A Neurofeedback-Driven Humanoid to support Deep Work

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ABSTRACT

High performance is desired in the workplace, even with swarms of robots on their way in the Fourth Industrial Revolution. Our research focuses on the population of knowledge workers, who are typically expected to sit in one space for extended periods while performing deep, intellectual and creative work. For those who work predominantly using computers, there is growing scope to augment task performance using artificial virtual agents. This trend is evident in the adoption of voice-based, and gesture-based applications that allow users to issue vocal or gestural commands while their hands are occupied on primary tasks. Even though multimodal interaction may yield more productivity than solely mouse and keyboard interactions, it may still impose a significant cognitive load on the user. We propose the modeling of a smart motivational humanoid assistant that is personalized to interact with human users without explicit commands, and instead via wireless sensors that can perceive the operator's brain activity. The humanoid engages with the human using effective nudges through neurofeedback.

Keywords: Robotics, Neurofeedback, Deep Work

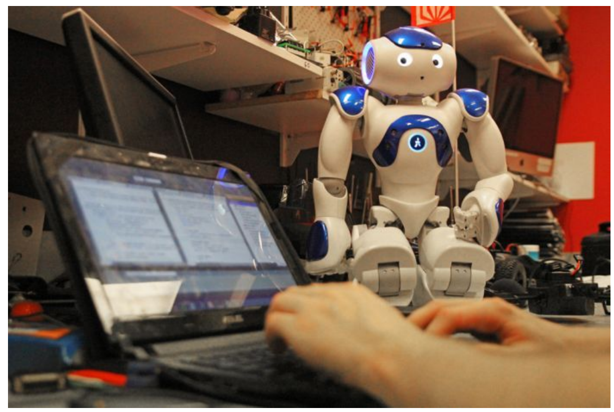

Figure 1. Proposed context of use shows Nao humanoid interacting with a knowledge worker that wears a Muse neurofeedback headband while completing work tasks using a computer in the office workspace. Image courtesy ABC Gold Coast: Damien Larkins.

1. Introduction

Knowledge workers perform "non-routine cognitive jobs" whose ideas and concepts are responsible for the growth and development of businesses around the world. In the US, knowledge workers constitute almost 50% of the workforce [1]. They work with tools and automation that relieve them of many tasks, enabling them to deeply immerse themselves into the difficult knowledge tasks that cannot be automated [2]. The research question arises, how should human workers interact with complex automated technologies, which is itself a knowledge-work task? And, can this be done in a way that enhances deep cognitive work?

While the work environments of knowledge workers vary widely across different industries, this paper focuses on the office workspace and to the knowledge worker operating a computer system on a desk to complete a range of work activities. The primary artifacts in this context are the computer, and the top surface of the desk as shown in Figure 1. The knowledge worker may be a novice or an expert who may be succeeding on tasks, making errors, overloaded or distracted. Tasks may vary from writing documents, responding to email, computing calculations or debugging software code. Secondary artifacts in the office space such as lamps, toys, books, posters and windows may be used for changing mood, taking a break or sparking creativity.

The organization includes all supervisors and team-mates who interact with the knowledge worker to perform work tasks using the artifacts. Situations may be normal, abnormal or emergency scenarios that determine the relevant interactions during operation time. Situation complexity is often caused by interruptions, context-switching, and high workload conditions.

One predominant problem in environments such as these is the propensity for the knowledge worker becoming distracted to the detriment of work completion. Due to the reduced attention or impaired alertness, the inevitable net result is increased human error, and reduced ability to work safely, and productively [3] and decreased job satisfaction [4]. Human-centered design of the humanoid robot as a collaborative team-mate may enhance the task performance and psychological well-being of the knowledge worker. The robot should not cause stress and discomfort but incorporate social signals, cues and norms into the planning and control architecture to ensure psychological safety of the knowledge worker [5].

In this paper, we present the first steps of research into developing a computational model for a humanoid robot to support the cognitive needs of knowledge workers by increasing the duration and depth of their cognitive work. The second section of this paper outlines the state-of-the-art research on the psychological state of flow, neurofeedback-driven nudges, and human-robot interaction. In the third section, we present a design rationale for the smart personalized humanoid assistant. A demonstration of the agent-based framework was conducted to analyze the effects of the neurofeedback processing, and action planning modules. In the final section of the paper, we discuss the implications of neurofeedback-driven nudges, and conclude with limitations of our research, and suggestions for future work.

2. Related Work

2.1 Deep Work and Flow State

Knowledge workers are exposed to both internal and external distractions and interruptions that lead to suboptimal productivity, increased stress and dissatisfaction with their work. The average knowledge worker spends 30 percent of their daily time on email, and another 30 percent on team communication and Internet activities [2]. A significant portion of lost time is spent in context-switching, where additional time is lost before an interrupting task is started, and after it ends [6].

Distractions between episodes of knowledge work are a significant source of lost productivity and dissatisfaction due to the difficulty in accomplishing work goals. If these periods of distraction can be decreased or eliminated, the resulting ability to focus and complete tasks may positively impact on productivity.

Flow is defined as "the state in which people are so involved in an activity that nothing else seems to matter; the experience itself is so enjoyable that people will do it even at great cost, for the sheer sake of doing it" [7]. In the workplace, flow occurs when individuals, teams or organizations operate with optimal focus, and perform without apparent effort, which yields a heightened sense of motivation, intrinsic satisfaction, and peak outcomes [8, 9].

Flow experiences are not always easy to attain and sustain, but developing the ability to control attention may be an effective way to find and maintain flow [10]. Concentration is a significant component of achieving flow [11]. To establish the flow state, the human must focus attention on the activity, and goals at hand. Our hypothesis is that if the operator is aware of their state of concentration, they will be better able to drive towards deeper levels.

2.2 Neurofeedback and Nudges

Attention focus is a trainable skill that may result in reaching the flow state [12]. One way to train sustained attention is to provide a sensitive feedback signal so human users can learn to sense upcoming lapses earlier and prevent them from occurring in behavior [13]. Neurofeedback training has produced outcome gains in sustained attention [14], and has been used for the purpose of cognitive enhancement and as a therapeutic tool [15].

Neurofeedback is a category of biofeedback that is based on brain electrical signals recorded by bio-sensors placed on the head of humans. Neurofeedback involves the collection of the brain signals, classification and presentation of a stimulus to make individuals aware of their brain states and how to self-regulate certain brain-based processes [16]. In general, effective use of biofeedback requires specialized equipment to convert physiological signals into meaningful cues or a trained biofeedback practitioner [17].

To be effective working with the most difficult knowledge tasks in a domain, human workers often rely on external aids such as rituals, reminders and mental hacks, which this work collectively calls "nudges". This set of work-related nudges are used mostly on an ad-hoc basis to propel workers to deep levels of concentration and achievement. Nudges are used in behavior science to positively influence people while preserving their freedom of choice, and without engaging their deliberative capacities [18, 19].

The purpose of the reinforcement learning loop shown in Figure 2 is to help the knowledge worker achieve, and maintain a flow state while performing tasks. The aim is to have the Nao humanoid monitor and mirror the human's state so that it can effectively motivate them with nudges when they drift off task, and become invisible when their task performance is in the flow state.

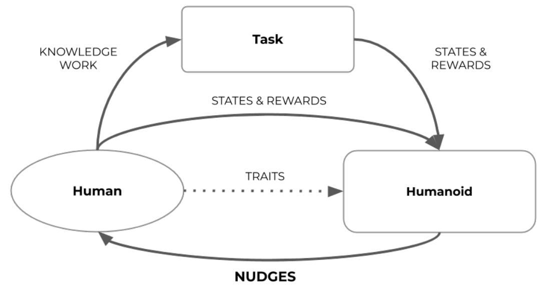

Figure 2. The reinforcement learning control model depicts the human completing work tasks in an operational environment that allows interactions with the humanoid agent. Percepts of human state and traits represent the agent's observations over time. The reward signal is obtained based on the humanoid's likeness to the human's subsequent flow state, and task completion. The humanoid performs nudge actions that consistently target stimulation towards deep flow.

The proposed nudges incorporate sound, physical motion, and other visual cues, and aims to combat boredom, fatigue, anxiety, distractions and habitual behaviors that may lead to under-performance during knowledge work. The nudges are delivered using traits of transparency and expressiveness versus autonomy and accuracy [20], good automation etiquette versus socially-agnostic behavior [21], and empathetic verbal apology over sterile error codes [22, 23].

Andujar et al [24] proposed that adapting humorous smart technologies in the workplace can be beneficial for employee retention and the improvement of employees' positive emotional state. The designers of humanoid interactions are recommended to consider how to detect negative responses resulting from the uncanny valley effect (where people react with unease seeing humanoid behavior that closely, but not perfectly, matches human behavior), and design robot behaviors to mitigate this by using humor or apology to overcome the robot's disagreeable appearance [25, 26, 27].

2.3 Cognitive and Collaborative Robots

Cognitive robotics involves the use of bio-inspired methods for the design of sensorimotor, cognitive, and social capabilities in autonomous robots [28]. Reggia et al [29] designed a cognitive humanoid robot framework with components that center on top-down control of a working memory that retains explanatory interpretations that the robot constructs during learning. The core function of our humanoid robot is to learn about the mental and emotional states of the knowledge worker and respond in a way to support their cognitive needs.

Collaborative robots are designed to physically interact with humans in a shared workspace instead of replacing them [30]. The humanoid robot proposed in this research provides personalized interacts with different knowledge workers while conducting work tasks in their workspaces. This interaction model is non-competitive co-operation by mutual understanding where authority is traded between human, and collaborative robot [31].

The sense of presence, and enjoyment that people feel with a robot can be manipulated by changing its social abilities [32]. In particular, the aesthetics, functionality, embodiment, situatedness, and morphology of humanoid robots can affect its interactions [33]. For example, Jo et al [34], found that interactions with physical and virtual humanoid robots produced a statistically significant effect in increasing human creativity. Automation inaccuracy can degrade human trust, comfort, and acceptance [35]. For these reasons, the humanoid's expressions and feedback are designed as a clear imitation of the knowledge worker's flow state.

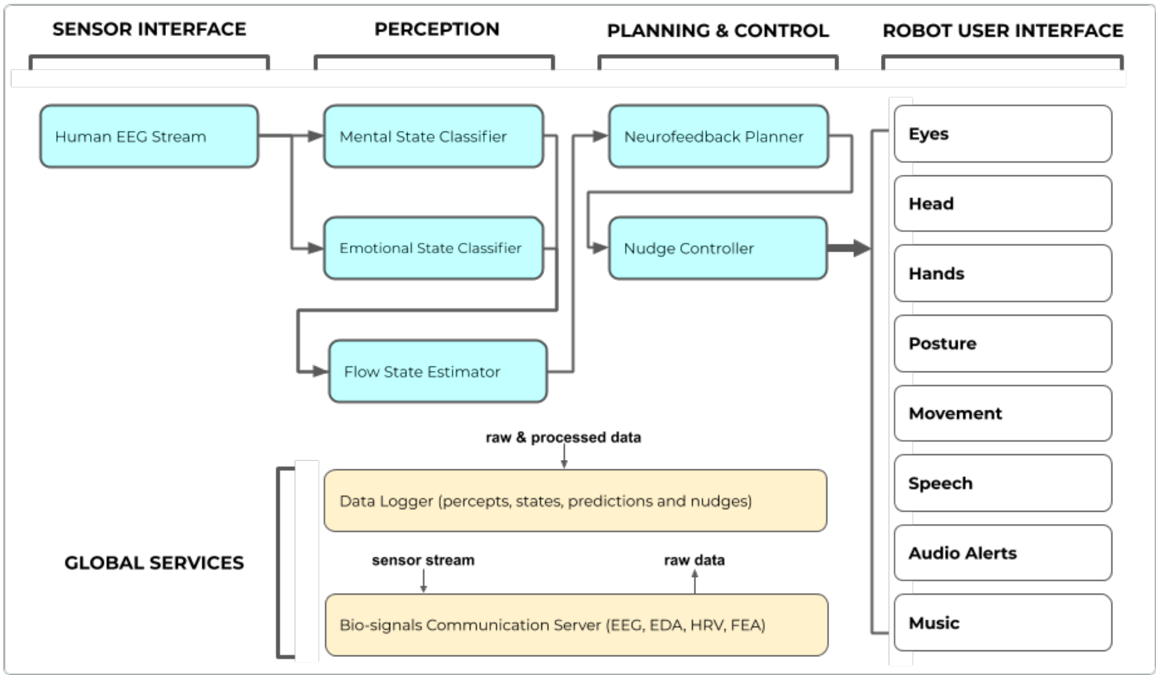

Figure 3. Pipeline architecture of the neurofeedback-driven humanoid where the modules process data on server and client threads in parallel.

3. Deep Work Humanoid Implementation

The humanoid obtains its bio-sensing capability from modules that process raw brain sensor data, classify human state, and plan appropriate nudges. The humanoid listens to the nudge controller, and executes nudges through expressive actions with its effectors.

3.1 Human EEG Stream

The human electroencephalogram (EEG) stream is collected from four EEG electrode bio-sensors on the Muse headband [36]. The sensor locations using the standard 10-20 coordinates are analogous to the prefrontal regions (AF7 and AF8) and the temporal regions (TP9 and TP10). The raw EEG data are sampled at 220 Hz on the four channels. The raw EEG data are transported to the server database via a mobile device interface that is capable of being synchronized with motion and other bio-signals.

3.2 Mental and Emotional State Classifiers

Noise and artifacts such as blinks and jaw clenches are filtered from the raw EEG data using a bandpass filter between 1 Hz to 75 Hz. The filtered EEG data are segmented into 4-second epochs without overlap. A short-term Fourier transform on each segment produces power spectral density (PSD) features in 5 frequency bands (delta, theta, alpha, beta and gamma). PSD features are classified using a recurrent neural network (RNN) with long short-term memory (LSTM) units. The mental states are engaged or disengaged. The emotional states are bored (B), happy (H) or anxious (A).

3.3 Flow State Estimator

In our research, the flow concept is operationalized with two dimensions: human skill and task challenge. Flow is modeled as the region where there is a balance between the human skill and task challenge. Flow is estimated as a discrete state ($\text{Distracted}_{\text{B}}$, $\text{Shallow Flow}_{\text{B}}$, $\text{Distracted}_{\text{A}}$, $\text{Shallow Flow}_{\text{A}}$, $\text{Shallow Flow}_{\text{H}}$ and $\text{Deep Flow}_{\text{H}}$) measured 4 seconds after presentation of the nudge.

3.4 Neurofeedback Planner

A common approximation to reinforcement learning (RL) problems is to ignore noise, which assumes full observability by learning and planning in observation space rather than a latent state space [37]. However, such approximations break down when using the Nao robot due to non-determinism in the actuators [38], and the EEG signals are stochastic due to sensors noise and artifacts. Therefore, the RL control model in Figure 2 is a discrete-time partially observable Markov decision process (POMDP). A Deep Q Network (DQN) is used to obtain the policy that maximizes the expected sum of rewards. The policy is used to plan and map the optimal nudge to the estimated flow state of the knowledge worker.

3.5 Nudge Controller

In order to help the knowledge worker maximize on deep work, the humanoid nudges with gestural feedback, reminders of task goals, and, in some cases, modifies the challenge level of the task relative to the skills of the knowledge worker. Nudges are conveyed in the form of expressive actions that the robot executes based on probabilistic computations of percepts, predictions and rewards. These humanoid expressions that are shown in Figure 4 represent stimuli to deliberately influence the knowledge worker by mimicking their mental and emotional state while motivating transition to deep flow.

3.6 Global Services

The architecture has a set of global services for logging percepts of raw data, PSD features, classified states, predictions and nudges. Streams of bio-sensor packets are transferred and aggregated via Bluetooth and User Datagram Protocol (UDP). The bio-sensor packets are synchronized and logged with discrete timestamps. Nudges are communicated from the server over Wi-Fi to the robot.

3.7 Robot User Interface

Only dependable robot architectures can be accepted for supporting "human-in-the-loop" conditions and human–robot teams [39]. Humanoids are a special case because they intrinsically present multiple control points for grasping, moving the head for perception, assuming postures, walking, and so on [40]. We hypothesize that a tangible interactive robot with the form factor of a warm, competent, and sensitive humanoid will be acceptable, and effective in knowledge work scenarios. The Nao humanoid supports the required human-like motor capability and has a high level of expressiveness that is capable of delivering a variety of nudges in Figure 4, which makes it suitable for our human-robot teamwork function. According best practices for social robots [26, 41, 42], we designed the humanoid to exhibit the following social characteristics:

- perceive, and express emotions;
- communicate with body language, and sound;
- exhibit a distinctive personality, and character;
- perceive natural cues (gaze, facial expression, head posture).

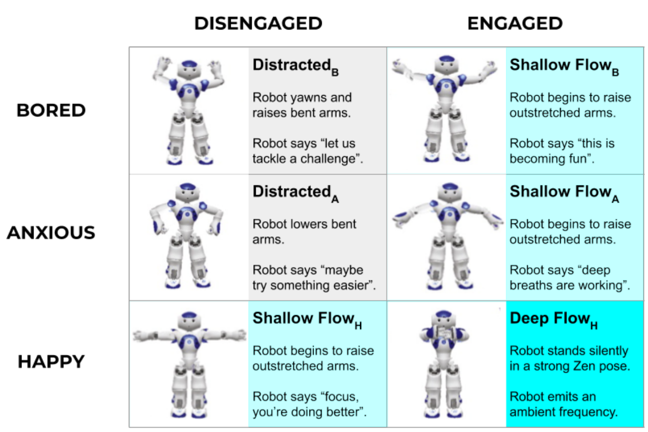

Figure 4. The six nudge categories of the Nao robot represent a sparse encoding that correlates expressions to the flow state, which is a product of mental and emotional state of the knowledge worker.

The expressions of the robot in Figure 4 are timely interactions with the knowledge worker without overt commands. These expressions strategically auto-encode the flow state of the knowledge worker into the metaphor of a Zen practitioner. The fluid movements of the humanoid are coupled with silence, music or motivational phrases spoken by the robot. Within the six categories of expressions, there is granularity of the phrases and sounds to improve salience and mitigate monotony. Silent motions avoid distracting the knowledge worker unnecessarily, and simple phrases minimize the cognitive load required to understand the robot.

According to Breazeal [41], the importance of feedback, and the readability of expression in this process cannot be underestimated in human-robot interaction. As the human applies the social model to understand the robot, they are constantly observing the robot's behavior, and manner of expression to infer its internal states. This allows the person to predict, and understand the robot's behavior only if the robot's expression is readable (the intended signal is appropriately interpreted by the human). The robot's expression reliably maps to the internal state being expressed, and this internal state adheres to the human's mental model of the robot.

4. Demonstration

In this section we review a demonstration of the architecture, showing how the pipeline architecture ingests classified mental and emotional states from EEG data, and then decides which nudge to produce on the humanoid robot. The synthetic dataset used in this demonstration simulated 2,000 trials i.e 100 work-hours. The trials were randomly sampled from 18 types of knowledge work scenarios. Each scenario type exhibited an overarching emotional state e.g. boring, anxious or happy. In order to simulate different frequencies of distractions, the scenarios were combined with the following types of perturbations in mental state:

- Engaged for 3 minutes
- Disengaged for 3 minutes
- Engaged for 90 seconds then disengaged for 90 seconds
- Disengaged for 90 seconds then engaged for 90 seconds
- Engaged then disengaged alternating every 1 minute
- Engaged then disengaged alternating every 12 seconds

The 3-minute scenario graphically depicted in Figure 5 shows a situation where a knowledge worker is in an overarching happy emotional state but experiencing intermittent 12-second distractions. Given this processed data from the humanoid's sensor and perception layer, the resultant flow state is handed to the neurofeedback planning and nudge control layers then an expression is communicated to the robot's user interface.

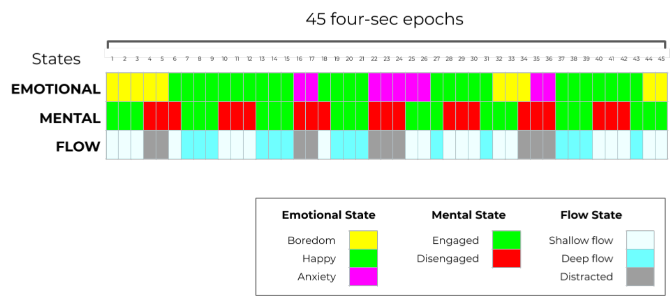

Figure 5. Visualization of a knowledge work scenario showing the emotional, mental and flow states over 45 epochs of sensor data after pre-processing and classification in the humanoid's software pipeline.

We adopted a Q-Learning approach as the baseline reinforcement learning (RL) control method for the neurofeedback planner. The RL method was implemented in Python to approximate the action-value function of the optimal policy. The Q-Learning algorithm used temporal differences to update the scores its Q-Table.

The data was split 50:50 into training and test sets, and reused across all experimental cases. The ε–greedy algorithm was used to make use of the exploration-exploitation tradeoff, and a linear function was used to decrement ε over the scenarios. Three reward functions were used to generate the different policies. The state-based function calculated reward based on the value of the resulting state if it was predicted. The distance-based reward function used the distance between the resulting state and the predicted state. The combo function represented a weighted combination of both measures. The nudges from the neurofeedback planner were tested on the Nao humanoid via the nudge controller. The following tables summarize the nudges resulting from the computational model for discussion.

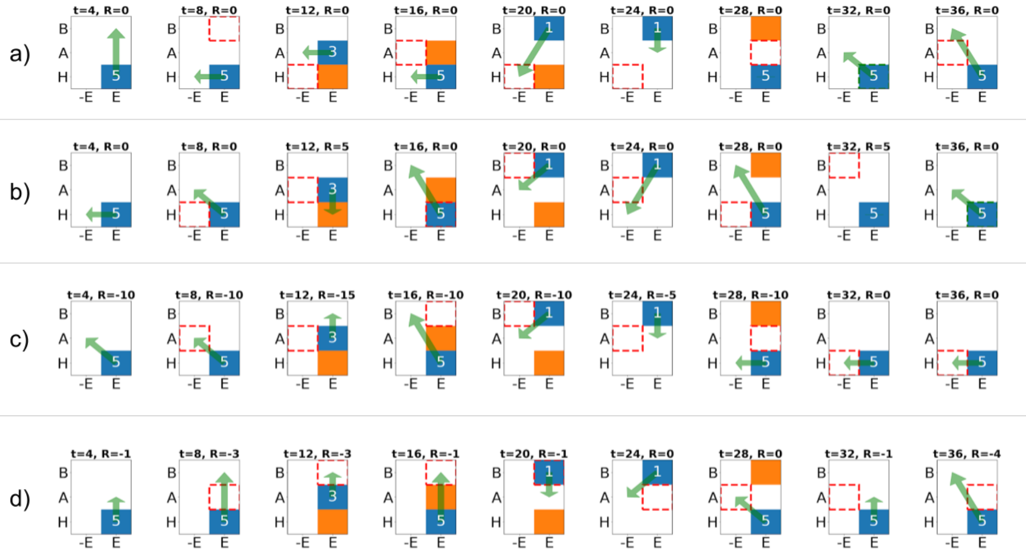

Figure 6. Comparison of policies for knowledge work scenarios across 9 four-sec epochs. The plots represent (a) before the humanoid was trained, and after training with (b) state-based reward, (c) distance-based reward, and (d) a combined state- and distance-based reward. The green arrows depict the attempted nudge. The blue cell represents the current observation, and the orange cell represents the previous observation. The dashed square highlights the previous nudge, where red indicates an incorrect prediction and green indicates a correct prediction.

4.1 Discussion

Figure 6 shows a comparison of three policies that were learned by the agent based on three different reward functions. Nudges in the baseline (a) appeared to be random and independent of observations. The state-based reward function in section (b) shows a different set of nudges, which yielded low rewards on the predictions. The distance-based reward function in section (c) depicted a more constrained set of nudges, which were closely related to the current observation. The combo-based reward function demonstrated that it is possible to combine benefits from multiple reward signals.

The nudges used in this demonstration were delivered every 4 seconds during the given knowledge scenario. When executed on the Nao, even though some nudges were silent, the number of nudges was relatively highly across the scenarios on average. This is likely to make the humanoid a distraction to maintaining flow and deep work. When the humanoid is deployed, an alternative approach to implement the neurofeedback planner would be to only nudge after (1) a stabilized period of the flow state, (2) after dwelling in distraction for 10 seconds, and (3) after task completion. The nudge after completing the scenario may be planned by classifying the knowledge worker's flow performance over the scenario and recommending the next task from a task list based on its estimated duration and challenge relative to the knowledge worker's skill.

5. Conclusion

This main goal of this research was to develop a computational model that effectively applies human-robot interaction in the deep knowledge work domain to augment human performance. The architecture presented in this paper offers a lightweight framework for investigating biofeedback-sensitive aids to deep cognitive work. Our hope is that this framework lowers the barrier for future research into the efficacy of different nudge regimes.

Breazeal, Aly, and others are adamant that the long-term emotional effects of humanoid interactions on humans need to be investigated [43, 44]. Issues arising of ethical concern include overreliance on automation [45], and potential manipulation of people through social robots [46]. Some AI algorithms may suffer from inaccuracies in the training data or may possess vulnerabilities to errors, and biased rules, which may lead to inaccurate profiling [47].

Notwithstanding the challenges and ethical issues, there is a possible design of the future where robots do not replace humans but enhance them to make a positive difference in the world. The impact of effective neurofeedback-driven humanoids that support deep work is potentially significant in terms of economic productivity, and social well-being of knowledge workers.

5.1 Future Work

Real human- and real humanoid-in-the-loop experiments are an exciting part of the next steps. Beyond the theoretical experiments reviewed in this paper, humanoids with simulation-trained neurofeedback planners will be compared with those trained with real world experience. Then we can determine if the humanoid's effectiveness may be improved by tailoring personalized nudges that fit the traits and preferences of specific knowledge workers.

Future studies will examine "attention" in greater detail, e.g. nudges that help knowledge workers to train their focus on task relevant stimuli, and boost their immunity to distraction. It is noted that a human can be focused and attentive on a distracting stimulus. This differentiation will require laboratory research with motion tracking to provide an objective measure of how attention is directed, and controlled by the knowledge worker during tasks.

Advanced work in feature engineering can improve the humanoid's accuracy and responsiveness. For example, the environment's reward signal that is currently controlled by task list completion and humanoid flow similarity may be augmented by human-centered metrics such as joy and positive affect, which may increase the reliability of the neurofeedback planner.

On the hardware side, the sensor interface may be extended to include different bio-signals such as facial expression, heart-beats, skin conductance, etc. The purpose of multimodal bio-signal fusion would be to increase classification accuracy, and improve the explainability of our deep learning models.

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