GETTING INTO FLOW!? ENHANCE FLOW-LIKE EXPERIENCES AND LEARNING PERFORMANCE THROUGH PERSONALIZED LEARNING ACTIVITIES

Research in Progress

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Abstract

Although intelligent learning systems provide new opportunities for personalizing learning activities, important design questions remain. To unleash the full impact of such systems, it is vital to examine how the use of Bayesian knowledge tracing can provide learners personalized learning activities and shape their flow experience, performance, and continuity intention. Further, this study explores the moderating role of a growth mindset on the relation between learning task adaptation and flow experience. I rely on electroencephalography to increase the internal validity of flow measurements. The study builds on Flow Theory and aims to empirically unveil the influence of an intelligent personalization of learning processes. The next step will be an experiment with 80 participants following the developed experimental design to evaluate flow experiences in intelligent learning systems. The results of this experiment aim to guide educational designers with prescriptive knowledge on how to design flow-like learning experiences in intelligent learning systems.

Keywords: flow experience, knowledge tracing, personalized learning, intelligent learning systems.

1 Introduction

Everybody is different – and thus, learners differ in personality (Rüdian et al., 2019), their mindset toward learning (Crum et al., 2017), prior experiences (Vygotsky, 1980), and their skillset and prior knowledge (Oda et al., 2014). As learners take an active part in their learning process, every learner may have unique experiences and develop their own reality. Constructivist research is grounded on a relativist ontology that subscribes to the view of "multiple realities", implying that each learner's knowledge may significantly differ from others. The constructivist perspective, therefore, confirms that learners require individual tutoring based on their experiences to learn the most effectively (Vygotsky, 1980). Inherently, the gold standard to help learners acquire and comprehend knowledge is still a personal human teacher (Oda et al., 2014). Human educators are capable to recognize learners' knowledge gaps, anticipating their needs, and suggesting suitable learning activities based on the knowledge gaps. However, educational institutions struggle to offer this kind of individual support due to financial and organizational constraints (Seaman et al., 2018; Ritz et al., 2022).

Nowadays, information technology is often used to support or enhance the learning process and technology-mediated learning systems are paving the way for new personalized education tailored to the learners' needs (Gupta and Bostrom, 2009). As the deployment of technology-mediated learning systems continues to proliferate across schools, universities, and vocational training, the concomitant availability of online learning data pertaining to such systems is increasing. This data encompass a vast range of information about the learning process, including the utilization of course materials, the frequency and duration of system access, and information about video consumption. Organizational learning academies and massive open online course platforms such as Coursera, opendedx, or Udacity promise a high potential for the personalization of learning journeys on the platforms (Brinton et al., 2015). Intelligent learning systems (ILS) are a new subcategory of technology-mediated learning systems which stand apart through the implementation of artificial intelligence (AI). Berente et al. (2021) conceive AI as the frontier computational advancements, wherein the emulation of human intelligence is leveraged to confront an expanding array of decision-making problems. The authors perceive three interrelated facets of AI based on AI management literature, including autonomy to act without human intervention, learning based on historical data, and inscrutability (Berente et al., 2021). Today, machine learning (ML) is the most predominant approach to AI systems (Hofmann et al., 2019). While the role of traditional learning management systems was primarily to support human teachers, intelligent systems are able to act autonomously and take over the role of a teacher to track knowledge and adapt the learners' process (Abdelrahman et al., 2023). One technique to understand and track learners' performance in ILS is called knowledge tracing. An agent is trained to model the knowledge and behavior of a learner over time and can predict how students perform in future interactions and learning outcomes (Piech et al., 2015).

Currently, the application, and thus the relevance, of ILS increases significantly: AI in the education market is expected to increase to $80 million by 2030, from which half of this market share is accounted by learning platforms and virtual facilitators (Global Market Insights, 2022). The recent launch of ChatGpT, and its underlying technology generative AI, has evoked massive discussions on future developments of AI in education. Baidoo-Anu and Owusu Ansah (2023) emphasize that generative AI can promote personalized and interactive learning, increase formative assessments, improve language translation, and provide automated essay grading. There is a large variety of use cases for using AI to personalize learning processes in education, including the personal recommendation of learning activities, nudging for self-regulated learning, tracking and analyzing student performance, and the provision of smart and interactive learning content (Ritz and Grueneke, 2022). In alignment with the constructive perspective, the individualization of learning processes promises to increase learners' achievements and outcomes (Greller and Drachsler, 2012). Further, these individualized processes can increase learning efficacy (Hsieh and Wang, 2010) and effectiveness (Govindarajan et al., 2016), as well as stimulate intrinsic activation and motivation (Nandigam et al., 2014). This burgeoning trend raises the question of how knowledge tracing of an ILS can take over the role of a human teacher by tracking knowledge and behavior data to determine optimal challenge levels of learners' learning processes, how learners respond to personalized learning activities in the ILS, and how it impacts learners' learning outcomes and continuance intention.

Flow theory posits that learners who solve cognitive tasks with an optimal challenge level based on their skills will lead to increased flow states (Hoffman and Novak, 2009). The theory justifies why personalized learning activities can result in enhanced learning performances. However, previous studies have only applied fixed methods to determine an optimal challenge level of a learner (e.g., Sampayo-Vargas et al., 2013; Esteban-Millat et al., 2014). AI-based systems, such as bayesian-inference-based recommendation systems, enable an intelligent recommendation on personalized learning activities which improve with the time the learner is using the system. However, it is still unclear how such a dynamic method for the determination of challenge level can improve flow experience and learning performance (Furini et al., 2022). To unleash the impact of such ILS it is, therefore, necessary to investigate how learners react to such interactions with an ILS, and how they perceive the experience when receiving learning activities, and what downstream effects this has on learners' experience and behavior. Therefore, I propose the following research question (RQ):

RQ: Does an intelligent personalization of learning activities intensify the learner's flow experience and improves learning performance?

Building on Flow Theory, I develop an experimental design to empirically uncover the influence of optimized task difficulty for learning activities on flow experience and learning performance. I use electroencephalography (EEG) for an objective measurement of flow states to increase the internal validity of the study. To the best of my knowledge, this study is among the first to use EEG for measuring flow in the context of online learning. The results will shed light on how intelligent recommendations of individualized learning activities enhance flow-like learning experiences and how these experiences, in turn, shape the perception of learning experience and behavior. Additionally, I aim to guide practitioners with prescriptive knowledge on how to design and improve personalized learning experiences in ILS.

2 Theoretical Background and Hypotheses Development

2.1 Intelligent Learning Systems

Technology-mediated learning systems have lately evolved from mere learning content management and delivery to highly advanced, technological platforms (Andergassen et al., 2015). Beck et al. (1996) were among the first to publish a paper on the application of AI in education. Until now, many researchers published on the phenomenon and have introduced several new concepts frameworks, and terms used for intelligent learning systems (Fardinpour et al., 2014). While intelligent tutoring systems aim to provide instructional advice on a one-to-one basis (Sedlmeier, 2001), adaptive learning systems per se do not need to use AI or ML algorithms and can also rely on different statistical methods (Jonsdottir et al., 2015). The "intelligence" of an ILS stems from the implementation of AI and ML and thus, belongs to the system class of AI-based systems (Legner et al., 2017). Fardinpour et al. (2014) have developed a set of tools and features to evaluate the "intelligence" of such a system. An ILS requires to contain at least three parts; (1) the identification of information about the learner (e.g., detection of knowledge level, personality types, current emotions, or motivation) which is stored in a knowledge base, (2) the analysis of this information using ML to (e.g., clustering personality types, predicting learning outcomes and failure rate in a course, or determining suitable learning activities according to knowledge level), and (3) and the pedagogical intervention including the personalized learning journey (e.g., adapting learning interface, speed of learning, or recommending suitable learning content and activities) (Sedlmeier, 2001; Cui et al., 2018).

This study's focus lies on the personalization and adaptability of such systems. Knowledge tracing is the foundation to adapt learning activities to the individual (Piech et al., 2015). The task of modeling learners' learning journey is difficult and informed by several research domains. The two predominant approaches are Bayesian knowledge tracing and performance factor analysis. The first uses a Bayesian Network to model student learning, while the latter relies on logistic regression to predict learners' performance (Y. Wang and Beck, 2013). Bayesian knowledge tracing allows the modeling of learners' latent knowledge state as a set of binary variables, whereby the variable either stand for understanding or non-understanding of a single construct (Piech et al., 2015). Based on these variables, the model can estimate the probability of learning a new skill or managing the exam (Yudelson et al., 2013).

2.2 Intelligent Learning Systems and Flow

How can the use of an ILS and its feature of personalized learning activities impact learners' experiences? An important concept to describe such an experience is the flow construct (Csikszentmihalyi, 1990; Agarwal and Karahanna, 2000). Flow research had its origin in the desire to understand intrinsically motivated and autotelic activities, where humans lose self-consciousness and are distorted by temporal experiences (Nakamura and Csikszentmihalyi, 2002). Such a flow state is characterized by a high level of immersion, positive feelings, and optimal challenge levels (Ghani et al., 1991). Existing studies analyzed how and when flow occurred, and how to measure flow when using information systems. Previous research has examined many direct antecedents of flow experiences in online learning, including challenges and skills, lecturers' attitudes, content, and personalization (Esteban-Millat et al., 2014). The theory posits that a flow state can be intensified when users conduct tasks that fit their skills and therefore provides the optimal degree of challenge for them (i.e., by balancing boring and extremely challenging experiences). According to Engeser and Rheinberg (2008), there must be a certain level of challenge, otherwise, a feeling of apathy takes place. If a learning activity is too challenging and exceeds the skill set of the learner, the person might get anxious and frustrated. Contrarily, with a task that is not challenging enough, learners may get bored and do not focus on the task. The design of an optimal challenging learning activity is a difficult mission for educational designers and instructors.

In the context of online learning, Esteban-Millat et al. (2014) emphasize the importance of personalization of learning activities as a new way to adapt task difficulties to the challenge level, which was not considered in previous flow studies in an online learning context. Greater levels of flow lead to increased perceived hedonic value (i.e., enjoyment), a heightened level of satisfaction with the learning activity, and higher engagement and attention during the learning process (Agarwal and Karahanna, 2000).

Although the concept of flow during learning experiences was investigated in the context of online learning, existing studies focused mainly on static methods for task difficulty adaptation. By implementing bayesian knowledge tracing in an ILS it becomes possible to conduct intelligent task difficulty estimations for learners and recommend optimal challenges to the user based on prior experience and performance (Piech et al., 2015). Relying on bayesian-inference-based recommendations allows recommending learning activities with regard to finding the optimal challenge level for an individual. Previous research has shown that personalized challenges (based on static difficulty manipulations) can intensify the flow of learning compared to an impersonalized activity (Esteban-Millat et al., 2014). The research of (Martínez-López et al., 2015) already revealed the first insights into how intelligent recommendations can improve flow experiences for online store consumers. Thus, I believe that such a personalization positively influences the flow experience during learning compared to a non-personalized recommendation of learning activity.

H1: Learners with an intelligent personalization of the task challenge level will have higher levels of flow experience than learners with a non-intelligent personalization of the task challenge level.

2.3 The Impact of Flow on Learning Outcomes

Prior studies suggest that flow experience during learning can improve learning (e.g., Sampayo-Vargas et al., 2013; Chaker et al., 2022). In marketing research, the literature analysis of (Hoffman and Novak, 2009) identified several studies that have identified an existing relationship of flow on learning. For instance, Hoffmann & Novak 1996 identified that flow in computer-mediated environments can increase consumer learning about products. Rossin et al. (2009) demonstrated that flow experience is generally associated with four aspects of improved task performance: objective performance, perceived learning, perceived skill development, and satisfaction). In the context of learning, a study by Sampayo-Vargas et al. (2013) proposed that personalization of the learning activity regarding its difficulty can have positive effects on learning outcomes. This experiment is largely relevant, amongst others, for massive open online course platforms, which want to improve the learning experience of their users (C.-C. Wang and Hsu, 2014) as it could potentially also decrease dropout rates and improve user experience in ILS (Goopio and Cheung, 2021). Thus, I propose:

H2: Greater levels of flow experience based on intelligent personalization of the task challenge level (compared to non-intelligent personalization) have a positive effect on learning performance.

Csikszentmihalyi (1990) points out that users in their flow state feel some sense of enjoyment and the experience is intrinsically rewarding. This experience offers improved value to the user and influences the intent to utilize the system continually (Bhattacherjee, 2001). A recent study by Zhao and Khan (2022) discovered that learners' flow experience can have a significant positive effect on continuous intention.

H3: Greater levels of flow experience have a positive effect on continuance intention.

2.4 Influencing Conditions: The Role of Mindset during Learning

Flow has been found to only arise when a learner's skills match the difficulty of a task (Hoffman and Novak, 2009). Regarding online learning, there must be an optimal match between the learners' knowledge and their learning activity.

A growth mindset can be characterized as a belief that regards intelligence as malleable or improvable, while a learner with a fixed mindset rather views intelligence as a fixed trait that is given and unchangeable (Dweck, 2012). Existing research revealed that the effect of mindset changes the meaning of challenges. Learners with a growth mindset perceive challenges as opportunities to grow their abilities and do not see challenging tasks as a threat to sense their limited skills (Molden and Dweck, 2006). Learners with a growth mindset tend to embrace lifelong learning and enjoy personal growth (Ng, 2018). Contrary to this, learners with a fixed mindset tend to see negative feedback as a challenge to their intelligence and try to avoid such situations (Murphy and Thomas, 2008). A recent study by Caniëls et al. (2023) found that a growth mindset is positively and significantly related to work. The authors reason that growth mindset humans have a higher challenge tolerance before feeling threatened which allows them to experience flow in an easier way (Caniëls et al., 2023). Cutumisu and Lou (2020) found that a growth/fixed mindset significantly moderated the relationship between feedback-seeking and learning, figuring that a growth mindset leads to seeking challenges. Therefore, I hypothesize:

H4: The positive effect of an intelligent personalization of the task challenge level on flow experience is moderated by the mindset.

Figure 1 shows the complete conceptual model.

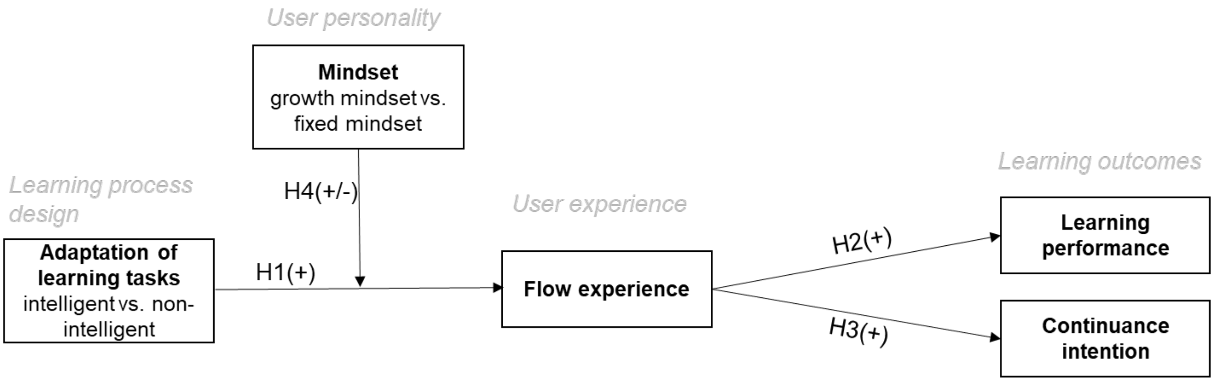

Figure 1. Research model.

3 Research Method

3.1 Experimental Design

The laboratory experiment is based on a within-subjects design, as it is required for EEG analysis to enable comparisons between conditions (Kim et al., 2019). Participants will test two conditions of which the former contains non-intelligent task difficulty adaptation and the latter comprises the intelligent task difficulty adaptation based on Bayesian knowledge tracing. Computational thinking is becoming one of the most important skills in the 21st century (Nouri et al., 2020), which has been investigated previously regarding flow experiences (e.g., Hooshyar et al., 2021). Thus, I use computational thinking tasks in the experiment to test the effect of non-intelligent vs. intelligent task difficulty adaptation on flow and in turn, learning performance and continuance intention.

To calibrate the difficulty levels of computational thinking tasks prior to the experiment, I will rely on a student cohort of 500 students in computer science to solve the computational thinking tasks by Lafuente Martínez et al. (2022). Afterward, I will use an expert panel to evaluate the difficulty levels of the tasks. Recent approaches enable automated difficulty estimation of tasks (e.g., Benedetto et al., 2023), which could be implemented in future research.

I will use bayesian-inference-based recommendations to facilitate a personalized recommendation of these learning tasks. While a classical definition of probability is grounded based on frequencies of events, in Bayesianism probability is calculated on our knowledge of events. The model is based similar to the approach of Ngaffo et al. (2020). The model is fed by past knowledge of the learner assessed in a pre-survey of a user and completed tasks. The chosen approach aims to estimate the probability with which a user would solve a task with an unknown difficulty level.

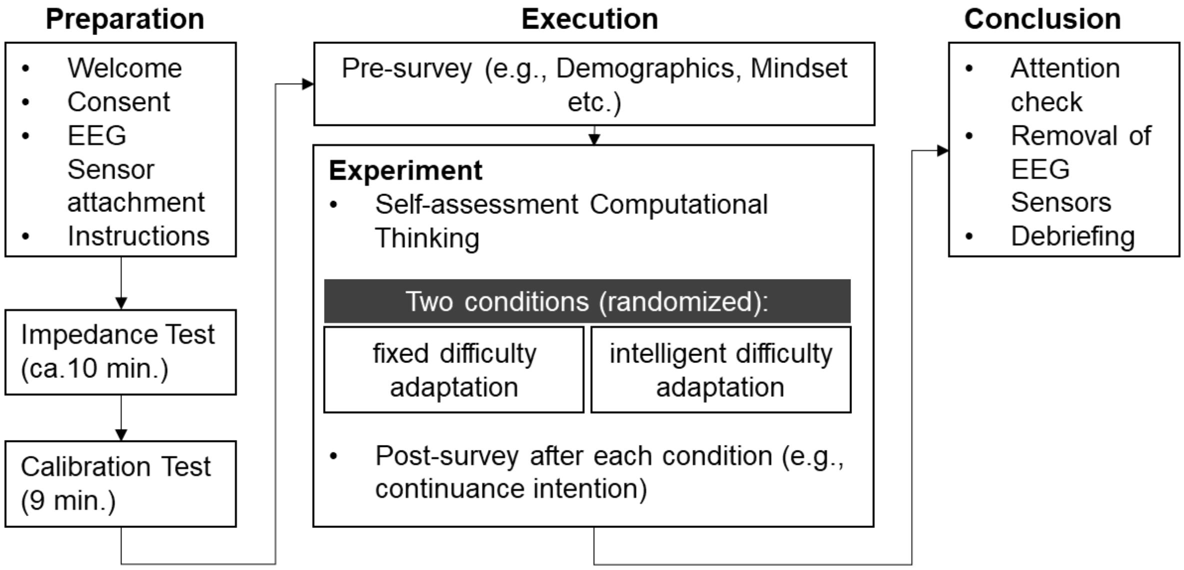

Figure 2. Experiment Procedure.

Figure 2 provides an overview of the procedure of the experiment. First, participants get a briefing about the experiment and will discuss potential risks. When consent is provided, I start the EEG sensor attachment. Afterward, an impedance test for EEG data quality is done and then a calibration test takes place. Then, they answer a pre-survey regarding demographic data and mindset. Since energy level and sleep quality have a significant impact on the data quality and influence the experimental results (Kaiser et al., 2021), I included these questions in the pre-survey. Participants then enter the learning tool prototype to answer a self-assessment about their computational thinking experience. Randomization takes place and participants do one condition after the other.

Participants receive both conditions (fixed task difficulty adaptation and intelligent task difficulty adaptation). In the fixed difficulty adaptation condition, they receive 10 tasks with a fixed difficulty adaptation only based on the self-assessment. In the other condition, participants receive 10 tasks with intelligent difficulty adaptation (Booth et al., 2017). In the latter, the self-assessment is taken as a starting point for the algorithm and adapted dynamically after each question. In both conditions, participants receive immediate feedback as this is a factor that could potentially influence flow experiences. After each condition, participants answer questions regarding continuance intention. Finally, an attention check is done, EEG sensors are removed and a debriefing will take place.

3.2 Participants

I aim to recruit around 80 participants from a student pool of a major public University in Europe. Since the EEG is an objective measurement, this is a sufficient number for EEG studies (Katahira et al., 2018). Participants are restricted to higher education and are required to be proficient in the English language, must be well rested and had a good night sleep. Lefthanders are excluded from the study since a third of them possess different brain structures (Moravec et al., 2019).

3.3 Measures

The independent variable is the method of task difficulty adaptation displayed to the participants. One condition uses fixed difficulty adaptation to optimize task challenge levels, while the other condition contains an intelligent knowledge tracing method to adapt task difficulties dynamically. To assess computational thinking experience, participants will conduct a self-assessment on the learning platform. This will be the input for the difficult adaptation of the first task. The self-assessment consists of 17 items based on the scale of Korkmaz et al. (2017). All items are rated on a seven-point Likert scale ranging from 1 (“strongly disagree”) to 7 (“strongly agree”). The scale includes constructs of *creativity*, *algorithmic thinking*, *cooperativity*, *critical thinking*, and *problem-solving*.

EEG is an important medical imaging technique that can read the electrical activity in the scalp, which is generated by brain structures (Teplan, 2002). In the educational context, the tool has been applied, for instance, to analyze attention in multimedia learning (Ni et al., 2020). To collect the data I will use the ABM X-10 Alert device from Advanced Brain Monitoring. The device comprises nine electrodes (F3, F4, Fz, C2, C4, Cz, P3, P4, and Poz) and allows for recording high-quality and real-time EEG data as it is not sensitive to participants’ movements (de Guinea et al., 2014).

Neurophysiological flow experience: The flow experience of humans is a subjective state which researchers previously often measured by conducting surveys (i.e., Hilken et al., 2017) or observations-based coding (i.e., Addessi et al., 2015). However, verifying the positive effects of flow measurement with increased objectivity is of high value to increase the internal validity of flow studies. Recent work of researchers (i.e., Katahira et al., 2018; Metin et al., 2017) applied EEG to identify flow and engagement in research settings. A study by Knierim et al. (2018) provides insights into the neurophysiology of flow by consolidating different EEG measurement approaches. The authors report that most EEG studies describe the frontal activity for flow. Increased task difficulty was previously characterized by increased frontal theta band activity, decreased alpha activity, and right frontal beta band (Knierim et al., 2018). I follow the EEG measurement of Katahira et al. (2018) by measuring theta activities (frontocentral, left frontal, right frontal), alpha activities (frontocentral, left-frontal, right frontal, right central), and left occipital beta. Their study proposes that theta activities in the frontal areas are higher in the flow and the overload conditions than in the boredom condition, alpha activities are lower compared to people on the overload condition, and left occipital beta activity is lower in flow condition compared to boredom condition (Katahira et al., 2018).

Survey-based flow experience: will be measured additionally after each task as a means to substantiate or explain certain findings. The flow scale of (Katahira et al., 2018) is used to measure flow after each task.

Learning performance: The number of questions correctly will be measured for each condition.

Continuance intention: The intention of users to continue using information systems is measured with the scale of Bhattacherjee (2001).

Mindset: The scale of Dweck (1996) is applied to measure growth/ fixed mindset.

Control variables: I control for age, gender, academic degree, quality of sleep, and energy level which are measured in the pre-survey.

3.4 Pre-Test for Task Difficulty Calibration

To ensure that different task difficulties can be detected by EEG, I conducted a pre-test for calibrating the computational thinking tasks. Before the experiment set-up, I clarified how the EEG works to all participants and they declared consent. First, participants conduct the pre-survey (as explained in section 3.1). Then, the participants performed three computational thinking tasks by Lafuente Martínez et al. (2022) that varied in difficulty (an exemplary task can be seen in Figure 3). Thus, these tasks were used as stimuli to test how the different tasks affect theta and alpha activities. After the tasks, participants needed to answer a post-survey. Finally, I collected demographic data, including age, gender, and highest school degree.

For the pre-test task calibration, a total of 3 participants participated. All participants have previous experience with computational thinking and hold a master’s degree (or higher). The duration of the pre-test varied between 25min. – 45 min.

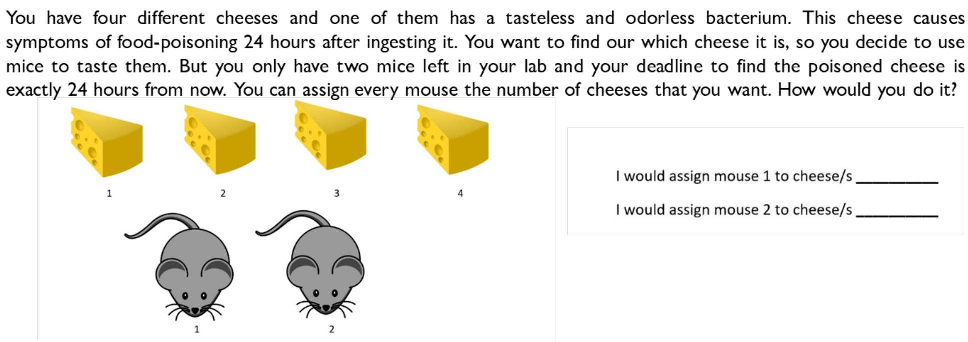

Figure 3. Expemplary Computational Thinking Task by Lafuente Martínez et al. (2022)

The results of our pre-test show the effect of the difficulty of computational thinking tasks on participants' theta and alpha activities. The results of the pre-test reveal that the theta of participants in task 1 was the highest (m=5,543 Hz) followed by task 2 (m=5,4505 Hz). Participants of task three had the lowest theta condition (m=5,0115Hz). Alpha activity is lowest in task 1 (m= 1,456 Hz), which was also perceived as the one with the highest theta. Task 2, however, seems to be less involving (m= 3,5135Hz).

A first indication of the flow state can be revealed for the first task (depicted in figure 3). According to Katahira et al. (2018), the flow state is characterized by increased theta and decreased alpha activities.

4 Conclusion and Outlook

This research-in-progress paper proposes an experimental design to investigate the impact of an intelligent task difficulty adaptation for learning activities on learners' flow experience and in turn, learning performance and continuance intention. I conducted a pre-test for the task calibration and have first indices that task difficulty influences participants' theta and alpha activities. In conclusion, this research-in-progress is a first step to shed light on flow experiences in ILS and paves the way for improved personalized online learning experiences.

The study design is not without any limitations. First, the pre-test can only be used for calibration purposes and thus, could confirm the operationalization of flow measurements. However, I only included participants with a similar skill level in computational thinking and did not randomize participants. The realization of the experiment will be crucial to increase the validity and generalizability. Another limitation of the conceptual model is related to the measurement of learning performance. We can only apply a formative measurement of learning performance but not a summative learning performance (e.g., the course grade).

Once I conduct the study and analyze the results, I expect to contribute to flow theory by empirically exposing the influence of Bayesian knowledge tracing as a new way to select optimal learning challenges. With this experiment, I further aim to shed light on the mediating role of mindset on the relationship of intelligent task difficulty adaptation and flow experience. Future studies could build on this research by conceptualizing ILS and their potential and further exploring the impact of intelligent difficulty optimization methods on users' flow experience. A future research path could be the design of EEG-adaptive intelligent learning systems that allow real-time task adaptation. Finally, this study aims to guide practitioners with prescriptive knowledge on how to design and improve flow-like learning experiences in ILS.

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