reichenbach (2005) performed a similar study that sought to determine how the actual intensity of facial stimuli affected perceived intensity and accuracy. It was found that participants displayed high accuracy in perceiving happy face intensity, high recognition accuracy for happy faces, and gave low task difficult ratings for happy faces. It was also found that the happy facial expressions led to the fastest ceiling effect for recognition accuracy. Participants were able to recognize the happy facial expression starting at just 10% intensity. This reiterates quick decoding for happy facial expressions.

Understanding the effects that different emotional facial expressions and their intensities have on humans' ability to decode is critical in determining the most effective stimuli to use as ambient displays.

Chernoff Faces

Chernoff faces were created to represent multivariate data in a way that would allow the viewer to gain information in a quick, yet complete manner. For example, some of the original Chernoff faces were used to represent fossil data. The Chernoff faces displayed information pertinent to the fossils (i.e., inner diameter of embryonic chamber, total number of whorls, maximum height of chambers in last whorl, etc.) through variations including, but not limited to the faces: head shape, eye size, mouth size/shape, and eyebrow size/slant. Chernoff's rationale was that due to the extreme familiarity of faces, people would easily detect differences in the configuration of a face, even if the differences were small ones (Chernoff, 1973). It was expected that people would at least be able to examine faces more quickly than examining a row of numbers. Assuming that this is true, a schematic facial expression should act as a superb source of information output.

Chernoff faces have up to 18 characteristics that can be manipulated (Nelson, 2007). When representing multivariate data (e.g., the fossil data) it is beneficial to have multiple facial elements that can be manipulated and used for representing various data. However, when representing univariate data (i.e., a single percentage score) it seems that having a lower number of manipulated facial features is more beneficial. Therefore, it could be problematic to have several individual facial elements for the human to properly decode. If a human naturally decodes a face as a whole rather than in parts; it may be counter-intuitive to present them with a face that requires the decoding of several features (parts) of the face. As Montello and Gray (2005) state, it is more beneficial to have a stimulus that communicates information univariately rather than multivariately when the goal is to give the user a single quantity. A pseudo-Chernoff face may be a remedy for this dilemma (Montello & Gray, 2005). This “pseudo-Chernoff” face could be created by systematically manipulating one facial characteristic, while holding all others constant. To properly convey a simple quantitative score the Chernoff face may only need to have one facial characteristic manipulated. Through this manipulation, the human may be more apt to decode the Chernoff face accurately and quickly, while noticing subtle changes (Kabulov, 1992).

The issue of whether interpreting Chernoff faces is a relatively less attention-demanding task is of primary importance to the current study. Previous studies have investigated the effectiveness of Chernoff faces as a pre-attentive stimulus with mixed results. A study concluded that Chernoff faces are not processed pre-attentively, and do not benefit users more than other modes of visual information display (Morris, Ebert, & Rheingans, 2000). The process of identifying the characteristics (eyebrow slant, eye size, nose length) of the Chernoff face was said to be a serial process. Participants’ accuracy of target stimuli identification improved when they were given more time and less distracters, indicating that the task was not pre-attentive (Morris, Ebert, & Rheingans, 2000). A similar study investigated data visualization and used Chernoff faces as one of the “glyph stimuli” to discover which data visualizations were the most effective (Lee, Reilly, & Butavicius, 2003). Glyphs are data visualizations that are characterized by their attempt to display multivariate data through the manipulation of features on the glyph that correspond to raw data. It was found that participants had lower accuracy scores and took longer to answer questions when exposed to the glyph stimuli (Lee, Reilly, & Butavicius, 2003). This indicates a serial processing of information from the Chernoff faces, which is in agreement with the findings of Morris, Ebert, & Rheingans (2000).

A study investigating perceptual sensitivities found that children process Chernoff faces differently than adults (Tsurusawa, Goto, Mitsudome, Nakashima, & Tobimatsu, 2007). Children focus more on individual features, while adults process a face in a more holistic pattern. These findings seem to be discrepant with the previously mentioned studies. Perhaps adults do not decode Chernoff faces to the degree of serial processing as suggested by other studies. If adults decode in a faster more parallel manner, then Chernoff faces may allow for pre-attentive processing. Of particular interest is how the participants differed on their interpretation of the mouth angle presented. Children significantly differed from adults in their evaluation of the Chernoff face as a function of the angle of the stimuli's mouth. Children evaluated the faces as more emotional as the curvature of the mouth changed, while the adults were significantly below the children's evaluation score. Supposedly, this is a consequence of children's lack of holistic face processing ability (Tsurusawa, Goto, Mitsudome, Nakashima, & Tobimatsu, 2007). An additional finding bolstered Chernoff faces' potential value as a quantitative display. This was the participants' ability to evaluate the stimuli in discrete steps (Tsurusawa, Goto, Mitsudome, Nakashima, & Tobimatsu, 2007). Basically, participants could follow the incremental facial feature changes in the Chernoff faces; similar to the hypothesis by Chernoff (1973). Although children and adults may process Chernoff faces differently, it can be inferred that Chernoff faces can demonstrate human facial expressions effectively.

A previous study used schematic faces (line faces similar to Chernoff faces) as stimuli to determine whether the “anger superiority effect” was apparent while using a visual search paradigm (Ohman, Lundqvist, & Esteves, 2001). The study found schematic faces to be identified quickly and accurately, with schematic faces representing anger/threatening emotion leading to the most pre-attentive reaction times. The visual search paradigm was reconfigured throughout the experiment by adding more distractor stimuli. This was done in an effort to make a more difficult visual search task, which would test for serial versus parallel search. Following each of these iterations, the threatening facial expression was shown to be the most decodable (faster and more accurate) stimuli (Ohman, Lundqvist, & Esteves, 2001). This is important because it indicates that the threatening schematic face is processed in parallel, or without using much attention. The results of this study show that schematic faces can be processed in parallel and that there is potentially an “anger superiority effect” for these types of stimuli (Ohman, Lundqvist, & Esteves, 2001).

If Chernoff faces are manipulated properly, giving the right amount of useful information, they will fulfill the heuristic of sufficient information design as an ambient display. To reiterate, the main issue concerning Chernoff faces is whether they can be interpreted pre-attentively, with minimal attentional resources. Once this issue is understood with more clarity, the efficacy of facial expressions in the form of Chernoff faces to be ambient displays will be evident.

Age-Related and Cultural Effects on Decoding

Despite the ease with which humans are able to decode emotional facial expressions, it is still moderated by age. Age can alter a person's ability to correctly perceive and understand the facial expression that is presented to them. Neuropsychological research has shown that age-related issues in facial expression decoding may be a result of problems with the medial temporal lobe (Orgeta & Phillips, 2007). The amygdala is housed here, which corroborates with previous research that suggests the amygdala is necessary for facial expression decoding (Whalen, 1998; Morris, 1998). Despite these age-related issues; a competing theory has been asserted regarding older adult's ability to decode emotional facial expressions. The socioemotional selectivity theory asserts that social behavior is essentially a byproduct of time (Carstensen, Issacowitz, & Charles, 1999). In a sense, time can be thought of as the chronological age of a human. As the human ages, they essentially have less time to live and fulfill goals. This affects the way they view their decisions and weight their goals. The two types of goals that make up the socioemotional selectivity theory are knowledge-based and emotion-based goals (Carstensen, Issacowitz, & Charles, 1999). Younger adults are more likely to pursue knowledge-based goals because they have more time potential. The trade off for knowledge in lieu of emotional goals appears to be a worthy endeavor. Older adults supposedly take the opposite approach and view emotional-based goals as top priority. Older adults' view time as a non-renewable resource, and seek to spend anytime they have left enjoying positive emotional experiences (Carstensen, Issacowitz, & Charles, 1999).

According to the socioemotional selectivity theory, older adults may actually be more aware of certain emotional situations and images than non-emotional (Orgeta & Phillips, 2007). Orgeta and Phillips (2007) showed older adults as being more accurate at identifying positive facial expressions, opposed to negative facial expressions. Older adults were found to identify positive emotions as accurately as younger adults. There was no significant difference between the older adults and younger adults in terms of identifying positive facial emotions (i.e., happiness and surprise). However, older adults were significantly worse than younger adults at identifying negative facial emotions (i.e., sadness, anger, and fear). The results of this study indicated that there is an age-related difference for the decoding of negative facial expressions, but not positive facial expressions (Orgeta & Phillips, 2007). The ease of recognition for certain emotional expressions is a phenomenon pertinent to this research area. As Orgeta and Phillips (2007) showed, older adults may have a positivity bias that allows them to overcome any cognitive decrements that interrupt other emotional decoding, thus decoding positive facial expressions as accurately as younger adults. Other research has supporting data showing that positive expressions (e.g., happiness) are processed more quickly, supported by faster N170 latencies (Batty & Taylor, 2003). Perhaps this quick processing attributes to the robustness of the happy facial expression compared to other expressions.

A previous study manipulated the factors of chronological age and the participant's working self-concept to determine if the positivity effect could in fact be evoked in younger adults, and likewise the negativity effect in older adults (Lynchard & Radvansky, 2012). During the experiment the participant would complete a possible selves orienting task. The older adults completed the younger possible selves orienting task, while the younger adults completed the older possible selves orienting task. Essentially, this made the participant's working self-concept the opposite of their chronological age. The results showed a reversal of stereotypical age-related emotional information processing. Younger adults displayed a positivity effect, which is thought to be a unique attribute of older adults. Similarly, older adults displayed a negativity effect, which is thought to be unique to younger adults (Lynchard & Radvansky, 2012). This study showed that more than just chronological age plays a role in the socioemotional selectivity theory. Humans are subject to emotional information processing biases based on less concrete variables such as their working self-concept.

Decoding facial expressions is a cross-cultural behavior that is a critical part of human life. There are six basic emotions that transcend culture. These are: anger, happiness, fear, surprise, disgust, and sadness (Ekman & Friesen, 1975). These emotions can be represented with facial expressions (Lee, 2006; Batty, 2003). Because these facial expressions are not confined to specific cultures, it puts no restraints on the ability of different people groups to successfully decode these facial expressions. It appears that increasing age is a factor that may cause differences in aspects of facial expression decoding, while cultural background seems to be of no hindrance. The unique quality that facial expressions have in their prevalence and familiarity in human culture makes them a good candidate for an ambient display. This quality of facial expressions allows the heuristic of matching the system to the real world to be met.

Limitations of Previous Literature

The previous literature has provided a foundation for knowledge about facial expressions, but there are limitations to these studies. The Hess (1997) study presented emotional facial expressions in a single-task format. The participants viewed the image and rated it on the emotionality and intensity that they perceived. This methodology does not clarify whether facial emotion decoding is truly resource/attention-free as neuropsychological studies suggest. A dual-task experiment should be implemented to properly measure attention usage. In order to gain this data; measures of response time, accuracy, and subjective workload should be used. The Hess (1997) study also measured decoding accuracy for each facial expression image through the presentation of several emotion scales at once. The participant was presented with seven emotional labels, which they manipulated to show the intensity of emotion for the previous picture. Instead of presenting seven individual scales, it seems to be less complicated to present one scale or to have a quick input device (e.g., keyboard number keys) after the image is viewed.

The Hess (1997) study presented facial expression intensity in increments of 20 % intensity. This intensity scale may not provide enough precision or a complete spectrum of facial expression decoding data. The Orgeta and Phillips (2007) study also presented only four intensity levels. The number of intensity levels may need to be increased (i.e., create smaller increments of percentage changes between each stimuli) to capture a more accurate representation of participants' ability to decode facial expression. Another limitation in the Orgeta and Phillips (2007) study was the facial images were presented in increasing order as the participant advanced through the experiment. This method may have led to participants forming an anticipation bias that the next facial image was going to be more expressive.

Previous research has also provided evidence that age-related effects may cause differences in the ability for humans to properly decode facial expressions. It has been shown that older adults are worse at identifying negative facial expressions (i.e., sadness, anger, and fear). Older adults struggled significantly versus younger adults in properly recognizing the negative emotions at intensity levels of 50 %, 75 %, and 100 %. It appears that older adults have a higher recognition threshold for certain negative emotions than younger adults. Basically, older adults do not pick up on negative facial stimuli as easily as younger adults and need more intense facial expressions to determine the appropriate emotional state (Orgeta & Phillips, 2007). In order to determine if theories such as the socioemotional selectivity theory pertain to Chernoff face recognition, there needs to be an independent variable of age with levels of younger and older adults.

The variable of gender of the facial expression stimuli could be considered a confounding variable. Hess (1997) used two male and two female actors to create facial expressions for their study. Results of this study showed that the gender of the stimuli (i.e., actors) did influence participant rating accuracy. For the expressions of happy and sad, there was an interaction of the gender of the stimuli x intensity of the expression

(Hess, 1997). Because of this reported interaction, it would be beneficial to use non-gender specific stimuli to eliminate this confounding variable.

Previous studies have looked at users' ability to properly decode facial expression type (Ekman & Friesen, 1975), intensity (Tsurusawa, Goto, Mitsudome, Nakashima, & Tobimatsu, 2007; Hess 1997), and the effectiveness of Chernoff faces (Chernoff 1973; Tsurusawa, Goto, Mitsudome, Nakashima, & Tobimatsu, 2007; Morris, Ebert, & Rheingans, 2000). The purpose of the current study is to examine the users' ability to accurately decode a quantitative value from Chernoff facial expressions.

Overview of the Current Study

In order to determine the attention usage by the participants, a dual-task methodology was used. Our study used the dual-task paradigm to measure the attention-demanding characteristics of facial displays. The Hess (1997) study measured participant's decoding accuracy with several scales after each trial. This method may create confusion for the participant, and not accurately record participant decoding time. The interface should allow for quick and simple input of the facial expression intensity from the participant. The current study used only one measurement scale (direct key entry) after each trial to eliminate any confusion for the participants about what the scales are measuring and give a better approximation about how quickly the participant can decode the facial expression. In the Orgeta and Phillips (2007) study the facial expressions were shown in increasing order. This technique was not replicated in the current study. Instead, a randomized sequence of facial expression stimuli was used to control for any biases that could be formed due to participant expectations. The Chernoff face stimuli were manipulated differently compared to previous research (Chernoff, 1973; Tsurusawa, Goto, Mitsudome, Nakashima, & Tobimatsu, 2007; Morris, Ebert, & Rheingans, 2000). Only the mouth was manipulated in order to gain understanding about the affect of this one variable on decoding. Finally, the current study used a more precise facial expression intensity scale than previous research (Hess, 1997; Orgeta & Phillips, 2007). To accomplish this, a facial expression scale presenting emotions in increments of 10 % was used. Our assumption was that by making these modifications the current study would be able to address the research question with more accuracy.

Hypotheses of the Current Study

The first hypothesis (H_1) was that there would be no age differences in facial decoding performance in the happy facial expression condition, but that there would be decoding performance differences in the sad facial expression condition. The rationale behind expecting no age difference in the happy facial expression condition is based on the socioemotional selectivity theory and research that supports positive expressions as more identifiable; referred to as the “happy face advantage” (Ekman & Friesen, 1975; Orgeta & Phillips, 2007; Calvo & Lundqvist, 2008). The rationale for the age-related difference in the sad facial expression condition is based on older adults’ difficulty in perceiving sad facial expressions (Orgeta & Phillips, 2007), and the negativity effect seen in younger adults (Lynchard & Radvansky, 2012).

The second hypothesis (H_2) was related to the rationale of hypothesis H_1 (i.e., effect of the happy face advantage), namely that even in the presence of another task, there would be no age differences in happy facial expression decoding because of its presumed pre-attentiveness. However, we assumed that sad facial expression decoding would require attentional capacity, and thus be affected by the presence of a dual-task. If the decoding of happy facial expression is actually resource-free (Lee, 2006; Whalen, 1998; Morris, 1998), then facial decoding in the dual-task phase should be equivalent to decoding in the single-task condition. There will be similar performance scores for younger and older adults in the happy condition; regardless of phase (single or dual). This indicates that the happy facial expressions are able to mitigate the dual-task decrement that would be expected for stimuli that demand more attention, which we expect to be the sad facial expressions. Older adults' performance with sad facial expressions is expected to be worse (compared to their single-task baseline), due to their low negative emotional sensitivity (positivity bias) and the added cognitive load of the dual-task. We also expect younger adults' performance to decrease due to the additional cognitive load of the dual-task condition, which we expect will degrade any benefit of the negativity bias. Additionally, research has shown younger adults to be more quick and accurate at decoding happy expressions versus sad facial expressions (Hess, 1997; Calvo & Lundqvist, 2008).

METHODS

Participants

Eighty-three participants (42 younger adults, 41 older adults) were recruited for the current study. The younger adult age range was 18 – 21 (*M* = 18.6, *SD* = .89) and the older adult age range was 65 – 84, (*M* = 72.4, *SD* = 5.19). Younger adults were recruited from psychology courses and received class credit for participation. Older adults were recruited from a pre-existing database of volunteers who lived in the surrounding communities. Older adults received $25 for participation.

Design

This study was a 2 (age group: younger, older) x 2 (facial expression condition: happy, sad) x 10 (facial expression intensity: 0%-90%) x 2 (task phase: single, dual) mixed-design. Age group was a quasi-independent grouping variable. Facial expression condition was between-groups, while facial expression intensity and task phase were within-groups. The dependent variables measured were: the speed (ms) for the block task, the speed (ms) of response on the facial expression task, the amount of “misses” on the facial expression task, the amount of blocks cleared, facial expression intensity rating, and decoding accuracy (i.e., slope value) of the correspondence between the face presented and the facial expression intensity rating.

Materials

The experiment was presented on 19-inch LCD monitors and participants made responses using the keyboard. Participants were seated in office chairs about 18-24 inches from the screen in a laboratory environment. The experiment was programmed using Real Basic.

Surveys & Abilities

Participants completed a computerized cognitive abilities battery. These tests gathered information on participants’ working memory, perceptual speed, and vocabulary. Participants also completed a computerized version of the NASA-TLX survey to measure subjective workload.

Tasks

The block task was a game similar to the game Tetris (Appendix A). The block task consisted of moving multi-colored blocks. The main objective of the block task was to “clear” block rows or columns by manipulating the blocks using the arrow keys and space bar. To successfully “clear” a block row or column, the participant was required to align three blocks of the same color. This task was used in the dual-task as the primary task due to its supposed high attentional demand.

The purpose of the facial expression decoding task was to identify the level of emotion presented by a computer-generated facial expression (Appendix B). The facial expression stimuli were rendered using the statistical program R. This allowed the experimenter to have control over the faces and manipulate their facial expression intensity as desired. The facial expression stimuli were line drawings composed of black lines on a white background. This eliminated any confounding variables due to the gender, ethnicity, or age of the stimuli. There were 19 images: 9 happy stimuli (ranging from 10% expressive – 90% expressive), 9 sad stimuli (ranging from 10% expressive – 90 % expressive), and one neutral stimulus (0 % expressive), see Appendix C. The range of expressiveness was chosen from 0%-90% in an effort to make a match between the key number pad and the expression levels. The images were 170 pixels by 250 pixels.

Procedure

Participants were randomly assigned to experimental conditions (happy or sad) prior to the experiment. The participants were given an informational letter before the experiment began. The experiment consisted of three phases. The participants completed two subsequent single-tasks (i.e., the block task and facial expression decoding task) to record baseline data on their abilities, and to become familiar with each task. To examine the attentional demands of decoding Chernoff faces, participants then engaged in the dual-task phase. Participants were instructed to focus on the block task (i.e., primary task) and consider it to be the most important task. This spatial-manipulation task was chosen due to the expectation of being cognitively taxing for the participants. Participants were told to try to complete the facial expression decoding task (i.e., secondary task) effectively, but not to sacrifice their primary task performance during the dual-task phase.

In phase 1, participants performed the block task in a single-task environment. The participant had to reach a pre-set score (based on number of blocks cleared) to complete the task. Once the participant completed this phase, the program proceeded to phase 2. In phase 2 of the experiment, participants were asked to respond to Chernoff facial expressions that were flashed on the computer screen. The participants were in one of two facial expression conditions (i.e., happy or sad) and only saw faces related to their facial expression condition.

Once phase 2 began, the Chernoff facial expression appeared in a window on the computer screen. The facial expressions were shown in a randomized order in regard to their intensity level. During the time interval that the facial expression was present, participants attempted to respond to the facial expression using the number keys. If the participant did not hit a number key before this time elapsed then a “miss” was recorded. Regardless of whether the participants had responded or missed making a response, after three to five seconds (randomized facial expression appearance time) the screen went back to being blank until the next trial. There were 60 trials in each condition (i.e., 6 exposures to each of the stimuli for a specific condition). After the participants were exposed to all 60 stimuli the program proceeded to phase 3.

In phase 3, participants were exposed to both phases 1 and 2 simultaneously (see Appendix D). This created a dual-task situation. The task goals defined for the two single-tasks remained the same for the dual-task phase. However, participants were told to treat the block task as the primary task. This phase continued until all facial expression stimuli were presented to the participants. After the participants completed the experiment, the computer loaded the computerized NASA-TLX survey. Subsequently, the battery of computerized cognitive abilities tests was loaded for the participants to complete. Once the participants completed the cognitive abilities battery they were finished with the study and permitted to leave.

RESULTS

Participants' data were removed based on two criteria: 1) if they missed all the faces presented in phase 3 (i.e., indicating little attention paid to the secondary task), or 2) if they were 2 standard deviations below the group average for clearing blocks in phase 3 (which indicated little attention being paid to the primary task). Participants' who had marginally low performance (on either of the aforementioned criteria); subsequently had their cognitive abilities test results examined. If the participant had a cognitive ability test score 2 standard deviations below the group average (on any of the three ability tests), then their data were removed from the final analysis. This criteria resulted in the removal of nine participants: six participants due to missing all the faces presented in phase 3, one participant who scored 2 standard deviations below the group average for clearing blocks, one participant who missed most of the faces presented in phase 3 (55 out of 60) and scored 2 standard deviations below the group average on two cognitive ability tests, and one participant was removed because they participated in the pilot testing for the current study.

The following results section is organized by task phase (i.e., single or dual). To remind the reader, phase 2 was the single-task for facial expression decoding and phase 3 was the dual-task condition. The results of the single-task facial expression decoding condition (phase 2) inform hypothesis H_1, while the dual-task facial expression decoding condition (phase 3) results are directly relevant to hypothesis H_2. In the single-task facial expression decoding condition (phase 2), the following dependent variables were analyzed: intensity key pressed, facial expression decoding accuracy, facial expression response time (ms), and the amount of face misses for the facial expression task. In the dual-task portion (phase 3), the following dependent variables were analyzed: intensity key pressed, facial expression decoding accuracy, facial expression response time (ms), the amount of face misses for the facial expression task, and computed workload from the NASA-TLX survey. An alpha level of .05 was used for all of the following statistical tests. Tests for the assumption of normality (i.e., histogram, Q-Q plot) and homoscedasticity were conducted and showed the data met the assumption for normality and homoscedasticity. For all mixed measures ANOVAs, the number of levels of the repeated measures IV (i.e., single task phase, dual task phase) was less than three, so sphericity was assumed.

Phase 2 (Single-task, Facial Expression Decoding Only)

Intensity Key Pressed

As participants were presented faces during phase 2, they were asked to give intensity ratings about each face. In order to give these intensity ratings, participants' used the keyboard number keys as the input device. The intensity key pressed ratings for a participant were averaged across all trials for phase 2. This yielded a mean intensity key pressed value that could be analyzed as a function of facial expression condition, age group, and face presented. The intensity key pressed ratings were also necessary for the calculation of decoding accuracy, which will now be explained.

Decoding Accuracy

In the facial expression decoding task, participants were asked to view facial expressions that were flashed on the computer screen (heretofore called "face presented") and to respond with an intensity rating ("intensity key pressed"). The facial expressions presented ranged from 0 (neutral) to 9 (very expressive). Decoding accuracy was operationalized as the correspondence between the face presented and participants' intensity key pressed. The regression slope of participants' correspondence was used to quantify decoding accuracy.

A hierarchical regression analysis was conducted to predict intensity key pressed as a function of age group, facial expression condition, and face presented. The predictor variables of age group and facial expression condition were dummy-coded. The predictor variables were entered in three steps, which resulted in three different models. The first step contained the following predictor variables: face presented, facial expression condition, and age group. These predictor variables represented all of the main effects tested (model 1). The second step contained the predictor variables from model 1 with the addition of the following two-way interactions: age group x facial expression condition, face presented x age group, and face presented x facial expression condition (model 2). The third step contained all of the predictor variables from model 1 and model 2 with the addition of the following three-way interaction: face presented x age group x facial expression condition (model 3).

The three models were tested for their ability to significantly predict participants' intensity key pressed. Model 1 accounted for 44.4 % of the variance of intensity key pressed, (R^2 = .444, $F(3, 826) = 220.11$, $p < .001$). Model 2 accounted for 51 % of the variance of intensity key pressed, (R^2 = .510, $F(6, 823) = 142.62$, $p < .001$). Model 3 accounted for 51.1 % of the variance of intensity key pressed, (R^2 = .511, $F(7, 822) = 122.66$, $p < .001$). The addition of the two-way interactions in model 2 resulted in a R^2 change value of .065, or 6.5 %, while the addition of the three-way interaction in model 3 resulted in a R^2 change value of .001, or 0.1 %. The addition of the three-way interaction (via model 3) did not add a significant amount of predictive power to the model.

The non-significance of the hypothesized three-way interaction of face presented x age group x facial expression condition ($b = -.11$, $t(822) = -1.39$, $p = .165$), caused slope comparisons to be confined to the two-way interactions in model 2. The two-way interaction terms in the hierarchical regression were a method to test for a significant difference between the regression line slopes. Therefore, when a two-way interaction was found to be significant, it was showing the two regression slopes to be significantly different. First, main effects and interactions for intensity key pressed will be addressed, followed by interactions related to decoding accuracy.

Main Effects and Interactions for Intensity Key Pressed

There was a significant main effect of face presented on participants' intensity key pressed, (b = .53, t(826) = 25.27, p < .001), which meant participants were generally able to discriminate the various levels of face presented. As the actual face presented stimuli increased from 0 % to 90 %, there was a .53 unit increase for intensity key pressed by the participants. There was a significant main effect of facial expression condition, (b = .57, t(826) = 4.67, p < .001). This main effect revealed a significant increase in mean intensity key pressed between the sad facial expression condition (M = 4.49, SD = 2.15) and the happy facial expression condition (M= 5.06, SD = 2.47). There was no main effect of age group, (b = .01, t(826) = .09, p = .928).

The two-way interaction of age group x facial expression condition was significant, (b = -.64, t(823) = -2.82, p < .01). Due to the dichotomous nature of the predictor variables (happy, sad; younger, older), the lines only contain two data points (i.e., mean values of intensity key pressed). The interaction can be conceptualized as the difference between the differences in mean values of intensity key pressed for each age group. The difference between the means (i.e., slope), for younger adults was .88, which is significantly different than the difference between the means, .25, for older adults. Slopes were found using the following formula: $b = \frac{Y2-Y1}{X2-X1}$, where the mean values were used for Y and facial expression condition coding (0 = Sad, 1 = Happy) was used for X. As Figure 1 illustrates, the two-way interaction was a result of the significantly greater increase in mean intensity key pressed in the younger adult group as a function of facial expression condition compared to older adults.

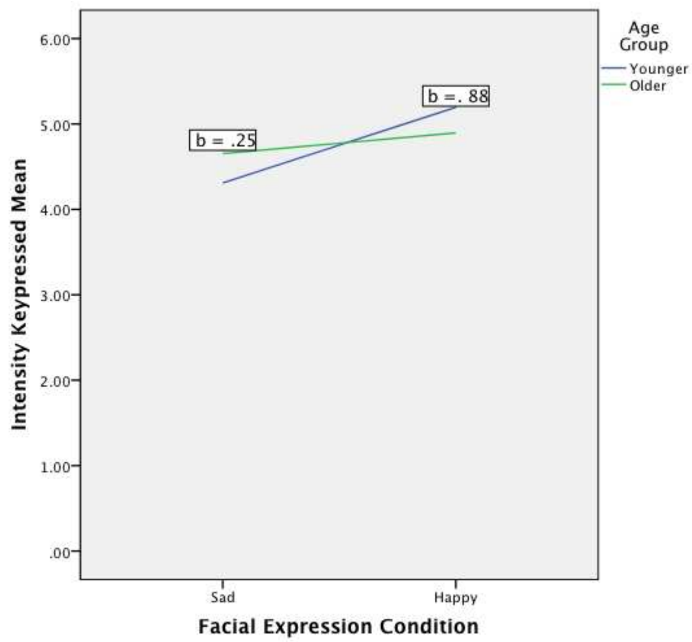


Figure 1. Mean intensity key pressed by facial expression condition for younger and older adults.

Interactions for Decoding Accuracy

The two-way interaction of face presented x age group was significant, (b = -.18, t(823) = -4.46, p < .001). This indicated that in general, younger adults were significantly better than older adults at accurately decoding the faces presented. Participants' facial expression decoding values were compared between the younger age group and the older age group, resulting in an observed significant decrease in slope (i.e., a younger adult slope of b = .63 versus an older adult slope of b = .43), illustrated by Figure 2.

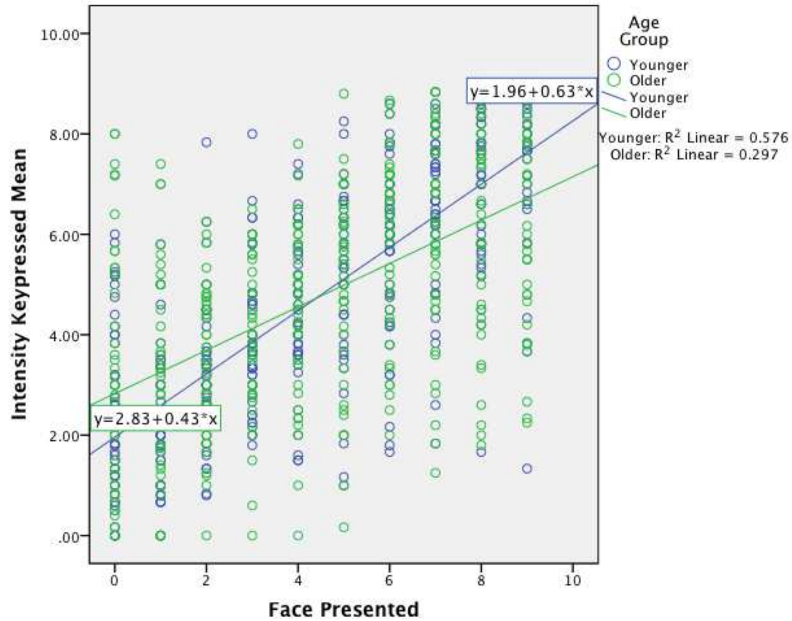


Figure 2. Mean intensity key pressed by face presented for younger and older adults.

The two-way interaction of face presented x facial expression condition was significant, (b = .35, t(823) = 8.78, p < .001). This indicated that all participants were generally more accurate at decoding the happy facial expression condition than the sad facial expression condition. This two-way interaction is illustrated by Figure 3. Participants' (collapsing across age group) facial expression decoding values were compared between the sad facial expression condition and happy facial expression condition, yielding a significant difference in slopes (i.e., a sad slope of b = .35 versus a happy slope of b = .71).

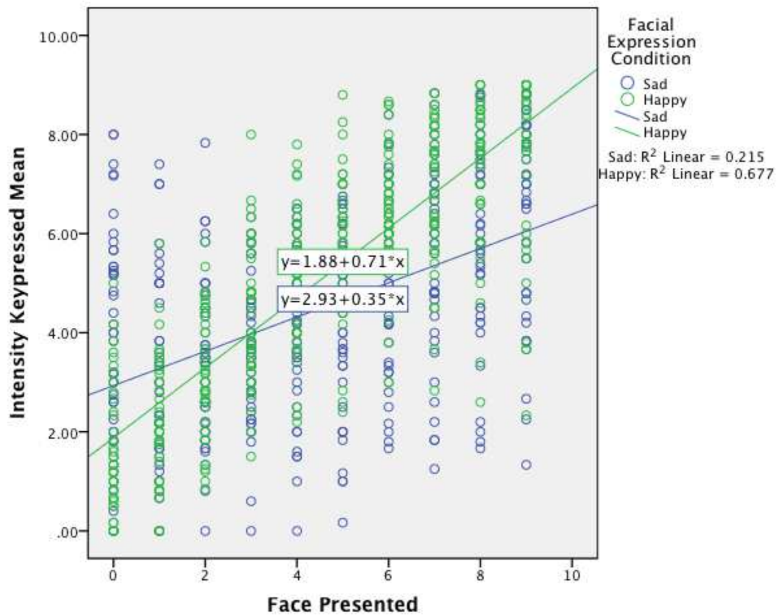


Figure 3. Mean intensity key pressed by face presented for sad and happy facial expression conditions.

The three-way interaction for face presented x age group x facial expression condition was not significant ($b = -.11$, $t(822) = -1.39$, $p = .17$). This means that facial expression decoding accuracy did not differ as a function of age group and facial expression condition. This does not support hypothesis H_1, which predicted no age differences in decoding accuracy in the happy facial expression condition, while predicting an age difference in the sad facial expression condition.

Intensity Key Pressed Response Time

The speed at which participants made responses could be interpreted as the level of attentional demand required of the stimuli. The purpose of measuring intensity key pressed response time was to examine whether attentional demand changed as a function of facial expression condition, age group, or an interaction of facial expression condition x age group. The response time for a participant was operationalized as the time in milliseconds (ms) it took a participant to depress a number key when presented with a facial expression. The facial expression would appear randomly throughout phase 2 (every 3-5 seconds) to avoid a predictable appearance interval. However, the face appeared or was shown for the same amount of time for every trial (2 seconds for younger adults, 2.5 seconds for older adults). Response time data was discussed in terms of seconds for ease of understanding.

A 2 (age group) x 2 (facial expression condition) ANOVA was conducted to analyze participants' response time data. A significant main effect was found for age group ($F(1, 81) = 317.80$, $p < .001$). Younger adults' response time ($M = 1.27$ s, $SD = .11$ s) was significantly faster than older adults' response time ($M = 1.9$ s, $SD = .20$ s). There was no main effect for facial expression condition ($F(1, 81) = .342$, $p = .56$), and no significant interaction for age group x facial expression condition ($F(1, 81) = .03$, $p = .86$). Regardless of facial expression condition, younger adults had significantly faster response times than older adults; illustrated by Figure 4.

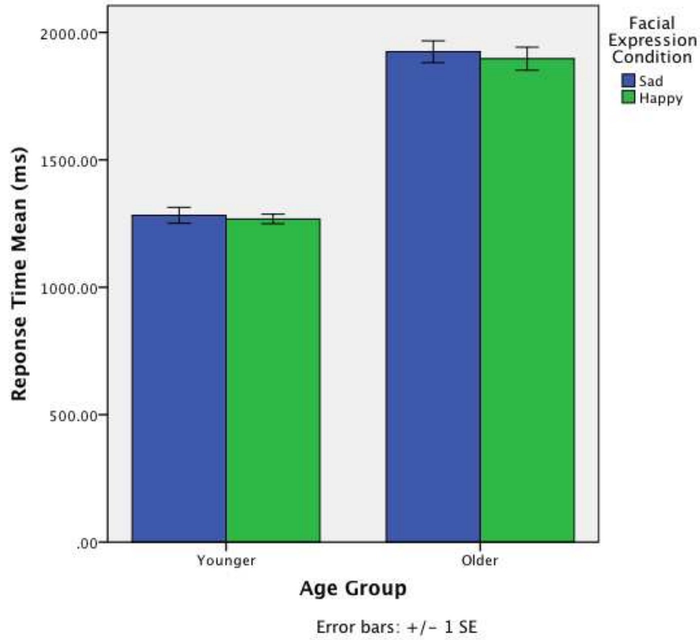


Figure 4. Mean response time (ms) by age group for sad and happy facial expression conditions.

Face Misses

The extent that participants "missed" identifying faces in the allotted time could be used to understand the attention demanding characteristics of the faces. We anticipated pre-attentive faces to be less "missed" compared to faces that required more attention. Face misses were operationalized as situations where the participant did not respond, or failed to press the number key (i.e., intensity key pressed) within the allotted time interval. When participants "missed" a facial expression it was recorded, and misses were summed and averaged for participants' experimental session.

A 2 (age group) x 2 (facial expression condition) ANOVA was conducted to analyze participants' amount of misses. A significant main effect was found for facial expression condition ($F(1, 81) = 5.9$, $p = .02$). Participants in the sad facial expression condition had significantly more misses ($M = 8.53$, $SD = 5.48$) than participants in the happy facial expression condition ($M = 6.05$, $SD = 3.6$). There was no main effect of age group ($F(1, 81) = 2.68$, $p = .11$), and no interaction for age group x facial expression condition ($F(1, 81) = 3.66$, $p = .06$). Figure 5 highlights the main effect of facial expression condition and the marginally significant interaction between age group x facial expression condition.

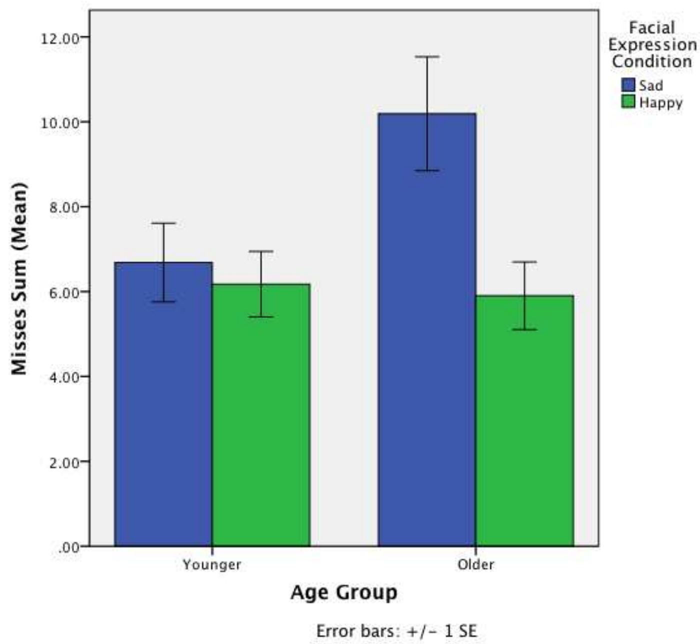


Figure 5. Mean number of face misses by age group for sad and happy facial expression conditions.

In sum, the results of the analysis of task phase 2 show that the variables of face presented, facial expression condition, and age group had a significant effect on participants' performance. The significant main effect of face presented on participants' intensity key pressed showed a positive linear trend for intensity key pressed as the variable of face presented increased. The significant main effect of facial expression condition on intensity key pressed revealed a significant increase in mean intensity key pressed when comparing between the sad facial expression condition and the happy facial expression condition. The significant main effect of age group on response time showed younger adults' response time was significantly faster than older adults' response time. The significant main effect of facial expression condition on face misses showed participants in the sad facial expression condition had significantly more misses than participants in the happy facial expression condition. The significant two-way interaction of age group x facial expression condition showed a significantly higher intensity key pressed for younger adults compared to older adults, when comparing between the sad and happy facial expression condition. The significant two-way interaction of face presented x facial expression condition showed participants in the happy facial expression condition had significantly higher decoding accuracy than those in the sad facial expression condition. However, the lack of a three-way interaction suggested that the happy face advantage for decoding was not significant for older adults. The significant two-way interaction of face presented x age group showed younger adults had a significantly higher decoding accuracy than older adults.

Examination of the aforementioned data was from task phase 2 (single-task phase) where presumably, all attention was devoted to the facial expression decoding task. To examine the attentional demands of facial decoding, performance in the facial expression decoding task was examined in the context of a dual-task environment (phase 3).

Task Phase 3 (Dual-task, Block Task and Facial Expression Decoding)

In task phase 3, participants were given a primary task (block game) and a secondary task (facial expression decoding). This dual-task paradigm allowed participant performance data from phase 2 to be compared to phase 3 (i.e., attention divided situation). The purpose of the following analyses was to determine the extent to which facial expression decoding was disrupted (i.e., dual-task cost) by the block task.

In phase 3, intensity key pressed and decoding accuracy were operationalized as described in phase 2. However, the new independent variable of task phase provided a method to compare performance variables as a function of single or dual-task.

A hierarchical regression analysis was conducted to predict intensity key pressed as a function of age group, facial expression condition, face presented, and task phase. The predictor variables of age group, facial expression condition, and task phase were dummy-coded. The predictor variables were entered in four steps, which resulted in four different models. The first step contained the following predictor variables: face presented, facial expression condition, age group, and task phase. These predictor variables represented all of the main effects tested (model 1). The second step contained the predictor variables from model 1 with the addition of the following two-way interactions: age group x facial expression condition, face presented x age group, face presented x facial expression condition, face presented x task phase, task phase x age group, and task phase x facial expression condition (model 2). The third step contained all of the predictor variables from model 1 and model 2 with the addition of the following three-way interactions: face presented x age group x facial expression condition, task phase x age group x facial expression condition, face presented x task phase x age group, and face presented x task phase x facial expression condition (model 3). The fourth step contained all of the predictor variables from model 1, model 2, and model 3, with the addition of the following four-way interaction: face presented x task phase x facial expression condition x age group (model 4).

The models were tested for their ability to significantly predict participants' intensity key pressed. Model 1 accounted for 43.6 % of the variance of intensity key pressed, (R^2 = .436, F(4, 1552) = 299.92, p < .001). Model 2 accounted for 49.3 % of the variance of intensity key pressed, (R^2 = .493, F(10, 1546) = 150.34, p < .001). Model 3 accounted for 49.6 % of the variance of intensity key pressed, (R^2 = .496, F(14, 1542) = 108.33, p < .001). Model 4 accounted for 49.6 % of the variance of intensity key pressed, (R^2 = .496, F(15, 1541) = 101.21, p < .001). The addition of the two-way interactions in model 2 resulted in an R^2 change value of .057, or 5.7 %, while the addition of the three-way interaction in model 3 resulted in a R^2 change value of .003, or 0.3 %. The addition of the four-way interaction resulted in no significant R^2 change compared to model 3.

As expected, (due to the low R^2 change value from model 2 to model 3), the hierarchical regression showed non-significant values for all of the task phase related three-way interactions: task phase x age group x facial expression condition (b = .08, t(1542) = .21, p = .83), face presented x task phase x age group (b = -.02, t(1542) = -.35, p = .72), and face presented x task phase x facial expression condition (b = -.05, t(1542) = -.85, p = .40). This meant no two-way interactions significantly changed across the predictor variable of task phase (e.g., face presented × facial expression condition did not change due to task phase). It was determined that model 4 did not yield a significant four-way interaction, (b = -.14, t(1541) = -1.1, p = .269). Due to the non-significant results of the three-way and four-way interaction terms, the following analyses concentrate on model 1 and model 2. Slope comparisons will be confined to only two-way interactions related to model 2. The analyses of model 1 and model 2 give a simplified overview (i.e., less complex interactions) of the effect of task phase on participant performance.

Main Effects and Interactions for Intensity Key Pressed

There was no main effect of task phase on participants' intensity key pressed, (b = .09, t(1552) = .927, p = .354). As participants' moved from single to dual-task there was no significant difference for intensity key pressed values. The non-significant main effect of task phase can be thought of as a manipulation check, indicating that participants did not give the facial expression stimuli significantly different mean intensity ratings in the single-task phase versus the dual-task phase.

There was no significant two-way interaction for facial expression condition x task phase, (b = .18, t(1546) = .99, p = .32). Facial expression condition did not have a significant effect on the difference between the differences of means (i.e., slope) for intensity key pressed, when comparing across task phase.

A significant two-way interaction was found for age group x task phase, (b = .39, t(1546) = 2.17, p = .03), illustrated by Figure 6. Task phase had a significant effect on the difference between the differences of means (i.e., slope) for intensity key pressed, when comparing across age group. Slopes were found using the following formula: $b = \frac{Y2-Y1}{X2-X1}$, where the mean intensity key pressed values were used for Y and age group coding (0 = Single, 1 = Dual) was used for X. The slope for younger adults (b = -.05) was significantly different from the slope for older adults (b = .27). The change in mean intensity key pressed, as a function of task phase for older adults, was significantly greater than younger adults.

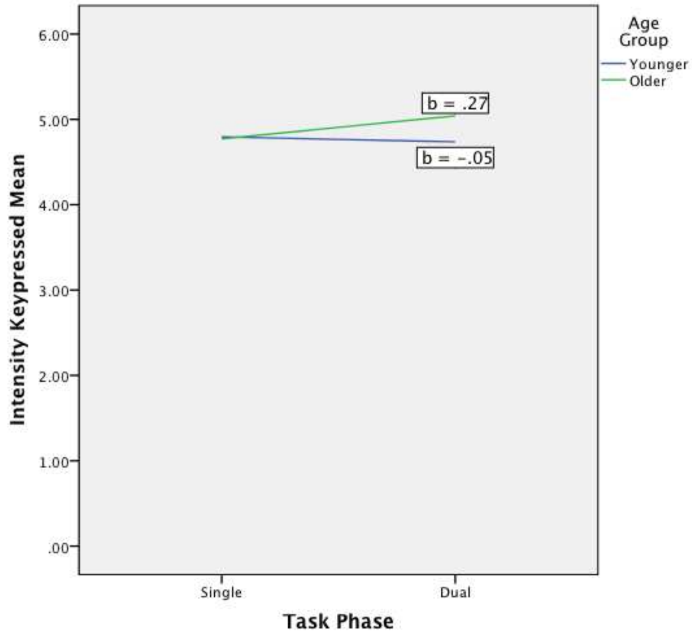


Figure 6. Mean intensity key pressed by task phase for younger and older adults.

Interactions for Decoding Accuracy

There was no significant two-way interaction of face presented x task phase, (b = .04, $t(1546) = 1.17$, $p = .24$). Participants' decoding accuracy (when collapsing across age group and facial expression condition) was not significantly affected by the task phase of the experiment. The slope values for each task phase did not significantly differ.

No significant three-way interactions were observed as a function of task phase. The three-way interaction of task phase x age group x facial expression condition was not significant ($b = .08$, $t(1542) = .21$, $p = .83$), the three-way interaction of task phase x face presented x age group was not significant ($b = -.02$, $t(1542) = -.35$, $p = .72$), and the three-way interaction of task phase x face presented x facial expression condition was not significant (b = -.05, $t(1542) = -.85$, $p = .40$). The non-significance of these three-way interactions indicated that no two-way interactions significantly differed across task phase. The significant two-way interaction of face presented x age group shown in the single-task phase, remained significant (b = -.20, $t(720) = -4.14$, $p < .001$) in the dual-task phase, illustrated by Figure 7. This meant the significant interaction between face presented x age group (i.e., younger adults had significantly higher decoding accuracy than older adults) in the single-task, was replicated in the dual-task. The two-way interaction of face presented x facial expression condition shown in the single-task phase, remained significant (b = .30, $t(720) = 6.13$, $p < .001$) in the dual-task phase, illustrated by Figure 8. This meant the significant interaction between face presented x facial expression condition (i.e., happy condition was significantly higher for decoding accuracy than sad condition) in the single-task was replicated in the dual-task. Essentially, this showed there was no dual-task cost for these two-way interactions.

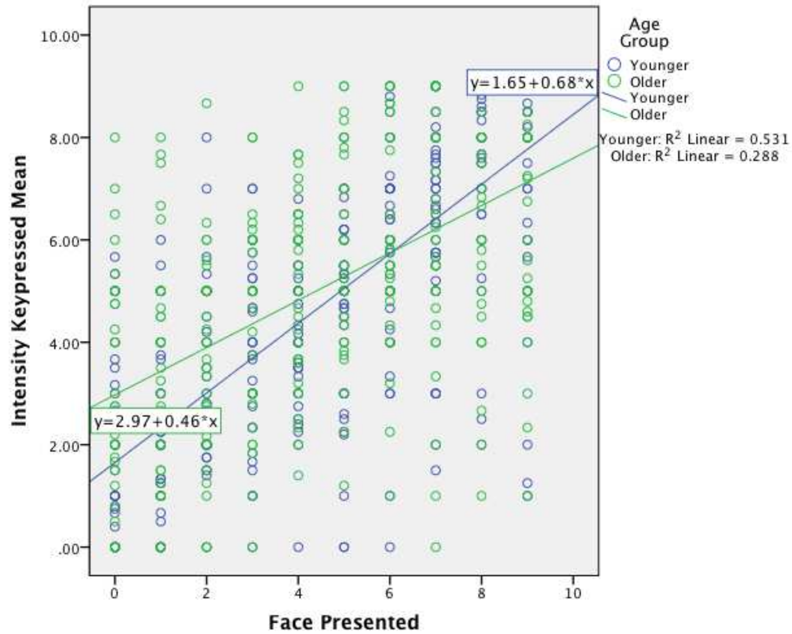


Figure 7. Mean intensity key pressed by face presented for younger and older adults (dual-task).

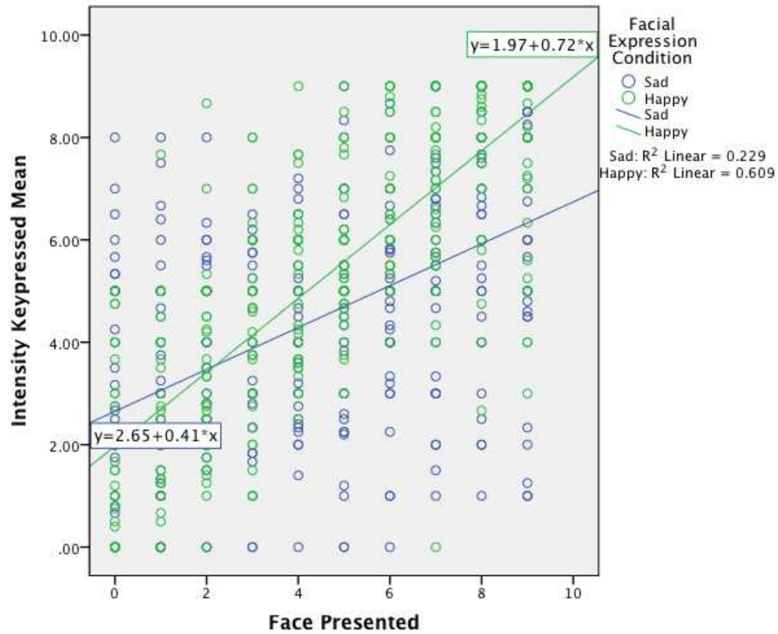


Figure 8. Mean intensity key pressed by face presented for sad and happy facial expression condition (dual-task).

The four-way interaction of face presented x task phase x facial expression condition x age group was not significant, (b = -.14, t(1541) = -1.11, p = .27). This finding showed that no three-way interactions significantly differed across task phase. This showed a lack of dual-task cost for the interaction of face presented x facial expression condition x age group. In the single-task happy facial expression condition, the significant two-way interaction for face presented x age group (b = -.23, t(426) = -5.03, p < .001) remained significant in the dual-task happy facial expression condition, (b = -.32, t(384) = -5.58, p < .001), illustrated by Figures 9 and 10. This meant the significant interaction between face presented x age group (i.e., younger adults had significantly higher decoding accuracy than older adults) in the single-task happy facial expression condition, was replicated in the dual-task happy facial expression condition.

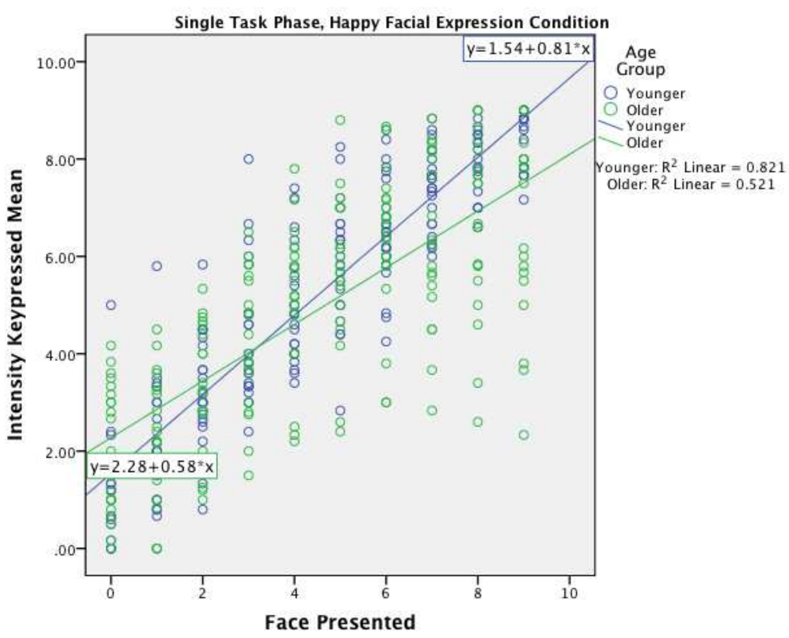


Figure 9. Mean intensity key pressed by face presented for younger and older adults (single-task, happy facial expression condition).

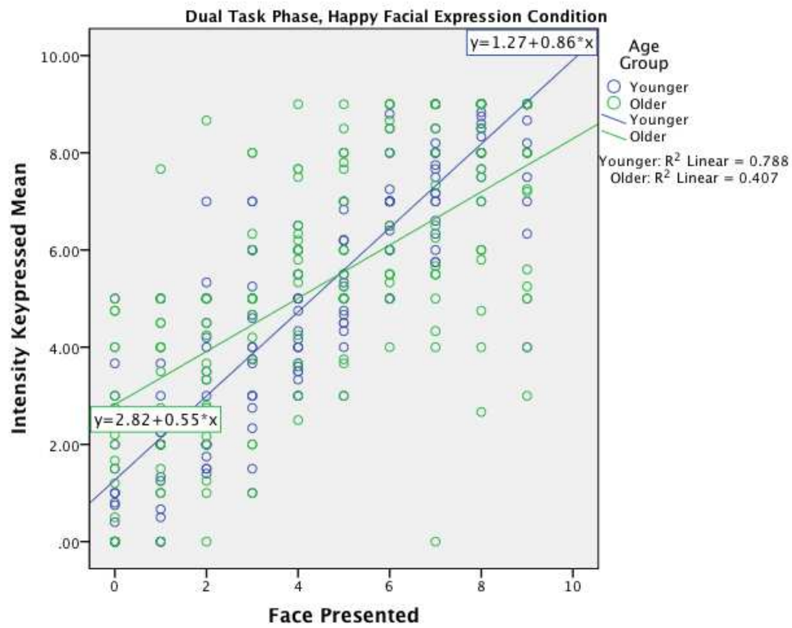


Figure 10. Mean intensity key pressed by face presented for younger and older adults (dual-task, happy facial expression condition).

In the single-task sad facial expression condition, the non-significant two-way interaction for face presented x age group (b = -.12, t(396) = -1.82, p = .07) remained non-significant in the dual-task happy facial expression condition (b = -.07, t(335) = - .86, p = .39), illustrated by Figures 11 and 12. This meant the non-significant interaction between face presented x age group (i.e., younger adults had similar decoding accuracy as older adults) in the single-task sad facial expression condition, was replicated in the dual-task sad facial expression condition.

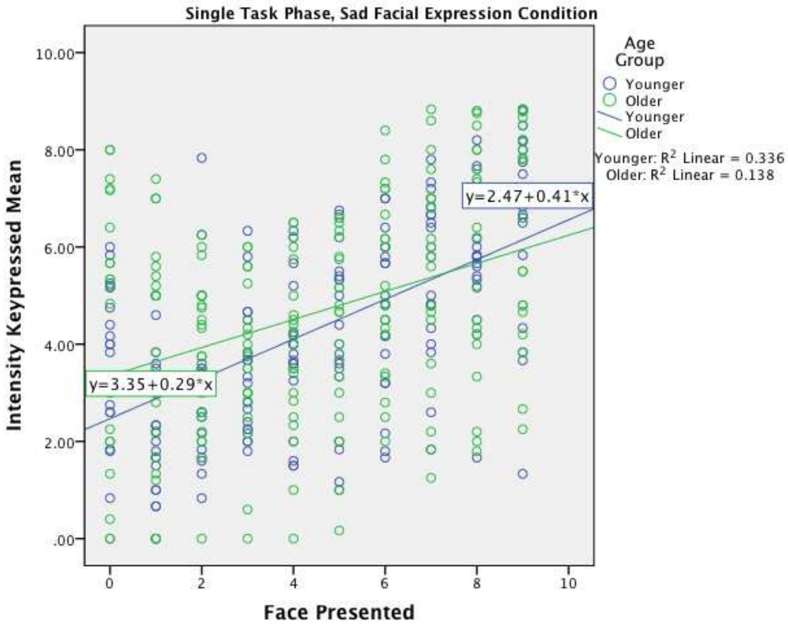


Figure 11. Mean intensity key pressed by face presented for younger and older adults (single-task, sad facial expression condition).

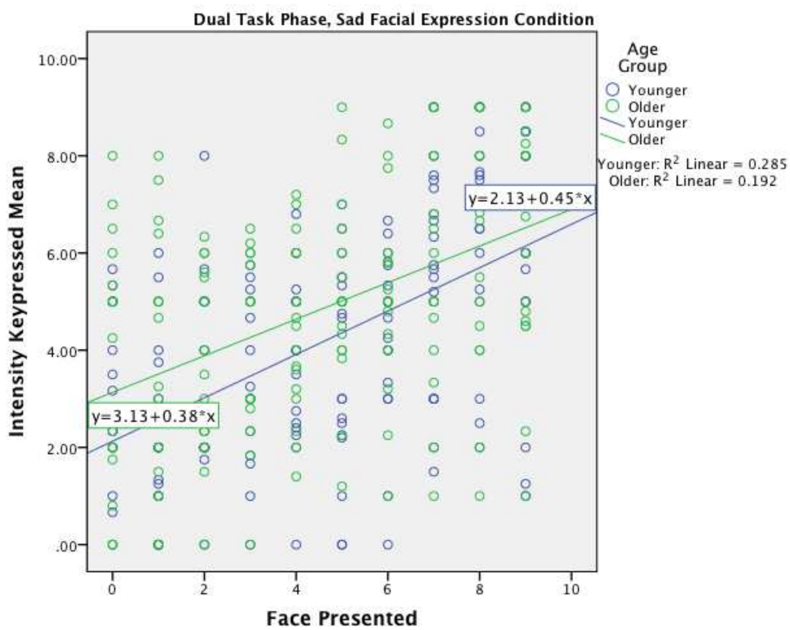


Figure 12. Mean intensity key pressed by face presented for younger and older adults (dual-task, sad facial expression condition).

Intensity Key Pressed Response Time

A mixed measures ANOVA was conducted on the response time data for facial expression decoding. There was a significant main effect of task phase on response time ($F(1, 79) = 34.34$, $p < .001$), illustrated by Figure 13. Response time for task phase 2 (M =1.59 s, SD = .36 s) was significantly faster than reaction time for task phase 3 (M = 1.72 s, SD = .38 s). There were no significant interactions for task phase x age group, task phase x facial expression condition, or task phase x age group x facial expression condition. There was a significant main effect for age group on response time ($F(1, 79) = 345.50$, $p < .001$). Response time for younger adults (M = 1.34 s, SD = .24 s) was significantly faster than for older adults (M = 1.98 s, SD = .24 s), illustrated by Figure 14. The main effect for facial expression condition was not significant, nor was the interaction of age group x facial expression condition.

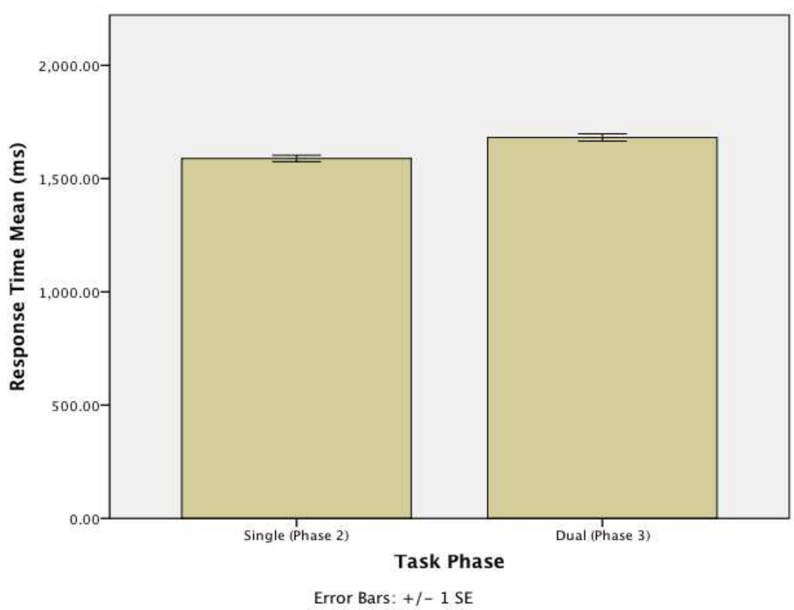


Figure 13. Mean response time (ms) by task phase.

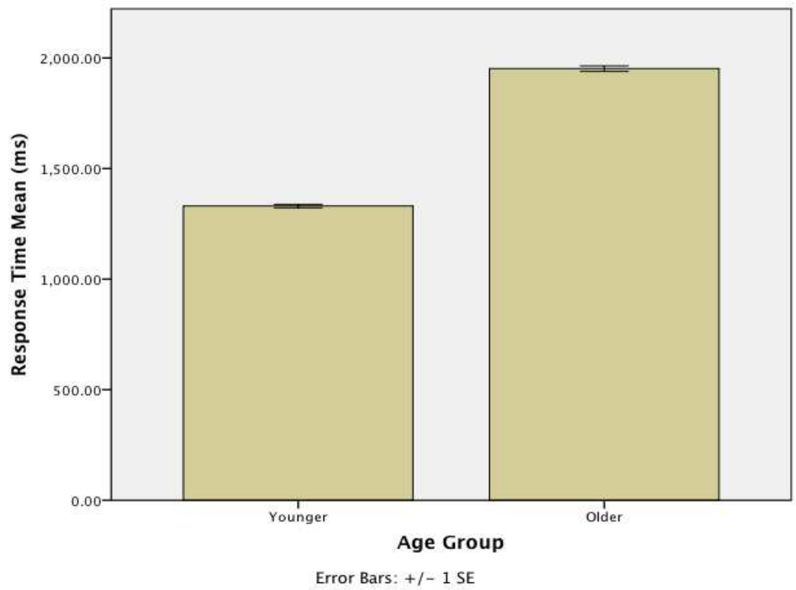


Figure 14. Mean response time (ms) by age group.

Face Misses

A mixed measures ANOVA was conducted on the amount of face misses between the single and dual-task phase. A significant main effect was found for task phase (F(1, 79) = 276.68, p < .001), such that participants had fewer misses in the single-task (M = 7.24, SD = 4.74) compared to the dual-task (M = 33.55, SD = 14.10), illustrated by Figure 15. There were no significant interactions for task phase x facial expression condition, task phase x age group, or task phase x facial expression condition x age group. There was no significant main effect for facial expression condition or age group. There was also no significant interaction for facial expression condition x age group.

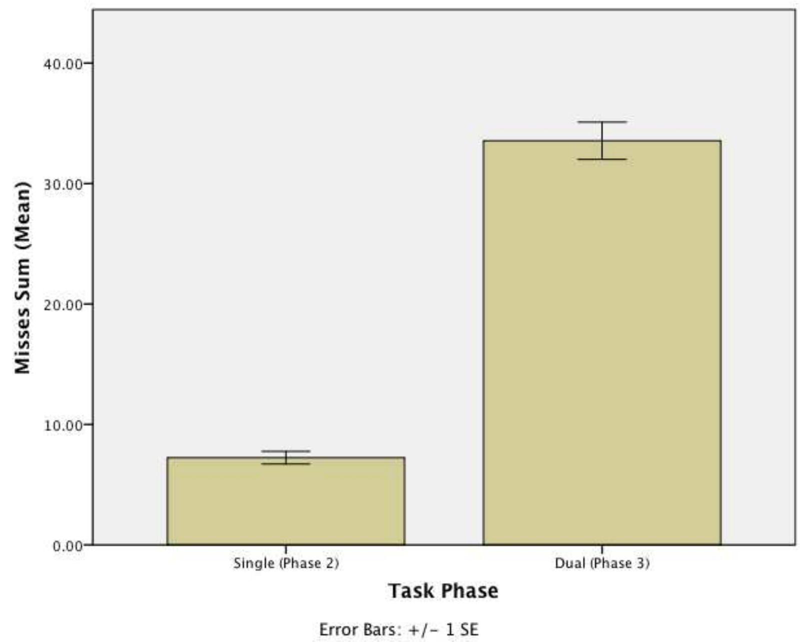


Figure 15. Mean number of face misses by task phase.

Blocks Cleared

A 2 (age group) x 2 (facial expression condition) ANOVA was conducted on the number of blocks cleared in the dual-task phase. There was a significant main effect for age group ($F(1,79) = 160.29$, $p < .001$), such that younger adults cleared significantly more blocks ($M = 46.95$, $SD = 10.37$) than older adults ($M = 20.07$, $SD = 8.61$), illustrated by Figure 16. There was no significant main effect of facial expression condition or significant interaction of age group x facial expression condition.

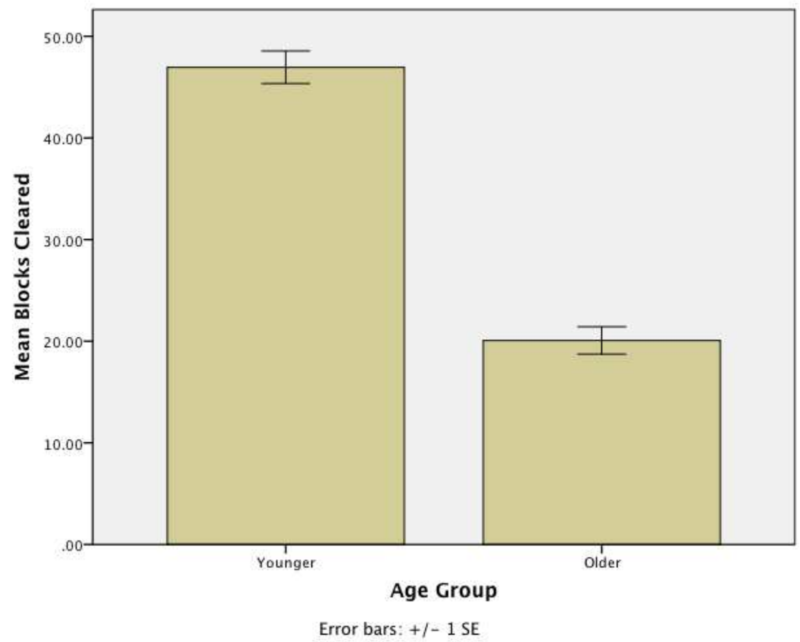


Figure 16. Mean blocks cleared by age group.

NASA-TLX Survey

The NASA-TLX subjective workload survey was given to all participants in order to assess the amount of perceived workload they experienced during the dual-task phase of the experiment. Data was only collected after the dual task phase, so a comparison across task phase could not be analyzed. A 2 (age group) x 2 (facial expression condition) ANOVA was run to determine if the independent variables of age group and facial expression condition had a significant effect on computed workload. There was no significant main effect for age group ($F(1, 78) = .17$, $p = .68$), for facial expression condition ($F(1, 78) = 2.41$, $p = .13$), or for the interaction of age group x condition ($F(1, 78) = 1.64$, $p = .21$). Neither age group nor facial expression condition significantly affected participants' subjective workload, illustrated by Figure 17.

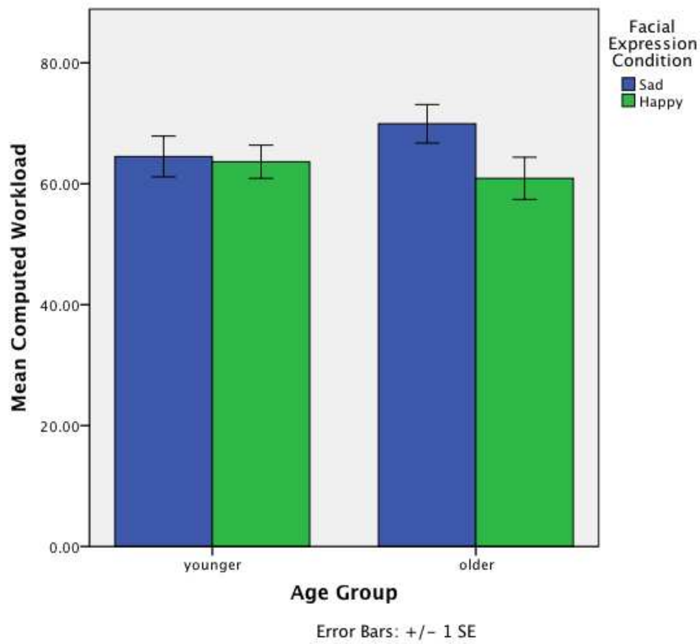


Figure 17. Mean computed workload by age group for sad and happy facial expression conditions.

In sum, the results of the analysis of task phase 3 show that facial expression decoding accuracy did not significantly differ as a function of task phase, but the measures of intensity key pressed, response time, and face misses did show a dual-task cost. There was a main effect of task phase on response time for all participants, which showed faster response times in phase 2 compared to phase 3. A main effect of age group showed older adults to be significantly slower in response time compared to younger adults. There was also a main effect of task phase on the amount of faces that were missed, which showed more faces were missed in phase 3 than phase 2, however this did not differ by age group or facial expression condition. The two-way interaction of age group x task phase was significant and showed mean intensity key pressed significantly increased for older adults across task phase compared to younger adults.

DISCUSSION

The goal of the current study was to investigate whether Chernoff face stimuli could serve as ambient (i.e., relatively resource-free) indicators of quantitative information, using a dual-task paradigm. It was hypothesized (H_1) that a significant three-way interaction would occur between face presented x age group x facial expression condition for decoding performance in the single-task phase. Both age groups were expected to have similar decoding accuracy (i.e., similar regression slopes) in the happy facial expression condition, but non-similar slopes in the sad facial expression condition. This age-related difference in decoding accuracy as a function of facial expressions being happy or sad, was based on literature indicating positive facial expression provided a decoding advantage (Bartneck & Reichenbach, 2005; Calvo & Lundqvist, 2008; Rellecke, 2011), and literature that suggested older adults could decode positive facial expressions as accurately as younger adults (Orgeta & Phillips, 2007).

Hypothesis 1: A Three-Way Interaction of Age Group, Facial Expression Condition, and Face Presented

Hypothesis 1 was not fully supported. The current experiment revealed that the interaction between face presented x age group x facial expression condition for decoding performance in the single-task phase was not significant. However, it was found that the relationship between younger and older adults' decoding accuracy did significantly change due to facial expression condition. There was an age-related difference in decoding accuracy in the happy face condition. Younger adults' significantly higher decoding accuracy in the happy facial expression condition was unexpected due to the "happy face advantage" that was anticipated for older adults (Ekman & Friesen, 1975; Orgeta & Phillips, 2007; Calvo & Lundqvist, 2008). There was not an age-related difference in decoding accuracy in the sad face condition. The absence of an age-related difference in decoding accuracy in the sad facial expression condition was also unexpected. The similarity of decoding accuracy performance between younger and older adults in the sad face condition was not hypothesized, and may be evidence of the lack of a negativity effect for younger adults, which was based on previous research (Lynchard & Radvansky, 2012).

Participants' (collapsed across age group) had higher decoding accuracy when they were presented with happy facial expressions. This finding supports a general "happy face advantage" across age group and suggests that when compared to sad Chernoff facial expressions, happy Chernoff facial expressions are more advantageous for decoding. In terms of using a Chernoff face for the display of quantitative information; the use of happy facial expression was shown to be an overall more decodable stimuli. This finding corroborates with previous research that also provides evidence of more accurate happy face decoding (Hess, 1997). While this finding doesn't fully support hypothesis 1, it does add support to the general hypothesis that happy Chernoff faces would be decoded the most accurately compared to sad Chernoff faces.

Younger adults had significantly faster response times compared to older adults, regardless of the facial expression condition. This was not expected and did not support the hypothesis that happy facial expression would allow older adults to maintain a similar response time as younger adults in the happy facial expression condition (i.e., happy face advantage). Previous research showing the capacity of quick decoding for happy facial expressions (Calvo & Lundqvist, 2008) was paired with the socioemotional selectivity theory (Carstensen, Issacowitz, & Charles, 1999) to reach the concept of older adults decoding happy facial expression with quickness. Since response time was interpreted as a measure of attentional demand on the participant, it was inferred that older adults' incurred a higher attentional demand when performing the facial decoding task. The non-main effect of facial expression condition showed that happy and sad facial expressions were responded to with similar response times within age groups. This was expected for younger adults (i.e., no decrement in response time due to facial expression condition), but not for older adults. The non-significant difference for older adults' response times in terms of facial expression condition indicates no response time advantage for either facial expression.

The main effect of facial expression condition on faces missed indicated participants in the sad facial expression condition missed significantly more faces than participants in the happy facial expression condition. This supports the general idea that happy faces are more quickly (i.e., perhaps pre-attentively) decoded than sad faces. This finding partially supports hypothesis 1. It was expected for older adults to miss significantly more sad facial expressions, but younger adults were expected to see no change in faces missed across facial expression condition. The main effect of facial expression condition showed that sad Chernoff faces were missed significantly more regardless of age group. However, this preliminary finding indicating a pre-attentive or resource-free quality of happy faces was more thoroughly investigated in phase 3, where additional attentional demand was placed on the participants.

The finding of participants' significantly higher decoding accuracy for happy facial expressions can be paired with participants' lower amount of misses for happy facial expressions. This forms a case that happy facial expressions are generally more easily decodable than sad facial expressions, which is consistent with previous research (Hess, 1997; Bartneck & Reichenbach, 2005; Calvo and Lundqvist, 2008). The results yielded from the testing of H_1 gave evidence that happy facial expressions have a significant advantage for decoding, in situations of low attentional demand. However, it is important to remember that older adults performed significantly lower than younger adults in terms of decoding accuracy (when collapsed across facial expression condition) and response time. This suggests that older adults had difficulty decoding the Chernoff facial expressions. Because of this finding, Chernoff facial expressions ability to transcend age group as a type of ambient display is suspect.

An aspect of the current study that may have contributed to the absence of an older adult happy face advantage (in phase 2) was the amount of intensity levels for the variable of face presented. Unlike previous studies (Hess, 1997; Orgeta & Phillips, 2007), faces in the current study changed incrementally by 10 % on a scale from 0 % - 90 %. Thus, we may have increased the amount of discrimination required of our participants. It was shown in previous research that 10 % intensity level steps were too small to be discriminated, and participants were not as accurate in their decoding (Bartneck & Reichenbach, 2005).

The manipulation of only one facial feature may not have been optimal for facial expression decoding in adults. A plausible explanation for older adults' lower decoding accuracy was the simplistic level of face manipulation used on the Chernoff faces (i.e., only the mouth was manipulated). Perceiving slight changes in mouth curvature of the Chernoff faces may have been too difficult a task for older adults. A previous study suggested that children (ages 11-12) were more successful at recognizing changes in single features (e.g., mouth, eyebrows) than adults (ages 20-45) (Tsurusawa, Goto, Mitsudome, Nakashima, & Tobimatsu, 2007). This was due to the lack of development of holistic facial expression decoding in children. The current study generalizes this finding to older adults due to their observed lower slope value in facial decoding accuracy. Potentially, the ability for people to discern slight manipulations of a single facial feature is negatively associated with age. The concept of a "pseudo-Chernoff face", which manipulated only one facial feature, was shown to be difficult for older adults to decode. Although the percentage information conveyed by the Chernoff face was univariate in nature, it may be more helpful to manipulate multiple facial features to communicate such information. The holistic manipulation of a face (i.e., mouth, eyes, eyebrows, etc.) could provide a better decoding accuracy for both younger and older adults. The idea presented by Montello and Gray (2005) of communicating data univariately seems to have been misapplied to facial expression in the current study. Unintentionally, we may have created a more difficult decoding task by manipulating only one facial characteristic.

Hypothesis 2: A Four-Way Interaction of Age Group, Facial Expression Condition, Face Presented, and Task Phase

It was hypothesized (H_2) that participants' performance across age groups in the dual-task condition would not significantly decline when in the happy facial expression condition, while a dual-task cost would be observed in the sad facial expression condition. This expected finding was linked to the happy face advantage used as a basis for hypothesis 1 (Ekman & Friesen, 1975; Orgeta & Phillips, 2007; Calvo & Lundqvist, 2008).

The four-way interaction associated with hypothesis 2 was not supported, and confirmed that the three-way interaction of face presented x age group x facial expression condition did not significantly differ across task phase. Decoding accuracy in the dual-task phase was statistically similar to the single task phase. Every interaction that involved decoding accuracy as a function of task phase yielded non-significant results. This was an unexpected finding and presents a question as to why there was no dual-task cost.

The main effect of task phase and main effect of age group on response time suggests that the dual-task phase was contributing to a decrease in performance. Therefore, the prediction that happy facial expressions do not produce a significant increase in response time was not supported. The happy face stimuli used in our study were not immune to dual-task cost. As previous research has stated, (Morris, 1998; Whalen, 1998) the potential advantage of using a face as an ambient display is the face's ability to not add any cognitive load on the user, specifically in an attentional demanding situation. Response time data has shown Chernoff facial expressions do not meet this requirement, and hence may not be good ambient displays. The main effect for age group suggested that older adults were significantly slower at decoding facial expressions. The slower response time for older adults was also seen in the single task phase.

The amount of misses a participant incurred was significantly different based on task phase. Participants recorded significantly more misses on average (by a factor of 4) in the dual-task condition than the single-task condition. Just as response time indicated a dual-task cost, so do the amount of misses observed for participants. This finding does not fully support hypothesis 2. Since misses significantly increased for both happy and sad facial expressions, there was no apparent happy face advantage. The significant main effect for facial expression condition shown in phase 2 (i.e., sad faces yielded more misses) was not shown in phase 3.

Participants' number of blocks cleared for the block game (in the dual-task phase) was significantly different based on age group. Younger adults cleared more blocks than older adults when completing the dual-task. This finding suggests that younger adults were able to complete the primary block task at a higher level than older adults. There was no significant main effect of facial expression condition, which showed participants did not significantly differ in number of blocks cleared based on which facial expression condition they were placed.

One potential answer to the question of no dual-cost for decoding accuracy is that the primary task in the dual-task phase was not engaging enough. The relationships for the two-way interactions observed in phase 2 may not have significantly changed in phase 3 because participants' were not being exposed to a high attentional demanding situation (i.e., relative to phase 2). However, the data from response time and amount of face misses provide evidence that the dual-task condition was causing dual-task cost among participants. The lack of dual-cost for decoding accuracy may be explained by the significant difference observed between decoding accuracy as a function of age group in phase 2. Younger adults had a significantly higher decoding accuracy (collapsing across facial expression condition) than older adults in the single-task phase (phase 2). However, younger and older adults may have experienced a floor effect in decoding accuracy that prevented the expected significant decrease in decoding accuracy (in the sad facial expression condition) from phase 2 to phase 3. This indicates that participants' significantly lower decoding accuracy for sad Chernoff facial expressions might not be directly due to the additional attentional demand of phase 3, but is due to the general difficulty of decoding the sad Chernoff facial expressions. Similar to the single task phase, the facial expression stimuli may not have conveyed emotion clearly enough (possibly due to the manipulation of only one facial feature) to result in the expected three-way interaction across task phase.

One possibility for the consistent slower response times for older adults, as previously mentioned, is related to the stimuli. The stimuli were potentially more difficult for the older adults to decode. This detracts from the universal usability (i.e., usable for all age groups) of Chernoff faces as a method for communicating information. A second possibility is that the input of decoding facial expression was more physically taxing for the older adults. Using the number pad may have been a difficult input for older adults who have joint disorders (e.g., arthritis) or other physical aliments. A more novel input mode (e.g., speech) may provide a way to avoid the confounding variable of input mechanism.

When looking at the response time and face misses data, there is an underlying concept pertaining to Chernoff faces that may explain the dual-task cost. Previous research claimed that Chernoff faces were not processed in parallel and were more difficult to decode (Morris, Ebert, Rheingans, 2000). The concept that Chernoff faces are not pre-attentive and are processed serially adds support to the dual-task cost seen in the current study.

The age-related effect found for the number of blocks cleared gave evidence that younger adults became better adapted to the dual-task phase than older adults. The proficiency shown by younger adults in the block task could help explain why there was a younger adult advantage for decoding accuracy in the dual-task phase. Older adults' significantly lower decoding accuracy in the dual-task could be attributed to the difficulty of the block task. The cognitive demands of the block task may have caused older adults to experience a significant performance decrement when compared to younger adults, in both the number of blocks cleared and decoding accuracy. Due to the lack of an effect of facial expression condition, it can be inferred that the happy face advantage shown in the dual-task was not due to participants' inappropriate allocation of attention in the dual-task. Essentially, participants' higher decoding accuracy in the happy face condition was not due to their neglect of the primary task.

In sum, the results gained from the comparison of performance measures across task phase indicated attention-demanding environments degrade the decoding of Chenoff faces. While decoding accuracy performance did not show a dual-task cost, response time and amount of face misses revealed a significant dual-task cost. Based on decoding accuracy performance, happy facial expression appear to be more beneficial than sad facial expression in an attention-demanding environment. Even though the happy facial expression condition shows significantly higher decoding accuracy, it is not immune to dual-task cost in terms of response time and the amount of misses incurred. Younger adults experienced less decrement in overall performance compared to older adults in the dual-task. Results from the number of blocks cleared by participants in the dual-task phase showed younger adults out performed older adults on the primary task. The block game appeared to be more cognitively demanding for older adults, which may have led to lower decoding accuracy. The dual-task cost seen for response time and face misses indicated that Chernoff facial expressions create a significant demand on users' attention. Therefore, Chernoff faces do not have an observed benefit for communicating information in a resource-free manner.

There were a few limitations to this study that could be improved upon in future research. The facial expressions stimuli could have been manipulated to take advantage of more facial features when conveying expression. Future studies could measure decoding performance for Chernoff faces with variations of manipulated facial characteristics (e.g., manipulation of mouth and eyes, versus manipulation of mouth, eyes, and eyebrows). Another limitation was only having participants complete a NASA-

TLX survey after the dual task phase. It would be beneficial to have participants complete the NASA-TLX survey after the single-task as well. This would allow for comparison of subjective workload between task phases in an effort to gain another measure of dual-task cost. A trust rating measure was not included in the current study, but could be in a future study as a measure of subjective trust concerning the facial expressions. It would be interesting to observe how a participants' trust is affected by the independent variables of: age, facial expression intensity, and facial expression condition. Understanding which faces receive significantly different trust ratings would add an interesting element to a future study. Another improvement for the current study involves the placement of the Chernoff face in the computer program. The peripheral position of the Chernoff face may have put participants at a disadvantage for decoding. A future study may place the facial expression in a more centralized location. A final improvement could be to add more facial expression conditions. Previous literature has expressed an "anger superiority" effect (Ohman, Lundqvist, Esteves, 2001), which could be investigated using Chernoff facial expressions.

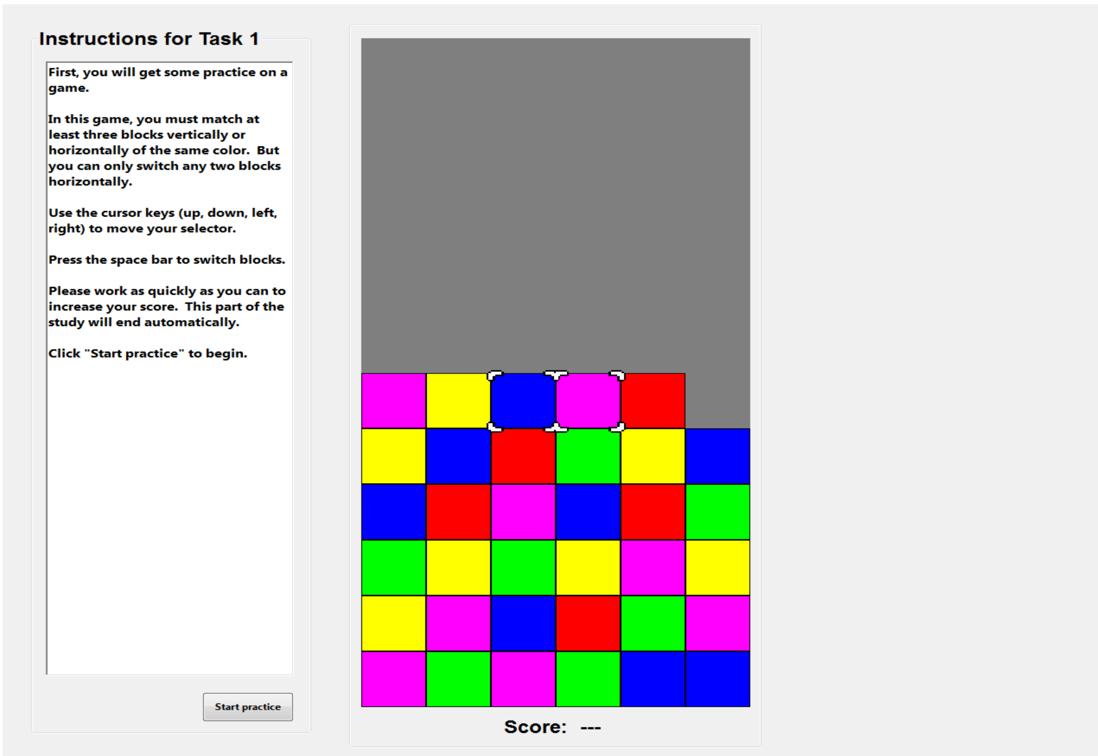
CONCLUSION

The results of this study suggest that Chernoff faces communicate facial expression more effectively when happy facial expressions are used. However, older adults have more difficulty in decoding Chernoff facial expressions. There is also a dual-task cost for the decoding of Chernoff faces in terms of increased response time and a higher amount of faces missed. The ability for Chernoff faces to act as effective ambient displays was not supported by this study, but more research on Chernoff faces should be conducted to further explore their usefulness in communicating information.

APPENDICIES

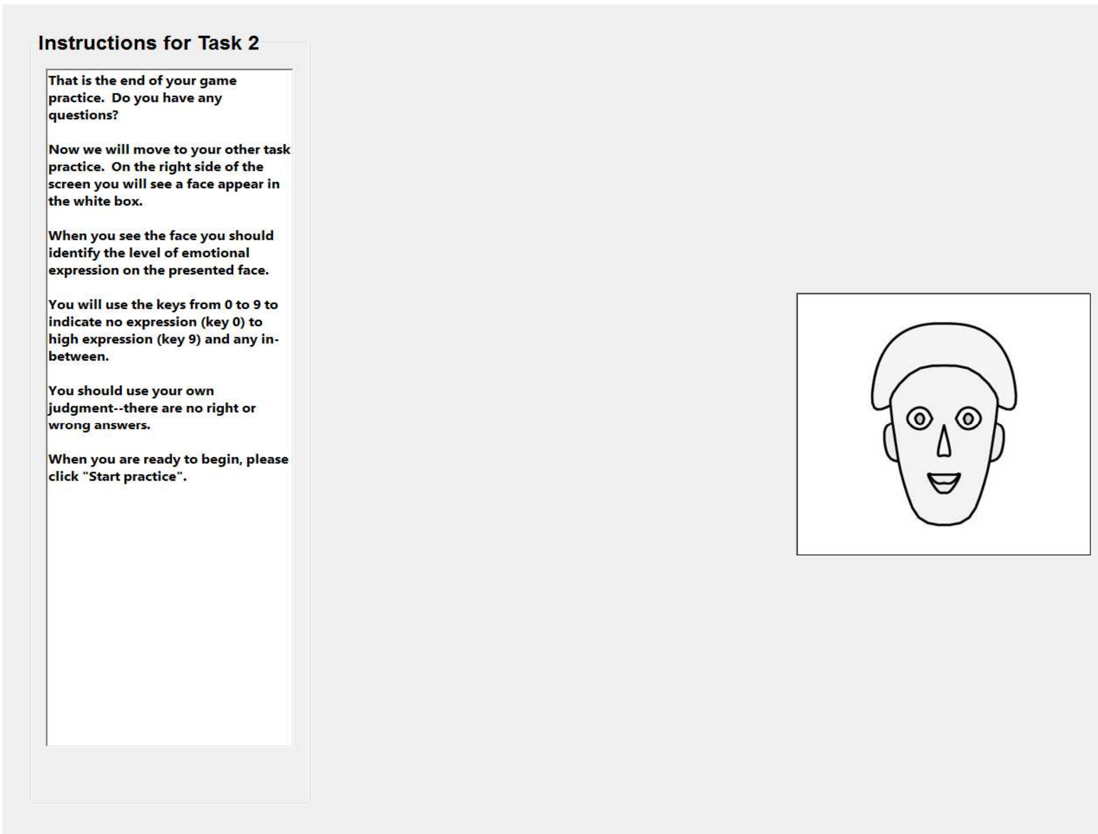
APPENDIX A

Screenshot of Block Game Task (Phase 1)



APPENDIX B

Screenshot of Facial Expression Decoding Task (Phase 2)



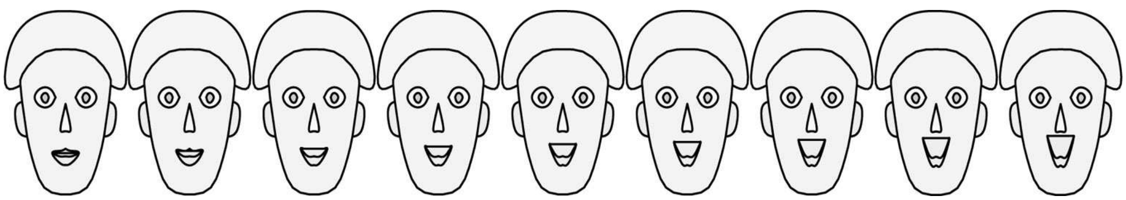
APPENDIX C

Chernoff Facial Expression Stimuli Organized by Expression and Intensity

Neutral Facial Expression

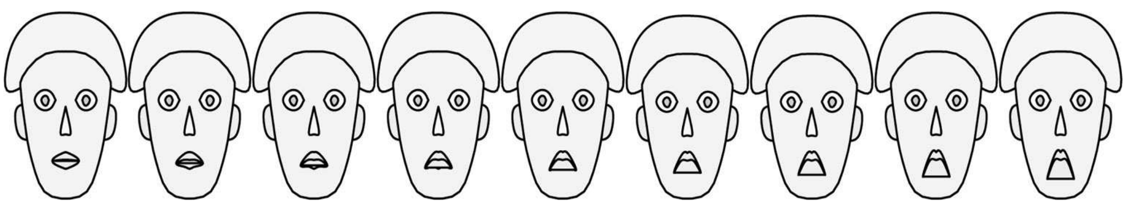
% 0

Happy Facial Expressions



% 10 20 30 40 50 60 70 80 90

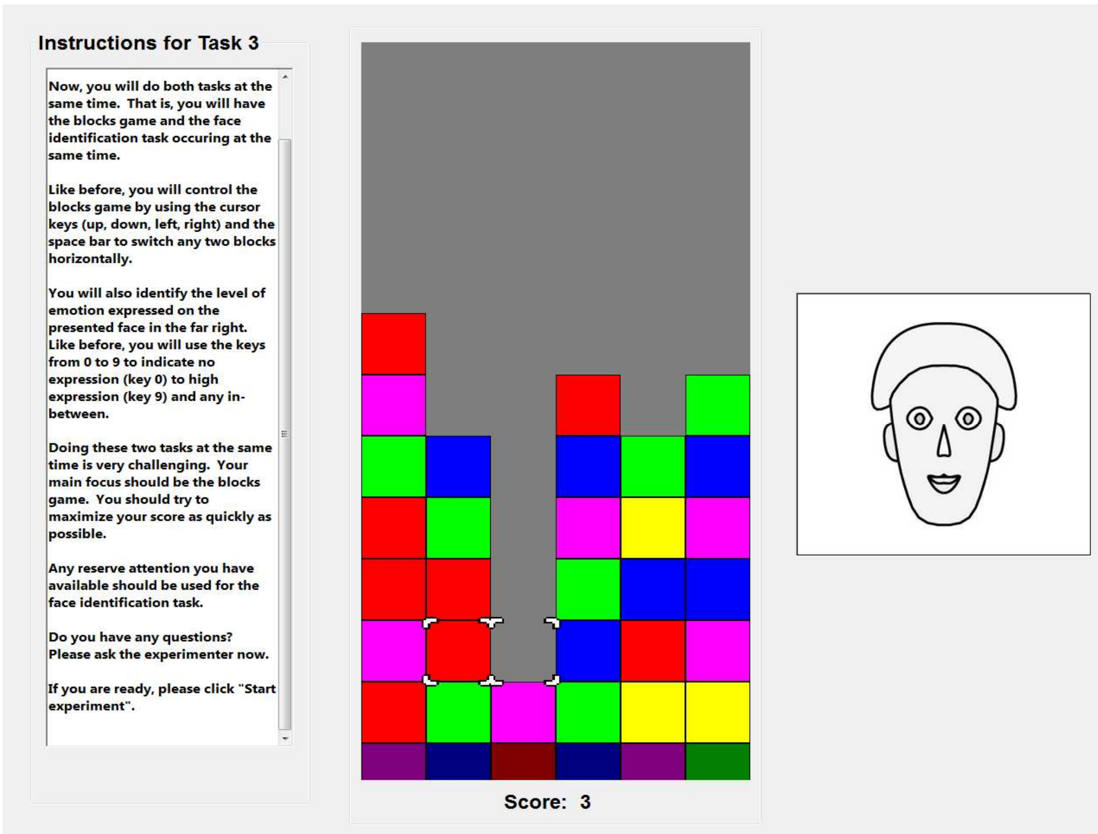
Sad Facial Expressions



% 10 20 30 40 50 60 70 80 90

APPENDIX D

Screenshot of Block Task and Facial Expression Decoding Task (Phase 3)



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