Help, Don’t Control: Measuring User Emotional Background in AI Assistant Interaction

Anastasiia Satarenko
an.sat@macpaw.com
MacPaw Inc.
Kyiv, Ukraine

Abstract

As AI assistants shift from answering questions to executing actions, small interaction choices can influence users’ moment-to-moment experience. We report an exploratory lab study (N=20) measuring users’ Emotional Background (EB) during three local device-maintenance tasks in a prompt-based assistant and a menu-based baseline interface. We derived an EEG-based EB index and triangulated it with eye tracking and post-task questionnaires. EB trajectories were task-dependent: the prompt-based assistant produced higher EB for straightforward app deletion, while the baseline yielded higher EB for malware checking and troubleshooting. EB decreases appeared to cluster around three interaction moments: formulating an initial request, encountering negatively framed system-health terminology, and processing rapid or ambiguous automation of consequential actions. Survey responses indicated greater willingness to delegate non-personal tasks than personal communications. We discuss these patterns as preliminary evidence and outline design considerations for pacing, framing, transparency, and prompt scaffolding.

CCS Concepts

• **Human-centered computing → User studies**; *Laboratory experiments*; **Empirical studies in HCI**.

Keywords

Emotional Background, EEG, Eye-tracking, Usability Testing

ACM Reference Format:
Anastasiia Satarenko. 2026. Help, Don’t Control: Measuring User Emotional Background in AI Assistant Interaction. In *ACM Conversational User Interfaces 2026 (CUI ’26), July 21–24, 2026, Bremen, Germany*. ACM, New York, NY, USA, 6 pages. https://doi.org/10.1145/3816046.3816285

1 Introduction

This is a test local citation [31]

Artificial Intelligence (AI) technology is increasingly being incorporated into apps and websites, with AI Assistants (AIAs) emerging as one of the most promising and rapidly evolving applications. As AIAs shift from answering questions to executing actions, interaction becomes a negotiation of control. Small design choices, such as confirmation, pacing, framing, and explanation, may shape users’ comfort in the moment. In this work, we adopt a product-centered perspective on Emotional Background (EB) and analyze how design choices, system behavior, and User Experience (UX) writing shape the user experience. To ensure conceptual clarity, following Damasio’s concept of "background feeling" [12], we define EB as an ongoing, low-intensity feeling internalized in the body that continuously affects our conscious experience. While these feelings are subtle, unlike emotions in a traditional sense, and can go unnoticed by the person, analyzing them with an Electroencephalogram (EEG) can provide insight into the background of bodily sensations that precede and shape our emotional responses. The importance of EB during app usage [22] is especially significant for first-time users [13] as it can strongly influence their early experience with the product. Ignoring EB can affect users’ early experience, customer loss, and long-term retention. Additionally, using EB as an evaluation method helps anticipate user stress and discomfort, promoting a more user-centered approach that improves both retention and satisfaction. While prior work has examined trust, adoption, and attitudes toward AI assistants, less is known about how users’ affective state fluctuates during the moment-by-moment execution of assistant-mediated tasks. In this work we investigate how various tasks in a prompt-based AIA for local device maintenance affect users’ EB, how EB differs between personal and non-personal tasks delegated to an AIAs, and how EB changes can be captured during task completion. We measured users’ EB across several tasks, identified the most prominent drops, and conducted a survey to examine how users feel about delegating specific tasks to an AIA. Based on these findings, we present preliminary design considerations and hypotheses for creating AIA interfaces that support a more positive and stable EB during interaction.

2 Background

Previous research on AIAs and AI-based chatbots has examined anthropomorphic features and personality [24] [18] [27] [33], user relationships with AIAs [29][23], emotional attachment [9] [4][3], and trust as a driver of adoption and retention [25] [16]. Prior work also suggests a link between EB and trust in interfaces, showing that positive emotions can increase trust [11] and shape users’ willingness to engage with AIAs in everyday contexts [30] [8] [2]. However, most of this work emphasizes attitudes toward AIAs rather than users’ moment-to-moment affective experience during task execution, which may be especially important, as interaction unfolds through system initiative, prompt interpretation, and varying degrees of automation.

To assess such affective responses during interaction, prior HCI and neurophysiological research has used several measurement approaches, including the Layered Emotion Measurement tool [10], and multimodal approaches that combine screen recordings, facial

ACM ISBN 979-8-4007-2741-2/2026/07
https://doi.org/10.1145/3816046.3816285

recognition, galvanic skin response, and questionnaires [17]. In this research, we use EEG to track moment-to-moment changes in EB and relate them to specific interface events during task completion.

Russell's circumplex model [26] provides a basis for interpreting emotional responses along valence and arousal dimensions. In this study, we use it to interpret EEG-based EB results as indicators of users' affective responses during interaction tasks, with higher EB values indicating more positive affect and lower EB values indicating more negative affect. More positive affect may suggest greater openness or engagement, while more negative affect may suggest caution, defensiveness, or disengagement [20]. This is relevant for interface evaluation because users may perceive one interface more favorably than another due to a more pleasant emotional response, even when traditional usability metrics are similar [1]. This motivates our focus on EEG-based EB to examine how AI-assisted interaction design may shape users' moment-to-moment emotional responses during task execution.

3 Method

To evaluate users' EB during task completion, we used an exploratory mixed-methods lab design that combined EEG, eye tracking, post-task questionnaires, and interview responses. This design was chosen to capture both time-resolved physiological changes during interaction and participants' subjective interpretations after task completion. EEG was used to identify moment-to-moment EB fluctuations, eye tracking helped link these fluctuations to specific interface events, and the survey contextualized participants' attitudes toward delegating personal and non-personal tasks to an AIA. Physiological data were interpreted in relation to interface events and contextual participant feedback rather than as standalone indicators of emotional state. The study was conducted by Beehiveor, the Ukrainian Center of Neuromarketing and Behavioral Research[1], an independent third-party organization compensated for its services. We recorded EEG and eye-tracking data to capture time-resolved physiological changes and link them to specific interface points. EEG was recorded with a Neuroelectrics Starstim 20 (20-channel) system (1000 Hz per manufacturer specifications), and gaze data were captured with a stationary Gazepoint eye tracker. The test followed a within-subject design, in which all participants performed the same three tasks illustrated in Table 1, in two interfaces (Oasis, CleanMyMac), in counterbalanced order and completed identical surveys after the completion of the task. The study was conducted in person in a controlled office setting.

3.1 Recruitment and Participant Details

A total of 20 participants (10 men and 10 women, aged 20–30) were recruited by the Ukrainian Center of Neuromarketing and Behavioral Research and compensated for their participation. From a pool of willing participants, individuals were randomly selected to reduce sampling bias. All participants were informed about the study's design, goals, methods, and the technology used, and provided informed consent prior to participation. Participation was voluntary, and participants could pause or withdraw at any time without penalty. Between tasks, participants were offered short breaks to mitigate fatigue. Participants reported moderate technical literacy and sufficient familiarity with the task domain to complete the study. None had prior experience with the prototype interface. Before the tasks, participants completed a short briefing and equipment setup/calibration. Raw EEG and eye-tracking data were anonymized during collection and permanently deleted after the report and statistical analysis were completed. The study was conducted in accordance with the ACM Publications Policy on Research Involving Human Participants and Subjects.

3.2 Study Materials

We developed an AI-based assistant, hereafter referred to as "Oasis" (Fig2), that can interact with the user's local environment, perform actions on the user's computer, access personal documents and files with permission, display system status, suggest apps, and generate different output formats, as illustrated in Fig. 1. For this study, all Oasis outputs were triggered either by user prompts or by system status, and actions were completed only with the user's permission.

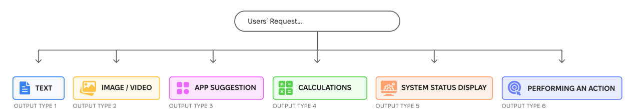

Figure 1: AIA possible workflows

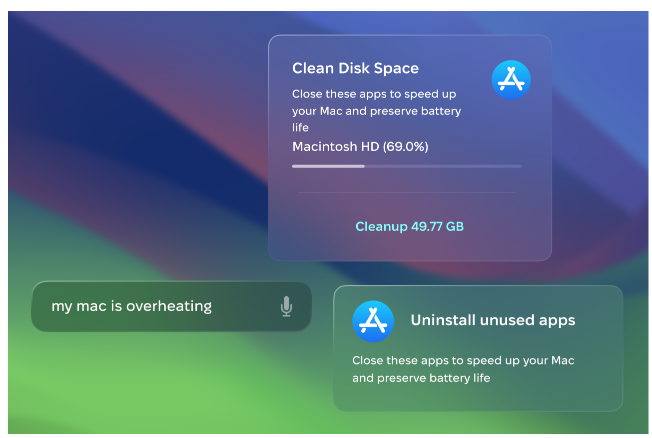

Figure 2: Oasis interface with multiple potential outputs shown beside the input field for illustrative purposes.

For this case study, to measure EB in an AIAs, we also needed a "baseline" of EB levels for the same tasks in a predetermined, dynamic graphic interface. We compared Oasis to "CleanMyMac" (CMM) 3, a familiar menu-based Mac optimization utility with comparable functions. This baseline interface represented a conventional, predefined graphical UI, allowing us to contrast it with Oasis's generative, prompt-based interaction model.

[1] https://beehiveor.com/rnd

Table 1: Task Description and Success Criteria

#	Task Description	Success Criteria
1	Delete the unused apps on your computer.	User deletes his unused apps.
2	Check if your computer has any malware.	User can certainly say whether there are any viruses on their computer.
3	Your computer is overheating, and you don't know why. Find out the reason and fix it.	User finds what would solve the problem in their opinion, and is satisfied with the result.

Figure 3: CleanMyMac baseline interface used for the study.

3.3 Data Evaluation

Although EEG was collected across channels, our analysis focuses on the right temporal region (T4) as a proxy for within-task affective fluctuations. Given EEG's limited spatial specificity, we interpret this metric as a relative within-participant signal and triangulate it with eye-tracking and questionnaire responses for context. The Emotion Understanding Index is derived from EEG data by analyzing brain activity in the right temporal region (T4). It is calculated using the formula: Index $= \frac{\text{theta + alpha}}{\text{beta + gamma}}$. This ratio reflects the balance between lower-frequency activity (theta and alpha), commonly associated with a relaxed wakeful state [14] [15], and higher-frequency activity associated with active task processing and emotional responses (beta and gamma) [7]. This EEG-based ratio approach is consistent with prior work [19] in affective computing and neuroscience. However, it is important to emphasize that EEG does not explain the causes behind peaks or drops in EB. Instead, it operates in a binary manner, indicating whether a user's emotional response increases or decreases at a given moment, without fixed boundaries.

To examine whether the descriptive differences observed in mean EB values were statistically supported, we conducted separate one-way ANOVA tests for each task, comparing EB values between the two interface conditions. Because this was an exploratory study with a small sample, the tests were used to identify patterns for interpretation rather than to establish generalizable effects. This task-level analysis was selected to remain consistent with the study's comparative design and to allow future extensions with additional interface conditions or task types.

4 Findings

Across all three tasks, CMM generally showed higher EB than Oasis. In Task 1, CMM was higher at most steps, particularly during "App Opening" and "Action," although the interface difference was not statistically significant, $F(1, 6) = 1.76$, $p = 0.233$. In Task 2, CMM maintained higher EB across all steps, while Oasis showed especially low values during "App Opening" and "Seeing Results", $F(1, 6) = 5.89$, $p = 0.029$. In Task 3, CMM again showed higher EB across most steps, especially during "App Opening" and "Action", $F(1, 6) = 5.70$, $p = 0.038$. The results suggest that interface design significantly shapes users' EB within interfaces, but it is strongly task-dependent.

The figures below show the arithmetic mean of EEG EB measurements for all participants at each task step, reflecting users' relative EB levels. The indices shown in the Y-axis are the activity of the brain, which is measured in arbitrary units that do not have fixed boundaries and are interpreted relative to the task.

Task 1: Delete the unused apps on your computer. During the "action" step, Oasis showed lower EB (Fig. 4).

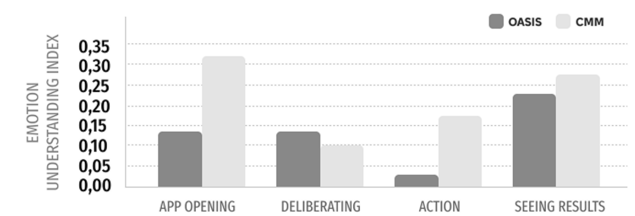

Figure 4: EB Results for Task 1

This may be explained by the constrained choice set in the Oasis prototype, which reduces cognitive load [34] and speeds up decision-making, but may also lead to a more detached or neutral emotional response because there are fewer elements for users to engage with emotionally. For example, when users were tasked with uninstalling apps with Oasis, the process was completed so quickly and effortlessly that it caused confusion and wariness. During the test, most users were startled by how immediate and seamless the action was, especially since uninstalling an app is typically seen as a major, irreversible step. The lack of friction or a clear confirmation step left some users uncertain (therefore lowering their EB), as they expected greater gravity for such a significant task.

Task 2: Check if your computer has any malware. Some indicators for Oasis cross the "negative threshold" (Fig. 5), signaling a decrease in EB when users encounter certain terms.

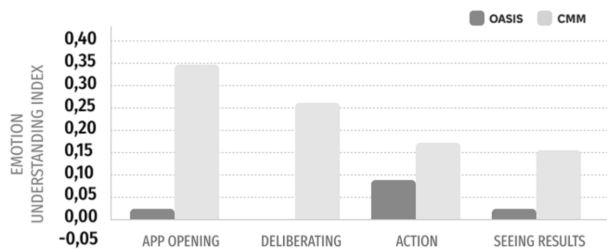

Figure 5: EB results for Task 2

In this case, thinking about or typing words such as "virus" may cause an aversive response, as mental imagery and imagined threat can engage emotional and physiological processes that overlap with responses to perceived threats [21] [6]. The word "virus" carries strong negative connotations, prompting a rejection of the very idea it represents. This reduction in EB may be explained by the negative associations that such terms can evoke, including danger, threat, or harm. As a result, users may experience discomfort or anxiety when engaging in actions related to these negative concepts.

Task 3: Your computer is overheating, and you don't know why. Find out the reason and fix it. EB indicates a more positive affective state in both cases (Fig. 6). The only phase in which EB is lower for the AIA condition is during app launch. This may stem from the interface's interaction model, which requires users to formulate a request to achieve their goal. In contrast, CMM presents users with a menu of predefined options, allowing them to browse and find something that meets their needs without the pressure to construct a request. The final step, "seeing the result", was excluded from the analysis because participant expectations and resulting outcomes varied substantially. This led to highly dispersed data, making it difficult to evaluate consistently.

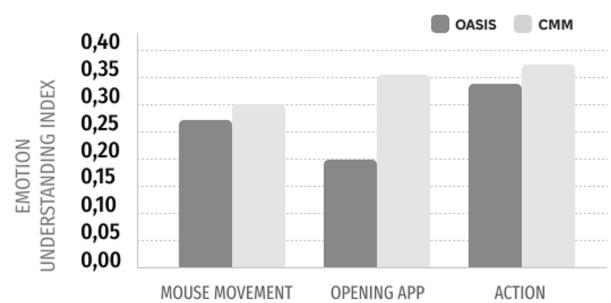

Figure 6: EB results for task 3

Taken together, the three tasks suggest that EB responses were not determined solely by interface type but also varied with task context, wording, and the degree of perceived control. Oasis appeared more emotionally challenging in moments where users had to formulate requests, interpret negatively framed concepts, or process rapid automation of consequential actions. CMM appeared more stable in tasks where predefined options reduced uncertainty. However, these patterns should be interpreted as exploratory because the study was designed to identify candidate interaction moments for future testing rather than to establish generalizable effects.

Exit Survey. We also conducted a survey with the test participants, in which we measured their EB when asked about tasks they would delegate to their AIAs. The "ref" values correspond to the initial task instructions presented at the beginning of this testing stage. Numbered task list (Fig. 7):

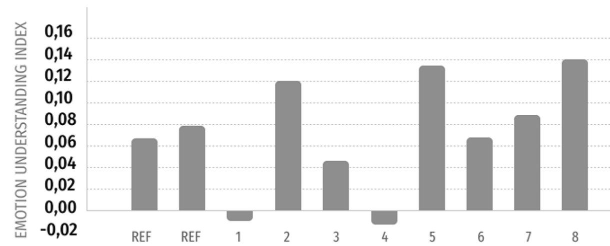

Figure 7: Exit Survey

(1) Clean up unnecessary files, (2) Access to calendars, emails, Zoom, and Google Meet, (3) Protection against viruses, (4) Email management and replying to emails, (5) Downloading videos, (6) Manage tasks and projects, (7) Conversion, editing, and document management, (8) Password manager/generator. The lowest scores are associated with the tasks of deleting unnecessary files and managing and responding to emails, both of which involve handling the user's personal data and content. Users are most positive about access to their calendar, Zoom, Google Meet (typically work-related tools), downloading videos, or creating and managing passwords, which are tasks that do not require access to a person's photos and files and do not take control over personal communications, which may explain the higher comfort level with these tasks.

5 Discussion and Implications for Design

EEG results indicate that emotional comfort decreases when users feel rushed by automation, encounter negatively framed concepts, or are uncertain about how and why the system acts. In contrast, emotional stability and engagement increase when interactions are transparent, positively framed, and allow the user to feel in charge of the process. These patterns reveal that users' emotional well-being in AIAs interactions is not solely determined by usability, but by how interfaces support trust and a sense of control.

Synthesizing these observations, we outline a set of preliminary implications for the design of emotionally aware AI assistants.

1. Balancing system speed with user processing pace. Although AI systems are designed to be efficient and fast, they should incorporate elements that simulate a "thinking process" within the interface by introducing a slight delay or visual or textual feedback, indicating that the system is processing the user's request thoughtfully. For high-impact actions, brief pauses, progress feedback, or confirmation steps may help users process what the assistant is doing and preserve a sense of control.

2. Mitigating emotional friction with neutral or positive framing. EB readings dropped drastically when users engaged with negatively charged terms such as "virus" or "malware". This suggests that linguistic framing may contribute to avoidance or discomfort responses. Interfaces that involve "negative" or threat-related actions should reframe them using neutral or positive language, e.g., "optimize system health" rather than "remove virus". Assistant behavior can further minimize anxiety by allowing the system to carry out these operations in the background, always with explicit user consent. By doing so, users are not forced to confront the negative concept directly, reducing emotional friction.

3. Build trust through transparency and gradual exposure. Trust in AI systems develops incrementally. To bridge the trust gap, AIA interfaces should communicate clearly and transparently by providing visible explanations of how data is accessed, used, and protected, narrating each action taken in response to user input. Start small by introducing AI involvement through low-stakes, low-risk tasks that help users build confidence before progressing to more personal or high-impact interactions.

4. Provide contextual guidance in open-ended prompts. Lower EB observed during the app opening (prompt formulation) stage suggests that AIA interfaces should provide light guidance during open-ended prompt creation, such as contextual hints or example phrases, to reduce uncertainty and maintain engagement.

6 Limitations

It's worth noting that results may differ across users of varying ages and technological proficiency levels. Younger users may be more comfortable delegating tasks to AIAs because technological familiarity can lower emotional barriers [32] and convenience may outweigh privacy concerns [28], whereas older adults may be more cautious, especially with sensitive tasks [5]. We also acknowledge that the sample is geographically homogeneous, as all participants were recruited from Ukraine, which may limit the generalizability of the findings to other cultural contexts and user populations. Additionally, because self-reporting was used only in the post-experiment survey, there was no direct comparison between subjective and physiological EB measures. The findings are also bounded by the limited prototype and restricted set of tasks, as EB responses may be shaped by specific interface elements and may differ across other interface designs and interaction contexts. Therefore, these results should be interpreted as exploratory and as a basis for future research.

7 Future research

Future research should examine EB during longitudinal real-world assistant use to reduce novelty effects and capture interactions with varying stakes. Future studies should also include moment-by-moment self-report or interview probes alongside physiological measures, allowing closer comparison between users' subjective experience and EEG-derived EB patterns.

8 Conclusion

This study explored how different task types influence users' EB in a prompt-based AIA, compared personal and non-personal task delegation, and evaluated EEG as a method for capturing these responses. Across tasks, EB decreases appeared most often around prompt formulation, negatively framed system-health terminology, and rapid or ambiguous automation, suggesting that pacing, framing, and perceived control may be important design considerations for AIAs. EEG revealed subtle emotional fluctuations, showing that EB decreases during moments of confusion, over-automation, or when tasks involve personal information. Users maintained higher emotional stability in neutral, low-risk tasks, underscoring the importance of perceived control and framing. Based on these findings, we outline preliminary design considerations, emphasizing thoughtful pacing, positive or neutral task framing, and transparent communication to help maintain a stable EB. These results suggest the potential value of EEG-informed evaluation for guiding emotion-centered design and developing AIAs that support calm, confident user experiences.

Acknowledgments

We thank the Armed Forces of Ukraine for providing security to complete this work. We thank Nataliia Stulova, Iryna Pastukhova, and Oleksandr Frankiv for providing assistance in preparing this manuscript.

References

[1] Anshu Agarwal and Andrew Meyer. 2009. Beyond usability: evaluating emotional response as an integral part of the user experience. In *CHI '09 Extended Abstracts on Human Factors in Computing Systems*. ACM, Boston MA USA, 2919–2930. doi:10.1145/1520340.1520420

[2] Bibaswan Basu, Sanjit K. Roy, and Chrysostomos Apostolidis. 2025. Unveiling the Charisma of Artificial Intelligence: How Voice Assistants Captivate Users and Emotionally Influence User Experience. *Psychology & Marketing* 42, 9 (Sept. 2025), 2334–2351. doi:10.1002/mar.22233

[3] Changzhuo Chen. 2024. How Attachment Style Influences the Para-friendship between Users and Intelligent Personal Assistants. In *Proceedings of the 2024 3rd International Conference on Artificial Intelligence and Intelligent Information Processing*. ACM, Tianjin China, 172–179. doi:10.1145/3707292.3707361

[4] Nuo Cheng and Ruifeng Yu. 2026. Measuring and understanding emotional attachment in human–AI relationships. *Ergonomics* (Feb. 2026), 1–20. doi:10.1080/00140139.2026.2622539

[5] Catherine Diaz-Asper, Chelsea Chandler, and Brita Elvevåg. 2024. PROMOTING USER TRUST IN AI: THE CASE OF LANGUAGE TECHNOLOGIES. *Innovation in Aging* 8, Supplement_1 (Dec. 2024), 280–280. doi:10.1093/geroni/igae098.0912

[6] Nadine Dijkstra and Stephen M Fleming. 2021. Fundamental constraints on distinguishing reality from imagination. doi:10.31234/osf.io/bw872

[7] Ana Garcia, Carlos Enrique Uribe, Maria Clotilde H. Tavares, and Carlos Tomaz. 2011. EEG and Autonomic Responses During Performance of Matching and Non-Matching to Sample Working Memory Tasks with Emotional Content. *Frontiers in Behavioral Neuroscience* 5 (Dec. 2011), 82. doi:10.3389/fnbeh.2011.00082

[8] Antje R.H. Graul, Aaron R. Brough, and Mathew S. Isaac. 2022. How emotional attachment influences lender participation in consumer-to-consumer rental platforms. *Journal of Business Research* 139 (Feb. 2022), 1211–1217. doi:10.1016/j.jbusres.2021.10.064

[9] João Guerreiro and Sandra Maria Correia Loureiro. 2023. I am attracted to my *Cool* Smart Assistant! Analyzing Attachment-Aversion in AI-Human Relationships. *Journal of Business Research* 161 (June 2023), 113863. doi:10.1016/j.jbusres.2023.113863

[10] Gijs Huisman, Marco Van Hout, Elisabeth Van Dijk, Thea Van Der Geest, and Dirk Heylen. 2013. LEMtool: measuring emotions in visual interfaces. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. ACM, Paris France, 351–360. doi:10.1145/2470654.2470706

[11] Myounghoon Jeon. 2024. The Effects of Emotions on Trust in Human-Computer Interaction: A Survey and Prospect. *International Journal of Human–Computer Interaction* 40, 22 (Nov. 2024), 6864–6882. doi:10.1080/10447318.2023.2261727

[12] Mark Johnson. 2001. The Feeling of What Happens: Body and Emotion in the Making of Consciousness (review). *The Journal of Speculative Philosophy* 15, 4 (2001), 323–326. doi:10.1353/jsp.2001.0038

[13] Nahye Kim, Bonseung Koo, Jaehwa Yoon, and Kwangsu Cho. 2016. Understanding the Formation of User's First Impression on an Interface Design from a

Neurophysiological Perspective – EEG Pilot Study. In *HCI Korea 2016*. The HCI Society of Korea, Korea, 139–145. doi:10.17210/hcik.2016.01.139
[14] W. Klimesch. 1999. EEG alpha and theta oscillations reflect cognitive and memory performance: a review and analysis. *Brain Research. Brain Research Reviews* 29, 2-3 (April 1999), 169–195. doi:10.1016/s0165-0173(98)00056-3
[15] Wolfgang Klimesch, Robert Fellinger, and Roman Freunberger. 2011. Alpha Oscillations and Early Stages of Visual Encoding. *Frontiers in Psychology* 2 (May 2011), Article 118. doi:10.3389/fpsyg.2011.00118
[16] Yuting Liao, Jessica Vitak, Priya Kumar, Michael Zimmer, and Katherine Kritikos. 2019. Understanding the Role of Privacy and Trust in Intelligent Personal Assistant Adoption. In *Information in Contemporary Society*, Natalie Greene Taylor, Caitlin Christian-Lamb, Michelle H. Martin, and Bonnie Nardi (Eds.). Vol. 11420. Springer International Publishing, Cham, 102–113. doi:10.1007/978-3-030-15742-5_9
[17] Damien Lockner and Nathalie Bonnardel. 2021. Emotion and Interface Design. In *Advances in Artificial Intelligence, Software and Systems Engineering*. AHFE Open Access, USA, n/a. doi:10.54941/ahfe100554
[18] Gale M. Lucas, Jonathan Gratch, Aisha King, and Louis-Philippe Morency. 2014. It's only a computer: Virtual humans increase willingness to disclose. *Computers in Human Behavior* 37 (Aug. 2014), 94–100. doi:10.1016/j.chb.2014.04.043
[19] Jose L. Marroquin, Thalia Harmony, Veronica Rodriguez, and Pedro Valdes. 2004. Exploratory EEG data analysis for psychophysiological experiments. *NeuroImage* 21, 3 (March 2004), 991–999. doi:10.1016/j.neuroimage.2003.10.031
[20] Rocco Mennella, Emma Vilarem, and Julie Grèzes. 2020. Rapid approach-avoidance responses to emotional displays reflect value-based decisions: Neural evidence from an EEG study. *NeuroImage* 222 (Nov. 2020), 117253. doi:10.1016/j.neuroimage.2020.117253
[21] Carey K. Morewedge, Young Eun Huh, and Joachim Vosgerau. 2010. Thought for Food: Imagined Consumption Reduces Actual Consumption. *Science* 330, 6010 (Dec. 2010), 1530–1533. doi:10.1126/science.1195701
[22] Renato Nascimento, Carlos Dias Limeira, André Luís Santos de Pinho, and José Guilherme Santa Rosa. 2014. Emotion, Affectivity and Usability in Interface Design. In *Design, User Experience, and Usability. User Experience Design Practice*, Aaron Marcus (Ed.). Springer International Publishing, Cham, 339–346. doi:10.1007/978-3-319-07638-6_33
[23] Nurhafihz Noor, Sally Rao Hill, and Indrit Troshani. 2022. Artificial Intelligence Service Agents: Role of Parasocial Relationship. *Journal of Computer Information Systems* 62, 5 (Sept. 2022), 1009–1023. doi:10.1080/08874417.2021.1962213
[24] Corina Pelau, Dan-Cristian Dabija, and Irina Ene. 2021. What makes an AI device human-like? The role of interaction quality, empathy and perceived psychological anthropomorphic characteristics in the acceptance of artificial intelligence in the service industry. *Computers in Human Behavior* 122 (Sept. 2021), 106855. doi:10.1016/j.chb.2021.106855
[25] Minjin Rheu, Ji Youn Shin, Wei Peng, and Jina Huh-Yoo. 2021. Systematic Review: Trust-Building Factors and Implications for Conversational Agent Design. *International Journal of Human–Computer Interaction* 37, 1 (Jan. 2021), 81–96. doi:10.1080/10447318.2020.1807710
[26] James A. Russell. 1980. A circumplex model of affect. *Journal of Personality and Social Psychology* 39, 6 (1980), 1161–1178. doi:10.1037/h0077714
[27] Lisa Schadelbauer, Stephan Schlögl, and Aleksander Groth. 2023. Linking Personality and Trust in Intelligent Virtual Assistants. *Multimodal Technologies and Interaction* 7, 6 (May 2023), 54. doi:10.3390/mti7060054
[28] Sujay Shalawadi, Florian Echtler, and Dimitrios Raptis. 2024. Dr. Convenience Love or: How I Learned to Stop Worrying and Love my Voice Assistant. In *Nordic Conference on Human-Computer Interaction*. ACM, Uppsala Sweden, 1–14. doi:10.1145/3679318.3685364
[29] Marita Skjuve, Asbjørn Følstad, Knut Inge Fostervold, and Petter Bae Brandtzaeg. 2021. My Chatbot Companion - a Study of Human-Chatbot Relationships. *International Journal of Human-Computer Studies* 149 (May 2021), 102601. doi:10.1016/j.ijhcs.2021.102601
[30] Eliot R. Smith, Steven Sherrin, Marlena R. Fraune, and Selma Šabanović. 2020. Positive Emotions, More Than Anxiety or Other Negative Emotions, Predict Willingness to Interact With Robots. *Personality and Social Psychology Bulletin* 46, 8 (Aug. 2020), 1270–1283. doi:10.1177/0146167219900439
[31] Xia Song, Bo Xu, and Zhenzhen Zhao. 2022. Can people experience romantic love for artificial intelligence? An empirical study of intelligent assistants. *Information & Management* 59, 2 (2022), 103595. doi:10.1016/j.im.2022.103595
[32] Claus J. Tully. 2003. Growing Up in Technological Worlds: How Modern Technologies Shape the Everyday Lives of Young People. *Bulletin of Science, Technology & Society* 23, 6 (Dec. 2003), 444–456. doi:10.1177/0270467603260812
[33] Ertugrul Uysal, Sascha Alavi, and Valéry Bezençon. 2022. Trojan horse or useful helper? A relationship perspective on artificial intelligence assistants with humanlike features. *Journal of the Academy of Marketing Science* 50, 6 (Nov. 2022), 1153–1175. doi:10.1007/s11747-022-00856-9
[34] Tingting Wu, Alexander J Dufford, Laura J Egan, Melissa-Ann Mackie, Cong Chen, Changhe Yuan, Chao Chen, Xiaobo Li, Xun Liu, Patrick R Hof, and Jin Fan. 2018. Hick–Hyman Law is Mediated by the Cognitive Control Network in the Brain. *Cerebral Cortex* 28, 7 (July 2018), 2267–2282. doi:10.1093/cercor/bhx127