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Learning in the Loop: Task Load and Motivation in a Neuroadaptive Learning System

par

Katrina Sollazzo

Alexander John Karran

HEC Montréal

Co-Directeur de recherche

Sylvain Sénécal

HEC Montréal

Co-Directeur de recherche

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Nom de l'étudiant(e) : KatrinaSollazzo

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Cochercheurs : Sylvain Sénécal; Patrick Charland; Bella Tadson; Noémie Beauchemin; François Courtemanche; David Brieugne; Amine Abdessemed; Salima Tazi; Alexander John Karran; Jared Boasen; Ioana Mihaela Stefanescu; Katrina Sollazzo; Thaddé Rolon-Mérette; Alejandra Ruiz Segura; Hajar Laghmari; Uriel Karerwa

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Résumé

L'intégration croissante des technologies numériques dans les contextes éducatifs nécessite des systèmes adaptatifs capables de répondre dynamiquement à la fois à la performance des apprenants et à leurs états cognitifs sous-jacents. Alors que les systèmes traditionnels de tutorat intelligent s'adaptent généralement à partir de mesures comportementales, les avancées récentes en neurotechnologie soulignent le potentiel des données neurophysiologiques en temps réel pour fournir une rétroaction plus nuancée et individualisée. Ce mémoire explore le potentiel d'un système neuroadaptatif, piloté par un indice de charge de tâche, afin d'améliorer la performance et l'engagement dans une tâche d'apprentissage. Lors d'une expérience contrôlée en laboratoire, 51 participants ont été assignés aléatoirement à l'une des trois conditions (contrôle, motivation extrinsèque, neuroadaptative) et ont effectué une tâche d'apprentissage en ligne répartie en quatre blocs, avec enregistrement continu des données physiologiques et neurophysiologiques. Les participants ont également rempli des mesures auto-déclarées d'engagement et de motivation intrinsèque. Les résultats indiquent que les participants sous motivation extrinsèque ont démontré une meilleure performance dans les derniers blocs. À l'inverse, le groupe neuroadaptatif a atteint des performances comparables à ceux du groupe contrôle mais avec une charge de tâche significativement réduite, expliquée par une diminution des niveaux de thêta frontal et d'alpha pariétal, suggérant une allocation plus efficace des ressources cognitives. Ces résultats soutiennent l'intégration de rétroactions neurophysiologiques en temps réel pour une instruction personnalisée, avec des implications pratiques pour l'adoption élargie en éducation numérique.

Mots clés : système neuroadaptatif, BCI (brain-computer interface), EEG, charge de tâche, apprentissage, motivation extrinsèque

Méthodes de recherche : expérimentation, recherche quantitative, mesures neurophysiologiques

Abstract

The growing integration of digital technologies in educational contexts necessitates adaptive systems capable of responding dynamically to both learner performance and underlying cognitive states. While traditional intelligent tutoring systems typically adapt based on behavioural performance metrics, recent developments in neurotechnology highlight the potential for real-time neural data to provide more nuanced and individualized feedback. The thesis investigates the potential of a neuroadaptive system driven by a task-load index to enhance performance and engagement during a digital learning task, by sustaining optimal cognitive states for learning. In a controlled laboratory experiment, 51 participants were randomly assigned to one of three conditions (control, extrinsic motivation, neuroadaptive), and completed a four-block digital learning task, while physiological and neurophysiological data were continuously recorded. Participants also provided self-reported measures of engagement and intrinsic motivation. Findings suggest that participants in the extrinsic motivation condition demonstrated superior performance in later blocks. Conversely, those in the neuroadaptive condition achieved performance comparable to controls, but with significantly reduced task load, explained by lower levels of frontal theta and parietal alpha band activity, suggesting more efficient cognitive resource allocation. These findings advance the development of neuroadaptive learning systems by empirically validating the role of real-time, neurophysiological-based feedback in personalized instruction, thereby offering practical applications for broader adoption in digital education.

Keywords: neuroadaptive system, BCI (Brain-computer Interface), EEG, task load, learning, extrinsic motivation

Research methods: laboratory experiment, quantitative research, neurophysiological measures

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List of abbreviations and acronyms

HCI: Human-computer interaction

TL: Task load

CL: Cognitive load

ZPD: Zone of proximal development

IM: Intrinsic motivation

EM: Extrinsic motivation

BCI: Brain-computer interface

EEG: Electroencephalography

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A special shoutout to the YouTube channel *Calmed by Nature*, the soundtrack to this degree, there's nothing quite like 5 hours of Fall Library Cafe Ambience with Calm Jazz Music & Rain for Studying, Focus, & Relaxation.

And with that, this thesis ends – but the next is about to begin just with a new project name. What comes after *Gremlins*? *Goblins*? *Gargoyles*?

Introduction

In an era defined by rapid technological advancement, understanding how humans learn and perform has never been more critical. Broadly, human-computer interaction (HCI) is the study of the dynamics between users and information technology (Card et al., 1983). HCI is a multidisciplinary field that borrows from cognitive science, human factors ergonomics, and computer science. Combining these fields enables the design of functional, intuitive, and efficient systems while aligning with human needs and capabilities. Recent developments in HCI benefit from neuroadaptive brain-computer interfaces (BCI). Brain-computer interfaces utilize neural activity to affect change in a system (Krol & Zander, 2017; Zander et al., 2016). The global BCI market is projected to generate a compound annual growth rate of 18.15% from 2025 to 2030 (Grand View Research, 2024). Recent developments show promise of neuroadaptive systems to improve daily life across multiple domains such as healthcare, aviation, and education. Many clinical trials, such as the Neuralink clinical trials (McBride, 2025) or those involving mood-altering brain implants (Devlin, 2025), have been in recent news, boasting of the potential benefits of BCIs. While clinical trials attract attention with invasive procedures, identifying effective, non-invasive methods of BCI implementation is the primary focus of researchers worldwide to ensure a higher likelihood of user adoption (Hsieh et al., 2025). Specifically, identifying non-invasive methods of BCI implementation facilitates neuroadaptive learning environments, allowing for more effective learning tailored to individuals' progress and abilities.

In addition to adaptive systems, motivation is a pertinent factor in enhancing learning experiences. Motivation has long been recognized as a key driver of effective learning (Deci & Ryan, 1985), influencing performance outcomes. It is an effective means of improving outcomes, particularly by targeting extrinsic motivation by incentivizing performance with monetary rewards. Nevertheless, feasibility and ethics are often called into question. For example, it is unrealistic to promise students $1 for every 10% they achieve on an exam. This challenge calls for the search of an alternate system in which to improve outcomes, that is, a system that is easily implemented, non-invasive, and effectively improves learning outcomes as well as, or better, than an extrinsic motivator. A neuroadaptive system is a likely candidate to meet these goals due to its ability to personalize the learning experience by responding dynamically to an individual's cognitive state (Krol & Zander, 2017; Zander et al., 2016). Additionally, new neuroadaptive systems are aiming to be scalable and non-invasive, making them more practical for widespread implementation in educational settings compared to extrinsic motivators.

Moreover, previous research has utilized measures of cognitive load (CL) to drive neuroadaptive systems in various contexts (Beauchemin et al., 2024; Mark et al., 2022). Drawing on cognitive load theory, CL is a multifaceted construct that broadly encompasses the mental effort necessary for engaging in a task or activity (Sweller et al., 2011). While CL is affected by additional factors such as the environmental context and task modality (Kirschner, 2002; Mayer, 2003), task load (TL), a construct beneath the umbrella of CL, solely focused on the mental effort required to engage in a computer-based task. Since task load is an underutilized construct, it warrants further investigation and precise operationalization to understand better its potential for driving a brain-computer interface (BCI) that optimally enhances learning outcomes. In the domain of neuroadaptive systems, it is postulated that countermeasures may play a similar role as extrinsic motivation in improving learning outcomes by maintaining an optimal cognitive state.

Addressing this research avenue is particularly important given the increasing adoption of adaptive systems in diverse learning environments, ranging from e-learning platforms to high-stakes professional training. It is necessary to validate the system with robust measurement tools (i.e. EEG) before piloting more widely accessible measures such as pupillometry.

This thesis seeks to explore the role of TL utilized as input to a BCI, and its potential impact on learning outcomes and user experience in a neuroadaptive system while considering the role of motivation. By examining TL as a dynamic factor, this research aims to contribute to a broader understanding of how such measures can inform and optimize user experiences. The findings have implications for validating TL as an indicator of executive function and its application in a wide array of domains, including education, workplace productivity, and critical infrastructure monitoring. Considering prior research, this thesis aims to disentangle the effects of motivation on neuroadaptive learning by posing the following research question:

How can neuroadaptive technologies reshape traditional approaches to online learning by addressing the limitations of extrinsic motivation?

We conducted a laboratory experiment with a three-group, between-subjects design to answer the research question. Participants completed a learning task while a 32-electrode EEG system recorded their neural activity, classifying their TL in real-time. Additional measures of motivation, engagement, and user experience were captured to better understand the user experience of interacting with a neuroadaptive system. Data were analyzed using an analysis of variance framework. Sensor-level, EEG-informed scalp topography maps were generated to achieve deeper insight into the cognitive processes at play during the encoding phase of the learning trials. These analyses allow for between-group comparison of the dependent variables in addition to comparison within groups across learning blocks.

This thesis provides theoretical contributions and practical implications. Placing the research at the intersection of neuroadaptive systems, TL, and motivation, this thesis provides insight into how these concepts can be leveraged to optimize learning outcomes in diverse educational and professional contexts. By introducing a novel application of TL as a driver for a BCI, this research expands the current understanding of adaptive systems, providing evidence in favour of the utility of measuring TL. The advancements discussed in this thesis hold the potential to revolutionize e-learning platforms, professional training programs, and other domains where cognitive optimization is paramount.

This thesis comprises four chapters. The first chapter, the introduction, establishes the foundation of the study. Chapter 2 presents the first article, a scientific recount of the methodology and findings of the research study, details the quantitative research design, assessing the effects of a neuroadaptive system on performance, motivation, and TL in a learning task. In addition, this article is in preparation for submission to the academic journal *ACM Transactions on Computer-Human Interaction.* Chapter 3 presents the second article, aimed at the general population, conveying the main contributions and the practical implications of the study presented in Chapter 2. This article is in preparation to be submitted to *The Conversation*, an independent news outlet that publishes evidence-based articles aiming to disseminate scholarly insights to the public. The thesis is completed by Chapter 4, the conclusion, summarizing the study and the overall contributions.

The following table summarizes the student's contributions to the various stages of the research project and the writing of the thesis. The percentages reflect the scope of the student's responsibilities and the extent of their efforts in executing each task.

Table 1. Contributions and Responsibilities in the Completion of the Thesis.

Research Activity	Contribution
Research Questions	Defining the research problem – **70%** - The broad research question was established prior - Implemented additional variables according to the literature
Literature Review	Development of the literature review – **90%** - Identification of existing literature on the topic - Assistance from supervisors on identifying seminal papers
Experimental Design	Planning and structuring the experiment – **75%** - Establishing experimental protocols and procedures - Collaboration with the lab on integrating tools and technologies
Pre-tests	Testing procedures prior to experimentation – **95%** - Pilot testing and refining protocols according to feedback - Validating tools and measures - Ensuring equipment functionality
Participant Recruitment	Recruitment and Management of Participants – **60%** - Recruitment facilitated by HEC's research panel - Management of participants was aided by the Tech3Lab research panel team
Data Collection	Systematic collection of research data – **100%** - Present during all data collection sessions
Analysis	Pre-processing the data – **30%** - The data pre-processing was conducted in part by the Tech3Lab team. Statistical Analyses – **90%** - EEG analyses were conducted in partner with Thaddé Rolon-Merette.
Writing	Writing of the thesis – **100%** - All thesis chapters were written independently, with feedback from the supervisors and co-authors of the articles.

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Chapter 2

Utilizing Task Load to Drive a Brain-Computer Interface in a Neuroadaptive Learning Task[1]

Katrina Sollazzo, Alexander John Karran, Sylvain Sénécal

Abstract

The major shift towards online learning calls for methods to tailor learning to individual user needs. A neuroadaptive system driven by a brain-computer interface (BCI) can dynamically adapt aspects of the learning interface in real-time based on the classification of a cognitive state, in this case, task load (TL). Task load, a construct under the umbrella of cognitive load, considers the mental effort required to complete a computer-based task. This study employed a three-group (n = 51) between-subjects design to investigate how motivation, a key element for engagement and performance, affects learning outcomes during a neuroadaptive learning task driven by a task load index. A 32-electrode electroencephalography (EEG) system captured frontal theta and parietal alpha band activity to classify TL as low, medium, or high. This classification drove the interface to adapt the presentation speed of the stimuli. The neuroadaptive group achieved results comparable to those of the control group. However, further investigation of the TL level throughout the task duration suggests the neuroadaptive group exerted less cognitive effort than the control group. In contrast, the extrinsic motivation group, who were promised a monetary reward based on performance, outperformed both the neuroadaptive and control groups, exerting similar effort as the control group. Topographic maps displaying alpha and theta activity reveal the emergence of distinct learning patterns during the encoding phase across groups.

[1] This article is in preparation for publication in *ACM Transactions on Computer-Human Interaction*

Introduction

Learning is fundamental to human development, allowing individuals to build on past knowledge, develop new skills, and adapt to new challenges. From early childhood to adulthood, effective learning is important for personal and professional growth. Many resources such as formal in-person education and online training modules, exist to facilitate learning. With considerable advancements in digital platforms, a significant shift has occurred toward online learning, which has emerged as a staple method of education at all levels. In 2022, 21.8% of Canadians over the age of 15 took part in formal training or learning online (Statistics Canada, 2023). In the context of this study, online learning is defined as any learning experience that takes place on a digital platform. As the popularity of online learning continues to grow, it is of vital importance that the learning experience is effective to ensure a successful educational experience (Hongsuchon et al., 2022). Online learning offers a compelling advantage as it can be adapted to each user's specific needs. Past research emphasizes the importance of tailoring teaching methods to the specific needs of the learner to optimize learning outcomes (Klašnja-Milićević et al., 2011; Tekin et al., 2015). However, imposing effective adaptations requires accurate measures of cognitive states.

Given the complexity of human cognition, psychological constructs are frequently utilized to assess these cognitive states accurately. Fostering suitable levels of motivation and engagement greatly impacts learning as seen in outcomes such as performance and learning speed (Duan et al., 2020; Liang et al., 2018). Motivation, both intrinsic and extrinsic, affects how individuals engage with tasks (Deci & Ryan, 1985). These two facets of motivation play complementary roles in promoting effective learning. Nevertheless, the relationship between motivation and engagement in online settings remains unclear and underexplored. Additionally, task difficulty can influence both motivation and engagement. The level of difficulty an individual confronts while facing a task, in combination with the amount of effort required to complete the task, referred to as task load (TL), can heavily influence their learning outcomes. Unlike cognitive load (CL), TL is a multifaceted measure of real-world task performance. Finding the right balance of TL is vital to ensure learners can perform at their optimal level. Understanding how TL impacts performance through motivation and engagement in an online learning task is essential to developing systems that ensure learners remain in their ideal learning zone.

It is possible to establish the best environment for individuals to learn using Vygotsky's concept of the Zone of Proximal Development (ZPD) (Vygotsky & Cole, 1978).. The ZPD delineates the ideal intersection of what an individual can accomplish on their own and what they can accomplish with scaffolding. Notably, the ZPD is unique for every learner. Traditionally, scaffolding is provided by teachers, mentors, or similar. However, with the rise of online learning, it is interesting to consider the role the platform plays in facilitating the learning experience. A logical next step would be to create an online learning interface that can adapt to TL while taking into consideration learner motivation to enhance learner performance, by maintaining each user's ZPD.

The current study aims to evaluate a neuroadaptive brain-computer interface (BCI) driven by an experimental TL index and its potential to enhance learning outcomes and engagement in a neuroadaptive system. Therefore, this study aims to answer the following question:

RQ: To what extent does motivation affect learning outcomes and engagement during a neuroadaptive task, driven by a task load index?

The remainder of this article explores the methodology used to investigate this causal relationship. Firstly, we present a review of the literature, providing a theoretical foundation and informing our research hypotheses. Secondly, we discuss a detailed explanation of the experimental design employed in the study. Thirdly, we present the results of our analysis. Finally, we interpret the results and discuss their implications and scientific contributions.

Background

Zone of Proximal Development in Online Learning

Vygotsky's framework of ZPD traditionally describes the zone in which adequate scaffolding allows an individual to learn (Vygotsky & Cole, 1978). The key idea is that the ZPD denotes the optimal zone for learning, where an individual can use their own experience in conjunction with a beneficial level of support to expand their knowledge. This framework has been previously drawn on in human-computer interaction (HCI) research. Ferguson et al. (2022) found that in a narrative game, AI-driven personalized instruction improved learners' performance, reducing their CL. The researchers successfully maintained a user's optimal ZPD by altering their cognitive state through real-time personalized instruction. Although previous research has reported on optimal ZPD and cognitive states, little is known thus far of how specifically a neuroadaptive BCI could alter an individual's cognitive state to improve learning outcomes.

Regarding online learning, the scaffolding necessary for individuals to succeed can take shape in the form of a neuroadaptive system. Neuroadaptive systems driven by a passive BCI use neural input from a source (such as EEG) to adapt the interface according to a classification index (Krol & Zander, 2017; Zander et al., 2016). Neural activity, typically brain waves, is used to infer a cognitive state, such as sustained attention (Karran et al., 2019), level of cognitive load

(Beauchemin et al., 2024) and mindfulness (Daudén Roquet et al., 2023), which in turn is used to adapt an interface based on a pre-determined classification of the cognitive state. The stated model is a closed biocybernetic loop (Pope et al., 1995), which comprises four iterative steps: 1. the individual's actions elicit specific brain activity, 2. the brain activity is measured and classified, 3. the system adapts depending on the classification, 4. the individual reacts to the adaptation triggering new brain activity, consequently closing the loop. There exists both an active and a passive form of non-invasive BCI (Zander & Kothe, 2011). In the active form, users consciously and purposefully attempt to alter their neural activity to elicit changes in the interface through the BCI. On the other hand, in the passive form, the user is unaware that changes in their activity subsequently cause changes in the interface, as it is done automatically.

Passive BCIs have been successfully used in a multitude of areas, including aviation (Borghini et al., 2022; Mark et al., 2022), driving (Alguindigue et al., 2024; Liu et al., 2015), and education (Sethi et al., 2018). In education, past research has focused on measuring key elements critical for learning. Serrhini and Dargham (2017) developed and validated a BCI that assessed attention as measured from alpha and beta wave frequency measurements during an online course. Apicella et al. (2022) proposed and validated an adaptive system based on cognitive engagement during cognitive tasks, intended to extend to online learning platforms. However, despite these advancements, there are still significant gaps in the literature regarding the objective measurement of cognitive states. In particular, TL is essential to assess as it is used as a measure of the cognitive state of an individual while they are immersed in a task (Hart & Staveland, 1988).

Given the critical role of TL in computer-based tasks, neuroadaptive countermeasures may improve user performance by keeping users in their optimal ZPD. As the ZPD implies the existence of two other states; cognitive underload and cognitive overload (Vygotsky & Cole, 1978), by dynamically adjusting to real-time TL classification, the system can help the user overcome this challenge, maintaining a cognitive state most conducive to learning.

Cognitive Load and Task Load in Neuroadaptive Learning Systems

Two main constructs have been previously studied to uncover cognitive mechanisms at play during learning: mental workload and CL. Mental workload is a multidimensional construct that is characterized by individual traits, cognitive states, and task criteria (Van Acker et al., 2018). Previous research has used the NASA TLX, a subjective measurement scale, to measure workload in online learning, reporting that students require increased effort in online learning (Febiyani et al., 2021). Moreover, increased workload elicits increased fatigue, negatively affecting learning outcomes (Kubicek et al., 2023). Drawing on cognitive load theory, CL is an umbrella construct for the mental effort and cognitive resources necessary to process and store information while performing a task (Sweller et al., 2011). Extensive research has been conducted commending the relevance of CL on digital tasks such as learning (Beauchemin et al., 2024; Skulmowski & Xu, 2022) and decision-making (Deck & Jahedi, 2015). However, CL is a broad construct that considers more than task difficulty and is affected by external factors such as environmental context and task modality (Kirschner, 2002; Mayer, 2003). Therefore, we argue that TL is better suited to assess users' cognitive state in a computer-based task than CL or mental workload.

Task load is an underutilized sub-construct of CL linked to task difficulty, focusing explicitly on the mental effort required to complete a computer-based task. Task load has been derived from mental workload to improve the classification of the cognitive process occurring while engaged in a task. The current study aims to employ a granular measure of TL, as compared to mental workload and CL, through electroencephalography (EEG). Research suggests that frontal theta is sensitive to expending cognitive resources (Xie et al., 2016), sustained attention, and working memory (Borghini et al., 2014). Conversely, parietal alpha is indicative of cognitive fatigue (Borghini et al., 2014). Therefore, we posit that an index created using multiple pairs of frontal theta and parietal alpha will exhaustively represent TL. This index will classify TL into three levels (low, medium, and high), triggering task-specific countermeasures in the interface and facilitating the user's performance of the task. Ultimately, the use of the TL-driven neuroadaptive system will adjust the interface in real time, maintaining the user at their optimal TL level, which acts as a proxy for their ZPD. The countermeasures elicited by the TL classifications act as the scaffolding learners require to preserve their optimal ZPD.

The Role of Motivation in Online Learning and Task Load

Motivation, both intrinsic and extrinsic, plays an essential role in learning. Ryan and Deci (2000, p.56) define intrinsic motivation (IM) as "the doing of an activity for its inherent satisfactions rather than for some separable consequence." Contrarily, they define extrinsic motivation (EM) as engaging in a task or activity with the desire to attain a specific outcome of value. Extrinsic motivation has been studied in various ways, most often as an incentive, typically of monetary value (Beauchemin et al., 2024; Duan et al., 2020; Liang et al., 2018). According to self-determination theory, both forms of motivation work in parallel to promote an individual's ability to learn (Deci & Ryan, 1985). While the two forms act on different mechanisms, together they support learning. Research suggests that there is an additive effect, rather than an interaction effect, of IM and EM on memory performance (Duan et al., 2020). It is suggested that EM promotes learning by minimizing distractions, while IM increases attention and activation of the reward system. Both mechanisms enhance memory formation.

As explained by the motivational intensity theory (Brehm & Self, 1989), the effort that one is willing to exert is directly related to the demand for the task. By isolating TL from CL, we can better investigate the role of motivation on learning. Zhozhikashvili et al. (2024) investigated the effect of IM on working memory. Specifically, they report that although IM is not associated with accuracy, participants who reported higher subjective IM applied additional effort when faced with more challenging tasks. This finding is reflected in increased frontal midline theta activity and greater alpha desynchronization.

Given the dual role of motivation on learning, it is expected that IM will moderate the relationship between the experimental group and performance. Extrinsic motivation is a treatment level in the experiment, as it would be impossible to disentangle the effects of the neuroadaptive system and monetary incentive. Therefore, EM is expected to further improve performance in a learning task, similar to the improvement yielded from utilizing a neuroadaptive system.

Examining the Impact of Neuroadaptive Countermeasures

Implementing a novel system of cognitive state classification and adaptation necessitates measuring the success of the system. The neuroadaptive system will be assessed by participant performance and TL across the task. Ultimately, we expect that through the implementation of countermeasures, the system will reduce the expenditure of cognitive resources, maintaining an optimal learning state for each user. Nonetheless, additional measures will bolster the results. Specifically, user satisfaction can be used to indicate how users perceive their interaction with the system (Griffiths et al., 2007), giving insight into the user experience. Similarly, asking participants about their intention to recommend the system to a friend or colleague can indicate the potential for broader adoption of a new technology (Blau et al., 2017; Rahman et al., 2022). Moreover, both these factors interplay with engagement. Therefore, engagement will also be measured psychometrically to indicate system success (Martin & Bolliger, 2018; Muzammil et al., 2020).

In summary, this study aims to address gaps in the literature by investigating the role of TL within a neuroadaptive learning task. Focusing on TL, rather than broader constructs such as CL or mental workload, allows for a more precise classification of users' cognitive state for real-time adaptation of the learning environment. This adaptive approach aligns with Vygotsky's framework of the ZPD (Vygotsky & Cole, 1978), as it aims to maintain a learner's optimal state for learning through dynamic modifications. Moreover, taking into consideration both intrinsic and extrinsic motivational factors is expected to enhance learning outcomes, providing a more nuanced understanding of their impact on user performance. Evaluating additional system success indicators will offer valuable insights into the user experience and the potential implications of the neuroadaptive system. Collectively, these findings will contribute to developing more effective and adaptive online learning platforms, ultimately bridging the gap between cognitive state adaptation and user-centered design.

Method

Participants

Fifty-one adults (24 female; age $M = 26.61$, $SD = 5.76$) participated in the study. The sample size is consistent with prior BCI studies using similar methods requiring intensive data collection (Apicella et al., 2022; Beauchemin et al., 2024; Karran et al., 2019). Participants were recruited from our institution's panel on the basis of good health, normal or corrected vision, no history of neurological disorders, and advanced understanding of French, both oral and written. Participants were compensated $60 and entered in a draw for a $200 Visa gift card, in line with the EM condition described in the following section. Ethical approval was obtained from the institution on March 27th, 2024, under the certificate 2023-5071.

Procedure

Participants were randomly assigned to one of three groups: Control (no reward, no adaptivity) (C; n = 19), reward and no neuroadaptive countermeasures (R; n = 16), neuroadaptive countermeasures and no reward (N; n = 16). Data collection sessions, conducted in French, lasted approximately 150 minutes. After providing informed consent and demographic information, participants underwent tool installation and signal verification (EEG impedance check and artifact inspection). Baseline tasks were included to establish reference measurements for physiological and EEG data. Participants completed a pre-task questionnaire establishing demographic information and prior knowledge of the task content, followed by four blocks of the learning task. Group R participants were informed they would earn one entry into a $200 prepaid Visa gift card draw for every 10% improvement in their block scores. Post-task questionnaires measured IM and engagement. Participants signed a compensation form for electronic payment and were thanked before departure.

Experimental Design

The study used a between-subjects, three-group design where the independent variables were EM and neuroadaptivity. EM was in the form of entries into a draw for a monetary reward, where the more correct responses during the task, the more entries participants believed they would receive. At the end of the study, all participants received the same number of entries in the draw.

Measures

To measure IM, we adapted the Intrinsic Motivation Inventory, originally developed by Ryan (1982). The scale consists of 7 subscales, totalling 45 items. Traditionally, each item is rated using a 7-point Likert scale from “not at all true” to “very true”. The scale was shortened to 11 items based on a 2011 study by Sun and Gao with a Cronbach alpha of .92. The current study’s Cronbach’s alpha calculation indicated a level of internal consistency of .69. Therefore, the three dimensions (interest $\alpha = .88$, effort $\alpha = .88$, and competence $\alpha = .95$) were investigated independently.

Perceived engagement was measured using an engagement scale developed by de Vreede et al. (2019). The scale is composed of three dimensions: affective engagement, behavioural engagement, and cognitive engagement. The scale is composed of 15 items in total. During the creation of the scale, the authors reported a Cronbach’s alpha of .73 for the cognitive factor, .92 for the behavioural factor, and .86 for the affective factor. Initially created to have a discipline-independent definition and measure of engagement, the scale has since been used to assess engagement with artificial intelligence (de Vreede et al., 2024). This study reported similar Cronbach’s alphas for the three factors: .90, .90, and .92, respectively. The scale was reduced to three items per dimension based on the highest factor loadings of the de Vreede et al. (2024) study. The current study’s Cronbach’s alpha calculation revealed an acceptable level of internal consistency ($\alpha = 0.72$), therefore the dimensions were combined.

We used the Net Promoter Score (NPS) developed by Reichheld (2003) to measure individuals’ intention to recommend. The NPS is a single-item scale scored on an 11-point Likert scale, where 0 denotes “not likely” and 10 denotes “likely”. To measure satisfaction, we used the Customer Satisfaction Score (CSAT) developed by Faris et al. (2010). It is a single-item scale, scored on a 7-point Likert scale where 1 represents "not satisfied" and 7 represents "satisfied". Prior knowledge was measured with two single-item questions to get a general idea of participants' knowledge of the task content, as well as a 10-item scale adapted from Flynn and Goldsmith (1999).

All scale items were presented as a sliding scale with an anchor on either end. This decision was made to maintain valid scores in a small sample by mitigating response bias.

Regarding physiological measures, heart rate variability (HRV) was calculated as the ratio of low-frequency power (0.04 Hz - 0.15 Hz) over high-frequency power (0.15 Hz - 0.4 Hz) (LF/HF) (Pagani et al., 1986) throughout each block. Electrodermal activity (EDA) was measured as average phasic EDA across each block, created from data recorded at 250Hz averaged every second (Benedek & Kaernbach, 2010). These two physiological measures were used as proxies for autonomic activation (Ghiasi et al., 2020).

Experimental Stimuli

The interactive user interface was adapted from Riopel et al. (2017). This specific task was chosen as it was anticipated that participants were likely to be unfamiliar with the content. The original task was comprised of 88 constellations. Of these constellations, 32 were selected for this learning task based on shape similarity to increase the task's difficulty. The stimuli were presented in four blocks. Each constellation was shown in conjunction with four possible responses for the participant to select. The interface displayed a countdown below the response options during the response portion and the feedback portion of each trial. See Figure 1 for a complete example of the stimuli. Response time was fixed at five seconds. Feedback time was fixed at five seconds for the C and R conditions. The feedback time for the N condition started at five seconds for the first trial, then varied by one second depending on the classified TL. The feedback time could vary between three and eight seconds, inclusively. Each constellation was presented twice per block, in a pre-determined randomized order, giving 64 trials per block.

Figure 1. *Example of the Constellation Stimuli*

Note 1. Left: Response stimulus, Right: Feedback stimulus

Instruments and Lab Setup

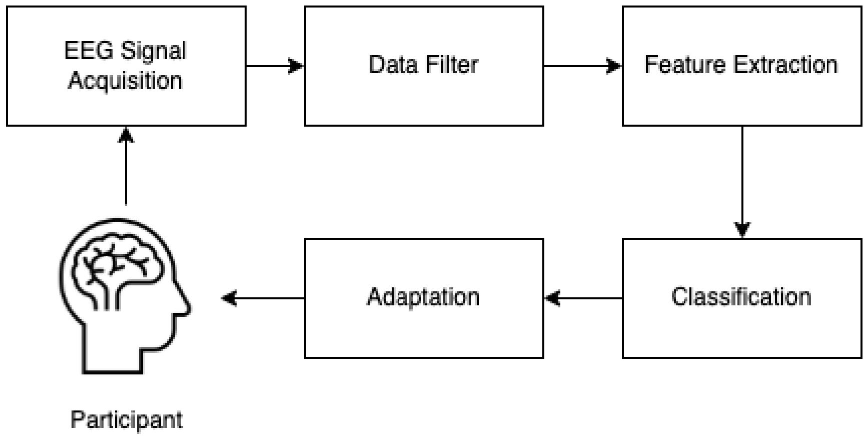
Participants were situated in a Faraday cage, equipped with a desk, a Lenovo monitor (1920 x 1080, 59.93 Hz), and a chair with adjustable height. There was a two-way mirror between the experimental room and the observation room, where participants could not see into the observation room. In the observation room, there were three computers and five monitors. There was a switch between two monitors to alternate which screen was displayed to the participant. The moderator communicated with the participant via a microphone and speaker. Data synchronization was possible through a sync box that delivered pulses from the COBALT Bluebox (Courtemanche et al., 2022; Léger et al., 2022) to Tobii Pro Lab every 60 seconds. The pulses could then be converted to UTC timestamps, which allowed for complete synchronization between all data sources.

Variations in brainwave activity were captured using the g.tec NAUTILUS wireless system (g.tec medical engineering GmbH, Schiedlberg, Austria), specifically using the g.SCARABEO active electrodes (g.tec medical engineering GmbH, Schiedlberg, Austria). A 32-electrode EEG montage was configured based on the 10-10 (Chatrian et al., 1985) and 10-20 international system (Klem et al., 1999), with adjustments made to ensure data were captured in the areas of interest. Eight electrodes were identified as crucial to measure TL (F1-4, CP1, CP5, P1, P5). PO3, PO4, O1, and O2 were remapped to accommodate this electrode selection. A ground electrode was placed at Fz, and a reference electrode was placed on the right earlobe as a common baseline to facilitate noise reduction and EEG signal comparison (Nunez et al., 1997).

EEG signals were recorded using Simulink, a Matlab-based software (version R2021b, IBM), with a real-time sampling rate of 250Hz. A simplified Simulink model can be found in Figure 2. All 32 channels were saved as raw EEG signals. Data for the eight electrodes of interest were processed in real-time with Bandpass (0.5Hz-50Hz) and Notch (58Hz-62Hz) filters. A Simulink block was also implemented for band-power extraction for the eight electrodes. Task load classification was a two-stage process. First, 16 ratios were calculated every second and classified as high or low based on the 1st and 3rd quartile average theta-alpha ratios from the Group C data. Majority voting dictated the TL classification per second of these high and low classifications. Second, a final TL classification was made every six seconds based on the previous six values to send to the interface through a lab streaming layer (LSL).

All measurement scales were administered via Qualtrics (Qualtrics, Provo, UT). Participant sessions were recorded using a Razer Kiyo Pro Ultra 4K Webcam mounted on the participants' monitor. An iPad Air was used to administer the consent and compensation forms via Qualtrics (Qualtrics, Provo, UT).

Figure 2. *EEG Process Model*



Note 2. Visual representation of the closed-loop BCI system.

EDA and ECG activity were recorded using the COBALT-Bluebox system (Courtemanche et al. 2022). Two EDA sensors were placed on the participant's non-dominant hand, fixed with a compression glove. We utilized a Lead 2 sensor configuration to measure heart rate, whereby one sensor was placed beneath each collarbone, and a third was placed on the participant's second-to-last rib on the left side.

Statistical Analysis

All statistical analyses were conducted in R Version 4.2.1 and RStudio Version 2023.09.1 (R Core Team, 2022). The "dplyr" (Wickham et al., 2023) package was used for data cleaning. All data visualizations were created using "ggplot2" (Wickham, 2016). The demographics table was created using the "table1" (Rich, 2021) package. Outliers were identified as data points that were above Q3 plus 1.5 times the interquartile range (IQR) or below Q1 minus 1.5 times the interquartile range. Score outliers were retained as they are indicative of interaction with the system. Due to data quality, sample size differed between analyses depending on the variable under investigation. Based on the nature of the data, a chi-square test or an ANOVA was used to assess group differences. A Shapiro-Wilk test was applied to assess the normality of the data for each variable. The test revealed a non-normal distribution of scores for satisfaction, intention to recommend, and engagement. In consequence, we opted to apply a non-parametric test, the Kruskal-Wallis test, to assess the hypotheses related to these variables in accordance with the literature (Siegel, 1957). Moreover, multiple linear regressions were run to test the hypotheses regarding IM and engagement. All ANOVAs were run using the anova_test function from the "rstatix" package (Kassambara, 2023), corrected for multiple comparisons using the Bonferroni adjustment. Linear regressions were run using the lm function from the base R stats package. Post-hoc pairwise comparisons were conducted with the pairwise_t_test function from the "rstatix" package (Kassambara, 2023). A mixed ANOVA was applied to assess the effect of group and block on the TL ratios during retrieval.

Results

Descriptive Statistics

Neither age nor gender significantly differed between groups. In addition, the level of education and prior constellation knowledge did not differ between groups. Thus, these variables were not used as covariates in testing the hypotheses. See Table 1 for complete demographic data.

Table 2. *Demographic Characteristics by Group*

	C (N=19)	R (N=16)	N (N=16)	Overall (N=51)	F	p	η_p^2 / χ^2
Education						.1651	11.701
Master	7 (37 %)	3 (19 %)	6 (38 %)	16 (31 %)			
University	8 (42 %)	11 (69 %)	9 (56 %)	28 (54 %)			
Prior Constellation Knowledge	2.72 (0.71)	2.88 (1.02)	2.90 (0.88)	2.83 (0.85)	0.222	.8020	0.009

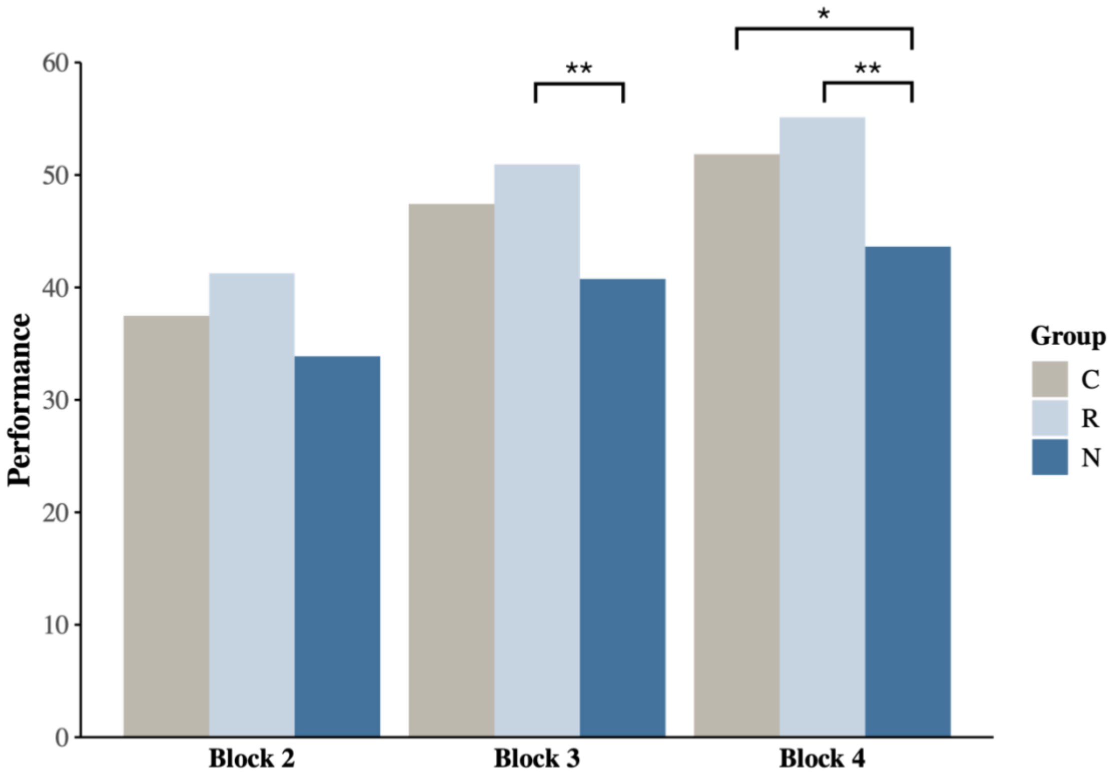
Note 3. F (2, 48). Values are presented as *M(SD)*

Hypothesis Testing

Performance by Group and Block

We hypothesized that performance would differ by group across learning blocks, where Group R would perform similarly to Group N, while better than Group C. Results show a significant effect of learning block on score F (2, 96) = 135.235, $p < .001$, $\eta_p^2 = .738$. As shown in Figure 3, there was a significant increase in scores across Block 2 (M = 37.50, SD = 12.40), Block 3 (M = 46.40, SD = 13.30), and Block 4 (M = 50.30, SD = 12.80). The interaction between group and learning block was not significant, F (4, 96) = 1.795, p = .144, $\eta_p^2 = .068$. Given the directionality of the hypotheses, one-tailed pairwise comparisons were performed. A pairwise t-test revealed a significant difference in score in Block 4 between Group R (M = 55.10, SD = 8.25) and Group N (M = 43.60, SD = 16.50, p = .0153). In Block 3, there was a significant difference between Group R (M = 50.90, SD = 10.80) and Group N (M = 40.80, SD = 14.50, p = .0449). In Block 4, there were trending differences between Group C (M = 51.80, SD = 10.50) and Group N (M = 43.60, SD = 16.50, p = .0780).

Figure 3. *Mean Performance by Learning Block*



Note 4. Mean participant scores across blocks, * $p < .1$; ** $p < .05$

Satisfaction and Intention to Recommend by Group

We expected that satisfaction and intention to recommend would differ by group. Results revealed no effect of group on intention to recommend. A second Kruskal-Wallis test was performed to identify group differences in satisfaction scores. The effect of group was significant significance $F(2) = 6.5135$, $p = .0385$, $\eta^2 = .0940$, where Group R ($M = 6.06$, $SD = 0.93$) tended to report higher satisfaction scores than Group N ($M = 4.88$, $SD = 1.36$, $p = .0390$).

Intrinsic Motivation as a Moderator Between Group and Score

We hypothesized that IM would act as a moderator between group and performance. Three multiple linear regressions were conducted to predict Block 4 scores based on group membership and each dimension of IM, with Group N as the reference group. The overall models for both interest and effort were not significant, with no significant main effects or interactions. The overall model for competence was statistically significant, F (5, 45) = 12, $p <$ .001, explaining 57.13% of the variance in scores ($R^2 = 0.5713$, adjusted $R^2 = 0.5237$). The main effect of competence was significant, $\beta = 8.093$, $p < .001$, where higher competence scores predict higher Block 4 scores. The interaction between Group R and competence was significant, $\beta = -4.67$, $p = .035$, suggesting that Group R's slope is less steep than Group N's.

Intrinsic Motivation as a Moderator Between Group and Engagement

We expected IM to moderate the relationship between group and engagement. Results show no effect of group on engagement. Three multiple linear regressions were conducted to predict engagement based on group membership and each dimension of IM, with Group N as the reference group. In the first model, the predictors were Group C and Group R, interest, and two interaction terms between group and interest. The overall model was significant, $F(5, 45) =$ 18.81, $p < .001$, explaining 67.64% of the variance in engagement ($R^2 = 0.6764$, adjusted $R^2 =$ 0.6404). Interest was a significant predictor of engagement, $\beta = 0.5007$, $p < .001$. In the second model, the predictors were Group C and Group R, effort, and two interaction terms between group and effort. The overall model was significant, $F(5, 45) = 4.592$, $p = .002$, explaining 33.79% of the variance in engagement ($R^2 = 0.3379$, adjusted $R^2 = 0.2643$). Effort was a significant predictor of engagement, $\beta = 0.4712$, $p = .003$. In the third model, the predictors were Group C and Group R, competence, and two interaction terms between group and competence. The overall model was significant $F(5, 45) = 3.264$, $p = .013$, explaining 26.61% of the variance in engagement ($R^2 = 0.2661$, adjusted $R^2 = 0.1846$). Competence was a significant predictor of engagement $\beta = 0.3422$, $p = .006$. In conclusion, none of the three IM dimensions moderate the relationship between group and engagement.

Physiological Measures by Group and Block

We expected physiological measures to differ by group and block, with parasympathetic dominance increasing in a stepwise manner (C < R < N). There were no significant main effects or interactions of phasic EDA on learning block or group. The model demonstrated a significant effect of group on ratio HRV F (2, 31) = 5.019, p = .0130, η_p^2 = .245. One-tailed, pairwise comparisons revealed ratio HRV differed between Group C (M = 1.170, SD = 0.456) and Group R (M = 0.808, SD = 0.292, p < .001), and Group C (M = 1.170, SD = 0.456) and Group N (M = 0.746, SD = 0.223, p < .001).

Task Load by Group and Block

We hypothesized TL would be higher in Group C and Group R than in Group N. The model revealed a group by block interaction on the average of the 16 TL ratios during retrieval F (6, 99) = 3.409, p = .004, η_p^2 = .171. One-tailed, pairwise comparisons uncover a significant difference between Group N (M = 2.99, SD = 0.535) and Group C (M = 6.37, SD = 4.47, p = .004) in Block 4. There was a trending difference between Group C and Group R (M = 4.12, SD = 1.84, p = .061) in Block 4.

Discussion

Summary of Main Results

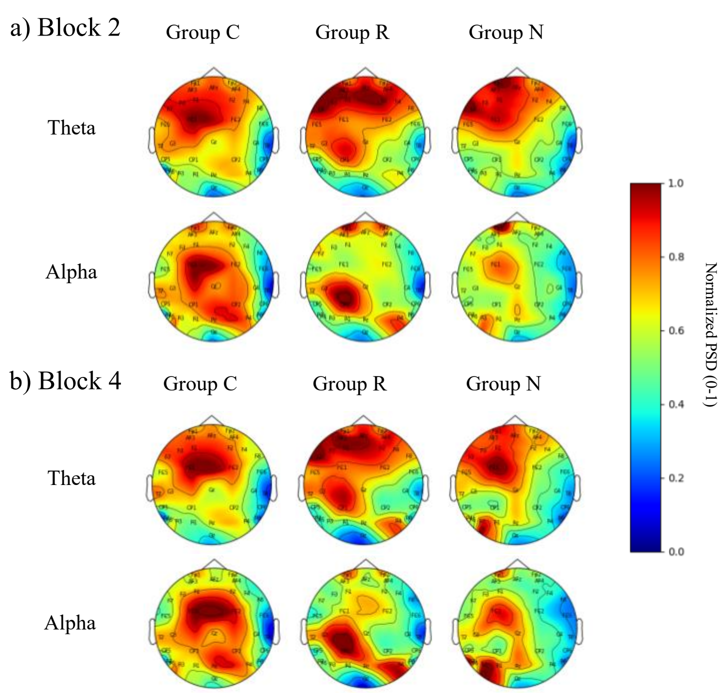
Across task blocks, there is an evident learning effect regardless of group membership. Further investigation revealed that Group R yielded higher scores in Block 3 and 4, indicating they may have learned more constellations. It is consistent with the literature that the promise of a reward improves memory formation (Duan et al., 2020). Though there is a lack of differentiation in overall scores across groups, the results suggest that Group N exerted less effort to achieve similar results as Group C in Block 4, as observed in the 16 TL ratios. It could be reasoned that the neuroadaptive countermeasures helped the participant remain in their ZPD, avoiding cognitive underload and overload. In line with motivational intensity theory (Brehm & Self, 1989), Group N received favorable adaptations for their current cognitive capacity, therefore reducing the need for elevated effort; additional effort was not needed as the system maintained a balance between task demands and cognitive resources. These results support the premise that the neuroadaptive system can effectively act as scaffolding within an online learning task. Thus, we highlight the potential of neuroadaptive systems to complement traditional motivational approaches by providing individualized support that adjusts in real time, enhancing the learning experience.

All three experimental groups presented theta dominance in Block 4 to different degrees of power spectral density. Prior cognitive research suggests that higher theta band power is associated with a higher allocation of cognitive resources to a task (Tsang & Vidulich, 2006; Xie et al., 2016). Notably, theta dominance has also been associated with increases in working memory and attention (Borghini et al., 2012, 2014). This finding explains the observed increase in TL, representing higher theta activity, in Group C in the last block of the task, as the user is on their last try to merit a good score, drawing on intrinsic motivation. Logically, theta dominance in Block 4 was the least prominent in Group N, indicating better allocation of cognitive resources without compromising performance.

To complement the results of the quantitative analyses, alpha and theta power were plotted at the sensor level in scalp topographic maps, across group and block, during the encoding phase of the learning task (see Figure 4). The EEG-based topographic maps illustrate the salient cerebral activity in the frontal and parietal areas, identifying distinct learning profiles by group. More specifically, alpha and theta activity present differently for each group across time. At the beginning of the learning task, Group R and Group N displayed similar activity, with medium to high frontal theta power and medium to low parietal alpha power. At the end of the learning task, parietal alpha power appears lower for Group R than Group N. Conversely, Group C begins the learning task with medium levels of alpha and theta power across the map. By the end of the learning task, Group C exhibits both high parietal alpha and frontal theta power.

Based on our knowledge of the role of parietal alpha and frontal theta oscillations in memory tasks, these findings are as expected. Both alpha and theta have been previously

Figure 4. *EEG-based Scalp Topography Maps*



Note 5. EEG-based topographic maps displaying alpha and theta activity by group in the encoding phase of Block 2 (a) and Block 4 (b).

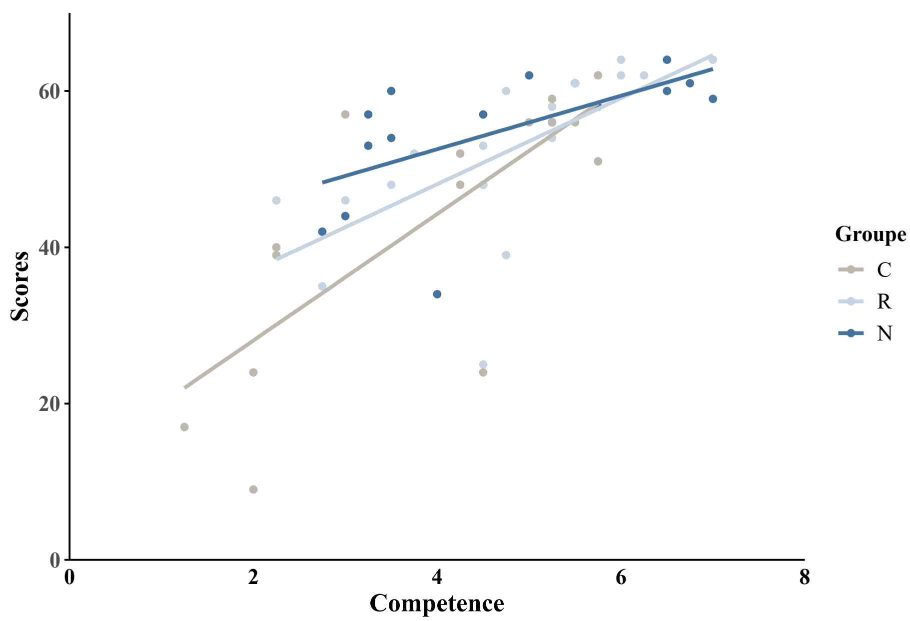
indicated to play important roles in encoding information. In particular, alpha activity may reflect rote rehearsal (Kapur et al., 1996) and visual attention and encoding (Medendorp et al., 2007). Additionally, parietal alpha may also indicate cognitive fatigue (Borghini et al., 2014).

Moreover, as previously discussed, frontal theta is a sensitive indicator of cognitive resource utilization (Xie et al., 2016), sustained attention, and working memory (Borghini et al., 2014). Considering these findings, we can estimate that Group C exhibited increasing cognitive fatigue and expenditure of cognitive resources across time. In contrast, the topographic maps suggest that Group N utilized fewer cognitive resources and exhibited more visual attention than Group C throughout the learning task, indicating faster associative decoding than Group C and Group R (Klimesch, 1997). This pattern further suggests that the neuroadaptive system successfully maintained Group N in their optimal learning zone (ZPD), without compromising learning outcomes. Moreover, the profile of Group R is similar to that of Group N. However, the visualization may indicate that they exhibit less visual attention than Group N towards the end of the learning task, expending more cognitive resources earlier on.

Regarding heart rate, Group R and Group N experienced lower ratio HRV. Research suggests that this indicates parasympathetic dominance (Pagani et al., 1986). Moreover, parasympathetic dominance could be attributed to lower levels of stress (Lin et al., 2011). However, the results did not show a difference in phasic EDA between groups or across blocks. Previous research has reported that changes in cognitive load are not linked to variation in phasic EDA (Shimomura et al., 2008). However, a consensus on the effect of cognitive load on phasic EDA has not been reached as other studies suggest that increases in cognitive load can potentially increase phasic EDA (Ikehara & Crosby, 2005; Shi et al., 2007). The convergence of the physiological results strengthens the validity of the observed effects in the EEG ratio.

The results point to a close relationship between engagement and IM, in that all three dimensions of IM predicted increases in engagement. This finding is supported by the literature testifying that IM positively influences learner engagement (Liu et al., 2024; Nagpal & M, 2024) and employee engagement (Sutha et al., 2023). Another significant aspect of IM, specifically perceived competence, is its relationship to performance. As shown in Figure 5, scores in Block 4 are significantly predicted by competence and group. Overall, higher perceived competence is associated with higher scores. However, this effect is not as prominent in Group R as in Group N. Potentially, the additive effect of motivation can explain this moderation. While IM and EM both contribute to performance, research suggests that when an incentive is directly tied to performance, IM has less of an impact on performance than EM (Cerasoli et al., 2014). This relationship is further explained by motivational intensity theory (Brehm & Self, 1989), where the effort is greater when an incentive is present, enhancing individuals' willingness to engage with the adaptive system.

Figure 5. *Interaction of Group and Competence on Block 4 Scores*



Note 6. Score is significantly predicted by Group and Competence.

Regarding satisfaction, CSAT scores differed among groups, where Group R reported being more satisfied with the interface than Group N. With a mean score of 6.06 (*SD* = 0.929) we can conclude that participants in Group R are satisfied with the system. This finding aligns with previous research that positively links satisfaction to monetary rewards (Boyce et al., 2010; Cheung & Lucas, 2015; Johnson & Krueger, 2006).

Taking into consideration all the indicators of system success, it is evident that, overall, the neuroadaptive system was successful in regulating TL. The system appears to have minimized stress levels, optimized performance requiring less cognitive resources, and benefited from dimensions of IM. Despite the lack of difference in phasic EDA and intention to recommend the system, learners overall show a more stable cognitive state and enhanced user experience while using the neuroadaptive system.

Theoretical Contributions

The current study extends our understanding of the implications of motivation and TL in a neuroadaptive learning context. First, the results demonstrate that neuroadaptive countermeasures can effectively act as real-time scaffolding to maintain learners in their ZPD. The dynamic nature of the neuroadaptive system allowed learners to operate within an optimal zone without experiencing underload or overload. This finding extends Vygotsky's original notion of ZPD by demonstrating that scaffolding can be automated through closed-loop neuroadaptive technologies.

Second, this study contributes to self-determination theory (Deci & Ryan, 1985) by illustrating how IM and EM work in parallel to support learning. The current findings demonstrate the nuance of the additive effect of IM and EM, highlighting how IM has less of an impact on performance when an incentive is present. Moreover, our findings reflect motivational intensity theory (Brehm & Self, 1989) where the amount of effort is in line with the presence of an incentive. In addition, motivational intensity theory expects the amount of effort to be proportional to task difficulty, or in our case TL. Participants in the neuroadaptive condition sustained performance while exerting less mental effort, aligning with the optimal imposed TL, extending the assumptions of motivational intensity theory into the domain of neuroadaptive learning.

Finally, this study has a significant methodological contribution. Existing applications of TL measurement under cognitive load theory (Sweller et al., 2011) have traditionally relied on subjective ratings such as the NASA TLX (Hart & Staveland, 1988). In contrast, the present study successfully utilized a neural activity to infer TL in real-time, enabling granular, non-invasive, and adaptive task adaptation. This technique validates the use of EEG-based metrics for monitoring TL and opens a new avenue for TL measurement beyond self-report.

Practical Implications

Given the demonstrated effectiveness of the present study in regulating TL through a neuroadaptive BCI, it is essential to examine the implications and feasibility of implementing such technology within authentic, real-world educational contexts. The research model indicates a decrease in TL (effort) as a result of an interaction with the neuroadaptive interface, maintaining a ZPD. Placed in an education context, students would benefit from exhausting fewer cognitive resources while learning a similar amount as they would without cognitive augmentation. However, it is essential to call into question that using such a system would require individuals to delegate their self-regulation of cognitive capacities to the adaptive technology. Students would have less autonomy in the classroom. Informed consent must be prioritized, ensuring students understand the implications of engaging with such technology (Burwell et al., 2017). Furthermore, there are other aspects to consider, such as the extent to which an educator is involved in manipulating the technology, who owns the collected data, and the state's role in the application of neurotechnology in the education system.

Limitations and Future Research Avenues

Despite the many insights gained, this study has several limitations. The adaptation took the form of a change in feedback presentation time. The timing was given a floor and ceiling value of 3 seconds and 8 seconds, respectively. This decision was made to fit with the rate of TL calculations. However, it remains to be investigated and validated whether a free range of feedback presentation time would be optimal. In the case of measuring IM and engagement, both scales were presented post-task. Since the task took 45 minutes to 1 hour to complete, it is possible that these scores were not representative of the initial learning blocks. Future studies should consider measuring these constructs between blocks.

Holistically, the scalp topography maps provide promising results that merit further investigation. The frontal and parietal areas discussed can be further mapped to the extensively studied Broadman’s areas, which would reveal additional, more salient insights into the cognitive mechanisms at work in the neuroadaptive learning task. Research points to Broadman’s areas 6, 8, and 39 to be exceptionally involved in working memory, specifically the encoding of semantic and visual information (Kapur et al., 1996; Medendorp et al., 2007). To offer a more granular investigation, additional analyses could examine neural oscillations based on specific event-related markers, visualizing connectivity through phase transfer entropy (Lobier et al., 2014). Future studies could employ more sophisticated techniques such as functional near-infrared spectroscopy (fNIRS), magnetoencephalography (MEG) or magnetic resonance imaging (MRI) to pinpoint the underlying mechanisms in the areas of interest. Our results are promising, showcasing group differences during a single task. Additional analyses, such as brain connectivity, would be interesting to conduct as a means of determining cortical activation patterns across groups and different tasks.

Considering EM's elevated performance and neuroadaptation's maintenance of an optimal learning zone, future research should couple these two variables. A neuroadaptive interface driven by a BCI that includes extrinsically motivating factors may further demonstrate increased learning capacities. In addition, the model could be tested and validated with a different target (learning psychological theories) or with a different type of learning task (solving math equations).

Conclusion

Ultimately, this study highlights the effects of motivation and TL in a learning task. The combined effects of IM and EM facilitate learning, working in parallel to enhance learning outcomes. EEG data and physiological measures indicate a reduction in TL following neuroadaptive countermeasures. Moreover, the topographic maps further stress the effectiveness of the neuroadaptive system to enable users to maintain optimal levels of TL, reducing cognitive strain while achieving similar outcomes to users without the system. The findings provide robust evidence highlighting the utility of measuring TL in learning environments. However, as neuroadaptive BCI technologies continue to evolve, it is vital to address the ethical considerations of widespread implementation in organizational contexts.

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Chapter 3

Time Well Spent: Tailoring Learning to Unlock Potential[2]

Katrina Sollazzo, Alexander John Karran, Sylvain Sénécal

In 2022, 21.8% of Canadians over the age of 15 took part in formal training or learning online [3]. As online learning continues to grow, it is essential to consider how we can create the optimal online learning environment. Advancements in personalized learning using neuroadaptive systems are shaping how we approach learning and motivation. Neuroadaptive systems use recordings of brain activity to generate changes in a training or learning interface, aiming to prompt a change in a user's behaviour [4]. In contexts such as driving [5] and aviation [6], neuroadaptive systems have been shown to improve performance and the overall user experience. These systems help users in a dynamic way by altering features such as the level of difficulty, feedback mechanisms, or the amount of time allotted for tasks [7].

Some neuroadaptive systems, like Neuralink [8], use highly invasive techniques that require a medical procedure. More commonly, non-invasive methods are used, which rely on data such as brain activity, eye movements, or heart rate to drive the system. Typically,

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[2] This article is in preparation for publication in *The Conversation.*
[3] Statistics Canada, "Selected Online Activities by Gender, Age Group and Highest Certificate, Diploma or Degree Completed."
[4] Krol and Zander, "Passive Bci-Based Neuroadaptive Systems"; Zander et al., "Neuroadaptive Technology Enables Implicit Cursor Control Based on Medial Prefrontal Cortex Activity."
[5] Alguindigue et al., "Biosignals Monitoring for Driver Drowsiness Detection Using Deep Neural Networks."
[6] Borghini et al., "Real-Time Pilot Crew's Mental Workload and Arousal Assessment During Simulated Flights for Training Evaluation."
[7] Dehais et al., "A Neuroergonomics Approach to Mental Workload, Engagement and Human Performance."
[8] Fiani et al., "An Examination of Prospective Uses and Future Directions of Neuralink."

neuroadaptive systems measure the cognitive state of an individual to determine what changes are needed to optimize the user experience [9].

Our study

We conducted a study to explore personalized learning using a neuroadaptive system based on task load, a cognitive state related to mental effort. Task load may be a critical factor in learning performance, and adjusting parameters, such as providing additional time for challenging tasks, could meaningfully impact performance. While task load is a key consideration in learning performance, there are other influences at play. Notably, motivation plays an essential role in learning [10]. Motivation can come from the self (intrinsic motivation) or it can come from an external source (extrinsic motivation; Ryan & Deci, 2000). Regardless, both types of motivation work in parallel to boost learning. Given the interplay between neuroadaptive systems, task load, and motivation, two key questions arise:

1. *How do personalized dynamic time changes promote learning?*
2. *What role does motivation play in an online learning task?*

While monitoring their brain activity with electroencephalography (EEG), participants completed a memory task. Participants were aiming to learn 32 constellations, a topic they were likely to be unfamiliar with. Participants were randomly assigned to one of three groups to compare different learning strategies. One group of participants were incentivized with a chance to win a monetary prize, based on their performance, in order to tap into their extrinsic motivation. Participants in the neuroadaptive group experienced changes in the learning interface

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[9] Beauchemin et al., "Enhancing Learning Experiences"; Karran et al., "Toward a Hybrid Passive BCI for the Modulation of Sustained Attention Using EEG and fNIRS"; Serrhini and Dargham, "Toward Incorporating Bio-Signals in Online Education Case of Assessing Student Attention with BCI."

[10] Duan et al., "The Effect of Intrinsic and Extrinsic Motivation on Memory Formation"; Liang et al., "How Intrinsic Motivation and Extrinsic Incentives Affect Task Effort in Crowdsourcing Contests"; Zhozhikashvili et al., "Working Memory Processes and Intrinsic Motivation."

based on the task load inferred from their brain activity. These changes were intended to maintain an optimal task load for learning.

What did we find?

On the surface, all three groups demonstrated a learning curve across the task, whereas the incentivized group performed slightly better in the latter stages. However, the brain activity revealed that participants in the neuroadaptive group achieved similar results as those in the control group, with less mental effort. We believe, this is because the system successfully optimized the timing of feedback to match their mental capacity. Each group employed different strategies to learn the material; they managed their cognitive resources differently across the learning task. The neuroadaptive group appeared to maintain focus, while the other groups seemed to experience cognitive fatigue.

Moreover, motivation played a role in engagement and performance. The more competent a person believed they were, the better they performed, with this relationship being pronounced in the incentivized and neuroadaptive groups. These findings suggest that motivation and cognitive regulation work together to create the optimal learning experience.

Best practices and recommendations

Even though this study employed a complex, highly technical research design, the key takeaway is quite simple: timing is everything. The findings highlight the critical role of time in shaping learning outcomes. As technology advances and neuroadaptive systems become more accessible, these systems should be implemented where possible to enhance performance. In cases where it is impossible, educators and managers should allow flexible time adjustments based on task complexity and each learner's individual needs. Moreover, breaks could be incorporated along with flexible pacing to avoid cognitive fatigue, particularly in tasks requiring continuous attention.

Moreover, the results suggest that both intrinsic and extrinsic motivation can significantly influence learning and overall performance. Tailoring strategies to leverage these motivational factors can further enhance learning outcomes. For example, offering an incentive, be it monetary or recognition-based, can boost extrinsic motivation, while creating a sense of competency and autonomy can foster intrinsic motivation.

Additionally, incorporating flexible pacing could optimize task load and maintain motivation by preventing frustration or disengagement caused by tasks that are too demanding or too easy. Allowing learners to work at a pace that aligns with their task load can keep them in the “sweet spot” of engagement, where they feel challenged but not overwhelmed.

By combining flexible timing with motivational strategies, educators and managers can create an environment that supports both sustained effort and a sense of accomplishment, ultimately leading to better learning and performance. Leveraging tools such as neuroadaptive systems may provide personalized experiences, empowering individuals to reach their full potential. By incorporating flexible timing and motivational strategies, educators and managers can take meaningful steps toward creating environments that are more supportive and adaptable to individual needs, ensuring time is truly well spent.

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Conclusion

Situated at the intersection of HCI and cognitive science, this thesis investigated how motivational factors affect learning outcomes and engagement during a neuroadaptive task, driven by a TL index. To achieve this goal, we applied a novel TL index in an EEG-informed BCI which powered a neuroadaptive system. This system presented a learning task where the time allotted for interaction with the feedback stimulus was adjusted in real time based on TL classification. Specifically, this thesis explored the following research question:

How can neuroadaptive technologies reshape traditional approaches to online learning by addressing the limitations of extrinsic motivation?

The findings suggest that the neuroadaptive countermeasures successfully maintained the ZPD of the neuroadaptive group by providing adequate scaffolding, allowing them to complete the task in their optimal learning state, based on the measurement of their experienced TL. Furthermore, the generation of sensor-level EEG-based scalp topographic maps revealed unique learning profiles for each group. While the TL values point to the presence of theta-dominance in all groups, it is evident that the neuroadaptive group had the lowest level of theta-dominance in Block 4. Coupled with the topographic visualization, we can infer that the neuroadaptive group exhibited a better allocation of cognitive resources throughout the task than the other groups.

Overall, the neuroadaptive system proved successful at regulating TL. Users who interacted with the system showed a more stable cognitive state, which allowed them to best manage their cognitive resources during the task.

Theoretical Contributions

The utilization of a TL index in a neuroadaptive online learning task in combination with motivational factors elicits multiple contributions to the theories in which they are grounded.

Regarding the neuroadaptive element, the TL-driven countermeasures successfully maintained learners' ZPD. Therefore, this study expands Vygotsky's ZPD framework to include neuroadaptive countermeasures as an adequate means of scaffolding (Vygotsky & Cole, 1978). These findings suggest the system actively combatted both cognitive underload and cognitive overload, further contributing to the current understanding of cognitive regulation. Additionally, examining the effects of EM and IM, the results support self-determination theory (Deci & Ryan, 1985) providing evidence of the additive effect of motivation on performance.

Practical Implications

The plethora of BCI research today shows promise for many real-world applications. The testing of the novel TL index in the neuroadaptive learning task is no different. This study demonstrates the utility of leveraging neurophysiological measures in educational and training contexts. Learners could take advantage of the preservation of cognitive resources from the interaction with a neuroadaptive system. However, employing these learning strategies in educational contexts has unique ethical considerations. Neuroethics is an emergent field that presents principal ethical considerations around neurotechnologies. Regarding the implementation of neuroadaptive technologies in an educational setting, it is important to consider several factors. As systems increasingly rely on neurophysiological data to optimize learning experiences, safeguarding learner privacy as they delegate their self-regulation to technology is paramount. This decrease in autonomy enforces the priority of having informed consent, drawing attention to the implications of engaging with such systems (Burwell et al., 2017). Addressing neuroethical concerns proactively will be essential for fostering trust, acceptance, and responsible adoption of neuroadaptive learning technologies in educational contexts.

Future Directions

Future studies should consider an experimental design that integrates additional measurements of the subjective variables to elicit additional insights into the user experience. While successful, current EEG-based neuroadaptive systems are complex and not ideal for widespread adoption in typical educational or training environments. Assessing the utility of simpler measures to drive the system, such as pupillometry through eye-tracking technology, could more feasibly lead to broader practical applications of the neuroadaptive system.

Additionally, the current system employed a logic-based method of classification. An important direction for future research involves the integration of advanced machine learning algorithms within a neuroadaptive learning environment. Harnessing deep learning solutions to classify cognitive states, future studies could enhance system responsiveness and personalization.

Future research can apply these findings to other areas of learning. In this study, we focused on associative memory, assessed with recognition-based recall. The neuroadaptive system employed in this study could be applied to other areas such as math learning, or more conceptual topics. Further validation of the system with a wide variety of learning targets will provide additional support for widespread implementation.

Concluding Remarks

This thesis highlights the critical role of motivational and neuroadaptive mechanisms in optimizing learning experiences and enhancing learner outcomes within digital environments. Bridging theoretical insights from psychology with HCI and empirical evidence derived from neurophysiology, the findings contribute to both theoretical expansion and practical innovation in neuroadaptive educational technology. Despite its limitations, this work presents a meaningful step toward tailored, cognitively sustainable digital learning experiences. Future research incorporating advanced approaches, such as machine learning, and varied task contexts hold significant promise for further refining and validating these systems. Ultimately, continued multidisciplinary approaches will remain pivotal in shaping the next generation of user-centered educational technologies.

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Appendices

Appendix A

Table 2
Items for Psychometric Scales

Construct	Items	Reference
Intrinsic Motivation	(7-point slider, strongly disagree - strongly agree) **Interest/enjoyment** • I enjoyed doing the constellation learning activity very much. • The constellation learning activity was fun to do. • I would describe the constellation learning activity as very interesting. • I thought the constellation learning activity was quite enjoyable **Perceived competence** • I think I am pretty good at the constellation learning activity. • After working at the constellation learning activity for a while, I felt pretty competent. • I am satisfied with my performance at the constellation learning activity. • I was pretty skilled at the constellation learning activity. **Effort/importance** • I put a lot of effort into the constellation learning activity. • I tried very hard on the constellation learning activity. • It was important to me to do well at the constellation learning activity.	Ryan, R. M. (1982). Control and Information in the Intrapersonal Sphere: An Extension of Cognitive Evaluation Theory. Journal of Personality and Social Psychology, 43(3), 450–461.

Engagement	(7-point slider, strongly disagree - strongly agree) **Affective engagement** • It made me happy to complete this task. • It was fun to complete this task. • I enjoyed completing this task. **Behavioural engagement** • I was being attentive to the task. • I was actively involved in completing this task. • I diligently completed this task. **Cognitive engagement** • This task was so absorbing that I forgot about everything else. • I did not think about anything else when completing this task. • I was fully immersed while completing this task.	de Vreede, T., Andel, S., de Vreede, G.-J., Spector, P., Singh, V., & Padmanabhan, B. (2019). What is Engagement and How Do We Measure It? Toward a Domain Independent Definition and Scale. 749–758.

Prior Knowledge	Please indicate your level of general knowledge of constellations (slider scale 1-10) Please indicate your level of general knowledge of astronomy (slider scale 1-10) To what extent do you agree or disagree with the following statements? (7-point slider, strongly disagree - strongly agree) • I know constellations pretty well. • I don't feel very knowledgeable about the theory surrounding constellations. • Among my circle of friends, I'm one of the "experts" on constellations. • I know the difference between astronomy and astrology. • Compared to most other people, I know less about constellations. • I am able to identify a large number of constellations by looking at the sky. • When it comes to constellations, I really don't know a lot. • I know the names of several constellations. • I like to learn about constellations. • I find constellations to be important and useful.	Adapted from: Flynn, L. R., & Goldsmith, R. E. (1999). A Short, Reliable Measure of Subjective Knowledge. Journal of Business Research, 46(1), 57–66. https://doi.org/10.1016/S0148-2963(98)00057-5
Satisfaction	Are you satisfied with the constellation learning system? (7-point slider, strongly disagree - strongly agree)	Farris, P. W., Bendle, N. T., Pfeifer, P. E., & Reibstein, D. J. (2010). Marketing metrics: The definitive guide to measuring marketing performance (2nd ed). Wharton School Pub.
Intention to recommend	How likely is it that you would recommend the constellation learning system to a friend, a colleague, or a member of your family? (10-point slider, not at all probable – very probable)	Reichheld, F. F. (2003). The One Number You Need to Grow. Harvard Business Review, 81(12), 46–55.