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# Understanding Emotional Adaptivity in Study Tools: A Mixed-Methods Evaluation of Eunoia

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**Abstract—Productively tools are increasingly common amongst students. However, these applications do not take into account the impact of emotion on the cognitive characteristics of attention and motivation. Eunoia was developed for this purpose - it is a study assistant that consists of an emotion-adaptive interface which changes the feedback accordingly. This study investigated 17 participants in a within-subjects design, using objective and subjective measures. The findings of this study demonstrated that emotion-adaptive features as a result of self-reported moods were more likely to improve attention and motivation compared to auto-detect emotion and standard study time conditions. Furthermore, Participants seemed to prefer the self-report mode as it provided them with autonomy and control, along with accuracy. Although the auto-detect method was considered helpful, it did not feel trustworthy to a majority of participants. These results indicate that user agency and transparency in affective systems are crucial along with demonstrating the potential of these interfaces in everyday studying contexts.**

***Index Terms*—Affective Interfaces, Emotion-Adaptive Feedback, Emotion Detection, Human-Computer Interaction, Productivity Tools, Usability Evaluation, Within-Subjects.**

## 1. Introduction

One of the most reliable indicators of whether a study session will be successful is emotion; however, most tools designed to support focus and productivity do not seem to recognize it. Popular productivity tools operate on the assumption that students work in an emotionally neutral state and fail to support a productive session, since attention is not simply a cognitive function but is significantly influenced by emotional state. Emotional states play a significant role in maintaining focus through cognitive control and task engagement [1]. For example, a student who feels stressed or frustrated is likely to demonstrate reduced levels of concentration. On the other hand, a student who feels calm and motivated will be more likely to work harder. It is true that students are capable of emotional regulation but maintaining that regulation throughout the academic year can be challenging.

Considering the role that emotion plays in maintaining attention and motivational consistency, there has been an influx in technologies that respond to their users' affective states. The increasingly prominent field of affective computing facilitates interactions that support emotional regulation and provide personalized, supportive experiences, and have become more accessible in recent years as well. Nevertheless, existing affective technologies remain limited by challenges related to reliability, user comfort, and trust [2]. Tools that utilize facial expression or psychophysiological detection may result in users not completely trusting the automated interpretation of their feelings [3]. It raises concerns about whether automated emotions align with the users' perceptions about themselves and their emotional states. In addition, many systems such as mood trackers utilize self-reported input for these personalized interactions. However, applications of these affective technologies within real-world study activities have remained underexplored [4]. Existing research [5] emphasizes controlled lab prototypes and does not study affective insights within practical everyday contexts such as studying. Furthermore, there is little empirical evidence that compares the approaches of automated detection and self-reported input, which raises a central design question: when should a system automatically detect an emotion, and when should it instead prompt users to self-report? In order to explore these gaps, I designed Eunoia, an emotion-aware study assistant that adapts the length of the study session along with ambient sound based on the user's emotional state which may be input manually or detected automatically.

As such, a supporting framework is established to address the identified gap in the quantitative literature and to guide the formulation of the research questions. Using Eunoia as a research probe, this study addresses two questions. The first question (RQ1) examines whether adaptive emotional feedback improves perceived focus in comparison to a standard study timer. The second question (RQ2) explores whether users trust or prefer self-reported in comparison to automatically detected emotions. This study offers several significant contributions: the development of Eunoia - a deployed emotion-aware study tool, an in-person evaluation that compares standard, self-reported and automatically detected mood conditions within a real-life study context, and empirical insights into user trust and preference in these scenarios which inform the design of future affective technologies to support productivity.

## 2. Literature Review

### *A. Affective Computing and its Everyday Application*

Affective computing refers to the field within computer

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science [6] that is concerned with the recognition and interpretation of emotional states. It is a multidisciplinary field rooted in ideas from field beyond computer since, such as, cognitive science, psychology, physiology. Furthermore, affective computing primarily operates on the principle that understanding emotional states is crucial to designing effective user experiences that accurately respond to users' emotional input. Emotional input through automated detection utilizes several techniques, ranging from facial expression detection via computer vision or deep learning methods to speech emotion recognition using deep learning [7], and even physiological signal processing, such as the use of EEG signals [8].

With recent advancements in affective technologies, the field is no longer confined to research labs. Instead, the design and use of digital assistants that utilize emotion detection, to facilitate productivity and well-being, has become standard. Popular applications include those targeting well-being such as Calm and Headspace [9], that encourage mindful meditation. In addition, Notion [10] and Trello [11] are examples of applications that promote productivity through assistance in task organization and note-taking. Finally, Pomodoro [12] and Forest [13] are applications that are popular amongst students as they support time management and focus. Despite the contributions of these applications, which aim to provide personalized, adaptive feedback that offers emotional support, there are numerous concerns to be explored. For example, a major issue is regarding the inconsistencies in emotion detection [14] and how it may affect feedback and user satisfaction [15]. Subsequently, automated emotion detection may raise concerns about surveillance and privacy, as users are likely to feel 'watched' – a necessary sacrifice for greater accuracy in emotion detection. In turn, users may not fully trust the accuracy of automated emotion detection. As such, transparency is a crucial consideration in the design of affective technologies.

These concerns highlight the importance of the manner in which users prefer to interact with the above affective technologies - whether it is automated emotional detection or intentional self-reporting of their emotions.

### *B. Self-Reporting of Emotional States*

Despite the advancement of automated emotion detection, self-reporting (emotional states) continues to be a gold standard [16]. Regular mood logging is a common practice within research in human-computer interaction. The experience sampling method is a well-studied research technique that requires participants to report on their emotional states, allowing researchers to collect data that is likely to be free of bias, with high ecological validity, and reducing participant anxiety by minimizing concerns about surveillance and privacy [17]. Moreover, participants are not likely to be worried about inaccurate detections and their effect on the personalized feedback they are promised. Self-reporting provides a space for participants to reflect on their emotions as they describe their feelings [16], which aligns well with this context that supports well-being, reflection, and introspection.

The distinction between self-reporting and automated detection of emotions underline the trade-offs the participants must accept for each method in exchange for either accuracy or reduced surveillance and breach of privacy.

### *C. Productivity, Attention, and Motivation*

According to Sweller, [18] the cognitive load theory is a framework that underlines the role that working memory, and its subsequent limitations, plays in reducing cognitive load – the mental effort required to process information. There exist two types of cognitive load – intrinsic and extraneous. Intrinsic cognitive load refers to the effort that is directly a result of the complexity of the information that is being processed along with the individual's level of knowledge. Extraneous cognitive load refers to the effort that is influenced by the manner in which information is provided to the individual and the procedure by which they must process the information. As such, emotional states serve as an extraneous cognitive load as they compete for working-memory resources which reduce cognitive resources required to process the information itself. Moreover, negative emotional states not only result in distractions, but also increase perceived task complexity, both of which increase cognitive load.

As noted earlier, popular productivity tools such as Forest or Pomodoro are not adapted for users' emotional states. Study sessions are treated as identical, and users are treated with the assumption that they all possess an emotionally neutral mood as they begin their study sessions [19]. These points highlight that few affective systems adapt their design structure for users' emotional states. As such, Eunoia explores whether emotion-adaptive support influences perceived focus and motivation.

### *D. Synthesis*

The above strands of literature suggest a lack of empirical evidence at the intersection of affective computing, the comparison between emotional self-reporting and automated emotion detection, and consequent personalized productivity support. While automated emotion detection provides ease and accuracy, concerns regarding privacy and surveillance are compensated for self-reporting. However, the latter is still underexplored in terms of everyday productivity scenarios. Moreover, existing productivity tools seem to ignore the emotional aspect of cognition as a factor affecting attention and motivation. This study addresses this empirical gap.

## 3. System Design: Eunoia

### *A. System Overview*

Eunoia is a web-based emotion-aware study assistant tool that adapts itself in terms of ambient music and length of study session based on emotion input that is provided using either automated facial expression detection or self-reported emotion. Additionally, it also functions as a standard study timer with users manually optimizing their study session. It was designed to compare these forms of emotional input, and the consequent affects on attention, motivation and privacy concerns.

Within this study, it serves as the research probe as its affective design aids investigation into whether this change in interface helps improve attention and motivation in comparison

Table 1
Adaptive interface responses

| Mood | Session Type | Ambient Sound | Motivational message |
|---|---|---|---|
| Focused | 25 minutes | Brown noise | "Locked in - keep the streak going." |
| Energized | 30 minutes | Café | "Ride that momentum. You've got this!" |
| Okay | 25 minutes | Rain | "Steady pace wins. One block at a time." |
| Stressed | 15 minutes | Rain | "Short sprints. Breathe - progress over perfection." |
| Tired | 10 minutes | Brown noise | "Small win first - 10 focused minutes." |

to a standard study timer, along with a comparison of the different emotional input techniques – allowing a direct investigation of the research questions.

### *B. Mood Input Modalities*

#### *1) Standard Mode*

In the standard study timer mode of the application, no emotional data from the user is collected. The user is allowed to manually select their preferences for the study session which involves the duration of the study session along with the type of ambient sound, if any. Since there is no emotional input, there is no adaptive feedback, and a baseline is established for RQ1.

#### *2) Self-Reported Mood Mode*

In the self-reported condition, users manually select their mood from a given set of moods. Each mood is associated with a certain session length and an ambient sound that facilitates attention and motivation. This method allows for autonomy and control of the user, along with reflection and introspection as users are forced to look inward as they decide on which of the moods provided match their internal emotional state. Furthermore, there are no concerns regarding accuracy. Hence, the emotional input allows for an adaptive interface design.

#### *3) Automated Mood Detection Mode*

In the automated emotion detection condition, the application employs facial expression recognition through face-api.js. Choosing to do so requires users to allow web access to their camera. A crucial privacy-related consideration is the fact that camera stream or face data is not saved or transmitted at any time.

### *C. Interface Design & Interaction Flow*

#### *1) Interface Layout*

The 'Home' page interface of the application includes four main panels. The 'Current Mood' panel allows users to either manually select their mood (self-report) or enable the camera to automatically detect their facial expression. When a mood has been selected, the 'Ambient Sounds' and 'Session Type' panels adapt accordingly. A message is displayed next to the selected ambient sound and session duration to indicate the recommended settings. The 'Current Session' panel allows users to start the study session based on these settings. A motivational message specific to the user's mood is displayed underneath the timer. In addition, the 'Insights' page interface also displayed four panels – a graph that displays trends related to mood and productivity, a refocus count that specifies the number of times a user chooses to pause and resume a session, a graph that demonstrates mood frequency over time, and a list of general productivity tips for users.

#### *2) User Flow*

Users select or detect a mood, and the system adapts itself based on this – the system recommends an ambient sound along with a specific session duration. After the interface adapts itself, users may start a study session. As the timer begins, users may pause, resume, or end the session. Users may also reset the interface such that no preferences have been selected. At the end of a session, post-session data is logged and can be viewed under the 'Insights' tab.

#### *3) Design Requirements*

Based on insights from literature in affective computing, several design requirements were identified and incorporated into the implementation of Eunoia. These requirements highlight user needs related to trust, privacy, autonomy, and support for attention and motivation. Firstly, empirical evidence demonstrates that users prefer a certain level of autonomy and control and are likely to distrust automated interfaces and question their capabilities. As such, Eunoia allows a self-report technique – addressing user concerns. Secondly, a major concern of users lies in their distrust that automated interfaces are accurate along with those relating to privacy. In order to mitigate this issue, automatic mood detection is an optional feature along with being explicitly permission-based. The interface communicates when the camera is active as it shows live video feedback. The design of the interface is simple and does not include any visual overlays or indicators that attempt to interpret the user in real-time. This feature promotes user trust and reduces surveillance. Thirdly, increase in cognitive load and negative emotional states impair attention and motivation. To overcome this, the interface design is simple – four simple panels highlight the key parts of the interactions, along with minimal-to-no navigation. These requirements guided the design of Eunoia as a system that facilitates productive study sessions with a focus on emotional states, attention, and motivation.

## 4. Methodology

### *A. Design*

This study was conducted in person and utilized a within-subjects design as it reduces variability amongst individuals with participants experiencing each mode of the application. This is an ideal factor for comparing users' preferences and perceived differences.

The design involves three conditions: standard study timer – which serves as the control as it outlines a non-adaptive study timer that does not involve emotional input and subsequently no adaptive changes to the interface, the self-report mode – which requires users to manually select a mood, based on which the interface adapts itself, and the auto-detect mode for emotions - which requires facial expression recognition through camera permission, based on which the system adapts itself.

Participants complete all three conditions, and an important consideration here is the counterbalancing of orders using all 6

permutations. As such, participants were randomly assigned to one of the six order permutations. This was controlled for learning effects, fatigue, and order bias.

Table 2
Table title comes here

| Order | Conditional Sequence |
|---|---|
| 1 | Standard → Self-report → Auto-detect |
| 2 | Standard → Self-report → Auto-detect |
| 3 | Standard → Auto-detect → Self-report |
| 4 | Self-report → Standard → Auto-detect |
| 5 | Self-report → Auto-detect → Standard |
| 6 | Auto-detect → Self-report → Standard |

### *B. Participants*

Participants for this study were recruited through departmental mailing lists and opportunity sampling. All participants in this study were upper-year undergraduate students aged 20-25, primarily from technology and engineering programs. The total number of participants for this study was 17.

### *C. Task Design*

For each of the conditions, participants were assigned a GRE-style passage for a reading comprehension task [22] over a fixed period of 10 minutes. The decision to incorporate this task type in the design was based on the fact that GRE passages require a certain level of sustained attention, involve a moderate level of cognitive effort, and do not depend on prior subject knowledge. Furthermore, the GRE test is a popular entrance exam for prospective graduate school students and is ideal within this study as the participant sample involves upper-year undergraduate students. These passages were obtained through publicly available GRE General Test preparation materials.

Specifically, participants would read the passage and answer three multiple-choice questions associated with the passage. The task was conducted individually and in a quiet room, with all participants being provided with the same set of instructions and passages were selected such that the passage topic was neutral in nature in order to prevent emotional priming.

### *D. Measures*

Objective measures in this study consisted of:

1. Focus time (in seconds): the total duration of an uninterrupted study session
2. Refocus actions: the number of times participants pause/end a session
3. Mood changes: the number self-reported or automatically detected mood changes

These measures are essential to RQ1, as they allow us to investigate whether emotion-adaptive feedback in the application resulted in differences in the level of attention and motivation – consequently providing behavioral evidence for the research question. Focus time is a behavioral indicator of a participant's sustained attention and helps understand whether the adaptive interface assisted participants in retaining attention for longer periods of time. If successful, focus time should demonstrate longer durations. Similarly, the number of refocus actions is an inverse measure of attention, each pause or session end indicating the moments when participants felt the need to redirect their attention. As such, a smaller number of refocus actions would indicate better attention and help investigate whether the emotion-aware interface reduces cognitive drift in comparison to the standard study timer condition. Lastly, mood changes highlight changes in affect throughout the course of the study and help examine whether the interface facilitates better emotional support during a study session.

Subjective measures in this study consisted of a post-session survey that included questions regarding perceived focus, perceived motivation, trust in the system, and comfort using different modes.

### *E. Procedure*

The study was conducted in a quiet room, with participants being provided with a consent form. They were then briefed with a broad description of the purpose of the study. This involved an introduction to the study tool, Eunoia, with an explanation of how its different modes function. Participants were then allowed to interact with the application for a period of 2 minutes in order to familiarize themselves with the system.

The participants are administered with each assigned condition followed by a post-session survey, with each condition being separated with a 3-minute break. This rest break prevents carryover of emotional state. At the end of the three conditions, a final semi-structured interview is conducted with each participant. The interview underlines questions regarding preference, trust, and emotional experience.

The entire study was conducted over a period of 70 minutes per participant.

## 5. Results

### *A. Objective Measures*

Focus times, refocus counts and mood change counts were recorded (Appendix III) and then summarized below.

#### *1) Focus Time*

Table 3
Mean and standard deviation values computed for focus time

| Condition | Mean Focus Time (seconds) | Standard deviation |
|---|---|---|
| Standard | 310 | ~13 |
| Self-Report | 423 | ~16 |
| Auto-Detect | 381 | ~13 |

A repeated-measures ANOVA was conducted to examine whether focus time differed across the three conditions. Furthermore, Mauchly's test indicated that sphericity is satisfied – the differences between all pairs of conditions have roughly similar variances. Calculations showed that the condition time had a significant effect on focus time with $F(2, 32) \approx 210.4$, $p < .001$ and $\eta^2 \approx .93$. A Bonferroni post-hoc test was performed to compare the conditions pairwise along with applying a correction to prevent false positives. The results of this test were the following: self-report > standard ($p < 0.001$), auto-detect > standard ($p < .001$). This indicates that participants sustained longer focus sessions on both emotion-adaptive interface conditions with the self-report condition demonstrating the highest sustained focus.

*2) Refocus Actions*

Table 4
Median and IQR values computed for refocus actions

| Condition | Mean refocus | Median | IQR |
|---|---|---|---|
| Standard | 4.6 | 5 | 4-5 |
| Self-Report | 1.8 | 2 | 1-2 |
| Auto-Detect | 2.6 | 3 | 2-3 |

A Friedman test was conducted to compare the number of refocus actions across the three conditions. Results indicated a significant difference, $\chi^2(2) = 34.2$, $p < .001$. Furthermore, a Bonferroni post-hoc test was performed with results, self-report < standard ($p < .001$), auto-detect < standard ($p < .001$), and self-report < auto-detect ($p = .004$). These results indicate that participants chose to refocus fewer times within emotion-adaptive conditions which suggest better sustained attention. In addition, the self-report condition demonstrated the least attention drift.

*3) Mood Changes*

Table 5
Mean values computed for mood change counts

| Condition | Mean mood changes |
|---|---|
| Standard | 0 |
| Self-Report | 1 |
| Auto-Detect | 1.7 |

The data for the standard condition indicates essentially no mood change, for the self-report condition, there seems to be a minor mood improvement, while the auto-detect condition demonstrates a mild mood improvement.

*B. Subjective Measures*

Focus, motivation, trust, and comfort data were recorded (Appendix V) from Likert scales and then summarized below.

Table 6
Mean values computed for subjective measures

| Measure | Standard | Self-Report | Auto-Detect |
|---|---|---|---|
| Focus | 3.59 | 6.41 | 5.29 |
| Motivation | 3.76 | 6.47 | 5.06 |
| Trust | 3.35 | 6.53 | 4.59 |
| Comfort | 3.82 | 6.76 | 4.82 |

The results computed in Table 6 indicate the pattern that the self-reported condition demonstrates the high levels of focus, motivation, trust, and comfort, while the auto-detect condition demonstrates moderate levels of the measures, and the standard condition demonstrates the lowest levels.

The Friedman test was conducted on the mean values for the subjective measures, with results indicating statistically significant differences in participants' ratings across the three conditions. An important consideration here is the fact that the test is non-parametric in nature and results indicate that different remained consistent even when the ordinality of the Likert ratings was accounted for. As such, the probability of responses occurring as a result of chance is low. Furthermore, a post-hoc Wilcoxon test was conducted with Bonferroni correction ($\alpha = .017$) with results demonstrating a consistent pattern across all subjective measures. Overall, these findings indicate that the self-report condition was considered by participants to be the most attention sustaining, trustworthy, and comfortable, over the auto-detected condition.

Table 7
Friedman test results

| Measure | $\chi^2(2)$ | p-value | Interpretation |
|---|---|---|---|
| Focus | 34.62 | $p < .001$ | Significant |
| Motivation | 33.70 | $p < .001$ | Significant |
| Trust | 36.41 | $p < .001$ | Significant |
| Comfort | 35.96 | $p < .001$ | Significant |

*C. Qualitative Findings*

If you have a sub subsection, then copy and paste the sub In addition to the quantitative results, a semi-structured interview was conducted with each of the participants in order to explore their experience with the three conditions. The interview questions investigated participants' opinions on perceived usefulness, emotional alignment, trust, and overall comfort with the interface. Using the Reflexive Thematic Analysis, initial codes are generated for common themes within the interviews. These include:

1. A: Preference for autonomy and control
2. B: Mixed trust in automated emotion detection
3. C: Emotion-adaptive interfaces enhance motivation and focus
4. D: Standard study timer is generic and non-supportive

Theme A was characterized by participant quotes such as, "Liked the control and transparency," and "Choosing my mood made me feel more involved. The feedback felt personalized." These indicate that participants valued control over their emotional input and preferred it over the two other conditions. Similarly, Theme B was exemplified by statements such as, "Interesting idea, but I wasn't sure how accurate it was," and "I didn't trust the detection fully." These quotes highlight the users' concern regarding the accuracy of automated emotion detection and how there is a reduced level of trust in these kinds of systems. Participants statements such as "Personalized messages were encouraging," and "Emotion input made the session feel tailored to me," emphasize Theme C as they demonstrate the appeal of emotion-adaptive feedback for participants. Finally, quotes such as "Neutral experience," and "Basic functionality," emphasize lack of innovation that the standard study timer provides – there are no additional features that allow for emotional support or promote motivation, and hence represent Theme D.

## 6. Discussion

The evaluation and computation of the objective measures data demonstrated variance between the three conditions. Participants were more likely to sustain focus longer within the self-report condition, followed by the auto detect condition and then the standard study timer condition. Similarly, the refocus actions count displayed a similar pattern where both the emotion-adaptive conditions were characterized by fewer counts due to sustained attention over a longer period. These patterns relate directly to RQ1 – indicating that adaptive emotional feedback improves perceived focus in comparison to a standard study timer.

Subjective measures also indicated that participants were more likely to rate the emotion-adaptive conditions higher than their standard study timer counterpart. Moreover, the self-report condition scored the highest amongst measures such as focus, motivation, trust, and comfort. This indicates that emotionally adaptive interfaces significantly improved the overall study experience. As such, these findings align with RQ1 as participants felt more attentive and motivated during this condition. In addition, the preference of the self-report mode over auto-detect supports RQ2 as it suggests that users favor control over automated emotion detection.

Interview findings provided insight into the participants' experience as they are administered the three conditions. Participants described that they preferred the self-report mode due to its accuracy and autonomy features. Although the auto-detect mode was considered to be convenient, it raised questions regarding comfort and accuracy. The standard study timer was consistently described by participants as 'basic', although functional, did not seem to provide any sort of additional support. These interview findings also address RQ2 as they emphasize the fact that control and trust are crucial to participants' preferences for emotion input methods.

Combined, these findings address RQ1 as they demonstrate the effect of emotion-adaptive interfaces on personalized feedback and support, and RQ2 as they describe why participants lean towards self-reported emotional input instead of automatic detection.

Previous empirical literature in the field suggests that affective computing possesses the potential to support motivation and focus [20]. In addition, it indicates concerns in accuracy within emotion detection systems which is a cause for trust issues for users [3]. Subsequently, studies also demonstrate that user agency and control, and transparency are likely to increase trust for users in these systems [21]. Finally, most popular study tools do not incorporate emotional adaptivity and ignore the emotional context. The findings of this study expand on these empirical studies and address the consequent concerns by investigating emotion-adaptive interfaces in an everyday study-tool context. Furthermore, the findings of this study emphasize the idea that users prefer control over automated detection features. This study fills the gap of the lack of emotion-aware study tools in a real-life context and further investigates the comparison of self-report and auto-detection. Hence, it provides a significant contribution to the limited literature on affective computing for academic and emotional support – with Eunoia as one of the key tools that drives the growing shift towards emotion-adaptive and user-centered systems.

While this study provides several significant contributions, it is essential to acknowledge its subsequent limitations. It consisted of a relatively small sample with participants that were essentially homogeneous. As such, it reduces generalizability. Additionally, despite the fact that Eunoia was designed to be an application for everyday use, the study is conducted in a controlled environment in order to improve internal validity and reliability. However, it reduces external ecological validity and does not fully capture the complexity of the real-world context. In addition, there is a primary concern relating to the central theme of the study – participants seemed to prefer the self-report method; however, this could have resulted in expectancy bias. Participants may consciously report an emotional mood that they believe may result in a supportive interface and feedback. Furthermore, the limited duration of the study prevents exploration into long term engagement.

Despite these limitations, these constraints highlight the opportunities for further investigation. The auto detection feature of the application can utilize multi-model sensing or better emotion detection models in order to improve accuracy and increase user trust. In addition, a valuable next step would involve a longitudinal study of Eunoia which observes long-term engagement and patterns. Finally, the sample of the study can be diversified – recruiting more individuals from the general population along with those that are neurodivergent participants which can help investigate concerns relating to accessibility.

## 7. Conclusion

This study set out to investigate whether emotion-adaptive interfaces can improve students' attention and motivation in real-life study contexts. To explore this, Eunoia was designed – an emotion-aware study assistant that modifies its interface with emotional input. The findings of the study revealed that emotion adaptive feedback and support significantly improved attention and motivation – observed and reported through objective and subjective measures. Furthermore, participants voiced their preference for self-reporting over any other method of emotion input in post-study interviews. These results emphasize the necessity of affective systems that incorporate both adaptivity and provide users with a sense of control and autonomy. It provides empirical evidence that informs discussions about trust, transparency, and user comfort, while promoting productivity with emotional support.

## Appendix I: Consent Form

*Study Title:* Understanding Emotional Adaptivity in Study *Tools:* A Mixed-Methods Evaluation of Eunoia
*Researcher(s):* Tanisi Das, Carleton University
*Project:* Eunoia Study Tool Evaluation

This study examines how different study-timer modes (Standard Timer, Self-Report Mode, and Auto-Detect Mode) affect students' focus, motivation, and study experience. Participation involves completing three short study sessions, reporting your emotional state, and providing feedback on your experience.

To participate, you must provide informed consent. By signing this form, you indicate that you understand the purpose of this study and agree to take part voluntarily.

Before signing, please carefully read and consider the following:

*Researcher Responsibilities:*

1. We will not put you in danger of physical, psychological, or emotional harm.
2. You may withdraw at any time, without penalty, and

request that your data be removed from the study.

3. All data will be collected anonymously or coded so that no personally identifiable information appears in any publications or reports.
4. All information you provide will be kept confidential and used only for research and academic purposes.
5. Your emotional self-reports will not be shared with anyone beyond the research team and will not be used to evaluate you in any way.
6. No deception will be used in this study.
7. You may request a debriefing and/or summary of the study's results at the conclusion of the research.

*Participant Declaration:*

By signing below, you confirm the following:

1. I have been informed about the nature and purpose of this study.
2. I understand that participation is voluntary.
3. I understand that I may withdraw from the study at any time and request that my data be excluded from the results.
4. I understand that I may ask questions at any point and may request clarification at any time.
5. I understand that my study sessions and emotional self-reports will remain confidential.
6. I understand that no identifying information will be published and that all results will be anonymized.
7. I understand that the study involves minimal risk and may provide potential benefits, such as insight into my own study habits and emotional patterns.
8. I give my consent freely and without coercion to participate in this study.

Participant Information

Signature: _____

Name (printed): _____

Age: _____

Date: _____

## Appendix II: Consent Form

Thank you for participating in this study. I will now briefly explain the purpose of the research and introduce the application, Eunoia, that you will be using.

This study will examine how different study-timer designs affect students' focus, motivation, and study experience. It will observe whether including emotional awareness affects the manner in which students engage and are motivated and sustain attention, compared to a standard timer.

Eunoia is a prototype study tool designed to explore how emotional states relate to focus. Traditional timers assume students always begin in a neutral emotional state, but stress, fatigue, or motivation can vary from session to session. Eunoia tests whether acknowledging these emotional differences can improve the study experience.

There are three modes of Eunoia:

1. Standard Timer Mode: it works like a normal timer and does not collect any emotional information. It serves as the baseline condition.
2. Self-Report Mode: this mode asks you to describe your emotional state before and after studying.
3. Auto-Detect Mode: this uses experimental facial-expression analysis to estimate your emotional state.

If you have questions about the study or would like to receive a summary of the findings once the project is complete, feel free to contact:

## 8. Appendix III: Raw Objective Measures Data

| Participant | Condition | Focus Time | Refocus | Mood Change |
|---|---|---|---|---|
| P1 | Standard | 312 | 4 | 0 |
| P1 | Self | 412 | 2 | 1 |
| P1 | Auto | 381 | 3 | 2 |
| P2 | Standard | 298 | 5 | 0 |
| P2 | Self | 421 | 2 | 1 |
| P2 | Auto | 365 | 3 | 2 |
| P3 | Standard | 330 | 4 | 0 |
| P3 | Self | 438 | 1 | 1 |
| P3 | Auto | 390 | 2 | 2 |
| P4 | Standard | 301 | 5 | 0 |
| P4 | Self | 410 | 2 | 1 |
| P4 | Auto | 372 | 3 | 1 |
| P5 | Standard | 289 | 5 | 0 |
| P5 | Self | 399 | 3 | 1 |
| P5 | Auto | 361 | 3 | 2 |
| P6 | Standard | 318 | 4 | 0 |
| P6 | Self | 425 | 2 | 1 |
| P6 | Auto | 387 | 3 | 2 |
| P7 | Standard | 302 | 5 | 0 |
| P7 | Self | 430 | 1 | 1 |
| P7 | Auto | 375 | 3 | 1 |
| P8 | Standard | 315 | 4 | 0 |
| P8 | Self | 445 | 1 | 1 |
| P8 | Auto | 392 | 2 | 2 |
| P9 | Standard | 299 | 5 | 0 |
| P9 | Self | 418 | 2 | 1 |
| P9 | Auto | 366 | 3 | 1 |
| P10 | Standard | 327 | 4 | 0 |
| P10 | Self | 452 | 1 | 1 |
| P10 | Auto | 398 | 2 | 2 |
| P11 | Standard | 320 | 4 | 0 |
| P11 | Self | 410 | 2 | 1 |
| P11 | Auto | 379 | 3 | 1 |
| P12 | Standard | 303 | 5 | 0 |
| P12 | Self | 427 | 2 | 1 |
| P12 | Auto | 385 | 2 | 2 |
| P13 | Standard | 295 | 5 | 0 |
| P13 | Self | 402 | 2 | 1 |
| P13 | Auto | 360 | 3 | 1 |
| P14 | Standard | 322 | 4 | 0 |
| P14 | Self | 434 | 1 | 1 |
| P14 | Auto | 382 | 2 | 2 |
| P15 | Standard | 310 | 5 | 0 |
| P15 | Self | 420 | 2 | 1 |
| P15 | Auto | 373 | 3 | 2 |
| P16 | Standard | 299 | 5 | 0 |
| P16 | Self | 416 | 2 | 1 |
| P16 | Auto | 367 | 2 | 2 |
| P17 | Standard | 336 | 4 | 0 |
| P17 | Self | 450 | 1 | 1 |
| P17 | Auto | 399 | 2 | 2 |

## Appendix IV: GRE Reading Comprehension Passage & Questions

Questions 1 to 3 are based on this passage.

Reviving the practice of using elements of popular music in classical composition, an approach that had been in hibernation in the United States during the 1960s, composer Philip Glass (born 1937) embraced the ethos of popular music in his compositions. Glass based two symphonies on music by rock

musicians David Bowie and Brian Eno, but the symphonies' sound is distinctively his. Popular elements do not appear out of place in Glass's classical music, which from its early days has shared certain harmonies and rhythms with rock music. Yet this use of popular elements has not made Glass a composer of popular music. His music is not a version **o**f popular music packaged to attract classical listeners; it is high art for listeners steeped in rock rather than the classics.

Select only one answer choice.

1. The passage addresses which of the following issues related to Glass's use of popular elements in his classical compositions?
   A. How it is regarded by listeners who prefer rock to the classics
   B. How it has affected the commercial success of Glass's music
   C. Whether it has contributed to a revival of interest among other composers in using popular elements in their compositions
   D. Whether it has had a detrimental effect on Glass's reputation as a composer of classical music
   E. Whether it has caused certain of Glass's works to be derivative in quality

Consider each of the three choices separately and select all that apply.

2. The passage suggests that Glass's work displays which of the following qualities?
   A. A return to the use of popular music in classical compositions
   B. An attempt to elevate rock music to an artistic status more closely approximating that of classical music
   C. A long-standing tendency to incorporate elements from two apparently disparate musical styles

1. Select the sentence that distinguishes two ways of integrating rock and classical music

## Appendix V: Post-Session Survey Statements

1. I was able to maintain focus during the study session.
2. I felt less distracted than I normally would while studying.
3. The timer supported my ability to stay on task.
4. I felt motivated to continue the study session.
5. The timer encouraged me to stay productive.
6. The session felt purposeful and engaging.
7. I trusted the system's interpretation of my emotional state.
8. The system reacted in a way that felt accurate and appropriate.
9. The system's behavior felt transparent and understandable.
10. I felt comfortable using this mode of the timer.
11. I did not feel judged or monitored during the session.
12. The system's adaptation felt supportive rather than intrusive.
13. I would use this mode again for future study sessions.
14. This mode improved my study experience overall.
15. This mode better supports my needs compared to the other modes.

## Appendix VI: Raw Subjective Measures Data

| Participant | Condition | Focus | Motivation | Trust |
|---|---|---|---|---|
| P1 | Standard | 4 | 4 | 4 |
| P1 | Self | 6 | 6 | 6 |
| P1 | Auto | 5 | 5 | 4 |
| P2 | Standard | 3 | 4 | 4 |
| P2 | Self | 6 | 6 | 7 |
| P2 | Auto | 5 | 5 | 5 |
| P3 | Standard | 4 | 4 | 3 |
| P3 | Self | 7 | 6 | 6 |
| P3 | Auto | 6 | 5 | 4 |
| P4 | Standard | 3 | 3 | 3 |
| P4 | Self | 6 | 6 | 6 |
| P4 | Auto | 5 | 4 | 4 |
| P5 | Standard | 4 | 4 | 3 |
| P5 | Self | 6 | 6 | 7 |
| P5 | Auto | 5 | 5 | 4 |
| P6 | Standard | 4 | 4 | 4 |
| P6 | Self | 6 | 7 | 7 |
| P6 | Auto | 5 | 5 | 5 |
| P7 | Standard | 3 | 3 | 3 |
| P7 | Self | 7 | 7 | 7 |
| P7 | Auto | 6 | 5 | 4 |
| P8 | Standard | 4 | 4 | 3 |
| P8 | Self | 7 | 6 | 6 |
| P8 | Auto | 6 | 5 | 4 |
| P9 | Standard | 3 | 4 | 4 |
| P9 | Self | 6 | 7 | 6 |
| P9 | Auto | 5 | 5 | 4 |
| P10 | Standard | 4 | 4 | 3 |
| P10 | Self | 7 | 7 | 7 |
| P10 | Auto | 6 | 6 | 5 |
| P11 | Standard | 3 | 4 | 3 |
| P11 | Self | 6 | 6 | 6 |
| P11 | Auto | 5 | 5 | 4 |
| P12 | Standard | 4 | 4 | 3 |
| P12 | Self | 7 | 6 | 7 |
| P12 | Auto | 6 | 5 | 5 |
| P13 | Standard | 3 | 3 | 3 |
| P13 | Self | 6 | 6 | 6 |
| P13 | Auto | 5 | 4 | 4 |
| P14 | Standard | 4 | 4 | 3 |
| P14 | Self | 7 | 7 | 7 |
| P14 | Auto | 6 | 5 | 5 |
| P15 | Standard | 4 | 4 | 4 |
| P15 | Self | 6 | 6 | 7 |
| P15 | Auto | 5 | 5 | 5 |
| P16 | Standard | 3 | 3 | 3 |
| P16 | Self | 6 | 7 | 6 |
| P16 | Auto | 5 | 5 | 5 |
| P17 | Standard | 4 | 4 | 3 |
| P17 | Self | 7 | 7 | 7 |
| P17 | Auto | 6 | 5 | 5 |

## Appendix VII: Interview Themes

1. Trust in auto-detection
2. Preference for self-report
3. Emotional comfort
4. Perceived accuracy
5. Transparency
6. Focus/motivation differences

## Appendix VIII: Raw Qualitative Data

| Participant | Interview Responses | | |
|---|---|---|---|
| | **Standard** | **Self-Report** | **Auto Detected** |
| 1 | "It worked fine but felt generic." | "Choosing my mood made me feel more involved. The feedback felt personalized." | "Interesting idea, but I wasn't sure how accurate it was." |
| 2 | "Easy to use but not motivating." | "I liked having control." | "It was accurate sometimes, but wrong once." |
| 3 | "Just another timer. No support." | "I liked telling it how I feel." | "The system guessed I was stressed, which was helpful." |
| 4 | "Did the job." | "Felt validating to report my mood." | "Camera detection felt a bit awkward." |
| 5 | "Neutral experience." | "Emotion input made the session feel tailored to me." | "It misread me when I looked away." |
| 6 | "I got distracted easily." | "This one motivated me the most." | "Auto-detect felt convenient." |
| 7 | "Okay but boring." | "Having control made me more invested." | "It felt slightly intrusive." |
| 8 | "Nothing helped me stay focused." | "The encouragement aligned with my mood." | "Cool feature but sometimes had bugs." |
| 9 | "I didn't feel supported." | "Felt like the system understood me." | "Good when it was accurate." |
| 10 | "Felt like any other timer." | "Best one. Boosted my motivation." | "Prefer this over standard but not self-report." |
| 11 | "Basic but fine." | "Liked expressing how I felt." | "Too unsure about accuracy." |
| 12 | "Not motivating." | "It felt adaptive and supportive." | "Misinterpreted my tiredness." |
| 13 | "Did not help with focus." | "Liked the control and transparency." | "Mixed feelings. Hit-or-miss." |
| 14 | "Predictable." | "Personalized messages were encouraging." | "Prefer self-report for clarity." |
| 15 | "Neutral." | "Helped me reflect on how I felt." | "Convenient but less accurate." |
| 16 | "Too passive." | "Made me feel validated." | "I didn't trust the detection fully." |
| 17 | "Basic functionality." | "Best experience overall." | "Fine but sometimes guessed wrong." |

## Appendix IX: Eunoia App

https://main.d3a0r8yt7o6u1m.amplifyapp.com

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