My fun Personal Flow and Effortless Attention in Knowledge Work using Active Inference

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***Abstract*—Knowledge work often involves unfamiliar experiences with goal-relevant percepts and rules to learn new information and create novel concepts. Attention is a prerequisite for practical knowledge work and generally requires significant cognitive effort to focus and sustain over time. The challenge of knowledge work is driven by the novelty and complexity of the task and correlates with the subjective enjoyment of the activity. Humans perceive flow as the optimal state of awareness during which task performance maximizes and self-awareness minimizes. Research studies on flow to date have a significant disagreement regarding what flow is and how to measure it. This paper proposes a formal human-task-context performance model of flow that integrates attention, surprise, and enjoyment to measure flow using active inference and Markov Decision Processes. We administered a cross-sectional questionnaire with KWs to obtain priors for our Bayesian model, capturing evidence about the flow components to make inferences about knowledge work performance. Our hypothesis states that when the human KW experiences flow at work, their ability to focus and sustain attention on the task is maximized, which minimizes their perceived ambiguity and stress, thereby resulting in effortless attention, which perpetuates flow.**

***Index Terms*—flow, attention, active inference, simulation**

I. Introduction

Knowledge workers (KWs) are experienced individuals whose work is primarily cognitive and involves the creation, distribution, or application of knowledge [1]. KWs interact with structured and unstructured data to deliberately add value, meaning and purpose. In spite of knowledge work being goal-oriented [2] and process-oriented, there are high levels of autonomy and ambiguity [3] specifying its inputs and outputs.

This paper proposes a contextual human task performance model to encapsulate knowledge work where the skill-to-demand ratio is flexible and attention is dynamic. We abstract knowledge work as cognitive functions based on goals, inputs, processes, and outputs. Context is the relevant side information such as time of day, location, etc. The contextualized human-task interaction relies on a set of constraints [4], which establish relationships among the human and tasks. Within a context, human-based limitations include the personal traits (e.g., flow propensity), capabilities, and preferences. Task-based constraints characterized are complexity, difficulty, and feedback. The model allows for mutable task goals, task switches and context switches by the KW.

Active inference encapsulates the interaction among the elements of the contextual human task performance model. It approaches understanding behaviour based upon the idea that the brain uses an internal generative model to predict incoming sensory data [5]. We use active inference to examine the KW's behavior in work situations with levels of demand varying from task underload to task overload. We selected the visual search and response task as a robust research paradigm to simulate and fit our contextual human task performance model to visually-based, target-seeking knowledge work tasks, e.g., a lawyer scrutinizing a million-dollar contract or an air traffic controller tracking radar targets at a busy airport.

Beyond Section I, "Introduction", which contextualizes flow performance of knowledge work, this paper links literature from cognitive psychology on flow and attention with theoretical work on active inference.

In Section II, "Background," we synthesize the components of flow experience into antecedents, behaviors, and consequences. This section applies principles of active inference to describe the process of focusing attention on task stimuli to increase task awareness and cause the emergence of flow through *effortless attention*.

In Section III, "Method," we leverage empirical datasets from a KW questionnaire to simulate the contextual human task performance model of flow under the free-energy principle. Emphasis was placed on operationalization of the flow components and the study of flow as a high-performance state of attention per unit effort.

In Section IV, "Results," we present the findings from the discrete event simulations of KWs as human agents interacting with a visual search and response task. We compared means and standard deviations of outcome variables across knowledge work scenarios with different levels of task demand.

In Section V, "Discussion," we explain findings from the simulations and demonstrate the insights related to concentration and effortless attention. We explore the relationship between flow propensity and flow emotion as personal flow dimensions of the questionnaire dataset.

In the final section, we conclude with the research outcomes and indications on how the contextual human task performance model of flow could advance neurotechnology using brain-computer interfaces and wearable biosensors.

II. Background

A. Antecedents, Behaviors and Consequences of Flow

Nine essential components drive the flow experience [6], which automates human task performance and results in enjoyable effortlessness [7], [8]. Table I organizes the nine flow components as the antecedents, behaviors, and consequences.

TABLE I
The Components of Personal Flow Experience

	Flow Component
Antecedents	1. Clear proximal goals
	2. Challenge and skill balance
	3. Immediate feedback
	4. Autotelic personality
Behaviors	5. Concentration on the task
	6. Merging of action and awareness
	7. Perceived control over task
Consequences	8. Loss of self-consciousness
	9. Time transformation

The first three task-based components and the human's autotelic personality are the antecedents of flow, i.e., preconditions for flow experience to occur. During task interaction, human behaviors, e.g., concentration on the task, are the experiential indicators of flow [9]. Concentrating on the task allows for the processing of more information, which improves task awareness and perceived task control. Self-reports confirm the consequences of flow after their occurrence. For example, the redirection of attention from the self and environment to the task is confirmed by accounts of time transformation and the loss of self-consciousness.

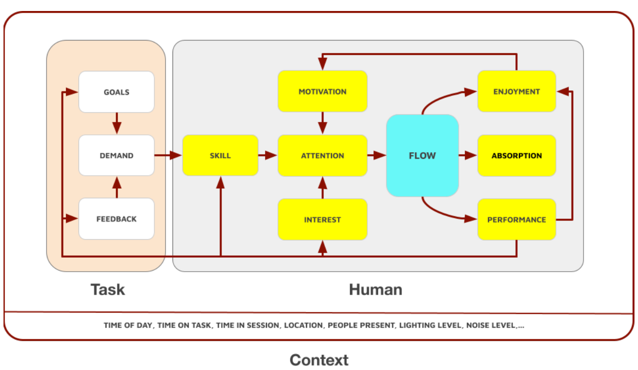

Fig. 1. The Contextual Human Task Performance Model of Flow Experience synthesizes the nine components of flow [6]

The cognitive control systems involved in producing flow include explicit skills that require conscious control and implicit skills that bypass consciousness [10]. This dichotomy explains the *automatization* of two critical processes during flow shown in Figure 1. The first process is the feed-forward control of the task stimulus that is sensed, perceived, and appraised through attention, which requires cognitive effort [11]. The second process is the feed-backward control of goal-directed decisions, actions, and emotions that motivate or inhibit attention [12].

B. Inducing Flow by Paying less Effort for more Attention

In this research with KWs, we treat *attention as a limited executive resource* [13], [14] that affects how sensory data is identified and manipulated to process goal-oriented functions. We, therefore, adopt an information-theoretic approach to articulate personal flow as a state of effortless attention where terms such as probability distributions, uncertainty, surprise, and precision are used to describe the transformation of stimuli into sensations into perceptions then actions.

KWs pay attention to themselves, their tasks and environments. In everyday language, the phrase "*pay attention to X*" implies that attention has a cost. In a basic form, attention is increased and focused by concentration [15], which has a *metabolic cost called cognitive effort* [14], [16], [17]. If a KW intentionally pays sufficient attention to the immediate work task consistently over time, the KW is likely to enter into the flow state and experience reduced effort, reduced perceived stress, and reduced uncertainty in task observations.

Treisman and Gelade [18] proposed the feature-integration theory of attention, in which the early step of attention involves the automatic and parallel registration of features, and the latter step of attention involves the focused and serial identification of objects. They used visual search tasks to show that a serial scan is imposed by defining a target among distractors using conjunctions of features, e.g., search for a red R in a display of red Ps and green Qs.

To test our idea of flow as a reduction in variational free energy, we simulated a visual search and response task that involved the human agent foraging for flow while selecting targets from different scenes of varying complexity. **We hypothesize that focused attention during human-task interaction tends to activate the flow state**. The framework in Table II organizes the different states of attention into the discrete flow state space with three levels, i.e. distracted, pre-flow, and deep flow.

TABLE II
The States of Attention and Personal Flow Experience

	Attentional State
Distracted	1. Divided Attention
	2. Alternating Attention
Pre-Flow	3. Selective Attention
	4. Focused Attention
Deep Flow	5. Effortless Attention

The following subsections apply psychological constructs of the attentional states to describe scenarios where the KW is foraging for deep flow experience in the experimental task.

1) Divided Attention: Distractions impact the amount of attention given to the primary task. During divided attention, some distractions become interruptions that degrade performance on the primary task. When attention is divided among multiple tasks, more time and executive resources are needed to switch between and integrate features [18]. Problems with inhibitory cognitive control may cause involuntary divided attention that prevents the KW from focusing attention [19].

2) Alternating Attention: It is natural for a KW to alternate their projects and tasks during the workday for both internal and external reasons [20]. A dairy study among KWs reported that 40% of task-switches were self-initiated [21]. The process of task-switching requires cognitive effort [22]. According to Baddeley [22], KWs need an accommodation period to unload the former task from working memory and load the cognitive representations of the new task. These unloading and loading operations of task-switching incur cognitive fatigue costs [23], especially during high frequency switches and when former tasks are left incomplete.

3) Selective Attention: As the KW concentrates selectively on a task, attention begins to focus on specific features within a subset of the task stimulus. Selective attention increases the probability of extracting and integrating the necessary features to consistently succeed on knowledge work. If the KW does not respond to complete the task, then the KW selectively shifts the focus of attention to observe a new subset of features within the task stimulus. The result of selective attention is a visual scan pattern over the task stimulus that orients towards novelty in the next subset and inhibits return to previously scanned target-absent subsets of the static task stimulus.

4) Focused Attention: As the KW repeats the steps of concentrating selectively, the visual scan patterns become skills or policies to guide attention so that the cycles of prediction and action can merge. When this happens, the KW becomes **absorbed in the task** since a majority of the attentional resources becomes focused on successful task performance [24]. Focused attention is the effect of increased concentration, which comes at the expense of cognitive effort. If there is little to no reward after the response, the expense of cognitive effort may be accumulated as cognitive fatigue.

5) Effortless Attention: During the KW's state of absorption in the task, the reduction of self-awareness may be associated with the neurological phenomenon called transient hypofrontality [10]. The savings in attention from the reductions of self-awareness may be redirected to task awareness. The availability of attention means that it comes at a lower effort, which causes the automatization of task performance and the onset of flow.

C. Flow Experience based on Active Inference

This section reviews the theoretical principles of active inference used to explain personal flow and effortless attention. Recall that the visual search and response task involves KWs searching through sets of distractors with the goal of quickly and accurately responding about the target's absence or presence in the set. The KW's internal generative model uses uncertainty represented as probability matrix of beliefs over the target stimulus relative to a sequence of visual sensations and cursor movements. By modeling transitions of attentional states in formal terms, we may better understand how attention is attenuated and how the flow experience emerges. Our the contextual human task performance model aims to determine if attention during flow becomes effortless due to reduced uncertainty and increased precision in human-task interactions.

1) Active Inference: Active inference provides a formal representation of behavior to demonstrate how a brain uses an internal generative model to predict incoming sensory data [5]. Consider a dataset $\boldsymbol{D}$ containing $\boldsymbol{N}$ points in (1), and a human agent with a prior distribution $P(\boldsymbol{M})$ over a set $\boldsymbol{M}$ of possible models.

$$\mathbf{D} = \{d_1, ..., d_N\} \tag{1}$$

Active inference requires KWs that are foraging for flow to pay attention to tasks and perform actions that yield the most information to update their internal models. The internal generative model represents a statistical structure, which has an updating process based on Bayes theorem in (2) that can be leveraged to allow prediction [25]. Prediction meaning that the results from active inference would hold consistently under a known range of different conditions processed by the internal model [26].

$$P(\mathbf{M}|\mathbf{D}) = P(\mathbf{M})\frac{P(\mathbf{D}|\mathbf{M})}{P(\mathbf{D})} \tag{2}$$

Shannon [27] proposed an information-theoretic definition in (3) where more information ($\boldsymbol{I}$) is gained from less predictable datasets with lower probabilities.

$$\mathbf{I} = -\log_2 P(\mathbf{D}) \tag{3}$$

By describing concentration in these formal terms, we can test what mediates attention and how the flow experience emerges. Our model aims to show that concentration during flow becomes effortless due to reduced uncertainty and increased precision in human-task interactions.

Understanding the decision to expend cognitive effort, as with any decision, comes down to investigating the relevant costs and benefits: how they are perceived, represented, and ultimately drive action selection [16].

2) Free Energy: Active inference is based on the premise that perception and learning can be described as minimizing a quantity known as variational free energy and that action selection, planning, and decision-making can be described as minimizing expected free energy [28]. Equation (4) expresses the likelihood of a policy as variational free energy, $\mathbf{F}$, which is a function of the internal generative model $P(\boldsymbol{D}, x)$ and an approximate posterior distribution over the hidden causes $Q(x)$ [29]. Active inference uses Bayesian inference to describe how an agent makes adaptive exchanges with its environment to minimize variational free energy [29]. The idea is that **every task-centered unit of attention, whether leading to success or failure, contributes to the resolution of uncertainty within the knowledge work task stimulus by helping to reduce free energy and expected surprise.** Given the assumption that a flow experience is the KW's preferred outcome, what action is the KW most likely to pursue? Can we use reductions in free energy to explain flow performance during knowledge work? We aim to formalize a generative model of flow performance that can provide an answer.

$$\boldsymbol{F} = E_Q[-\ln P(\boldsymbol{D},\, x)] - H[Q(x)] \tag{4}$$

3) Bayesian Surprise and Information Gain: Prediction-errors signal the degree to which sensory input is inconsistent with current beliefs. Prediction errors drive the system to find new beliefs – that is, adjusted probability distributions – so that they are more consistent with sensory input, and therefore minimize these error signals [28]. Only the observations that significantly shift prior beliefs to posterior beliefs yield the reward of wow and information gain [30]. This surprise $\boldsymbol{S}$ may be indicated by the difference between the distributions of the internal model as shown in (5).

$$S(\boldsymbol{D}, \boldsymbol{M}) = d[P(\boldsymbol{M}), P(\boldsymbol{M}|\boldsymbol{D})] \tag{5}$$

As an evaluation function, surprise helps us to formulate foraging for flow in terms of the seeking information rewards received during human-task interactions and updates of the internal model. Subsequent observations are presumed to be informative if the posterior distribution about the hidden states diverges from the prior distribution. In short, human-task interactions with high Bayesian surprise and information gain are likely to induce and sustain flow.

4) Foraging for Flow as Exploration and Exploitation: Under active inference, exploratory and exploitative behaviors arise as a result of free energy minimization. Likewise, Figure 1 characterizes knowledge work as an active inference process where the operator reduces the free energy within tasks seeking to learn, succeed and gain rewards.

For every human choice or interaction i, a flow state reward may be generated from a distribution with mean (μ_i), given the context and task demands. The aim is to learn model parameters $\mu_i, i = 1, ..., N$ for all human interactions to find the best interaction.

The foraging process starts with every human interaction initialized with a uniform priors $Beta(1, 1)$ about its mean. After $n_{i,t}$ interactions in time $1, ..., t$, the human agent updates its internal generative model to $Beta(S_{i,t+1}, F_{i,t+1})$, where:

$S_{i,t}$: number of 1s in $n_{i,t}$ human choices of interaction i

$F_{i,t}$: number of 0s in $n_{i,t}$ human choices of interaction i

The initial values of these variables (before any human interactions) are set to 0. (Observe that mean of posterior $Beta(S_{i,t+1}, F_{i,t+1})$ at time t is same as empirical mean $\hat{\mu_i}, t)$. The exploitative simulated human agent makes interaction i since its probability is the highest, i.e., $Pr(X_i > argmax_j X_j)$; whereas, an exploratory simulated human agent makes an alternative interaction a certain proportion of the times.

If KWs forage for the most surprising aspects of the task stimulus, it is possible to maximize the likelihood of the flow state and decrease the likelihood of other states. This fundamental strategy exploits the flow-inducing attributes of knowledge work and focuses attention on relevant task stimuli.

Given the observations of KWs performing this foraging behavior, we are applying the active inference to thinking about these behaviors being emitted by a generative model that shape how the KW responds to the task stimulus.

III. METHOD

Figure 2 depicts the cycle of methods used in this study to survey KWs, model and simulate their knowledge work activities in order to derive useful insights about the occurrences and predictions of flow experience. The methods fit into a larger research plan that is designed to research and develop a cognitive augmentation solution to amplify the performance of knowledge work.

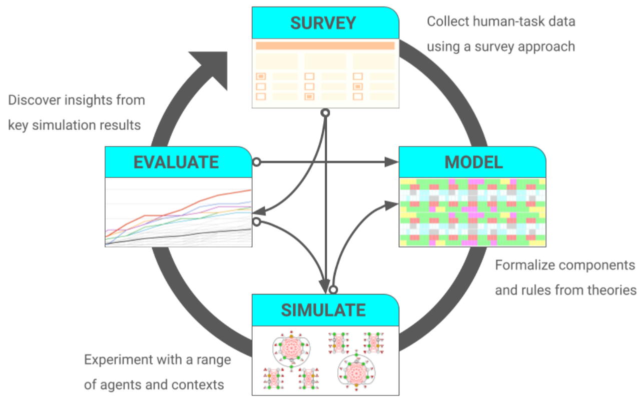

Fig. 2. The cycle of research methods used in this study.

A. Survey Knowledge Workers

We conducted a detailed questionnaire of 468 KWs from Amazon Mechanical Turk to probe their traits, behaviors, and preferences during knowledge work. The questionnaire was informed by previous interviews with KWs. We took a quantitative approach with the questions to obtain priors for subsequent knowledge work modeling and simulation.

The survey measured indicators of flow propensity in the form of personal traits such as morning-type vs evening-type, critical-thinker, well-organized, attentive, open to ideas, curious, agreeable, determined, patient, and self-motivated.

In terms of demands vs skills, the survey measured the how participants felt during different knowledge work situations, and how different outcomes affect their perceived skill levels. Participants rated the impact of different knowledge work situations on their interest and ability to concentrate.

The survey investigated the likelihood of specific aspects about the task, incentives and penalties to motivate the participant to continue tasks to the end. Correlations between effort and attention over were explored.

After rating how frequently they experience flow during knowledge work, participants described how they feel during the flow experience and how they distribute their attention among the task, self and environment. The effect of different task features and performance outcomes on the emotion of enjoyment was measured.

B. Model Human-Task-Context Performance

The agents modeled in this study are humans in given contexts performing given tasks. The contextual human task performance represents goal-based behaviors and activities. Table III shows the demographics and flow parameters of the human agent.

TABLE III
HUMAN AGENT FEATURES

Name	Range
Flow propensity	Never Sometimes About half the time Most of the time Always
Flow emotion	Apathetic Bored Neutral Happy Anxious Other
Mediators of attention	Extremely positive Somewhat positive Neither positive nor negative Somewhat negative Extremely negative
Influence of enjoyment on motivation	Extremely positive Somewhat positive Neither positive nor negative Somewhat negative Extremely negative
Influence of performance on interest	Extremely positive Somewhat positive Neither positive nor negative Somewhat negative Extremely negative

The mediators of attention were skill, motivation, and interest as depicted by the entities incident on the attention entity in Figure 1. We modeled the influences of: enjoyment on motivation, performance on interest, and performance on choice to continue, quit or switch the task.

Tasks were modeled in this study as work session nodes with goals, feedback and demands that are engaged by the human agent over variable time periods. The skill level of the human agent (i.e., novice, beginner, competent, proficient or expert) varies according to the task and its familiarity. Table IV shows distinct features of the task. Some of them are pre-defined by the human agent whereas others are confirmed by real-time observation, post-hoc metrics and self reports.

The human agent may **create, delete, edit, reorder, start, continue, complete, quit or switch a task**. The task demands **skill, interest, motivation, and attention** from human agents, and provides them with **feedback, rewards and penalties**.

TABLE IV
TASK FEATURES

Name	Range
Demand	Very easy Easy Medium Demanding Very demanding
Stage	Planning Before Beginning Middle End After

Table V highlights aspects of the context that encapsulates aspects of the environment, i.e., workspace, people present, lighting and noise level, along with temporal aspects of the contextual human task performance related to the day, task, work, and flow. The context interacts with the human agent by **limiting resource capacities, and influencing the perception of temporal and environmental factors**.

TABLE V
CONTEXT FEATURES

Name	Range
Time of day	Early Morning Morning Afternoon Evening Night Late Night
Time on task	0 - n seconds ($n \in \mathbb{R}$)
Time in session	0 - n seconds ($n \in \mathbb{R}$)
Session time in flow	0 - n seconds ($n \in \mathbb{R}$)
Workspace	Work Office Home Office Library Coffee shop Outdoors Other
People present	Yes No
Lighting	Bright Dull Natural Dark
Noise	Quiet Light Natural Loud

The context does not directly interact with the task but may indirectly skew the human agent's perception of the task's features, e.g., people present in the environment may positively influence successful performance and promote the choice to continue; whereas, people present in the environment may have an extremely negative influence on failed performance that causes the human agent to switch the task or context. The KW's context may influence interaction with the task stimulus, therefore, we keep contextual aspects constant during the simulation of the contextual human task performance model.

C. Simulate Knowledge Work

Knowledge work is made up of a stream of goal-oriented tasks. The human agents were categorized by their primary field of knowledge work, i.e., business, engineering, science, writing, music or arts. The preferred type of knowledge work based on familiarity and difficulty was also used as a factor.

There may be distractors that disrupt knowledge work and compete for attention. Some knowledge work is shallow, meaning that it is comprises low-value tasks that are easy to perform. On the other hand, deep knowledge work comprises high-value and demanding tasks.

In this paper, we used AnyLogic Personal Learning Edition 8.7.2 to implement the active inference process theory [31] within a cognitive model of contextual human-task interactions in a discrete event simulation of interdependencies between the flow components with the aim of discovering insights about the flow experience. The model was simulated as sequences of discrete events that trigger separate operations with queues, delays, and resource utilization.

A **visual search and response task** was modeled to identify how KWs discriminate and quickly identify target situations. In our visual search and response task, we simulate trials of KWs searching for a target among a set of distractors. In each trial, the KW performs a visual scan then decides whether the target is present in or absent from the task stimulus. The KW responds by actively controlling a cursor to click the target on the visual screen or clicks on the "no-target found zone".

In disjunctive search tasks, the target pops out of the task stimulus, and KW's reaction time is relatively unaffected by the number of distractors or the absence of the target [18]. In conjunctive search tasks where target discrimination is made more demanding by increasing the similarity between the target and distractors, the KW's reaction time increases linearly with the number of distractors, and the KW's reaction times are higher in target-absent trials relative to target-present trials [18].

The KW had to sense the visual data then recognize appropriate stored rules [4] in order to summarize the pattern of interest. If the KW clicks on the target or illusory , a hit or a false alarm is caused. Otherwise, inaction causes a miss or a correct rejection. Under the free energy principle, the KW makes action choices to reveal new information about the task.

In the process of the KW interacting with the task within the given context, cognitive workload expressed as a function of attention, performance, stress, and emotion counteracts task demands over time. The main problem under investigation consisted of estimating flow states from the simulation of contextual human task configurations with random perturbations being present in the human attentional process as well as in observations from the overall dynamical system.

The knowledge work simulation testbed flexibly accommodated various scenarios of human agent behavior and task interactions during normal, abnormal and emergency knowledge work situations. The simulation generates and processes random samples of human agents that are based on the prior distributions of KWs collected from the questionnaire. Our objective is to compute the posterior distributions of hidden cognitive states, given certain types of tasks and knowledge work situations.

IV. Results

Process flowcharts illustrate the inner workings of the contextual human task performance model at multiple levels of detail, and represent the logic and parameters used to uncover hidden dependencies between the flow components.

V. Discussion

Improved cognitive function following moderate short-term stress induction.

A. Pre-Attention and Proactive Attention

Memory-guided attention tasks show how learning of object locations through repeated visual search in complex scenes or environments facilitates performance in subsequent tasks.

Long-term, intermediate-term memory, and working memory guide attention at multiple timescales (Nobre and Stokes, 2019).

Memories are increasingly recognized to play an important role in influencing the degree of top-down control exerted on a given trial. They include both short-term traces between successive trials as well as intermediate memory traces that develop over task performance (Chiu and Egner, 2019)

VI. Conclusion

In this paper we have presented an empirically grounded functional classification of observable attention during different knowledge work situations. The different types of attention impact of how the flow experience is induced and sustained over time. Modeling and simulation was used to leverage a philosophy that many-sizes-fits-all solution to "testing" attention configurations across a wide range of idiosyncratic and generalizable conditions. We used the principles of active inference to model and simulate the contextual human task performance model, and demonstrate that effortless attention emerges during the flow experience.

This theoretical work has illustrated the computational mechanisms underlying effortless attention as phenomenon associated with personal flow and optimal situational awareness gain. Concentration requires attentional mechanisms that highlight relevant sources of information. Under active inference, attention can be thought of as the precision of sensory signals given their hidden causes. We appealed to this aspect of active inference by making the precision of the likelihood mapping between sensory signals and their hidden causes context-dependent. This allowed us to show that context-driven exploration arises as a result of down-weighting the precision of the context-irrelevant sensory signals, while maintaining the precision of the context-relevant sensory signals.

We hope that the contextual human task performance model presented here could inform the design of neurotechnology systems that can capture a wide range of behaviors and correspondingly balance personalized attention processes with group attention needs that could be contextually specified. Future work includes field studies in a larger variety of flow-inducing conditions. Collecting data from a participant pool conducting measurable knowledge work tasks would improve newer simulation models as well as training and evaluating a between-subject case-based reasoner to classify flow-state that does not require per-subject training.

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