Escuela de Gobierno y Transformación Pública
Tecnológico de Monterrey

The Impact of Artificial Intelligent Tools on Decision Making Behavioral and Neural Dynamics

Edmundo Molina-Perez
edmundo.molina@tec.mx
School of Government and Public Transformation
Tecnológico de Monterrey

Pedro Cortes
Tecnológico de Monterrey

Isaac Molina
Tecnológico de Monterrey

Fernanda Sobrino
Tecnológico de Monterrey

Mario Tellez
Tecnológico de Monterrey

Yessica Orozco
Tecnológico de Monterrey

Mitzi Castellón
Tecnológico de Monterrey

Steven Popper
Tecnológico de Monterrey

Luis Serra
Tecnológico de Monterrey

School of Government and Public Transformation

Working Paper No. 8

DOI: https://doi.org/10.21203/rs.3.rs-4651166/v1

Publication date: august, 2025

Abstract

Decision-making is a multifaceted cognitive process influenced by task complexity, information availability, individual cognitive strategies, and environmental settings. Yet, the neural mechanisms guiding everyday choices remain incompletely understood. This gap intensifies when integrating real-time aids, such as artificial intelligence tools (AIT), as cognitive decisionsupport especially for complex and ambiguous problems. This study explores the neural mechanisms of decision-making and examines how AIT influences these processes. Combining behavioral assessments and neurophysiological measurements, we investigate the dynamic interplay between human cognition and AIT through behavioral execution and electroencephalogram (EEG) activity. Experimental data from 54 participants suggest that in low-complexity decision-making, AIT is largely ignored in favor of heuristics. In high-complexity contexts, AIT positively influences decision-making outcomes while also increasing capacity for engagement with a challenging task as registered by EEG cortical activity. This suggests a non-linear effect of AIT in decision-making strategies highlighting its role as a complement to —rather than a replacement of—human cognitive processes.

Introduction

In decision-making research, integrating decision support tools, and most recently *artificial intelligence tools* (AIT) has become pivotal, offering novel insights into the cognitive processes' underlying complex tasks.[1,32] AIT have emerged as potent aids providing real-time support and guidance to individuals navigating intricate decision spaces. Yet, such tools' effectiveness differs greatly among users. These differences can be attributed to factors such as individual differences in cognitive styles, trust in technology, the decision context, and adaptability to novel decision-support systems. While some individuals seamlessly integrate AIT into their decision-making processes, others hesitate or rely on familiar cognitive strategies.

Understanding the nuances of AIT effectiveness is crucial for optimizing their use. Research shows that individual factors, including cognitive workload preferences and technology-related trust, significantly shape the interaction between users and AIT.[2,3] Moreover, individuals' adaptability to the evolving landscape of decision-support technologies contributes to the observed variability in outcomes.

Under typical conditions, when we make a choice, our brains engage in intricate neural computations that weigh the relevant factors.[4] The neural substrates involved in decision-making, encompassing regions such as the prefrontal cortex and other interconnected brain regions, orchestrate a symphony of activity as we navigate through options and select a course of action.[5] However, AIT introduces a new dimension to this process raising questions about how the human brain collaborates with and adapts to these advanced cognitive tools.

By studying this new dimension, our research represents a significant methodological advancement focusing not only on technological efficiency but also dynamic interactions between users and AIT.

Previous work predominantly focused on evaluating AI tools' efficiency without adequately addressing the dynamics of user interactions or acknowledging neuroscience's crucial role in current AI development.[6] Despite increasing research on artificially replicating the human brain using technologies such as memristors, the assumption remains that biological synapses are stable over time.[7] However, this perspective overlooks the dynamic nature of human cognition.

Many AI tools are built assuming that users are completely logical entities who exhibit stable behavior over time.[8] Yet, user behavior can change dynamically especially when interacting with AI systems. Introducing AI tools may lead to plastic changes in brain structures that in turn affect user behavior,[9] altering how the user interacts with tools. Therefore, studying users' physiological responses during AI interactions could offer valuable insights into these processes and aid in the development of more efficient and user-friendly tools. By incorporating both behavioral and neurophysiological measurements, our study goes beyond traditional approaches and provides a more comprehensive understanding of how AIT influences decision-making processes.

Results

In undertaking this study, we explored AIT's effect on decision-making across levels of complexity utilizing behavioral and neurophysiological measures. By employing the Iowa Gambling Task (IGT), a well-established paradigm for decision-making, we investigated how AIT influences participants' choices, reaction times, and neural oscillatory patterns.

After selecting, testing, and interviewing 27 participants under the conditions for our study (detailed in the "Methods" section), we performed an in-depth analysis. Participants were interviewed after each testing session to gather feedback on their decision-making process including their choices, the difficulties they encountered, and their perceptions of the AIT's usefulness. This led to somewhat surprising results that contribute to the broader understanding of cognitive and neural dynamics associated with AIT-assisted decision-making.

Behavioral Data

To analyze behavioral changes over the trials, visual representations were generated to provide insights into participant responses. Initially, mean values across all participants per experimental condition and trial were plotted in line graphs. Subsequently, smoothed conditional means with a 95-percent confidence interval were overlaid to improve data visualization and better understand trends across trials.

In the raw data for reaction time, an expected abrupt decline was observed in initial trials reflecting participant adaptation to the experimental task (Fig. 1). Overall, conditions without AIT exhibited faster reaction times with the low-complexity condition being the fastest. Conversely, the high-complexity condition with AIT demonstrated the slowest response time and failed to show the stabilization seen in other conditions.

Examining the score, the high-complexity condition without AIT exhibited no noticeable changes over 100 trials (Fig. 2). In contrast, the other conditions displayed a consistent increase that stabilized around the 30th trial. Notably, there were no discernible differences in scores among the low-complexity conditions. The high complexity with AIT conditions improved execution, although not to the extent observed in the low-complexity conditions.

For the analysis of variance (ANOVA) test, means per participant across all trials were calculated, and violin graphs were generated to compare probability distributions (Fig. 3). Reaction times exhibited higher variance and values in conditions using AIT. The low complexity without AIT condition demonstrated the fastest reaction time. ANOVA results revealed the most pronounced effect on AIT parameters with an observed interaction between both factors.

Referring to the mean scores per experimental condition, the low-complexity conditions demonstrated the highest scores as anticipated (Fig. 4). The high complexity with AIT condition exhibited a distribution pattern evenly spread along the *y*-axis, contrasting with the Gaussian-like behavior observed in the other experimental conditions. This suggests a high variance in scores for this specific condition indicating the influence of external factors on participant execution. Regarding scores, ANOVA revealed the most pronounced effect on complexity parameters with an observed interaction between the factors.

EEG Data Analysis

Initially, a comprehensive examination of overall electroencephalogram (EEG) activity was conducted. Minimal differences existed among the low-complexity conditions, whereas significant findings emerged at higher complexities. Specifically, in the absence of an AIT presentation, there was a decrease in EEG activity. Conversely, when an AIT was presented, an increase in EEG activity was noted across most of the brain cortex. This trend was consistent across most of the 18 recorded derivations, as Fig. 5A shows.

Upon further investigation into specific frequency bands, notable changes in activity patterns were identified. In the Theta band, primary differences were observed between various AIT conditions. Without AIT, a decrease in EEG activity occurred irrespective of task complexity, while the presence of AIT led to heightened EEG activity noticeably at higher complexities. Statistical analysis indicated that these changes were predominant in prefrontal and occipital derivations (Fig. 5B).

The Alpha band showed a substantial shift in activity patterns. Most EEG activity was observed in the lower-complexity conditions, although a similar response was seen in the high-complexity conditions with AIT. Notably, a stark contrast was observed in the higher complexity without AIT, where a decrease in EEG activity was evident compared to other experimental conditions. Statistical data suggested these changes occurred across most brain cortexes (Fig. 5C).

The Beta band exhibited a response similar to the Theta band and general activity with a relatively consistent pattern in lower-complexity conditions. However, a significant contrast emerged between lower activity in the higher complexity without AIT and increased activity when an AIT was present. In contrast to the Theta band, statistical changes were predominantly observed in the parietal and temporal cortices (Fig. 5D).

Similar to Alpha, the Gamma band presented a distinctive activity pattern (Fig. 5E). Across most experimental conditions a decrease in EEG activity was observed. An increase in EEG activity was noted specifically in higher-complexity conditions when presented with AIT. These changes were distributed across most of the brain cortex, albeit more discretely than in other EEG bands.

Discussion

The present research's primary objective was to assess the effects of AIT on decision-making behavioral and neurological outcomes at different complexities. Our initial expectation was an improvement in execution with the presence of an AIT, particularly at higher complexities with an associated decrease in EEG activity. However, contrary to our expectations, our results demonstrated that introducing an AIT improved execution but also increased EEG activity.

Behavioral analysis

Most of our initial hypotheses concerning behavioral data were confirmed. Analysis of response times revealed a decrease as trials progressed consistent with the typical learning component seen in tasks such as IGT where participants' decision-making improves over time.[10] Notably, the high complexity without an AIT condition exhibited a unique pattern. Unlike in most experimental tasks in which a decrease in reaction time accompanies execution improvement,[11] this experimental condition did not show such a progression. Despite a reduced reaction time, the score remained stable over 100 trials showing no improvement. One possible explanation is that participants may have reached a point of giving up on finding the correct answer.

Giving up on a cognitive task can significantly influence reaction times. When individuals encounter persistent difficulties or perceive the task as exceptionally challenging, they may actively abandon searching for the optimal answer.[12] This may result in decreased reaction times as participants opt for quick or intuitive decision-making rather than dedicating additional time to carefully consider available options which is supported by EEG data.[13] This phenomenon may arise from cognitive fatigue, perceived frustration, and adaptation of response strategies to minimize effort ultimately affecting cognitive tasks' decision-making speed. Thus, participants in this experimental condition may have perceived no discernible pattern or correct response prompting them to give up and shift to a faster approach to conclude the task promptly. During the interviews, several participants reported that they were unable to identify a deck that was better than the others. This feedback supports the notion that the lack of certainty regarding the best decision in the task led them to adopt a quicker, less reflective approach to complete the experiment.

The scoring data also provided insights into participant execution. As expected, most experimental conditions showed improvement as trials progressed. To observe a clear effect on behavioral and EEG data from using an AIT, a goal was to design an experimental condition that could not be resolved without it. This goal seemed to be achieved, as the high complexity without an AIT condition showed no improvement over 100 trials. A slight effect of AIT was anticipated for the low-complexity condition. However, such an effect was either not found indicating that throughout 100 trials execution in the lower-complexity condition did not differ significantly with or without AIT. This suggests that participants might have found heuristic alternatives that were more efficient than processing AIT information.

Heuristics or mental shortcuts emerge as swift and effective decision-making strategies when faced with environments characterized by information overload, by reducing cognitive complexities[14]. These simplifying responses enable individuals to reach conclusions more expediently, thus avoiding depletion of cognitive resources through exhaustive analysis. In settings where the problem is so complex that detailed analysis is not viable or even impossible, heuristic responses become invaluable. They offer satisfactory solutions without requiring in-depth data processing. Hence, in the lower-complexity condition, where the need for detailed information processing is minimal, participants were more inclined to ignore AIT suggestions and rely on heuristic approaches.

Intriguing findings emerged when analyzing data from the high-complexity AIT condition. While the anticipated pattern was a gradually improving performance, similar to the lower-complexity condition in the final trials, the data revealed no significant improvement in execution scores beyond trials 25 and 30. This result was perplexing, as the presence of decision support tools would typically lead to a more pronounced enhancement in efficiency.

A plausible explanation for this can be gleaned from the violin graphs which disclose distinct patterns in the distribution of this experimental condition compared to others. While the other distributions appeared relatively normal, the high complexity AIT condition exhibited an almost uniform distribution (Fig 4). This suggests a substantial variation in AIT's effectiveness among participants. Some individuals used AIT to enhance their execution significantly, while others found no utility, resulting in scores akin to those without AIT. The heterogeneity in responses underscores the individual variability in AIT's assimilation and application, contributing to the observed diversity in execution outcomes within this one experimental condition.

Individuals ignoring AI suggestions can be explained through cognitive overload, a condition where the information presented exceeds an individual's cognitive capacity to process it effectively.[15] Human cognitive resources are finite, and when faced with an overwhelming volume of information individuals may experience difficulties in assimilating, analyzing, and integrating data.[16] This overload often leads to a cognitive bottleneck hindering decision-making processes. In decision-making tasks involving AI suggestions, individuals may encounter situations for which the presented information, although generated by advanced algorithms, becomes too intricate or voluminous to be comprehensively processed within the available cognitive bandwidth. The capacity to manage information diminishes causing individuals to resort to simplified cognitive strategies, such as heuristics, to streamline decision processes and conserve mental resources.

Determining which individual characteristics influence the effectiveness or outright dismissal of AIT remains unclear.[17] While our study did gather some verbal feedback from participants, the specifics of what influenced their choices were varied and complex. During the interviews, participants provided insights into their decision-making processes including their reasoning behind accepting or ignoring AIT suggestions. Some mentioned difficulty in trusting the AIT, while others relied on their intuition or heuristic strategies indicating a diverse range of factors at play. Interestingly, many participants noted that they believed the AIT was incorrect and therefore chose to completely ignore it. This contrasts with the behavioral data, which clearly shows that the AIT did improve participant performance, albeit not to the extent observed in the low complexity conditions.

However, the complexity and variability of these responses made it challenging to pinpoint definitive characteristics influencing AIT's effectiveness. Additionally, some participants did not provide sufficiently detailed explanations making it difficult to draw concrete conclusions. Future research could benefit from a more structured approach to collecting and analyzing this type of qualitative data potentially uncovering clearer patterns and more specific individual characteristics that affect AIT utilization.

Neurophysiological analysis

EEG data analysis can provide valuable insights into the cognitive processes associated with AIT use. Traditionally, as task difficulty increases, a concurrent rise ensues in EEG activation indicating the intensified engagement of neural processes necessary for handling complex cognitive tasks.[18] When faced with a more challenging task, the brain recruits additional neural resources to process and integrate information leading to increased neural firing and synchronization. This heightened activity often is observed in specific frequency bands, such as Beta and Gamma, associated with cognitive functions such as attention, working memory, and information processing.[19,20] The increased EEG activation during more challenging tasks signifies deployment of cognitive control mechanisms and allocation of greater attentional resources. It reflects the brain's adaptive response to meet the demands of the task at hand.

The AIT condition was designed to provide cognitive support and an expected lower EEG activity in these conditions. In contrast, the conditions with higher complexity and without AIT would exhibit higher EEG activation. The results instead revealed an almost contrary pattern, particularly in the complex conditions, where low activation was observed without AIT, and high activation was noted with its presence. Minimal differences were found in EEG activity between the low-complexity conditions. As mentioned earlier, adopting a heuristic strategy could be one explanation for the lack of differences in the low-complexity conditions. In these conditions, inferring the best alternative was relatively straightforward since the decks presented no losses only wins. Most participants could identify the correct answer quickly making AIT's suggestions seemingly redundant. The EEG activity supports this interpretation. The patterns observed were quite similar with or without AIT indicating a comparable level of cognitive engagement regardless of AIT's presence in the low-complexity conditions.

The higher-complexity condition revealed a striking contrast in brain activity without AIT. Behavioral data suggested that participants reached a point of giving up in the search for the best alternative. This conclusion is substantiated by participants not showing improvement in their execution throughout 100 trials. In contrast to the other conditions, the score's progression is a flat line while reaction times decrease. If participants persistently attempted to find the correct answer, one would expect a slower pace of decrease or even an increase in response times. However, despite making relative mistakes response times continued to decrease at a pace similar to that of the low-complexity condition. Consequently, the decrease in EEG activity could be attributed to a lack of engagement in the task. For most participants, it seemed that there was no discernible correct answer leading them to respond expeditiously to finish the experimental condition. Verbal reports from participants further support this notion with some expressing confusion or indicating a belief that their choices did not matter in this particular condition.

Using AIT resulted in an increase in EEG activity at higher complexities while a decrease in EEG activity might have been expected. Two factors may have played a role—increased information input and individual mistrust in AIT. Yet, a third is suggested by the data: enhanced subject engagement in the face of an enhanced challenge being buoyed by the AIT.

In terms of information input, while AIT offers a potentially easier alternative to evaluating each option manually, it substantially increases the information presented to the participant. This includes raw numerical data for each alternative and an adaptive suggestion for possible actions. Participants in this condition not only had to rely on experience but also had to evaluate the information provided. Consequently, in the lower-complexity condition, this information largely was ignored. However, participants still had the option to disregard this information and rely solely on AIT's suggestions. With this strategy, participants should be able to determine the best response alternative in fewer than 25 trials. Yet behavioral data demonstrated that almost no participant relied solely on AIT's suggestions. While they considered such suggestions, they ultimately evaluated the information's veracity and applied a personal approach to the problem. This resulted in increased response times and higher EEG activity. The inclination to validate AI suggestions and incorporate personal judgment may reflect relative mistrust—that is, a cautious approach driven by concerns about AI-generated information's accuracy or reliability.

Mistrust in AIT would lead individuals to rely less on the provided AI-generated suggestions and more on their own judgment with significant influence on task execution. This mistrust may stem from various factors, including concerns about the information's accuracy, reliability, or appropriateness.[21,22] Individuals may question the AI system's ability to fully understand the task's complexity or adapt suggestions to the person's unique cognitive processes and decision-making strategies. Moreover, apprehensions about AI's lack of contextual understanding, potential biases, or limitations in learning from individual preferences can contribute to a sense of mistrust. Consequently, individuals may choose to validate AIT's suggestions against their own evaluation. This validation process can result in an increased cognitive load and longer decision-making times. Mistrust in AIT may see a paradoxical increase in task complexity as individuals reconcile the information provided by AIT with their judgments.

Nonetheless, AIT seems to function as a cognitive support tool in our experimental setting. Without AIT, participants appeared to abandon the search for an optimal answer.

When presented with an AIT, most participants persisted in trying to resolve the task, increasing scores as trials progressed—an effect not observed in the condition without AIT. Most participants used AIT as a guide, incorporating its suggestions into their decision-making process rather than following them blindly. This nuanced interaction with AIT suggests a balanced integration of AI support into individual decision-making strategies highlighting its role as a facilitator rather than a replacement for human cognitive processes as evidenced by the increase in cortical EEG activity.

We found interesting interactions for the experimental conditions when EEG activity is separated by frequency bands. The Theta band showed a pattern similar to the general cortical activation although it was mostly localized in the prefontal and occipital cortices. The Theta band is associated with cognitive processes such as attention, working memory, and mental engagement.[23] The observed patterns in Theta band activity suggest that the experimental conditions influence these cognitive processes. In the high complexity with AIT condition, Theta band activity increased, suggesting heightened engagement in attention and working memory processes. This aligns with the behavioral data, indicating that participants persisted in trying to resolve the task with AIT’s aid. Considering previous findings, the role of the prefrontal and occipital cortices in the observed EEG activity patterns becomes particularly significant. These brain regions are crucial for various cognitive processes, and their involvement sheds light on the neural dynamics associated with decision-making and the impact of AIT use in different complexities.

The prefrontal cortex, implicated in executive functions, attention, and decision-making,[24] showed distinctive patterns in Theta band activity. In the high complexity without AIT condition, the reduced Theta activity in the prefrontal cortex aligns with the behavioral data, indicating decreased engagement in attention and working memory processes. Conversely, increased Theta activity in the high complexity with AIT condition suggests heightened prefrontal cortex involvement when participants use AIT as a cognitive support tool.

Similarly, the occipital cortex, primarily responsible for visual processing and perception,[25] exhibited relevant patterns in Theta band activity. These findings suggest that the experimental conditions influence visual attention and processing demands in decision-making tasks. The increased Theta activity in the high complexity with AIT condition implies a greater engagement of the occipital cortex when participants receive visual information from AIT.

In the Alpha band analysis, a prominent observation emerges from the decrease in EEG activity across most of the brain cortex in the high complexity without AIT condition. The Alpha band is commonly associated with relaxation states, cortical arousal inhibition, and decreased cognitive load.[26] The marked decrease in Alpha band activity across most of the brain cortex suggests a shift in the neurophysiological state associated with AIT use in the experimental conditions. In the high complexity without AIT condition, the reduced Alpha band activity may reflect a reduction in cognitive load. This aligns with the behavioral data indicating potential disengagement or giving up in the search for the optimal answer.

The Beta activity pattern is similar to Theta's. Indeed, the Theta-Beta bands have been associated with similar cognitive processes including attention, working memory, and engagement in decision-making tasks.[27] In particular, the high complexity without AIT condition exhibited a notable decrease in Beta activity, suggesting a potential reduction in cognitive engagement and attentional resources. Conversely, in the high complexity with AIT condition, the Beta activity pattern showed an increase implying heightened cognitive engagement and attentional focus when participants used AIT.

Nonetheless, while Theta EEG activity changes occur mainly in the prefrontal cortex, for the Beta band they were found in the temporal and parietal cortices. These areas have been associated with distinct cognitive functions, and their involvement in Theta and Beta activity changes adds another layer of complexity to the interpretation of neural dynamics during decision-making tasks. Temporal and parietal areas have been linked to processes such as sensory integration, memory retrieval, and spatial processing.[28,29] The localization of Beta activity changes in these regions suggests a differential engagement of neural circuits associated with distinct cognitive functions. The unique involvement of the temporal and parietal cortices in Beta activity changes emphasizes the multifaceted nature of cognitive processing during decision-making. The interplay between Theta and Beta activity across different brain regions underscores the intricate neural networks implicated in integrating information, memory, and attentional processes.

The Gamma band exhibited a prominent increase in EEG activity specifically in the high complexity with AIT condition. Gamma band activity is commonly associated with cognitive functions such as information processing, perception, integration of sensory stimuli, and overall higher-order cognitive functions.[30,31] This observation implies an escalated cognitive demand unique to the experimental condition involving AIT. It is crucial to emphasize that AIT's role is to provide support rather than completely override cognitive functions. Consequently, an enhanced cognitive function was required to adeptly respond to the task demands, as reflected in the heightened Gamma band activity. Interestingly, this pattern does not seem to manifest in the other experimental conditions, possibly because of a heuristic approach's efficiency or a complete disregard for the task outcome.

The divergent patterns in EEG activity across different frequency bands shed light on the complex neural processes involved in decision-making tasks. Our findings emphasize the need to understand AIT's salience for decision-making behavioral outcomes and the neural dynamics involved. Future research could explore differences in decision support tool efficacy from alternative formats of presentation, address trust-related factors, and further dissect the neural mechanisms underlying adaptive decision-making in dynamic and complex environments. Ultimately, this study contributes to the growing body of literature bridging analytical decision support, artificial intelligence, cognitive neuroscience, and decision-making research.

Methods

Participants

Per a maximum variation sampling logic, 54 participants (19 males) with ages ranging between 18 and 37 years (mean = 25, standard deviation = 5) voluntarily agreed to participate in the experiment. No monetary incentives were provided. All participants were right-handed, had similar educational levels, and gave informed consent before testing. None of the subjects had a history of neurological or psychiatric disorders, drug abuse, or chronic illness. The research protocol and consent process underwent meticulous review and received approval from the Ethics Committee of the School of Medicine of Tecnologico de Monterrey in Mexico to ensure adherence to ethical standards.

Decision-Making Task

For this experiment, we used a modified version of the Iowa Gambling Task (IGT). The task featured a digital display of four decks from which participants had to select one per trial. Subsequently, feedback was provided indicating accrued gains and losses. The objective was to accumulate the most points over 100 trials per condition. There were two "good" decks with the highest overall gains and two "bad" decks with lower overall gains.

Each deck had a unique net gain value, calculated based on the aggregate points won versus lost over the entire deck (i.e., the sum of points won minus the sum of points lost). While all decks had positive net gain values, indicating net gains in the long run, there were subtle variations within each category. Specifically, one deck in each category was slightly superior to the other, determined by minimal statistical variance.

Wins ranged from 30 to 120 points per trial, with the "good" decks having the highest average gains. Losses ranged from 0 to 400 points per trial, with the "bad" decks having the highest average losses. Importantly, the overall net gain values of all decks ensured that no deck generated net losses over the course of the experiment.

Experimental Conditions

The experimental design was based on a 2×2 ANOVA, with the first factor corresponding to the complexity condition (low and high complexity levels) and the second factor referring to use of an AIT (with and without it). Thus, four experimental conditions were created:

1. low complexity without AIT,
2. low complexity with AIT,
3. high complexity without AIT, and
4. high complexity with AIT.

Each participant underwent all experimental conditions in a randomized order. After completing the decision-making tasks, participants were interviewed briefly to gather qualitative insights into their experiences. These informal, unstructured interviews focused on Perceptions of AIT, Decision-Making Strategies, Challenges Encountered, and Task Clarity.

The complexity condition was defined by the number of factors influencing the win ratio and, consequently, the amount of information needed to achieve the optimal outcome. In the lower-complexity condition (LOWC), decks provided a variable rate of wins without losses. Participants needed to consider only the uncertainty in the wins mean to identify the best choice alternative. In the high-complexity condition (HIGC), the same win ratios were maintained, but losses were introduced, varying from 0 to 400 points, with losses occurring between 40 and 50 percent of trials. Participants had to consider not only the variance in wins but also the variance and frequency of losses to respond effectively.

Regarding AIT availability, two experimental conditions existed: No AIT (NAIT) and with AIT (WAIT). In the NAIT condition, participants had information about overall winnings and losses, displayed continuously at the top of the screen (Fig. 6A). The feedback screen was displayed after a selection was made, lasted 2 seconds, and provided information on the chosen deck, associated wins, and applicable losses (Fig. 6C). In the WAIT condition, participants were informed explicitly about access to an AIT which, although not a real AIT, provided adaptive responses based on truthful information. The AIT offered two additional information sources: raw numerical information displaying mean wins and losses below each deck, and a suggestion for the current trial choice (Fig. 6B). The AIT's suggestion evolved through three stages: initially suggesting exploration of each alternative at least three times, then discarding bad decks and encouraging further exploration of good decks, and finally suggesting the best alternative after each good deck was chosen at least 10 times. This setup allowed for simulating a "learning" and adaptive tool for participants. The feedback screen for this condition replaced the AIT suggestion for the information on the chosen deck associated wins, and applicable losses (Fig. 6D).

EEG Recording

Adhering to the standard 10–20 system, 18 electrodes were placed to record EEG activity. Electrode impedance was maintained below 20 kiloohms (kΩ) during data collection. Linked ears were selected as a reference to mitigate contributions from the reference electrode and volume conduction to scalp correlations. EEG recordings were amplified using a Micromed polygraph with filters set at 1–50 hertz (Hz), and a sampling rate set at 1,024 Hz. Electrooculograms and electrocardiograms were recorded concurrently to identify eye and heart movement artifacts. A bipolar montage was employed with electrodes at the outer canthi of both eyes and on the front of the left wrist.

Experimental Setting

Volunteers participated in a two-hour experimental session. Initially, the overall experimental setup and associated risks were explained, and participants, upon agreeing, signed informed consent forms. Following this, general demographic data including age and education level were documented. Subsequently, participants were directed to the sound-attenuated EEG recording room where the temperature was maintained at 21–24°C. In this setting, the electrode cap and Tobii glasses were fitted, and task-specific and recording instructions were provided.

Participants executed the experimental task on a desktop computer using only the mouse for interface control. Initial instruction screens appeared providing participants with task-related information. Eight practice trials then were presented to ensure participants were familiar with the interface and understood the task rules. Once the practice trials were completed, the main experiment began. Participants were presented with blocks of 100 trials each. After completing a block, a stop screen appeared, and a brief break (approximately 3 minutes) was provided. Upon indicating readiness to continue, the next block started. A total of four blocks (one per experimental condition) were presented in a randomized order. The task was immediately halted upon completion of the last block, and all experimental equipment was removed.

Statistical Analysis

Several variables were recorded throughout the experiment including behavioral execution response time, accumulated wins, and trial scores. Given that some experimental conditions lacked losses, a direct comparison of win ratios was meaningless, so the trial score served as a valuable parameter to reflect participant performance. Each deck was assigned an intrinsic score based on its win ratio, with the best deck receiving a score of 1 and the worst receiving a score of 0. The remaining decks (lower good and higher bad) were assigned scores proportional to their respective win ratios, falling between 0 and 1. This scored data underwent analysis and comparison through a 2×2 ANOVA.

Meanwhile, with the EEG data, the recordings initially were segregated by experimental conditions. Following this, a meticulous manual inspection was conducted to identify and eliminate incoherent artifacts in the signal. Subsequently, an independent component analysis (ICA) was applied to eliminate coherent artifacts, such as those associated with heart rate, and other unwanted sources of noise. The processed signal underwent further analysis using a ANOVA design, incorporating Bonferroni correction for multiple comparisons. To analyze the signal further, a spectral analysis for each traditional EEG band was performed, including Theta (4–8 Hz), Alpha (8–13 Hz), Beta (13–30 Hz), and Gamma (30–50 Hz).

This comprehensive analysis aimed to explore and characterize the frequency-specific dynamics within the EEG signal providing valuable insights into neural activity patterns associated with different experimental conditions. All analyses were conducted within the MATLAB extension EEGLAB. The database and scripts required to replicate the analysis can be consulted in the dedicated github repository of this paper.[33]

Declarations

Funding:

This material is based upon work supported by the Air Force Office of Scientific Research under award number FA9550-22-1-0441. This study is supported by Tecnológico de Monterrey Challenge-Based Research Funding Program.

References

1. Jiang, F., Jiang, Y., Zhi, H., Dong, Y., Li, H., Ma, S., Wang, Y., Dong, Q., Shen, H., & Wang, Y. Artificial intelligence in healthcare: Past, present and future. *Stroke and Vascular Neurology*, **2**(4). https://doi.org/10.1136/svn-2017-000101 (2017).
2. Shin, D. Embodying algorithms, enactive artificial intelligence and the extended cognition: You can see as much as you know about algorithm. *J. Information Science*, **49**(1), 18–31 (2023).
3. , Sokol, M. B. Adaptation to difficult designs: Facilitating use of new technology. *J, Business and Psychology*, **8**(3), 277–296. (1994).
4. Herd, S., Krueger, K., Nair, A., Mollick, J., & O'Reilly, R. Neural mechanisms of human decision-making. *Cognitive, Affective, & Behavioral Neuroscience*, **21**(1), 35–57 (2021).
5. Kim, S., & Lee, D. Prefrontal cortex and impulsive decision making. *Biological Psychiatry*, **69**(12), 1140–1146 (2011).
6. Zador, A., Escola, S., Richards, B., Ölveczky, B., Bengio, Y., Boahen, K., Botvinick, M., Chklovskii, D., Churchland, A., Clopath, C., DiCarlo, J., Ganguli, S., Hawkins, J., Körding, K., Koulakov, A., LeCun, Y., Lillicrap, T., Marblestone, A., Olshausen, B., … Tsao, D. Catalyzing next-generation artificial intelligence through NeuroAI. *Nature Communications*, **14**(1), Article 1 (2023).
7. Cao, Z., Sun, B., Zhou, G., Mao, S., Zhu, S., Zhang, J., Ke, C., Zhao, Y., & Shao, J. Memristor-based neural networks: A bridge from device to artificial intelligence. *Nanoscale Horizons*, **8**(6), 716–745 (2023).
8. Desouza, K. C., Dawson, G. S., & Chenok, D. Designing, developing, and deploying artificial intelligence systems: Lessons from and for the public sector. *Business Horizons*, **63**(2), 205–213 (2020).
9. Hoehe, M. R., & Thibaut, F. Going digital: How technology use may influence human brains and behavior. *Dialogues in Clinical Neuroscience*, **22**(2), 93–97 (2020).

10. Steingroever, H., Wetzels, R., Horstmann, A., Neumann, J., & Wagenmakers, E.-J. Performance of healthy participants on the Iowa Gambling Task. *Psychological Assessment*, **25**(1), 180–193 (2012).
11. Kakigi, S., Shiwa, S., Matsuda, T., & Mori, T. Changes in contingent negative variation (CNV) as a function of paired associate learning. *Japanese Psychological Research*, **27**(1), 45–49 (1985).
12. Elliott, E. S., & Dweck, C. S. Goals: An approach to motivation and achievement. *J. Personality and Social Psychology*, **54**(1), 5–12 (1988).
13. Meckler, C., Carbonnell, L., Hasbroucq, T., Burle, B., & Vidal, F. To err or to guess: An ERP study on the source of errors. *Psychophysiology*, **50**(5), 415–421 (2013).
14. Kvam, P. D., & Hintze, A. Rewards, risks, and reaching the right strategy: Evolutionary paths from heuristics to optimal decisions. *Evolutionary Behavioral Sciences*, **12**(3), 177–190 (2018).
15. Paas, F., Renkl, A., & Sweller, J. Cognitive load theory: Instructional implications of the interaction between information structures and cognitive architecture. *Instructional Science*, **32**(1), 1–8 (2004).
16. Sweller, J., & Chandler, P. Why some material is difficult to learn. *Cognition and Instruction*, **12**(3), 185–233 (1994).
17. Sindermann, C., Yang, H., Elhai, J. D., Yang, S., Quan, L., Li, M., & Montag, C. Acceptance and Fear of Artificial Intelligence: Associations with personality in a German and a Chinese sample. *Discover Psychology*, **2**(1), 8 (2022).
18. Gundel, A., & Wilson, G. F. Topographical changes in the ongoing EEG related to the difficulty of mental tasks. *Brain Topography*, **5**(1), 17–25 (1992).
19. Deiber, M.-P., Meziane, H. B., Hasler, R., Rodriguez, C., Toma, S., Ackermann, M., Herrmann, F., & Giannakopoulos, P. Attention and working memory-related EEG markers of subtle cognitive deterioration in healthy elderly individuals. *Journal of Alzheimer's Disease*, **47**(2), 335–349 (2015).
20. Roux, F., & Uhlhaas, P. J. Working memory and neural oscillations: Alpha–gamma versus theta–gamma codes for distinct WM information? *Trends in Cognitive Sciences*, **18**(1), 16-25 (2014).
21. Lee, M. K., & Rich, K. Who is included in human perceptions of AI?: Trust and perceived fairness around healthcare AI and cultural mistrust. *Proc. 2021 CHI Conf. Human Factors in Computing Systems*, 1–14. https://doi.org/10.1145/3411764.3445570 (2021).
22. Shevskaya, N. V. Explainable Artificial Intelligence Approaches: Challenges and Perspectives. *2021 Intl Conf. Quality Management, Transport and Information Security, Information Technologies (IT&QM&IS)*, 540–543 (2021).
23. Uhlhaas, P. J., & Singer, W. Neural synchrony in brain disorders: Relevance for cognitive dysfunctions and pathophysiology. *Neuron*, **52**(1), 155–168 (2006).
24. Dixon, M. L., & Dweck, C. S. The amygdala and the prefrontal cortex: The co-construction of intelligent decision-making. *Psychological Rev.*, **129**(6), 1414–1441 (2022).
25. Ragni, F., Tucciarelli, R., Andersson, P., & Lingnau, A. Decoding stimulus identity in occipital, parietal and inferotemporal cortices during visual mental imagery. *Cortex*, **127**, 371–387 (2020).

26. Schapkin, S., Raggatz, J., Hillmert, M., & Böckelmann, I. EEG correlates of cognitive load in a multiple choice reaction task. *Acta Neurobiologiae Experimentalis*, 80(1), Article 1 (2020).
27. Basharpoor, S., Heidari, F., & Molavi, P. EEG coherence in theta, alpha, and beta bands in frontal regions and executive functions. *Applied Neuropsychology: Adult*, **28**(3), 310–317 (2021).
28. Pisoni, A., Turi, Z., Raithel, A., Ambrus, G. G., Alekseichuk, I., Schacht, A., Paulus, W., & Antal, A. Separating recognition processes of declarative memory via anodal tDCS: Boosting old item recognition by temporal and new item detection by parietal stimulation. *PLOS ONE*, **10**(3), e0123085 (2015).
29. Zhou, H., Cheung, E. F. C., & Chan, R. C. K. (2020). Audiovisual temporal integration: Cognitive processing, neural mechanisms, developmental trajectory and potential interventions. *Neuropsychologia*, **140**, 107396 (2020).
30. Jensen, O., Kaiser, J., & Lachaux, J. Human gamma-frequency oscillations associated with attention and memory. *Trends in Neurosciences*, **30**, 317–324 (2007).
31. Rieder, M. K., Rahm, B., Williams, J. D., & Kaiser, J. Human gamma-band activity and behavior. *Intl J. Psychophysiology*, **79**(1), 39–48 (2011).
32. Marchau, V. A., Walker, W. E., Bloemen, P. J., & Popper, S. W. Decision making under deep uncertainty: from theory to practice (p. 405). Springer Nature (2019).
33. Cortes, P. M., Molina-Perez, E., Molina, I., Sobrino, F., Orozco, Y., Tellez-Rojas, M., Castellón-Flores, A. M., Popper, S. W., & Serra-Barragan, L. Code and Data Repository for Study "The Impact of Artificial Intelligent Tools on Decision Making Behavioral and Neural Dynamics", GitHub repository (2024), https://github.com/PedroManuelCortes/NeuroAIT_DecisionMakingData

Figures

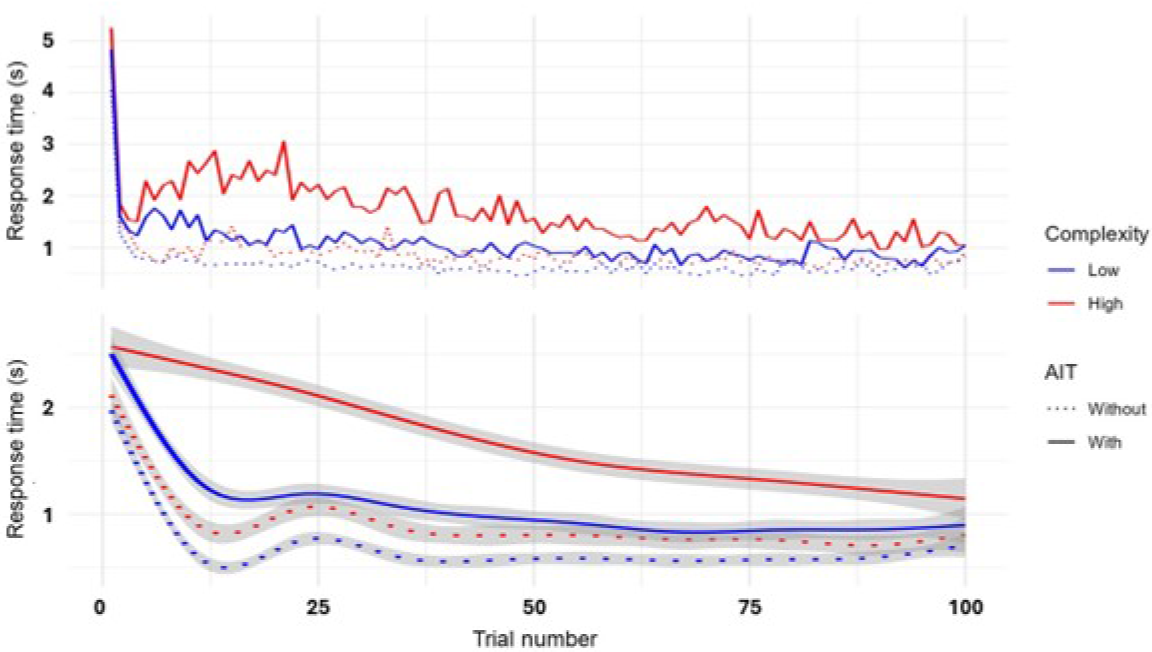


Figure 1

Visual representation of changes in response time across experimental conditions. The top graph illustrates the raw means per trial. The lower graph presents smoothed conditional means with a 95-percent confidence interval.

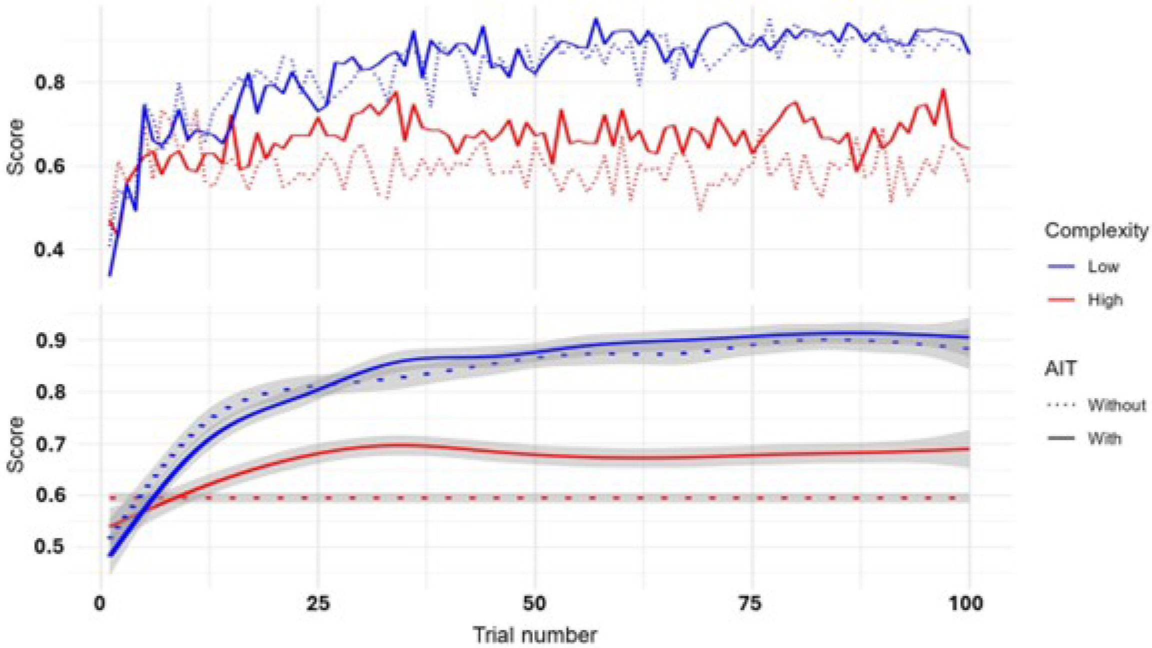
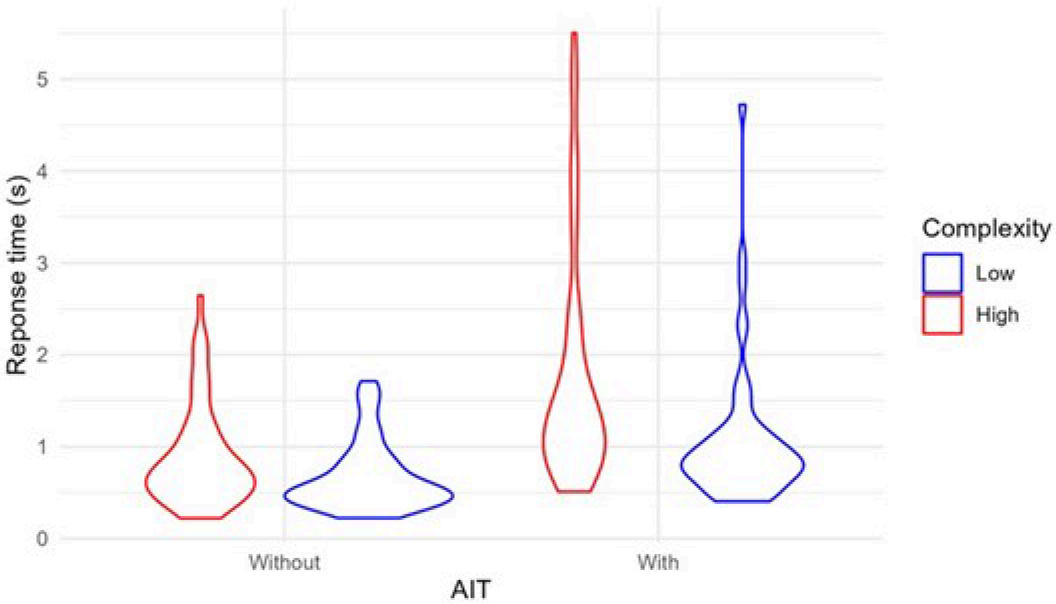


Figure 2

Visual representation of changes in score across experimental conditions. The top graph illustrates the raw means per trial. The lower graph presents smoothed conditional means with a 95-percent confidence interval.



Response time	DF inter	DF intra	F	p	ges
AIT	1	53	45.90	< 0.0001	0.1070
Complexity	1	53	26.98	< 0.0001	0.0384
Interaction	1	53	9.14	0.0039	0.0021

Figure 3

A violin graph (top) illustrates the means per participant of the response time. The violins' width reflects the probability density at different values, providing a visual representation of data distribution. A table (bottom) displays the analysis of variance (ANOVA) test results. DF = degrees of freedom; ges = generalized eta squared.

Score	DF inter	DF intra	F	p	ges
AIT	1	53	8.31	0.0057	0.0247
Complexity	1	53	195.68	< 0.0001	0.4148
Interaction	1	53	9.08	0.0039	0.0182

Figure 4

A violin graph (top) illustrates the means per participant of the response time. The violins' width reflects the probability density at different values, providing a visual representation of the data distribution. A table (bottom) displays the results of the ANOVA test. DF = degrees of freedom; ges = generalized eta squared.

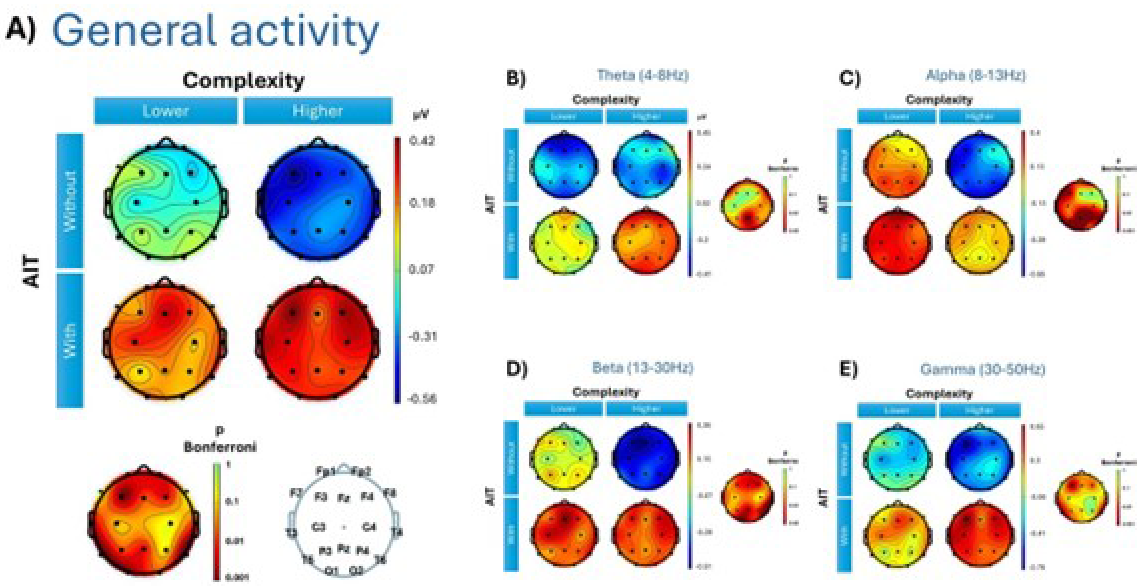


Figure 5

Topographic maps of (A) general; (B) Theta; (C) Alpha; (D) Beta; and (E) Gamma electroencephalogram (EEG) activity. The left section shows the general EEG activity maps for each experimental condition, accompanied by a map illustrating the distribution of p-values and the EEG derivations used in the analysis. The right section presents the EEG maps for each frequency band, along with the corresponding distribution of p-values with Bonferroni correction.

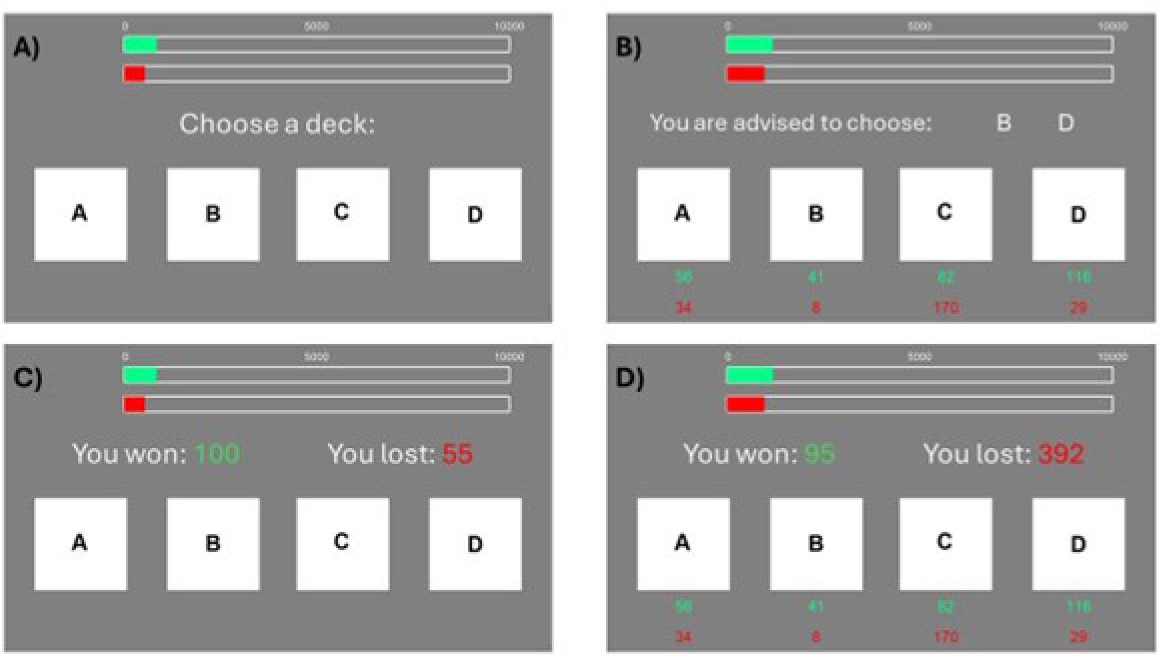


Figure 6

The top part of the image compares the task screen in both artificial intelligence tools (AIT) conditions: (A) without AIT and (B) with AIT. The lower part shows the feedback screen: (C) without AIT and (D) with AIT.