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Complexité des tâches et charge cognitive dans l'éducation ludifiée : Le rôle de la compétitivité des apprenants

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Résumé

Ce mémoire explore les interactions entre la complexité des tâches, la charge cognitive et les traits individuels, tels que la compétitivité, dans un contexte de ludification, avec un accent particulier sur l'éducation en sciences, technologies, ingénierie et mathématiques (STEM). Réalisée sous forme d'une étude en laboratoire avec un plan expérimental intra-sujet, cette recherche examine comment la complexité des questions influence la charge cognitive et la performance des apprenants, tout en investiguant le rôle modérateur de la compétitivité. Les participants ont été exposés à un stimulus expérimental interactif conçu comme un prototype haute-fidélité inspiré du jeu « Business Builders ». Ce prototype intégrait des éléments compétitifs, tels que des tableaux de classement et des systèmes de points, pour simuler un environnement d'apprentissage ludifié. Les tâches ont été réalisées à l'aide de SAP Analytics Cloud, une plateforme facilitant la visualisation et l'analyse de données. Chaque tâche était conçue pour varier en complexité, reflétant un nombre croissant d'étapes nécessaires pour arriver à la solution. Les résultats montrent qu'une augmentation de la complexité des tâches entraîne une augmentation significative de la charge cognitive. Cette charge cognitive accrue a un impact négatif sur la performance des apprenants. Cependant, les individus hautement compétitifs font preuve d'une plus grande résilience face à une charge cognitive élevée, maintenant des niveaux de performance supérieurs à leurs pairs moins compétitifs. Ces résultats mettent en lumière les interactions entre la complexité des tâches, le traitement cognitif et les traits individuels dans des contextes éducatifs ludifiés. L'étude propose des recommandations pratiques pour la conception d'environnements d'apprentissage ludifiés qui équilibrent engagement et efficacité. Elle suggère d'adapter la complexité des tâches et les éléments compétitifs aux traits individuels des apprenants. Le mémoire comprend également un article managérial proposant des stratégies pour adapter la ludification aux divers besoins des apprenants, en mettant particulièrement l'accent sur la création d'activités personnalisées et efficaces pour l'éducation STEM.

Mots clés : Ludification, Charge cognitive, Complexité, Compétitivité, Performance, Expérience des apprenants, Interaction humain-machine, Design pédagogique

Abstract

This thesis explores the interactions between task complexity, cognitive load, and individual traits, such as competitiveness, in a gamification context, with a particular focus on science, technology, engineering, and mathematics education (STEM). Conducted as a laboratory study using a within-subject experimental design, this research examines how question complexity affects cognitive load and learner performance while investigating the moderating role of trait competitiveness. Participants were exposed to an interactive experimental stimulus designed as a high-fidelity prototype inspired by the "Business Builders" game. This prototype was integrated with competitive elements, such as leaderboards and point systems, to simulate a gamified learning environment. Tasks were completed using SAP Analytics Cloud, a platform that facilitated data visualization and analysis, allowing participants to engage with progressively complex problem-solving scenarios. Each task was carefully designed to vary in complexity, reflecting an increasing number of steps required to arrive at the correct solution. The results show that increasing task complexity significantly raises cognitive load. This increased cognitive load negatively impacts learner performance. However, highly competitive individuals demonstrate greater resilience under high cognitive load, maintaining better performance levels compared to their less competitive peers. These findings contribute to Cognitive Load Theory by highlighting the interplay between task complexity, cognitive processing, and individual traits in gamified educational contexts. The study provides practical recommendations for designing gamified learning environments that balance engagement and effectiveness. It suggests tailoring task complexity and competitive elements to learners' individual traits, ensuring tasks are challenging but not overwhelming. The thesis also includes a managerial article proposing strategies to adapt gamification to the diverse needs of learners, with a particular emphasis on creating personalized and effective activities for STEM education.

Keywords: Gamification, Cognitive Load, Task Complexity, Competitiveness, Performance, Learner Experience, Human-Computer Interaction, Instructional Design

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Avant-propos

Le présent mémoire a été rédigé en suivant une structure par article conformément aux exigences du programme de Maîtrise ès Science en Gestion de HEC Montréal. Le premier article examine les interactions entre la complexité des tâches, la charge cognitive et les traits individuels, notamment la compétitivité, dans un contexte d'apprentissage ludifié en sciences, technologies, ingénierie et mathématiques (STEM). Cet article est en préparation en vue d'une publication éventuelle dans AIS Transactions on HCI. L'article est présenté avec l'accord des coauteurs.

Le second article est de nature managériale et constitue une synthèse et interprétation des résultats obtenus dans le premier article. Il propose des recommandations pratiques pour la conception de stratégies de ludification adaptées à l'éducation STEM. Le niveau de vulgarisation de l'article vise un public plus large en vue d'augmenter la portée des résultats et de les rendre accessibles à une communauté diversifiée d'éducateurs et de professionnels. Cet article est en préparation pour soumission à eLearning Industry journal.

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Introduction

Ces dernières années, les systèmes éducatifs ont subi des transformations significatives pour répondre aux exigences d'une société en rapide évolution, dominée par la technologie. L'éducation a déplacé son focus de la transmission traditionnelle des connaissances vers le développement des compétences du XXIe siècle, telles que la pensée critique, l'adaptabilité et la collaboration — des compétences essentielles pour naviguer dans les défis complexes à l'échelle mondiale. Parmi ces changements, l'éducation STEM — couvrant les sciences, la technologie, l'ingénierie et les mathématiques — a pris une importance particulière en raison de son rôle central dans l'innovation et la réponse à des besoins sociétaux cruciaux, tels que le changement climatique, les avancées en santé et le développement technologique (Bybee, 2010). Cependant, les disciplines STEM posent souvent des défis uniques, avec des concepts abstraits, des exigences complexes en résolution de problèmes et de fortes charges cognitives qui peuvent entraîner un désengagement et des résultats d'apprentissage médiocres pour de nombreux étudiants.

Pour relever ces défis, les éducateurs et les chercheurs se tournent de plus en plus vers des outils numériques pour améliorer l'apprentissage en STEM. Les simulations interactives, les laboratoires virtuels et les plateformes de visualisation de données permettent désormais aux apprenants d'expérimenter des concepts scientifiques et d'interagir avec des scénarios du monde réel qui seraient autrement inaccessibles (Siemens et al., 2015). Ces outils personnalisent les expériences d'apprentissage en permettant aux étudiants d'explorer les contenus STEM à leur propre rythme, favorisant ainsi l'accessibilité et l'inclusivité. Cependant, malgré ces avancées, l'engagement reste un obstacle clé dans l'éducation STEM. Les recherches indiquent que les apprenants en STEM éprouvent souvent des difficultés de motivation et de persévérance, en particulier dans les environnements numériques, où la nature abstraite des tâches et les interactions sociales limitées peuvent exacerber les sentiments d'isolement et la surcharge cognitive (Santhanam et al., 2016). Ainsi, favoriser un engagement durable et un apprentissage efficace dans les contextes STEM demeure un défi pressant.

La ludification s'est imposée comme une stratégie prometteuse pour relever les défis dans l'éducation STEM, notamment en raison de son potentiel à rendre l'apprentissage plus interactif et gratifiant. La ludification est définie comme l'utilisation d'éléments de conception de jeux dans des contextes non ludiques afin d'engager les utilisateurs et d'améliorer leur expérience (Deterding et al., 2011). Elle intègre des éléments tels que des points, des badges, des classements et des retours en temps réel pour transformer les environnements d'apprentissage afin d'instiller un sentiment de compétence chez les utilisateurs (Nacke & Deterding, 2017). Contrairement aux jeux complets, la ludification ajoute une couche ludique à des systèmes non ludiques tout en conservant leurs fonctions instrumentales, ce qui permet d'améliorer à la fois les résultats instrumentaux et l'engagement expérientiel (Liu et al., 2017). Ainsi, en tirant parti des motivations intrinsèques telles que la maîtrise, l'accomplissement et la reconnaissance, la ludification a le potentiel de rendre l'apprentissage STEM plus accessible et engageant, en particulier pour les apprenants qui pourraient autrement avoir du mal à maintenir leur intérêt pour ces matières exigeantes.

Le rôle de la compétitivité dans la ludification est particulièrement pertinent dans l’éducation STEM, où des éléments compétitifs sont souvent utilisés pour stimuler l’engagement. La compétitivité de trait, définie comme un désir général de se surpasser par rapport aux autres et d'apprécier la compétition (Newby & Klein, 2014), est un concept multidimensionnel qui inclut des dimensions telles que la dominance, l'affectivité compétitive et l'amélioration personnelle. Les classements, par exemple, incitent les apprenants à surpasser leurs pairs, motivant ainsi ceux qui possèdent une forte compétitivité de trait à s’investir davantage dans les tâches. Cependant, la compétitivité de trait est complexe et peut inclure des composantes telles que l'attitude hypercompétitive, qui se manifeste par un besoin indiscriminé de compétition et de victoire pour maintenir ou améliorer l’estime de soi (Fletcher & Nusbaum, 2008; Ryckman et al., 1990). Cette compétitivité peut être une arme à double tranchant; si certains apprenants prospèrent dans des environnements compétitifs, d’autres peuvent ressentir une anxiété accrue ou un désengagement, en particulier face à des tâches STEM cognitivement exigeantes. Cette variabilité souligne l’importance d’aligner les éléments ludifiés sur les profils psychologiques et les besoins motivationnels des apprenants pour éviter des résultats négatifs inattendus (De Raad & Schouwenburg, 1996).

Malgré l'intérêt croissant pour la ludification, des lacunes importantes subsistent dans la compréhension de son interaction avec les exigences uniques de l'éducation STEM. La plupart des études se concentrent sur ses avantages généraux, tels que l'augmentation de la motivation et de l'engagement, laissant de côté les fondements théoriques relatifs aux aspects cognitifs, qui restent largement sous-explorés par rapport aux théories de la motivation (Landers et al., 2015; Zainuddin et al., 2020). Peu de recherches examinent comment les différences individuelles, telles que la compétitivité de trait, influencent son efficacité dans les contextes STEM (Zainuddin et al., 2020). De plus, l'impact de la complexité des tâches et de la charge cognitive — des facteurs clés dans l'apprentissage STEM — sur les résultats de la ludification n'est pas entièrement compris. Ces lacunes soulignent la nécessité d'une approche nuancée pour concevoir des expériences d'apprentissage ludifiées qui tiennent compte à la fois des exigences cognitives des tâches STEM et des caractéristiques diversifiées des apprenants. En mettant davantage l'accent sur les théories cognitives dans l'étude de la ludification, cette recherche vise à combler ces manques critiques et à fournir des bases théoriques solides pour orienter la conception pédagogique dans des environnements STEM.

Guidé par ces perspectives, ce mémoire vise à approfondir la compréhension de l'influence de la ludification sur l'engagement et les résultats d'apprentissage dans l'éducation STEM. L'étude s'articule autour des questions de recherche suivantes :

Question de recherche 1 - Dans quelle mesure la complexité des questions influence-t-elle les performances des tâches, par l'intermédiaire de la charge cognitive, dans un contexte de ludification?

Cette question examine la relation entre différents niveaux de complexité des tâches, la charge cognitive et les performances dans les contextes STEM. En comprenant cette dynamique, l'étude vise à identifier les seuils à partir desquels la complexité des questions commence à entraver le traitement cognitif et l'apprentissage.

Question de recherche 2 - Dans quelle mesure la compétitivité de trait modère-t-elle la relation entre la charge cognitive et les performances des tâches dans un contexte de ludification?

En reconnaissant le rôle des différences individuelles, cette question explore comment la compétitivité de trait influence la résilience des apprenants face à la charge cognitive dans les tâches STEM. Elle examine notamment si les individus compétitifs sont mieux équipés pour gérer les exigences cognitives ou si une grande complexité réduit leur performance.

En répondant à ces questions, ce mémoire contribue à l'avancement théorique de la compréhension de la ludification dans l'éducation en intégrant des concepts issus de la théorie de la charge cognitive (Cognitive Load Theory, CLT) et des cadres théoriques sur les traits de personnalité. En explorant l'interaction entre la complexité des tâches et la compétitivité sur la charge cognitive et les performances dans des contextes STEM, cette recherche approfondit la compréhension des différences individuelles dans les environnements d'apprentissage ludifiés. Elle met également en lumière les effets nuancés des traits compétitifs sur l'apprentissage, en reliant les théories motivationnelles et cognitives pour proposer un cadre plus complet pour la conception pédagogique.

Sur le plan pratique, les résultats de ce mémoire offrent des recommandations exploitables pour la conception d'outils éducatifs ludifiés. En proposant des stratégies pour équilibrer la complexité des tâches et adapter les éléments de ludification aux profils des apprenants, comme leur niveau de compétitivité, cette recherche contribue à développer des environnements STEM d'apprentissage adaptatifs et inclusifs. Ces recommandations visent à accroître l'engagement, réduire la surcharge cognitive et optimiser les résultats d'apprentissage, répondant ainsi aux défis spécifiques de l'éducation STEM.

Ce mémoire s'articule autour de deux articles interconnectés qui abordent collectivement l'impact de la ludification sur l'engagement et les résultats d'apprentissage dans l'éducation STEM, en mettant l'accent sur les rôles de la charge cognitive, de la complexité des tâches et des différences individuelles telles que la compétitivité de trait.

Le premier article se concentre sur les aspects théoriques et empiriques de la ludification. Il examine comment la complexité des tâches influence la charge cognitive et les performances dans des environnements éducatifs ludifiés, tout en explorant le rôle modérateur de la compétitivité de trait. L'étude a été réalisée en laboratoire avec un design expérimental intra-sujet, impliquant 60 participants âgés de 18 à 65 ans, recrutés principalement parmi des étudiants ou diplômés récents. Les participants ont réalisé des tâches de complexité variable (faible, moyenne, élevée) conçues à l'aide d'un prototype interactif développé sur Figma, inspiré du jeu « Business Builders » (Léger et al., 2024) et utilisant la plateforme SAP Analytics Cloud pour visualiser des données. Les mesures incluaient la charge cognitive implicite (via la pupillométrie), la charge cognitive explicite (évaluée par le NASA TLX), la performance observée sur chaque tâche, ainsi que le trait de compétitivité de chaque participant. Après chaque tâche, les participants recevaient un feedback, visualisaient leur position sur un classement et répondaient à des questionnaires pour mesurer leurs perceptions. Les résultats ont été analysés avec des modèles statistiques avancés pour comprendre l'impact de la complexité des tâches et le rôle modérateur de la compétitivité sur la charge cognitive et les performances. Ces résultats fournissent des perspectives sur l'optimisation de la complexité des tâches afin d'équilibrer engagement et performance dans des environnements d'apprentissage ludifiés, tout en considérant le différences individuelles, telle que la compétitivité.

Le second article adopte une perspective pratique et managériale pour explorer comment les principes de conception de la ludification peuvent être appliqués pour créer des outils éducatifs efficaces et engageants. S'appuyant sur les conclusions du premier article, il offre des recommandations concrètes aux éducateurs et concepteurs pédagogiques, en particulier dans le domaine de l'éducation STEM. Cet article met l'accent sur des stratégies de personnalisation de la ludification pour répondre aux besoins diversifiés des apprenants, en veillant à équilibrer les exigences cognitives et motivationnelles afin d'améliorer les résultats d'apprentissage.

En synthèse, cette étude suggère plusieurs résultats clés. Premièrement, elle indique que l'augmentation de la complexité des tâches pourrait entraîner une hausse significative de la charge cognitive, ce qui influence la performance de manière non linéaire : la performance tend à augmenter dans un premier temps lorsque la charge cognitive est modérée, avant de diminuer lorsque cette charge devient excessive. Deuxièmement, les données suggèrent que la compétitivité de trait pourrait modérer cette relation : les individus hautement compétitifs semblent montrer une plus grande résilience face à une charge cognitive élevée, maintenant des performances supérieures comparées à leurs pairs moins compétitifs. Ces résultats contribuent à répondre aux questions de recherche en explorant les dynamiques potentielles entre la complexité des tâches, la charge cognitive et les traits individuels dans un contexte ludifié. Ils mettent également en lumière l'importance d’une approche personnalisée pour la conception d’environnements d'apprentissage, en tenant compte des différences individuelles et en optimisant la complexité des tâches pour favoriser l'engagement et les performances. Ces contributions théoriques et pratiques enrichissent la compréhension des défis uniques de l'éducation STEM et offrent des pistes concrètes pour améliorer l'efficacité des stratégies de ludification.

Ensemble, ces articles contribuent à la fois à la compréhension théorique et à la mise en œuvre pratique de la ludification, faisant progresser la recherche et fournissant des outils pour concevoir des expériences d’apprentissage adaptatives, engageantes et efficaces dans l’éducation STEM.

Étape	Contribution
Définition de la problématique	Problématisation, questions de recherche - 100%
Revue de littérature	Recherche et rédaction de la revue de littérature – 100%
Conception du design expérimental	Rédaction du protocole – 70% -Plan du protocole offert par le Tech3Lab, modifications importantes apportées Conception du stimulus sur Figma – 70% -Maquette existante fournie par ERPsim Lab, modifications importantes apportées Conception des taches – 70% -Certaines tâches du jeu Business Builders prises comme exemple Formulaire d'éthique – 10% -Majeure partie effectuée par l'équipe du Tech3Lab
Collecte de données	Pré-tests – 100% Recrutement des participants – 50% -Le panel HEC a grandement contribué au recrutement de nos participants. Modération de la collecte – 100%
Analyse des données	Analyse des données collectées – 90% -L'équipe du Tech3Lab s'est occupé de l'extraction des données
Rédaction du mémoire	Rédaction de toutes les sections du mémoire – 100%

Chapitre 2
The Effects of Task Complexity on Performance Through Cognitive Load and Trait Competitiveness in the Context of Gamification[1]

Abstract

Despite the widespread implementation of gamification in educational contexts, there is limited understanding of how task complexity and individual differences influence learning outcomes in such environments. Specifically, the impact of task complexity on task performance, mediated through cognitive load, remains underexplored. Additionally, individual traits like competitiveness, which can significantly affect motivation and engagement, have not been adequately examined as moderators in this context. This study addresses these gaps by investigating the role of task complexity and trait competitiveness in shaping task performance through cognitive load in a gamified educational setting. Using a within-subject experimental design, participants completed tasks of varying complexity levels while cognitive load was measured through self-reports and physiological indicators. The results revealed that higher task complexity significantly increased cognitive load, which in turn negatively impacted task performance. Moreover, trait competitiveness moderated the relationship between cognitive load and performance, with highly competitive individuals demonstrating greater resilience under increased cognitive load conditions. These findings contribute to existing literature by integrating cognitive load theory and motivational frameworks to better understand how task complexity and individual differences interact in gamified educational environments. The study offers practical implications for the design of educational interventions, suggesting that instructional strategies should consider both task complexity and learners' individual traits to optimize performance and engagement.

[1] This article is currently in preparation for submission to the scientific journal AIS Transactions on Human-Computer Interaction.

Keywords: cognitive load, task complexity, trait competitiveness, gamification, task performance, educational design.

2.1 Introduction

STEM — encompassing science, technology, engineering, and mathematics — has emerged as a cornerstone of modern education due to its pivotal role in driving innovation and addressing pressing societal challenges, such as climate change, healthcare advancements, and technological development (Bybee, 2010). These disciplines are essential for equipping learners with 21st-century skills, including critical thinking, adaptability, and collaboration. However, STEM education is not without its challenges. Its inherently abstract concepts, cognitively demanding problem-solving requirements, and complex tasks often result in disengagement and suboptimal learning outcomes for many students. These unique characteristics underscore the importance of exploring innovative approaches to make STEM education more accessible and engaging.

Gamification, defined as the use of game design elements like points, badges, and leaderboards in non-game contexts, aims to boost user motivation and interaction (Deterding et al., 2011). It leverages game mechanics to create meaningful engagement by addressing both experiential (e.g., enjoyment) and instrumental (e.g., achieving goals) outcomes (Santhanam et al., 2016). Studies highlight that gamification may have matured into a practice with established design principles that are now integrated across various industries, including education, health, and employee engagement (Nacke & Deterding, 2017). By drawing on the aspects of games that make them engaging, gamification transforms traditional learning environments into more interactive and enjoyable experiences, thereby fostering deeper cognitive and motivational involvement. When thoughtfully integrated into educational platforms, gamification can improve learners' motivation, reduce cognitive load, and enhance performance. This approach offers potential solutions for challenges observed in STEM education by making learning more dynamic and purpose-driven. However, the success of gamification depends significantly on the complexity of the tasks; finding the right balance of challenge is crucial—tasks that are too simple may lead to boredom, while overly difficult tasks may result in frustration or anxiety (Czikszentmihalyi, 1990).

In educational settings, gamification's success largely depends on its alignment with learners' intrinsic motivations and psychological needs, such as autonomy, competence, and relatedness (Ryan & Deci, 2000). For example, the use of leaderboards and badges can foster a sense of competence by providing feedback on progress, while customizable learning paths can enhance autonomy (Krath et al., 2021). However, individual differences, such as personality traits and competitive tendencies, also play a critical role in how learners respond to gamified elements. For instance, highly competitive individuals may thrive in environments with leaderboards, viewing them as motivational, while less competitive students might find them anxiety-inducing and distracting (Abril & Trinidad, 2022; Elliot et al., 2018). Poorly designed gamified elements, perceived as irrelevant or excessively competitive, can lead to disengagement and reduced learning outcomes, underscoring the need for thoughtful, context-sensitive design (Krath et al., 2021). These variations underscore the need to consider individual characteristics in gamification design to avoid unintended cognitive overload or disengagement and to enhance learning outcomes effectively.

While gamification has been praised for its potential to enhance motivation and engagement in educational contexts, its application remains fraught with challenges. Current research tends to focus on the positive outcomes of gamification, such as improved learning efficiency and motivation, but often neglects its negative effects and unintended consequences, particularly in complex educational tasks. Studies indicate that poorly designed gamified elements, like leaderboards and badges, can lead to unintended issues such as cognitive overload, demotivation, or even disengagement for certain learners (Toda et al., 2018). Moreover, individual differences, such as competitiveness and learning preferences, are often overlooked despite their critical role in determining the efficacy of gamified learning environments (Abril & Trinidad, 2022; Toda et al., 2018). This gap suggests a pressing need for a more nuanced understanding of how gamified designs interact with both the cognitive demands of tasks and the unique traits of learners, thereby ensuring equitable and effective learning experiences.

Despite the growing body of research on cognitive load and gamification, there remains a need to better understand how these factors interact to influence learning outcomes, particularly in complex educational tasks. While prior studies have explored the impact of task complexity on cognitive load and performance, they often overlook the role of individual differences such as trait competitiveness. Furthermore, although gamification is widely used to improve user engagement, its influence on cognitive processing in high-complexity tasks has not been fully elucidated.

This study addresses these gaps by investigating the following research questions:

RQ1: To what extent does task complexity impact task performance through cognitive load?

RQ2: To what extent does trait competitiveness moderate the relationship between cognitive load and task performance?

By examining these questions, the study aims to provide a more comprehensive understanding of how cognitive load, task complexity, and individual differences interact in gamified educational environments, contributing to the development of more effective instructional designs and HCI applications. It can be noted that, while the first question remains important, its main purpose is to serve as a foundation for the second question.

This study integrates Cognitive Load Theory (CLT) and trait competitiveness to investigate how task complexity and individual differences, such as trait competitiveness, affect performance in a gamification setting. Using a within-subject experimental design, participants completed tasks of varying complexity while cognitive load was measured through self-reports and physiological indicators. The experimental stimuli were based on the "Business Builders" game, an innovative platform developed collaboratively by HEC Montréal and SAP to provide students with practical experience in SAP Analytics Cloud, aimed at enhancing analytical thinking and supporting data-driven decision-making in real business scenarios (Léger et al., 2024). In this study, a high-fidelity prototype was created using Figma, drawing inspiration from Business Builders. This prototype incorporated gamified elements such as leaderboards and points to engage participants in data visualization and problem-solving tasks. Participants used SAP Analytics Cloud as a core analytical tool within the experiment, allowing them to generate insights through data visualization and analysis, thereby providing a practical educational experience that aligns closely with the study's objective of simulating real-world analytics challenges in an interactive, competitive environment. The findings reveal that higher task complexity increases cognitive load, which has a non-linear relationship with performance, ultimately negatively impacting it, and that trait competitiveness moderates this relationship, with competitive individuals demonstrating greater resilience under cognitive load. These results contribute to the understanding of how task design and individual traits interact, emphasizing the importance of balancing task complexity and considering personality traits to optimize educational outcomes.

This research offers actionable insights for designing personalized and effective gamification exercises, such as balancing task complexity to optimize cognitive load, tailoring gamification elements like leaderboards to individual competitiveness, and creating adaptive learning environments that accommodate diverse learner traits to enhance engagement and performance.

2.2 Literature Review

2.2.1 Task Complexity

Research on task complexity in education often emphasizes the relationship between task design, cognitive processing, and learner performance. Studies argue that cognitive task complexity is a critical factor in educational design, influencing not only learners' engagement but also their linguistic and cognitive development (Sasayama, 2016). Task complexity refers to the inherent cognitive demands of a task, which are determined by factors such as the number of elements involved and the relationships between them

(Wood, 1986). For example, tasks with a greater number of elements or requiring complex reasoning are generally considered to be more cognitively demanding.

It has been said that task complexity in education can be measured independently of task performance through objective methods such as dual-task methodology, time estimation, and self-rating measures (Sasayama, 2016). These approaches help validate whether the designed complexity of a task translates into actual cognitive load for learners. This distinction is crucial, as the perceived complexity of a task does not always align with its actual cognitive demands. When task complexity is not validated independently, it may lead to inaccurate assumptions about learners' abilities and the effectiveness of instructional designs.

In the context of complexity theory, studies highlight that educational tasks are part of a larger, dynamic system where unpredictability and interrelated elements play a significant role (Morrison, 2006). They argue that educational settings are complex adaptive systems, and task complexity should be understood in terms of the interactions between students, tasks, and the learning environment. This perspective suggests that effective educational design should account for these interactions to better manage cognitive load and facilitate learning (Morrison, 2006).

The concept of task complexity is further refined by it being defined through three dimensions: component complexity, coordinative complexity, and dynamic complexity (Wood, 1986). Component complexity refers to the number of distinct elements in a task, coordinative complexity involves the interrelationships between these elements, and dynamic complexity captures changes that occur over time. These dimensions offer a structured approach to analyzing and categorizing educational tasks based on their inherent complexity, which can be applied to optimize task design and sequencing in educational contexts. By understanding and validating task complexity, educators can create more effective learning experiences that are tailored to students' cognitive capacities and promote deeper learning (Morrison, 2006; Sasayama, 2016; Wood, 1986). This nuanced understanding of task complexity lays a critical foundation for examining how these elements interact with cognitive processing demands, or cognitive load, which will be explored in the next section as a key determinant of learners' capacity to manage and perform educational tasks effectively (Sasayama, 2016).

2.2.2 Cognitive Load and Learning Performance

Cognitive Load Theory (CLT) is a framework that describes the role of working memory in learning and how different instructional designs can optimize or hinder learning by manipulating cognitive demands (Sweller, 2020). CLT distinguishes between three types of cognitive load: **intrinsic load**, related to the inherent complexity of the content; **extraneous load**, which refers to unnecessary cognitive effort due to poor instructional design; and **germane load**, which enhances learning by facilitating schema construction and automation (de Jong, 2010; Sweller, 1988). The goal of instructional design is to manage these loads to avoid exceeding learners’ cognitive capacity, which can lead to reduced performance and learning.

While most research has focused on reducing extraneous load and optimizing germane load, recent studies have explored the interaction between cognitive load and motivation. Studies argue that cognitive load should be viewed as a motivational cost that can influence learners’ willingness to invest effort in a task (Feldon et al., 2019). When cognitive load is too high, learners may perceive the task as too demanding, leading to decreased motivation and engagement (Feldon et al., 2019). Conversely, when the task load is appropriately balanced, it can enhance motivation and persistence.

This balance of cognitive load might be particularly relevant in gamified educational contexts, where the intrinsic complexity of tasks could play a role in maintaining engagement without overwhelming learners (Sasayama, 2016). Additionally, individual differences, such as personality traits like conscientiousness and motivation, may influence the interaction between task complexity and learning outcomes, potentially shaping how cognitive demands are perceived and managed (De Raad & Schouwenburg, 1996).

2.2.3 The Influence of the Competitivity Trait on Learning Performance

Personality traits play a significant role in influencing how students approach learning, engage with academic tasks, and respond to challenges in educational settings (De Raad & Schouwenburg, 1996). Research in educational psychology often focuses on the impact of key traits such as conscientiousness, openness, and emotional stability on academic performance. For instance, conscientious students, who tend to be diligent, organized, and self-disciplined, often achieve higher grades and demonstrate better study habits, as they are more likely to set goals and maintain focus (Crozier, 1997) .

Beyond cognitive abilities, non-cognitive traits like self-efficacy, motivation, and curiosity contribute significantly to academic success (De Raad & Schouwenburg, 1996). Self-efficacy, the belief in one's own ability to succeed, encourages students to take on challenging tasks and persist through difficulties (De Raad & Schouwenburg, 1996; Wolfe & Johnson, 1995). Similarly, high motivation and curiosity drive students to explore new concepts and engage more deeply with learning materials, resulting in better retention and understanding (De Raad & Schouwenburg, 1996; Heckhausen & Heckhausen, 2018).

Competitiveness, a personality trait defined by the desire to outperform others, significantly influences academic performance, though its effects are contingent on context. Competitive individuals often excel in achievement-oriented settings where performance is evaluated comparatively (Abril & Trinidad, 2022). This trait can foster motivation, drive, and resilience, particularly in environments that reward high achievement. However, its impact is not uniformly positive. In highly competitive contexts, the pressure to outperform peers may lead to increased anxiety, stress, and maladaptive behaviors, such as avoidance of challenging tasks or unethical practices like cheating (Elliot et al., 2018; Van Yperen & Orehek, 2013).

Research underscores the multidimensional nature of competitiveness, encompassing aspects like dominance, personal enhancement, and enjoyment of competition. While dominance-driven competitiveness may emphasize outperforming others at any cost, personal enhancement focuses on self-improvement and mastery, even in the absence of direct comparison (Newby & Klein, 2014). These distinctions are critical, as different dimensions of competitiveness predict diverse outcomes in learning and performance. For instance, environments fostering "friendly competition" tend to leverage the positive aspects of competitiveness, enhancing engagement and achievement, especially in lower-performing contexts (Abril & Trinidad, 2022).

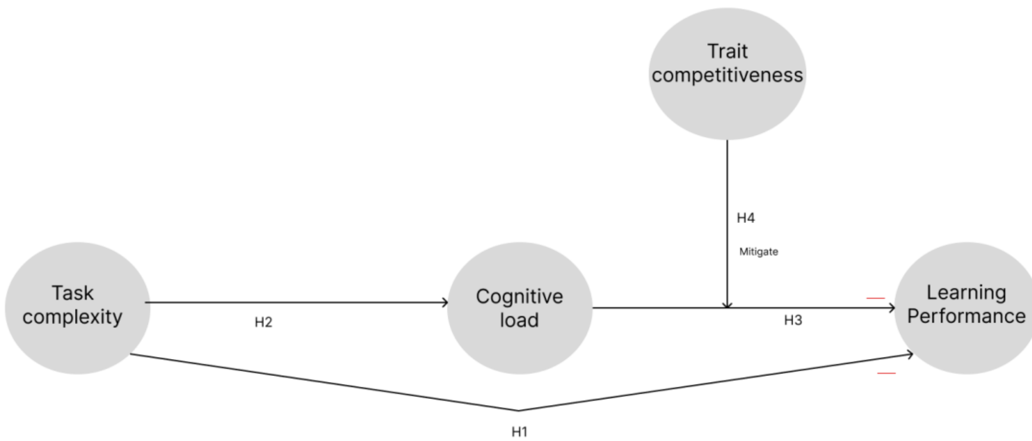
Trait competitiveness, linked to personality frameworks such as the Big Five, interacts with environmental factors to shape learning outcomes. Individuals high in competitiveness are more likely to adopt performance-approach goals—seeking success relative to peers—which positively influences academic achievement (Elliot et al., 2018). Conversely, performance-avoidance goals, driven by fear of failure, often lead to adverse outcomes. The interplay between trait competitiveness and perceived environmental competitiveness also highlights how personal tendencies and contextual perceptions jointly impact motivation and achievement strategies (Elliot et al., 2018).

Leaderboards and other gamified elements in education illustrate practical applications of competitiveness, leveraging social comparison and goal-setting behaviors to enhance motivation and engagement. However, their effectiveness depends on aligning the competitive dynamics with individual traits and the broader learning environment (Nacke & Deterding, 2017). While such tools can optimize student engagement when designed thoughtfully, overemphasis on competitive rankings without adequate support may amplify stress for less competitive students, undermining their benefits (Faust, 2021; Newby & Klein, 2014). Incorporating personality traits into educational research enables a more nuanced understanding of individual differences, guiding the development of tailored strategies that balance healthy competition with inclusivity for all learners (Faust, 2021).

2.3 Theoretical Foundation

The proposed model examines how task complexity affects task performance through cognitive load, with trait competitiveness moderating this relationship. Specifically, task complexity is hypothesized to increase cognitive load, which in turn negatively impacts performance. Trait competitiveness is positioned as a mitigating factor, potentially buffering the adverse effects of cognitive load on performance. This framework integrates cognitive and motivational perspectives, offering a nuanced understanding of the interactions between task complexity, cognitive processing, and individual differences in gamified learning environments.

Figure 1. Research Model



The theoretical link between complexity and cognitive load is grounded in CLT, which posits that task complexity significantly influences the cognitive resources required for learning and problem solving. Complexity, defined by the interactivity and number of elements in a task, determines the intrinsic cognitive load—how inherently demanding a task is based on its structure and learner expertise (Leppink & van den Heuvel, 2015; Sweller, 2020). It is further emphasized that high-complexity tasks, particularly those requiring means-ends analysis, impose significant cognitive demands, reducing the resources available for schema acquisition, a critical process for developing problem-solving expertise (Sweller, 1988, 2020). Effective instructional design mitigates these effects by reducing extraneous cognitive load through strategies like simplifying task structures and promoting goal-free approaches, thereby enhancing learning outcomes (Sweller, 1988). This theoretical framework underscores the need to balance task complexity to optimize cognitive processing and facilitate effective learning. It is schematically represented in figure 1.

Empirical studies corroborate the theoretical relationship between complexity and cognitive load, demonstrating that tasks with greater element interactivity impose higher intrinsic cognitive load. For example, it was found that increasing task complexity in simulated pharmacy environments may have led to measurable increases in intrinsic cognitive load, particularly when novices encountered tasks involving multiple interactive elements (Tremblay et al., 2023). Similarly, cognitive complexity of language tasks may have an influence on both perceived difficulty and mental effort through independent measures, such as reaction time and self-assessments, underscoring how increased task demands may heighten cognitive processing requirements (Sasayama, 2016). These findings emphasize the importance of adapting task complexity to learners' capabilities, as excessive demands can hinder performance and schema acquisition (Tremblay et al., 2023; Sasayama, 2016). Building on this theoretical and empirical foundation, the proposed hypotheses aim to investigate how task complexity impacts key outcomes in performance and cognitive load. Specifically, the following hypotheses are posited:

H1: As task complexity increases, task performance will decrease.

H2: As task complexity increases, cognitive load increases.

The relationship between cognitive load and performance has been said to follow a non-linear pattern, with performance peaking at an optimal level of cognitive load and declining when cognitive demands are either too low or too high. The roots of this proposal can be found in the Yerkes-Dodson Law, which states that performance increases with arousal or stimulation, but only up to a certain point, after which it will start to decrease (Yerkes & Dodson, 1908).

Studies proposed that working memory load is associated with curvilinear hemodynamic responses in the dorsolateral prefrontal cortex (DLPFC), reflecting optimal performance at intermediate cognitive loads (McKendrick & Harwood, 2019). These findings suggest that underload and overload states disrupt cognitive process integration, leading to decreased performance. Similarly, other studies found that task performance correlates positively with germane cognitive load but negatively with excessive intrinsic or extraneous cognitive load, further emphasizing the importance of maintaining an appropriate cognitive demand (Leppink et al., 2014). Building upon this theoretical and empirical foundation, the proposed hypotheses aim to investigate how cognitive load impacts performance. Specifically, the following hypothesis is posited:

H3: As cognitive load increases, performance will initially increase, before starting to diminish.

Studies suggest that individuals evaluate their abilities in relation to others, shaping their motivation and emotional responses (Festinger, 1954). When trait competitiveness is high, individuals view competition as an opportunity to excel, leveraging it to enhance motivation and performance by setting ambitious goals and persisting through challenges. However, for individuals with low trait competitiveness, the same context may amplify feelings of inadequacy, as comparisons with higher-performing peers exacerbate anxiety and avoidance behaviors. These contrasting dynamics emphasize the need for balanced competitive environments that accommodate varying levels of trait competitiveness, promoting engagement without fostering undue stress or disengagement.

Empirical studies provide substantial evidence for the effects of trait competitiveness on performance, supporting its theoretical underpinnings. For instance, it was suggested that trait competitiveness significantly predicts performance-approach and performance-avoidance goals, which subsequently influence achievement (Elliot et al., 2018). Their findings highlighted that students with high trait competitiveness were more likely to adopt performance-approach goals, leading to enhanced performance outcomes, while those with low competitiveness leaned toward performance-avoidance goals, often resulting in diminished performance (Elliot et al., 2018).

Empirical studies further highlight the relationship between competitiveness, emotions, and cognitive load. Studies suggest that positive achievement emotions, such as enjoyment, can significantly reduce cognitive load by facilitating effective problem-solving strategies and enabling learners to focus on relevant information (Sugiyo et al., 2018). This suggests that individuals with a preference for competition might experience greater enjoyment during competitive activities, which could lower cognitive load and enhance their capacity to process complex information. By optimizing germane cognitive load, these positive emotions may explain the link between high trait competitiveness and improved performance in challenging environments. This aligns with broader research connecting emotional states and learning efficiency, emphasizing the interplay between cognitive and affective factors (Sugiyo et al. 2018).

This theoretical and empirical foundation leads us to a hypothesis that aims to investigate how trait competitiveness moderates the relationship between cognitive load and performance. Specifically, the following hypothesis is posited:

H4: The higher the trait competitiveness, the smaller the effect of cognitive load on task performance.

2.4 Methodology

This study employs a game-based approach to teach data analytics, leveraging gamification elements to foster engagement and simulate real-world problem-solving scenarios. By using an interactive and competitive environment, participants engage in tasks that mimic the complexities of data analytics. The stimulus used for the study was a high-fidelity Figma prototype inspired by the "Business Builders" game, designed to incorporate gamification elements such as leaderboards and points. This setup allows for a closer examination of how task complexity affects cognitive load and performance, providing insights into individual differences like trait competitiveness. This game-based framework serves as a foundation for the experimental design and creates a practical context for testing the study’s hypotheses.

"Business Builders" is an educational game developed by the ERPsim Lab in collaboration with HEC Montréal, designed to simulate real-world business challenges in a gamified environment. The game focuses on decision-making and data-driven problem-solving through engaging scenarios such as supply chain resilience, sustainability portfolio management, and international market expansion. Participants analyze data, make strategic decisions, and interact with mechanics like leaderboards and performance feedback, fostering a competitive yet educational experience. In the context of this study, "Business Builders" serves as the foundation for the experimental tasks, providing a practical, gamified framework that aligns with the study's goal of exploring the effects of task complexity on cognitive load and performance, while highlighting individual traits like competitiveness (Léger et al., 2024).

SAP Analytics Cloud is a comprehensive cloud-based platform designed for data analysis, visualization, and business intelligence. It integrates various analytics tools to provide real-time insights, enabling users to create dynamic dashboards, perform predictive analytics, and generate visualizations to support data-driven decision-making. In this study, SAP Analytics Cloud served as the core analytical tool, allowing participants to process and visualize data required to complete tasks within the "Business Builders" Figma prototype. By utilizing this platform, the study simulated realistic data analytics scenarios, aligning with the study's objective of examining how task complexity affects cognitive load and performance. The use of SAP Analytics Cloud ensured that tasks mirrored professional data analysis processes, thereby enhancing the ecological validity of the experimental design (Waldorf, Germany; SAP SE, 2024).

2.4.1 Participants

In our study, we included participants who were either currently enrolled in or had recently graduated from college (CEGEP), undergraduate, or graduate programs. Participants were required to be familiar with graphs and charts (e.g., Excel) and at least somewhat comfortable with reading and listening to English instructions. A total of 60 participants took part in the study (31 females, 29 males), with 59 included in the final sample. Participant ages ranged from 18 to 65 years (mean: 27.08, SD: 7.32, median: 25.5). Each participant received a $30 compensation for their participation. While most participants were recruited through Panel HEC, additional participants were enlisted via convenience sampling and snowball sampling within the extended network. This project was approved by HEC Montréal’s Research Ethics Board under form number 2024-5934:396 (Nagano, n.d.).

2.4.2 Experimental Design

Our study employed a within-subject experimental design, where each participant completed tasks across three levels of task complexity (Low, Medium, and High) as the single independent variable. The sequence of tasks was randomized, and each participant completed two tasks at each complexity level. Participants were not recruited based on any specific personality traits, ensuring that the sample represented a range of individual differences, which is essential for understanding the generalizability of the findings. After each task, participants received feedback on their performance, viewed their position on a leaderboard, and completed a questionnaire. Following all six tasks, participants answered additional questionnaires before the recording tools were turned off.

2.4.3 Experimental Stimuli

Multiple stimuli were used in our experiment, beginning with a high-fidelity prototype of the *Business Builders* game by ERPsim Lab, developed on Figma (*Figma*, n.d.). Participants answered seven questions during the experiment. The first question was always a tutorial, designed to help participants familiarize themselves with the platforms. The remaining six questions were evaluated. To introduce randomization, six distinct groups were created within Figma, each representing a different order of task complexity (link). For example, Group 1 followed the order "simple, medium, complex.", as seen in figure 2. A leaderboard was presented after each question to foster a sense of competition among participants.

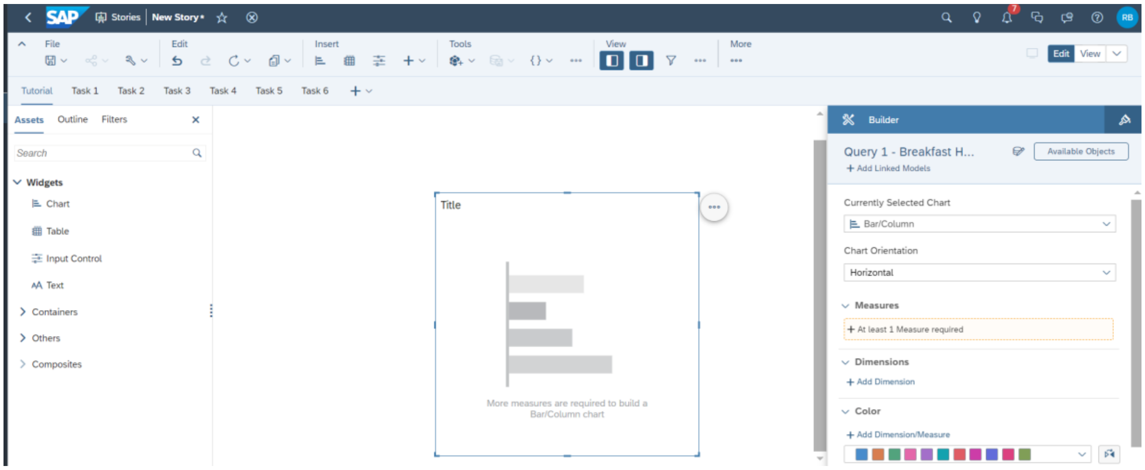
Figure 2. Questions Used for the Three Levels of Complexity

The questions were deliberately designed to vary in complexity by altering the number of essential steps required to produce an appropriate graphic to answer the question. This approach aligns with the reported concept that task complexity increases with the number of distinct actions needed for completion (Wood, 1986). Low-complexity questions required two essential steps, medium-complexity questions involved four to five steps, and high-complexity questions necessitated six to seven steps.

In this study, leaderboards and points were integrated as core gamification elements to enhance participant engagement and motivation. As studies suggest, gamification uses game design elements to create a "gameful" experience in non-game contexts, leveraging competitive and achievement-oriented behaviors intrinsic to gameplay (Deterding et al., 2011). Leaderboards facilitated structured social comparison, fostering a competitive environment that could increase motivation in educational settings. Points further supported this by offering quantifiable feedback, enabling participants to track their progress and improvements, aligning with the mechanics of gameful interaction (Deterding et al., 2011). The leaderboard structure used in the study is exemplified in Appendix H.

Another key stimulus in our experiment was the SAP Analytics Cloud platform (SAP, n.d.). On this platform, participants utilized data visualization tools to create graphs using pre-uploaded data sets. The interface of the software is as presented in figure 3. These graphs were necessary to answer the questions posed in the Figma prototype. The data sets used belonged to ERPsim Lab (ERPsim, n.d.). For access to the platform, please contact the ERPsim Lab or email rayane.benhenni@hec.ca.

Figure 3. Example Interface from SAP Analytics Cloud



2.4.4 Instruments and Lab Setup

Below is an overview of the types of data collected and the corresponding tools used during the experiment:

Explicit data was collected using Qualtrics, a survey platform widely utilized for academic and professional research. The specific version employed was the July 2024 release, developed by Qualtrics (Provo, Utah, USA; Qualtrics, 2024).

Observational data was recorded and analyzed using Microsoft Excel, version 2407, developed by Microsoft Corporation (Redmond, Washington, USA; Figma, Inc., 2024).

Implicit data, such as gaze tracking, was captured using Tobii Pro Lab software, version 1.241, produced by Tobii AB (Danderyd, Sweden; Tobii AB, 2024).

Descriptions of the participant side, observation side, and the synchronization of the equipment are included in the appendix for further details.

2.4.5 Procedure

Participants were welcomed and brought into the experiment room, where they were asked to leave their personal belongings on the observation side and ensure their devices were silenced. They were then seated on the participant side.

The session began with the moderator reading a scripted welcome message that explained the structure of the experiment, the number of tasks, the tools used, the approximate duration, and the compensation details. Participants were directed to read and sign the consent form on a tablet. Following this, the moderator verbally asked demographic questions, including age, gender identity, vision, and handedness.

The moderator then moved to the participant's side to sign the consent form and set up the eye-tracker calibration. Participants were then instructed to complete a pre-test questionnaire on their screen.

The experiment began with a tutorial task where participants watched a video demonstrating how to solve a sample question using SAP Analytics Cloud. After watching the video, participants attempted the tutorial task with guidance from the moderator as needed. Upon completing the task and reviewing an explanation, the moderator informed participants that the following tasks would be graded, and that no help would be provided.

For each task, participants were given instructions, attempted the task using Figma and SAP Analytics Cloud within a 5-minute time limit, reviewed the explanation, viewed their ranking on the leaderboard, and completed a post-task questionnaire. This process was repeated for six graded tasks.

After completing all tasks, participants completed a post-task questionnaire regarding their experience in the study. The moderator then conducted a brief interview to gather additional feedback about the tasks and overall experience.

Finally, the moderator stopped the data collection tools and guided them through signing the compensation form. The session concluded with the participant collecting their belongings and being escorted out of the lab.

2.4.6 Tasks

For the tasks, participants were required to answer the questions displayed on the "Business Builders" Figma prototype by using SAP Analytics Cloud to analyze and visualize data. Each task involved generating accurate insights from pre-uploaded datasets to address a specific problem. Participants created data visualizations, such as graphs or charts, by following a sequence of steps within SAP Analytics Cloud. These steps included selecting the appropriate dataset, applying filters, and using visualization tools to construct a graphic that met the requirements of the question. To assist with the tasks, participants had access to a printed data dictionary detailing the datasets included in the study.

To successfully complete a task, participants had to follow the correct method, as pre-established by the research team. If a participant guessed the correct answer without constructing the required visualizations in SAP Analytics Cloud, the task was marked as unsuccessful. Similarly, if a participant failed to provide an answer within the 5-minute time limit, the task was also considered a failure. This ensured that success was determined not just by the accuracy of the response but also by the proper application of the analytical process. The questions associated with all 6 tasks and the tutorial are detailed in Appendices A to G.

2.4.7 Measures

The study utilized a variety of measures to assess key constructs. Implicit cognitive load was measured using a psychophysiological approach, specifically through pupillometry (Krejtz et al., 2018). Explicit cognitive load was assessed via the NASA TLX, a self-reported measure that included six items evaluated on 100-point sliders. This instrument demonstrated high reliability with a Cronbach's alpha of .92 (Hart & Staveland, 1988). Trait competitiveness was also measured using a self-reported scale consisting of four items on a 7-point Likert scale, ranging from 1 (Extremely Disagree) to 7 (Extremely Agree). This scale showed strong internal consistency, with a Cronbach's alpha of .84, (Brown et al., 1998; Spence & Helmreich, 2014). Finally, learning performance was observed and scored based on the method participants used to answer the given question.

Additionally, as part of a manipulation check, we collected a measure of perceived complexity. After completing each task, participants were asked to rate how complex they found the task on a 7-point Likert scale, ranging from "extremely simple" to "extremely complex." The items used in the questionnaires are listed in Appendix P.

2.4.8 Statistical Analysis

Our analyses aimed to examine how task complexity affects learning performance, with a particular focus on cognitive load and pupil response as potential mediators. To perform these analyses, we used R for linear mixed-effects models, generalized linear mixed-effects models (mediation analyses), while SAS was used for data preprocessing and logistic regression (direct effects and moderation analyses). The data mapping details are documented in Appendix O.

First, we transformed the explicit cognitive load measure (log-transformed Task Load Index, or log_TLX) to meet the assumptions of normality required for parametric tests. This transformation ensured that statistical models could accurately capture the relationships between variables.

To evaluate the direct effects of task complexity on learning performance, we used linear mixed-effects models, allowing us to account for both fixed effects (task complexity) and random effects (variability between participants and repeated measures). Individual differences were specifically accounted for by including participant ID as a random intercept, which controlled for variability due to individual-specific characteristics.

Logistic regression models were employed to analyze binary performance outcomes, assessing the likelihood of success across different complexity conditions. This analysis provided insight into the overall impact of task complexity on learning performance.

To explore mediation effects, causal mediation analyses were conducted for three pairwise comparisons: low versus medium complexity, medium versus high complexity, and low versus high complexity. These analyses tested whether changes in cognitive load (log_TLX) or pupil response mediated the relationship between complexity and performance. By using simulations clustered by participant, we ensured robust estimates of indirect effects (ACME) and direct effects (ADE).

These statistical approaches were chosen to address the specific research questions. Linear mixed-effects models accounted for repeated measures and individual variability, logistic regression handled binary performance outcomes, and mediation analyses identified indirect pathways through cognitive and physiological changes. Together, these methods provided a comprehensive understanding of how task complexity influences performance, and the impact of trait competitiveness.

2.5 Results

2.5.1 Manipulation Checks

To confirm the relative differences in complexities between our questions, we incorporated manipulation check questions. The results of the pairwise comparisons indicated that the "low" complexity group was perceived to be significantly less complex than the "medium" complexity group, which was, in turn, perceived to be significantly less complex than the "high" complexity group.

The descriptive statistics for each complexity level are as follows: For the "low" complexity condition, the mean complexity rating was 2.05 with a standard deviation of 1.46 ($N = 120$). For the "medium" complexity condition, the mean was 3.839 with a standard deviation of 1.65 ($N = 120$). For the "high" complexity condition, the mean was 4.76 with a standard deviation of 1.56 ($N = 120$).

Pairwise comparisons confirmed significant differences between all complexity levels. Specifically, the difference between "low" and "medium" complexity conditions was highly significant ($p < .0001$), as was the difference between "low" and "high" complexity conditions ($p < .0001$). Additionally, the difference between the “medium” and “high” complexity conditions was also highly significant ($p < .0001$).

2.5.2 Descriptive Statistics

We collected descriptives statistics for the various variables that were under investigation in our study, mainly central tendencies as well as dispersion measures. Table 1 shows these results. We also gathered data on the trait competitiveness of each participant. The mean for that variable is 4.67 out of 7 on a Likert type scale. The standard deviation is 1.55.

Table 1: Descriptive Statistics of Collected Data for Each Complexity Level

Measure	Low		Medium		High	
	Mean	*Std Dev*	*Mean*	*Std Dev*	*Mean*	*Std Dev*
Success	0.93	0.25	0.48	0.50	0.33	0.47
Psychological Cognitive Load	-0.06	0.23	-0.04	0.23	-0.07	0.23
Self-reported Cognitive Load	16.98	13.58	33.05	20.60	41.29	18.75

2.5.3 Hypotheses Testing: Direct Effects

A linear mixed-effects model was conducted to examine the effect of complexity on performance. The Type III test revealed a significant main effect of complexity on performance, $F(2,299) = 35.96$, $p < .0001$ $F(2, 299) = 35.96$, $p < .0001$ $F(2,299) = 35.96$, $p < .0001$. Pairwise comparisons with Bonferroni-adjusted p-values indicated that performance was significantly lower in the high complexity condition compared to the low complexity condition (adjusted $p < .0001$ $p < .0001$ $p < .0001$), as well as in the medium complexity condition compared to the low complexity condition (adjusted $p < .0001$ $p < .0001$ $p < .0001$). These findings suggest that higher levels of complexity are associated with reductions in performance, as such, **hypothesis 1 is supported**.

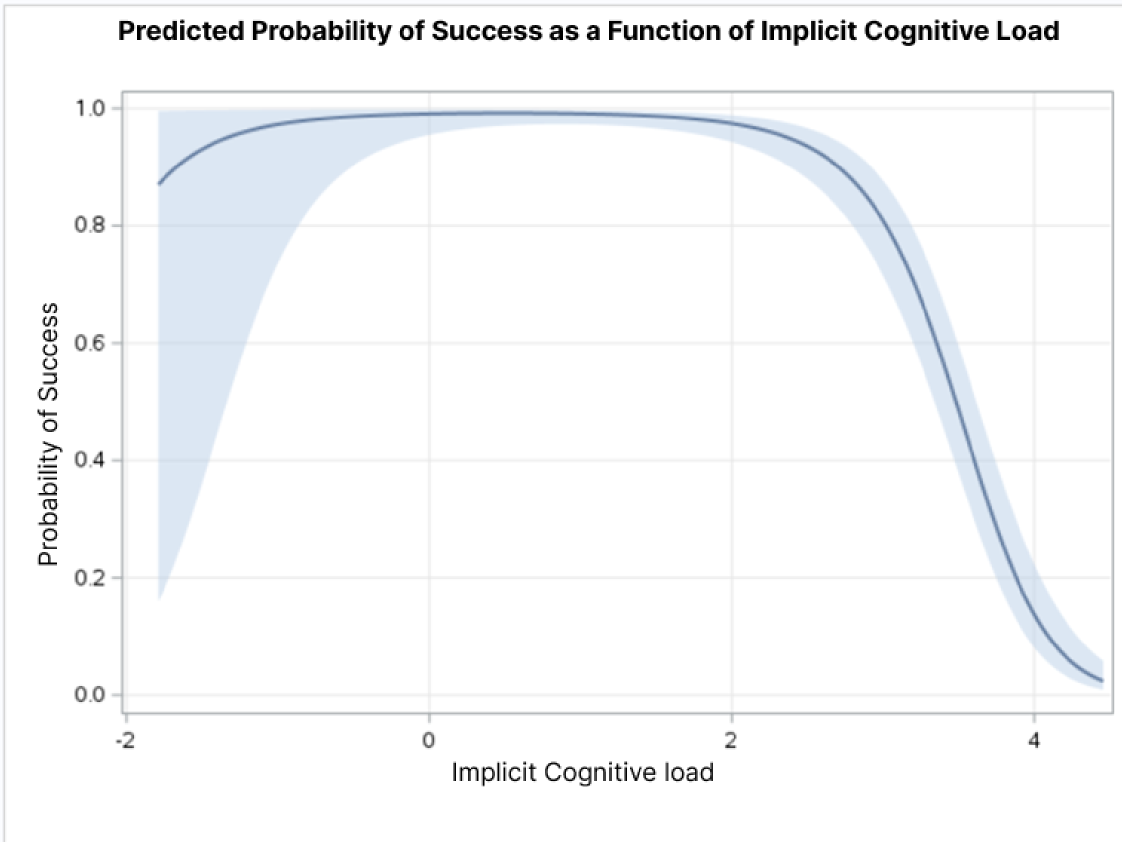
In a separate analysis, a linear mixed-effects model was conducted to examine the effect of task complexity on pupil dilation, a measure of cognitive load. The Type III test indicated a significant main effect of complexity on pupil dilation, $F(2,257) = 6.85$, $p = .0013$ $F(2, 257) = 6.85$, $p = .0013$ $F(2,257) = 6.85$, $p = .0013$. Pairwise comparisons with Holm-adjusted p-values showed that pupil dilation was significantly lower in the high complexity condition compared to the medium complexity condition (adjusted $p = .0010$ $p = .0010$ $p = .0010$). Additionally, the medium complexity condition was associated with significantly greater pupil dilation compared to the low complexity condition (adjusted $p = .0334$ $p = .0334$ $p = .0334$). No significant difference was observed between the high and low complexity conditions (adjusted $p = .2173$ $p = .2173$ $p = .2173$). These results suggest that cognitive load, as indicated by pupil dilation, is elevated under medium complexity compared to both high and low complexity. This shows that **hypothesis 2 is partially supported for pupil dilation**.

Another linear mixed-effects model was conducted to examine the effect of complexity on the log-transformed task load index (log_TLX). The Type III test indicated a significant main effect of complexity, $F(2,293) = 101.67$, $p < .0001$ $F(2, 293) = 101.67$, $p < .0001$ $F(2,293) = 101.67$, $p < .0001$. Pairwise comparisons with Holm-adjusted p-values revealed significant differences between all levels of complexity: high complexity was associated with significantly higher log_TLX compared to medium complexity (adjusted $p < .0001$ $p < .0001$ $p < .0001$), and both high and medium complexity resulted in significantly higher log_TLX compared to low complexity (both adjusted $p < .0001$ $p < .0001$ $p < .0001$). These findings suggest that increasing complexity levels are associated with greater cognitive load, as indicated by higher log_TLX values. This shows that **hypothesis 2 is supported for log-transformed task load index**.

Further analysis using a generalized linear mixed-effects model evaluated the effects of the squared term for pupil adjustment (pupil_adj*pupil_adj) and trait competitiveness on performance (success_method), with an alpha level of 10%. The effect of the squared pupil adjustment term reached significance at this threshold (Estimate = -2.6976, SE = 1.6112, $t(257) = -1.67$, $p = .0953$), suggesting a non-linear relationship between pupil adjustment and performance. This implies that as pupil adjustment increases, performance initially improves but then declines as pupil adjustment continues to rise. The Type III test of fixed effects confirmed a significant main effect for the squared term of pupil adjustment, $F(1, 257) = 2.80$, $p = .0953$, at the 10% level. In contrast, trait competitiveness had no significant effect on performance even at this relaxed threshold (Estimate = 0.08134, SE = 0.09845, $t(257) = 0.83$, $p = .4095$), with the Type III test also indicating no significant impact, $F(1, 257) = 0.68$, $p = .4095$. This is graphically represented in figure 4. This shows that **hypothesis 3 is supported for pupil dilation**.

Finally, a linear mixed-effects model was used to examine the effects of log-transformed task load index (log_TLX), the quadratic term for log_TLX (log_TLXlog_TLX), and trait competitiveness on performance (success_method). The quadratic term log_TLXlog_TLX was highly significant (Estimate = -0.5554, SE = 0.09651, $t(293) = -5.75$, $p < .0001$), suggesting a non-linear relationship between log_TLX and performance. Specifically, as log_TLX increases, performance initially rises but then declines as log_TLX continues to increase, a finding confirmed by the Type III test, $F(1, 293) = 33.12$, $p < .0001$. Trait competitiveness, however, had no significant effect on performance (Estimate = 0.02341, SE = 0.1396, $t(293) = 0.17$, $p = .8669$), with the Type III test similarly indicating no influence, $F(1, 293) = 0.03$, $p = .8669$. This shows that **hypothesis 3 is supported for log-transformed task load index.**

Figure 4: Fitted Values of Predicted Probability of Success as a Function of Implicit Cognitive Load



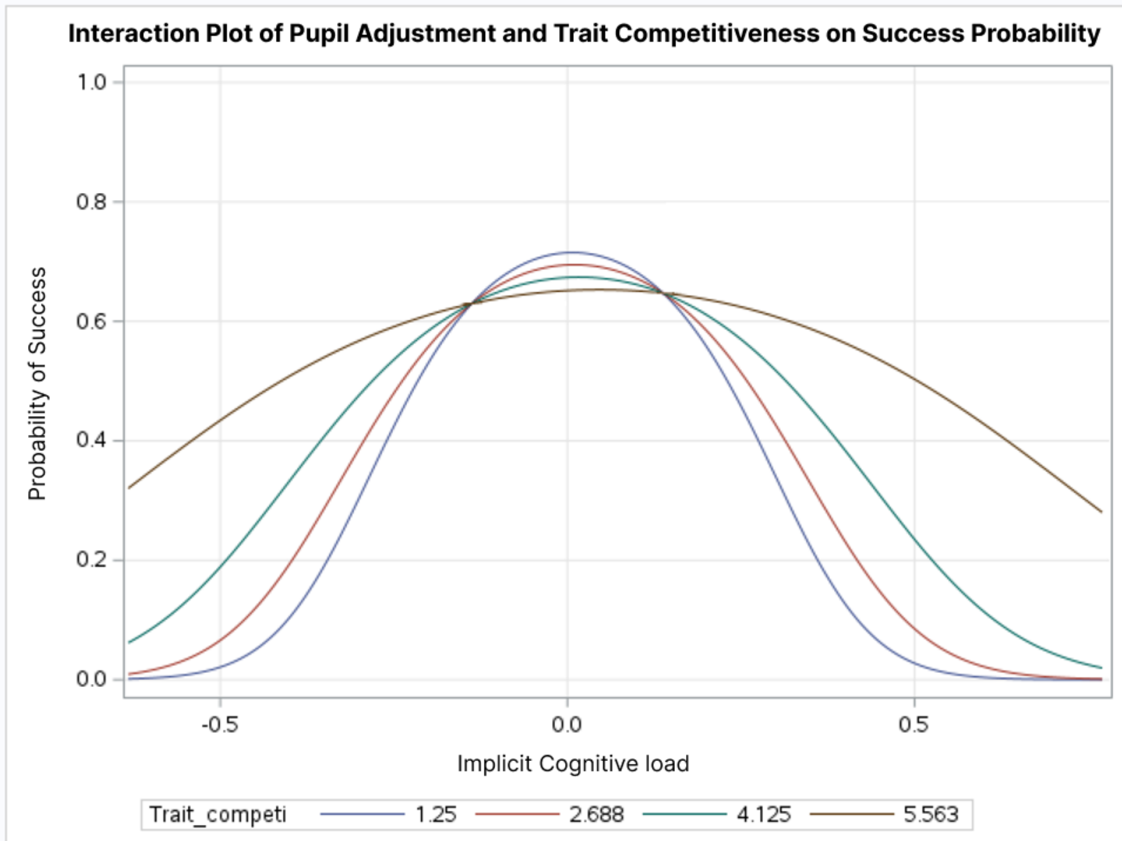
2.5.4 Hypotheses Testing: Moderations and Mediations

Moderations

A linear mixed-effects model was conducted to examine whether trait competitiveness moderated the quadratic relationship between pupil dilation (pupil_adj) and performance (success_method). The model examined whether trait competitiveness moderated the nonlinear relationship between pupil dilation and performance. The interaction term was significant, $F(1, 256) = 5.88$, $p = .0160$ (Estimate = 3.5939, SE = 1.4822, $t(256) = 2.42$). Given the one-tailed hypothesis, the p-value was divided by 2, resulting in $p = .0080$, supporting the hypothesized moderation effect at the 1% significance level. The positive direction of the interaction term indicates that higher trait competitiveness weakens the negative quadratic effect of pupil dilation on performance. In other words, while increased pupil dilation generally associates with reduced performance, this decline is less pronounced for individuals with higher trait competitiveness, aligning with the original hypothesis that higher competitiveness would mitigate the impact of cognitive load on success. This is graphically represented in figure 5. This shows that **hypothesis 4 is supported for pupil dilation.**

A linear mixed-effects model was also conducted to examine whether trait competitiveness moderated the quadratic relationship between cognitive load (log_tlx) and performance (success_method). The model tested whether trait competitiveness influenced the nonlinear relationship between cognitive load and performance. The interaction term between the quadratic effect of cognitive load and trait competitiveness was marginally significant at the $\alpha = 10\%$ level, $F(1, 292) = 2.47$, $p = .1174$ (Estimate = -0.04582, SE = 0.02918, $t(292) = -1.57$). However, since the direction of the interaction effect aligns with the quadratic effect of cognitive load, this suggests that higher trait competitiveness strengthens, rather than mitigates, the negative impact of cognitive load on performance, contrary to the hypothesis. Adjusting for the one-tailed hypothesis test yields a p-value of 0.9413, indicating a lack of support for moderation in the expected direction. This shows that **hypothesis 4 is NOT supported for log-transformed task load index.**

Figure 5: Interaction Plot of Pupil Adjustment and Trait Competitiveness on Success Probability



Mediations

The analyses were performed for three comparisons: medium vs. low complexity, medium vs. high complexity, and high vs. low complexity, using 1,000 simulations and clustered by participant.

For the **medium vs. low complexity** comparison, there was a significant indirect effect (ACME) of task complexity on performance through pupil dilation for both the control condition (Estimate = 0.00396, 95% CI [0.00003, 0.01], p = .05) and the treated condition (Estimate = 0.0118, 95% CI [0.0001, 0.03], p = .05). The direct effect (ADE) was significant and negative (Estimate = -0.422, 95% CI [-0.534, -0.31], p < .001), indicating that complexity had a strong direct negative impact on performance. The proportion mediated, however, was small and only marginally significant (p = .05), suggesting a limited mediation effect.

For the **medium vs. high complexity** comparison, the indirect effect (ACME) was significant for both the control condition (Estimate = 0.0162, 95% CI [0.0012, 0.04], p = .03) and the treated condition (Estimate = 0.0175, 95% CI [0.0012, 0.04], p = .03). The direct effect (ADE) was also significant and positive (Estimate = 0.1385, 95% CI [0.0169, 0.25], p = .036), indicating that higher complexity had a positive direct effect on performance. The proportion mediated was statistically significant (p = .048), suggesting a meaningful mediation effect.

For the **high vs. low complexity** comparison, the indirect effect (ACME) was not significant for either the control condition (Estimate = -0.0023, 95% CI [-0.0090, 0.00], p = .25) or the treated condition (Estimate = -0.0059, 95% CI [-0.0201, 0.00], p = .25). However, the direct effect (ADE) was significant and negative (Estimate = -0.567, 95% CI [-0.685, -0.45], p < .001), indicating a strong direct negative effect of task complexity on performance, with no evidence of mediation in this comparison. Detailed mediation analysis results for pupillometry are provided in Appendices L to N.

A series of causal mediation analyses were also conducted to examine whether cognitive load, measured by the log-transformed TLX scores (log_tlx), mediated the relationship between task complexity (low, medium, and high) and performance. The analyses were performed for three comparisons: medium vs. low complexity, medium vs. high complexity, and high vs. low complexity, using 1,000 simulations and clustered by participant.

For the **medium vs. low complexity** comparison, the analysis revealed significant indirect effects (ACME) for both the control condition (Estimate = -0.126, 95% CI [-0.207, -0.06], p < .001) and the treated condition (Estimate = -0.237, 95% CI [-0.299, -0.17], p < .001). The direct effects (ADE) were also significant and negative for both the control (Estimate = -0.188, 95% CI [-0.286, -0.10], p < .001) and treated conditions (Estimate = -0.299, 95% CI [-0.416, -0.18], p < .001). The proportion mediated was substantial and significant, with estimates of 0.289 for the control and 0.562 for the treated condition (both $p < .001$), indicating that a meaningful portion of the effect of complexity on performance was mediated by cognitive load.

For the **medium vs. high complexity** comparison, there were significant indirect effects (ACME) for both the control (Estimate = 0.1032, 95% CI [0.0542, 0.16], $p < .001$) and treated conditions (Estimate = 0.1058, 95% CI [0.0550, 0.16], $p < .001$). However, the direct effects (ADE) were not significant for either the control (Estimate = 0.0410, 95% CI [-0.0484, 0.13], $p = .408$) or treated conditions (Estimate = 0.0436, 95% CI [-0.0497, 0.14], $p = .408$). The proportion mediated was significant, with 0.7046 for the control and 0.7259 for the treated condition (both $p = .004$), suggesting that the mediation effect accounted for a large portion of the total effect of complexity on performance.

For the **high vs. low complexity** comparison, the indirect effects (ACME) were again significant for both the control (Estimate = -0.205, 95% CI [-0.308, -0.11], $p < .001$) and treated conditions (Estimate = -0.346, 95% CI [-0.417, -0.26], $p < .001$). The direct effects (ADE) were also significant and negative for both the control (Estimate = -0.229, 95% CI [-0.349, -0.13], $p < .001$) and treated conditions (Estimate = -0.369, 95% CI [-0.516, -0.23], $p < .001$). The proportion mediated was significant and substantial, with 0.357 for the control and 0.608 for the treated condition (both $p < .001$), indicating a strong mediation effect of cognitive load on the relationship between complexity and performance. Detailed mediation analysis results for log_TLX are provided in Appendices I to K.

The analyses showed significant indirect effects of task complexity on performance through pupil dilation for medium vs. low and medium vs. high complexity, but not for high vs. low complexity. Direct effects were significant for all comparisons, with negative effects for medium vs. low and high vs. low, and a positive effect for medium vs. high. Cognitive load significantly mediated the relationship between complexity and performance in all comparisons, with substantial proportions mediated for medium vs. low, medium vs. high, and high vs. low complexity.

2.6 Discussion

This study examined the influence of task complexity on cognitive load and learning performance within a gamification setting, while also considering the moderating role of trait competitiveness. The results suggest that increasing task complexity led to significant increases in cognitive load, as evidenced by measurements using both the NASA TLX and pupil dilation. Furthermore, the study showed that higher complexity levels negatively impacted learning performance. A non-linear relationship was also observed between cognitive load and performance, with optimal performance occurring at moderate levels of cognitive load. Finally, trait competitiveness was found to moderate the relationship between cognitive load and performance, although this effect varied across different measurement metrics. A higher trait competitiveness may have mitigated the negative effects of high cognitive load on performance.

The results support the hypothesis that complexity elevates cognitive load and diminishes performance, consistent with CLT. However, the nuances in pupil dilation between medium and high complexity tasks suggest that task design impacts cognitive processing in complex ways, potentially linked to task-specific strategies or learning plateaus.

The non-linear relationship between cognitive load and performance aligns with the theory that excessive load disrupts schema construction, while underload fails to sufficiently challenge learners. This supports the notion of an optimal cognitive load range for effective learning and task performance (McKendrick & Harwood, 2019). If we consider intrinsic cognitive load as a form of stimuli, its non-linear relationship with performance can also find meaning in the Yerkes-Dodson Law (Yerkes & Dodson, 1908).

The moderating effect of trait competitiveness was significant for pupil dilation but not for log-transformed TLX. This divergence may stem from differences in implicit versus explicit measures of cognitive load, suggesting that competitive individuals might unconsciously adapt better to stress, even if their subjective perceptions of load remain unchanged. The positive implicit response is aligned with theories that suggest that individuals shape their motivation and emotional responses as they evaluate their abilities in relation to others (Festinger, 1954). In other words, when their trait competitiveness is high, individuals may view competition as an opportunity to excel, as they set ambitious goals and persevere through challenges, which may increase their performance. The opposite may also be true however, for individuals with low trait competitiveness, as their feeling of inadequacy amplifies due to comparisons with higher-performing peers, which may exacerbate anxiety or avoidance behaviors, leading to lower performance.

The findings corroborate prior studies emphasizing the detrimental effects of excessive task complexity on performance (e.g., Sasayama, 2016; Tremblay et al., 2023). The observed non-linear relationship aligns with previous findings on cognitive load's curvilinear impact on performance (McKendrick & Harwood, 2019).

This study also extends prior work by integrating trait competitiveness as a moderating factor in gamified environments, a relatively underexplored area. Unlike previous research that treated gamification as universally beneficial, this study highlights the nuanced effects of individual traits on learning outcomes.

This study advances CLT by empirically testing the intricate relationship between task complexity, cognitive load, and performance in the context of gamified learning. By examining these elements together, the research sheds light on how increased task complexity influences cognitive processing and learning outcomes. Furthermore, the study highlights the moderating role of competitiveness traits, bridging cognitive theories with motivational frameworks. The findings demonstrate that competitive traits can shape learners' responses to cognitive load, thereby providing a nuanced understanding of how individual differences influence task performance in gamified environments. Importantly, the distinction between implicit and explicit cognitive load measures emerges as a key contribution to educational research, suggesting that learners may respond differently at subconscious versus conscious levels when faced with cognitive challenges. These contributions collectively advance the theoretical foundations of CLT and open avenues for integrating motivational and cognitive perspectives in the study of gamification and education.

The findings of this study provide actionable insights that can enhance the design of educational interventions. Firstly, it is essential to calibrate tasks to balance their complexity, ensuring that learners remain within an optimal cognitive load range. This balance helps prevent cognitive overload, which could negatively impact learning outcomes, while also avoiding tasks that are too simplistic and fail to engage learners. Secondly, gamification elements, such as leaderboards, should be tailored to align with individual competitiveness levels. By doing so, negative emotional or cognitive effects, such as anxiety or disengagement among less competitive learners, can be mitigated. Lastly, designing personalized gamified learning environments that leverage traits like competitiveness can foster greater engagement and resilience under cognitive load. Such adaptive systems have the potential to enhance learning experiences by accommodating individual differences and optimizing the interplay between motivation and cognitive demands.

While the results of this study are compelling, there are certain limitations that must be acknowledged. Firstly, when designing the tasks with different levels of complexity, the number of unique steps required to reach the result, was the only complexity parameter that was manipulated (Wood, 1986). Secondly, some of the measures employed, such as self-reported trait competitiveness and NASA TLX scores, are subject to potential biases, including social desirability and subjective interpretation. Lastly, the experimental setting used in this study may not fully replicate the complexities and dynamics of real-world learning environments, potentially restricting the applicability of the results to practical, non-controlled contexts. It can also be noted that this study focused solely on the immediate response to complexity and its interplay with cognitive load and competitiveness. The effects over a longer period of time were not considered.

Future research should investigate the long-term effects of gamified complexity on retention and the transfer of knowledge. This would provide insights into how gamification strategies influence learning outcomes over time, beyond immediate performance measures. Additionally, exploring other personality traits, such as conscientiousness or openness, as potential moderators in gamified learning contexts could broaden the understanding of individual differences and their impact on cognitive load and performance. Finally, there is a need to develop adaptive gamification systems that dynamically adjust task complexity and feedback based on learners' cognitive and motivational states. Such systems could optimize the balance between engagement and challenge, ensuring that learning experiences are both effective and personalized.

2.7 Conclusion

This study aimed to investigate how task complexity affects cognitive load and learning performance in gamification settings, while also exploring the moderating role of trait competitiveness. The motivation behind this research stemmed from the need to better understand how task design and individual differences influence learning outcomes, particularly in gamified environments.

The findings suggest that higher task complexity leads to increased cognitive load, which in turn reduces performance. Moreover, the relationship between cognitive load and performance followed a non-linear trajectory, with optimal performance achieved at moderate levels of cognitive load. Additionally, while trait competitiveness moderated the relationship between cognitive load and performance, the effects varied across different measures, providing nuanced insights into the interaction between motivation and cognitive processes.

This research contributes to the advancement of CLT by integrating personality traits and gamification principles, offering new perspectives on how to optimize learning environments. Practically, the study provides actionable recommendations for designing adaptive and personalized gamified educational systems that balance task complexity and cater to individual learner traits.

Looking ahead, this study highlights the importance of tailoring gamification strategies to individual differences and suggests exploring how these findings can be scaled to diverse educational contexts. By continuing to refine our understanding of the interplay between cognitive load, task complexity, and personality traits, future research can contribute to the development of more effective, equitable, and engaging learning experiences.

References

Abril, J. M. V., & Trinidad, J. E. (2022). *How competitiveness matters for students: Trait and perceived competitiveness in high- and low-performing contexts*. OSF. https://doi.org/10.31235/osf.io/5ce9n

Brown, S. P., Cron, W. L., & Slocum, J. W. (1998). Effects of Trait Competitiveness and Perceived Intraorganizational Competition on Salesperson Goal Setting and Performance. *Journal of Marketing*, *62*(4), 88–98. https://doi.org/10.2307/1252289

Bybee, R. W. (2010). *The Teaching of Science: 21st Century Perspectives*. NSTA Press.

Crozier, W. R. (1997). *Individual Learners: Personality Differences in Education*. Routledge. https://doi.org/10.4324/9780203130988

Czikszentmihalyi, M. (1990). *Flow: The psychology of optimal experience*. New York: Harper & Row. https://www.academia.edu/download/61507600/Flow_The_Psychology_of_Optimal_Experience20191213-16391-wlbah5.pdf

de Jong, T. (2010). Cognitive load theory, educational research, and instructional design: Some food for thought. *Instructional Science*, *38*(2), 105–134. https://doi.org/10.1007/s11251-009-9110-0

De Raad, B., & Schouwenburg, H. C. (1996). Personality in learning and education: A review. *European Journal of Personality*, *10*(5), 303–336. https://doi.org/10.1002/(SICI)1099-0984(199612)10:5<303::AID-PER262>3.0.CO;2-2

Deterding, S., Dixon, D., Khaled, R., & Nacke, L. (2011). From game design elements to gamefulness: Defining “gamification.” *Proceedings of the 15th International Academic MindTrek Conference: Envisioning Future Media Environments*, 9–15. https://doi.org/10.1145/2181037.2181040

Elliot, A. J., Jury, M., & Murayama, K. (2018). Trait and perceived environmental competitiveness in achievement situations. *Journal of Personality*, *86*(3), 353–367. https://doi.org/10.1111/jopy.12320

ERPsim. (n.d.). *60 Minute Meeting—ERPsim Lab*. Calendly. Retrieved August 30, 2024, from https://calendly.com/erpsimlab/60min

Faust, A. (2021). *The Effects of Gamification on Motivation and Performance*. Springer Fachmedien Wiesbaden. https://doi.org/10.1007/978-3-658-35195-3

Feldon, D. F., Callan, G., Juth, S., & Jeong, S. (2019). Cognitive Load as Motivational Cost. *Educational Psychology Review*, *31*(2), 319–337. https://doi.org/10.1007/s10648-019-09464-6

Festinger, L. (1954). *A Theory of Social Comparison Processes—Leon Festinger, 1954*. https://journals.sagepub.com/doi/abs/10.1177/001872675400700202

Figma: The Collaborative Interface Design Tool. (n.d.). Figma. Retrieved December 1, 2024, from https://www.figma.com/

Fletcher, T. D., & Nusbaum, D. N. (2008). Trait competitiveness as a composite variable: Linkages with facets of the big-five. *Personality and Individual Differences*, *45*(4), 312–317. https://doi.org/10.1016/j.paid.2008.04.020

Hart, S. G., & Staveland, L. E. (1988). Development of NASA-TLX (Task Load Index): Results of Empirical and Theoretical Research. In P. A. Hancock & N. Meshkati

(Eds.), *Advances in Psychology* (Vol. 52, pp. 139–183). North-Holland. https://doi.org/10.1016/S0166-4115(08)62386-9

Heckhausen, J., & Heckhausen, H. (Eds.). (2018). *Motivation and Action*. Springer International Publishing. https://doi.org/10.1007/978-3-319-65094-4

Krath, J., Schuermann, L., & von Korflesch, H. F. O. (2021). Revealing the theoretical basis of gamification: A systematic review and analysis of theory in research on gamification, serious games and game-based learning*. *COMPUTERS IN HUMAN BEHAVIOR*, *125*, 106963. https://doi.org/10.1016/j.chb.2021.106963

Krejtz, K., Duchowski, A. T., Niedzielska, A., Biele, C., & Krejtz, I. (2018). Eye tracking cognitive load using pupil diameter and microsaccades with fixed gaze. *PLOS ONE*, *13*(9), e0203629. https://doi.org/10.1371/journal.pone.0203629

Landers, R. N., Bauer, K. N., Callan, R. C., & Armstrong, M. B. (2015). Psychological Theory and the Gamification of Learning. In T. Reiners & L. C. Wood (Eds.), *Gamification in Education and Business* (pp. 165–186). Springer International Publishing. https://doi.org/10.1007/978-3-319-10208-5_9

Léger, P.-M., Babin, G., Robert, J., Gaudet-Lafontaine, F., Boutin, K.-D., Demazure, T. & Michon, J.-F. (2024). *Business Builders software* (Version 1.0) [Software]. HEC Montréal, Montréal, Québec, Canada.

Leppink, J., Paas, F., van Gog, T., van der Vleuten, C. P. M., & van Merriënboer, J. J. G. (2014). Effects of pairs of problems and examples on task performance and different types of cognitive load. *Learning and Instruction*, *30*, 32–42. https://doi.org/10.1016/j.learninstruc.2013.12.001

Leppink, J., & van den Heuvel, A. (2015). The evolution of cognitive load theory and its application to medical education. *Perspectives on Medical Education*, *4*(3), 119–127. https://doi.org/10.1007/s40037-015-0192-x

Liu, D., Santhanam, R., & Webster, J. (2017). Toward meaningful engagement. *MIS Quarterly*, *41*(4), 1011–1034.

McKendrick, R., & Harwood, A. (2019). Cognitive Workload and Workload Transitions Elicit Curvilinear Hemodynamics During Spatial Working Memory. *Frontiers in Human Neuroscience*, *13*. https://doi.org/10.3389/fnhum.2019.00405

Microsoft Corporation. (2024). *Microsoft Excel* (Version 2407) [Computer software]. Redmond, WA: Microsoft.

Morrison, K. (2006). Complexity theory and education. *APERA Conference, Hong Kong*, 28–30. https://citeseerx.ist.psu.edu/document?repid=rep1&type=pdf&doi=3a45a521a19135943f7c743c2ccaf63242969791

Nacke, L. E., & Deterding, S. (2017). The maturing of gamification research. *Computers in Human Behavior*, *71*, 450–454. https://doi.org/10.1016/j.chb.2016.11.062

Nagano. (n.d.). *hec| Tableau de bord—Nagano*. Retrieved August 30, 2024, from https://cer.hec.ca/

Newby, J. L., & Klein, R. G. (2014). Competitiveness Reconceptualized: Psychometric Development of the Competitiveness Orientation Measure as a Unified Measure of Trait Competitiveness. *The Psychological Record*, *64*(4), 879–895. https://doi.org/10.1007/s40732-014-0083-2

Qualtrics. (n.d.). *Qualtrics XM - Experience Management Software*. Qualtrics. Retrieved December 1, 2024, from https://www.qualtrics.com/

Ryan, R. M., & Deci, E. L. (2000). Self-Determination Theory and the Facilitation of Intrinsic Motivation, Social Development, and Well-Being. *American Psychologist*.

Ryckman, R. M., Hammer, M., Kaczor, L. M., & Gold, J. A. (1990). Construction of a Hypercompetitive Attitude Scale. *Journal of Personality Assessment*, *55*(3–4), 630–639. https://doi.org/10.1080/00223891.1990.9674097

Santhanam, R., Liu, D., & Shen, W.-C. M. (2016). Research Note—Gamification of Technology-Mediated Training: Not All Competitions Are the Same. *Information Systems Research*. https://doi.org/10.1287/isre.2016.0630

SAP. (n.d.). *SAP Analytics Cloud | BI, Planning, and Predictive Analysis Tools*. SAP. Retrieved August 30, 2024, from https://www.sap.com/canada/products/technology-platform/cloud-analytics.html

Sasayama, S. (2016). Is a ‘Complex’ Task Really Complex? Validating the Assumption of Cognitive Task Complexity. *The Modern Language Journal*, *100*(1), 231–254. https://doi.org/10.1111/modl.12313

Siemens, G., Gašević, D., & Dawson, S. (2015). *Preparing for the digital university: A review of the history and current state of distance, blended and online learning*. https://research.monash.edu/files/256525723/256524746_oa.pdf

Spence, J. T., & Helmreich, R. L. (2014). 11. Relationships with Parental Behavior and Attitudes. In *Masculinity and Femininity: Their Psychological Dimensions,* *Correlates, and Antecedents* (pp. 182–214). University of Texas Press. https://doi.org/10.7560/764439-012

Sugiyo, M., Sunawan, M., & Pranoto, Y. K. S. (2018). *The Role of Achievement Emotions to Cognitive Load*. 499–503. https://doi.org/10.2991/iset-18.2018.101

Sweller, J. (1988). Cognitive load during problem solving: Effects on learning. *Cognitive Science*, *12*(2), 257–285. https://doi.org/10.1016/0364-0213(88)90023-7

Sweller, J. (2020). Cognitive load theory and educational technology. *Educational Technology Research and Development*, *68*(1), 1–16. https://doi.org/10.1007/s11423-019-09701-3

Tobii AB (2024). Tobii Pro Lab (Version 1.241) [Computer software]. Danderyd, Sweden: Tobii AB.

Toda, A. M., Valle, P. H. D., & Isotani, S. (2018). The Dark Side of Gamification: An Overview of Negative Effects of Gamification in Education. In A. I. Cristea, I. I. Bittencourt, & F. Lima (Eds.), *Higher Education for All. From Challenges to Novel Technology-Enhanced Solutions* (pp. 143–156). Springer International Publishing. https://doi.org/10.1007/978-3-319-97934-2_9

Tremblay, M.-L., Rethans, J.-J., & Dolmans, D. (2023). Task complexity and cognitive load in simulation-based education: A randomised trial. *Medical Education*, *57*(2), 161–169. https://doi.org/10.1111/medu.14941

Van Yperen, N. W., & Orehek, E. (2013). Achievement goals in the workplace: Conceptualization, prevalence, profiles, and outcomes. *Journal of Economic Psychology*, *38*, 71–79. https://doi.org/10.1016/j.joep.2012.08.013

Wolfe, R. N., & Johnson, S. D. (1995). Personality as a Predictor of College Performance. *Educational and Psychological Measurement*, *55*(2), 177–185. https://doi.org/10.1177/0013164495055002002

Wood, R. (1986). Task complexity: Definition of the construct. *Organizational Behavior and Human Decision Processes*, *37*, 60–82. https://doi.org/10.1016/0749-5978(86)90044-0

Yerkes, & Dodson. (1908). *Classics in the History of Psychology—Yerkes & Dodson (1908)*. https://psychclassics.yorku.ca/Yerkes/Law/

Zainuddin, Z., Chu, S. K. W., Shujahat, M., & Perera, C. J. (2020). The impact of gamification on learning and instruction: A systematic review of empirical evidence. *EDUCATIONAL RESEARCH REVIEW*, *30*, 100326. https://doi.org/10.1016/j.edurev.2020.100326

Chapitre 3
Accounting for Individual Differences to Make Gamification More Effective: The Case of Competitiveness

Recent research highlights intriguing dynamics in how gamification engages individuals with varying levels of competitiveness. An experiment we conducted revealed that personality traits play a crucial role in shaping responses to gamified environments. For highly competitive individuals, gamified settings often boost resilience and motivation, creating a dynamic and engaging experience. Conversely, those with lower competitiveness may struggle, experiencing feelings of inadequacy or disengagement. This disparity in engagement underscores the importance of designing gamified systems that are inclusive and adaptable to individual differences.

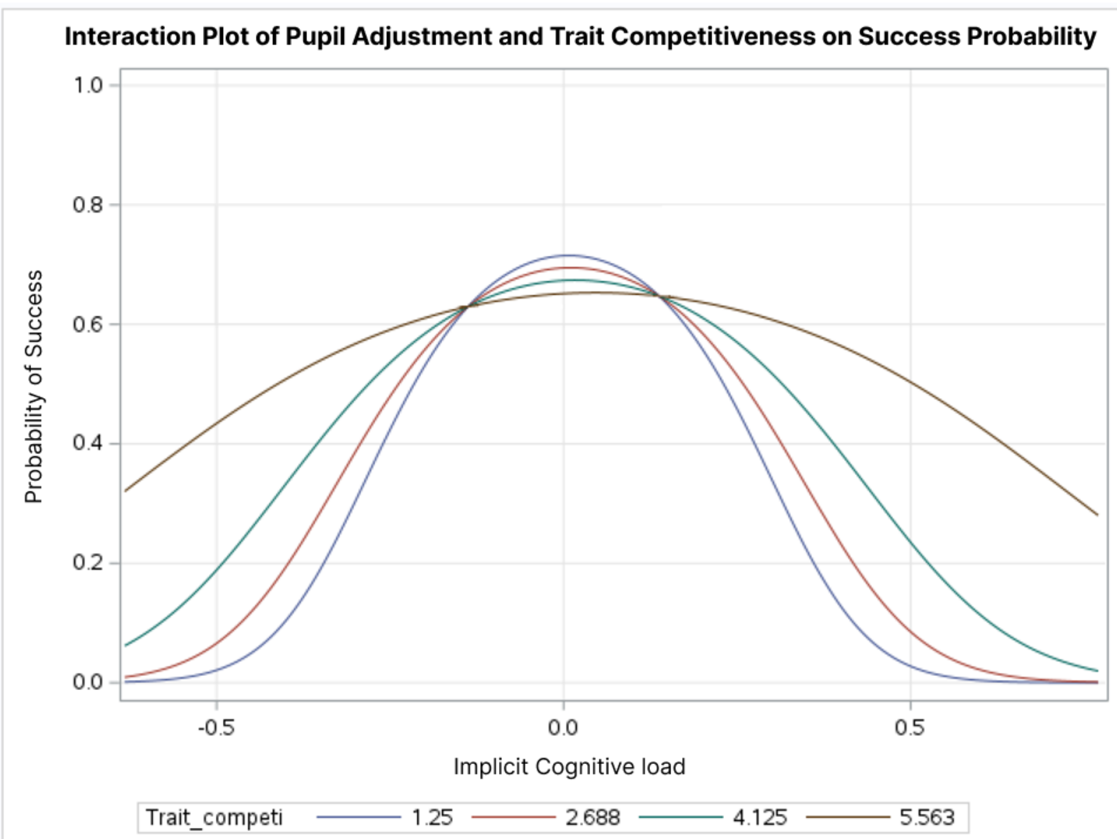
The varying impact of gamification can be understood as an issue of accessibility, rooted in the limited agency individuals have over their personality traits. These deeply ingrained characteristics shape how learners interact with gamified systems, making some naturally more aligned with competitive or feedback-driven elements than others. Without addressing this disparity, gamification risks fostering environments where certain learners thrive while others are left behind. To ensure equitable engagement, it is essential to design gamified systems that adapt to diverse personality traits and learning needs.

Methodology

The findings discussed here are based on a laboratory study conducted with 60 participants (59 included in the final sample) aged 18 to 65 years, recruited through HEC Montréal's participant panel and additional networks. Participants were exposed to tasks of varying complexity in a controlled setting. Using a within-subject experimental design, the study employed a high-fidelity prototype developed in Figma, inspired by the educational game *Business Builders*. Tasks were completed on the SAP Analytics Cloud platform, designed to facilitate data visualization and analysis.

Each participant completed six graded tasks (two for each complexity level: low, medium, high). These tasks varied in the number of steps required to create accurate data visualizations. For example, low-complexity tasks required two steps, medium-complexity tasks involved four to five steps, and high-complexity tasks demanded six to seven steps. After completing each task, participants received performance feedback via leaderboards and answered a questionnaire. Cognitive load was measured using NASA TLX for self-reported explicit load and pupillometry for implicit load. The study also assessed trait competitiveness through a validated self-reported scale.

The results suggested that increasing task complexity significantly raises cognitive load, which negatively impacts performance. However, individuals with high competitiveness showed greater resilience under high cognitive load conditions, maintaining superior performance levels compared to their less competitive peers, which is visually represented in the chart below. This underscores the importance of adaptable gamified designs to accommodate diverse personality traits and enhance inclusivity.



Recommendations to Bridge the Gap

To ensure gamification benefits a diverse range of learners, it is essential to tailor design elements to accommodate varying levels of competitiveness. Below are specific strategies, accompanied by real-world examples:

1. Inclusive Competition

Foster environments where competition motivates without alienating participants.

- Tiered Leaderboards: Implement leaderboards with multiple tiers or groups to allow learners to compete within their skill levels. For example, Duolingo, a language learning app that gamifies lessons through quick, interactive exercises, uses tiered leaderboards to enable users to engage in friendly competition regardless of their proficiency[2].

- Personal Progress Comparison: Apple Fitness+ is a fitness platform that offers guided workout videos combined with personalized activity tracking. It uses personal activity rings to track daily movement, exercise, and standing goals, allowing users to focus on self-improvement by comparing their current activity to their past achievements rather than competing with others[3].

2. Autonomy and Choice

Encourage learners to take ownership of their gamified experiences by providing flexibility.

- **Customizable Paths**: Minecraft Education Edition is an educational version of the popular sandbox game, designed to teach subjects like coding, history, and science through interactive projects. It allows learners to choose their own projects

[2] https://duoplanet.com/duolingo-leagues-the-essential-guide-everything-you-need-to-know/

[3] https://support.apple.com/en-ca/guide/watch/apd3bf6d85a6/watchos

and objectives, enabling them to explore topics like coding or architecture at their own pace and based on their interests, making the experience highly personalized[4].

- **Optional Challenges**: Nintendo's Ring Fit Adventure is a fitness game for Nintendo Switch that combines physical exercise with role-playing game mechanics. It allows players to engage in optional mini-games and fitness challenges tailored to their preferences, ensuring gamified elements align with individual goals and physical capabilities[5].

3. Non-Competitive Rewards

Offer incentives that emphasize individual growth over competition.

- **Story-Driven Progression**: Assassin's Creed Discovery Tour is an educational mode of the Assassin's Creed games, offering guided historical experiences without combat. It provides a narrative-driven educational experience, immersing players in rich historical settings with interactive stories and discoveries. This approach caters to individuals motivated by learning and exploration rather than rankings, fostering a deeper engagement through contextual and meaningful gameplay[6].

4. Collaboration Instead of Competition

Promote teamwork to achieve shared objectives, reducing the focus on individual rivalry.

- **Team-Based Tasks**: Escape room games are immersive puzzle experiences where players work together to solve challenges within a set time limit. Both physical and virtual versions of these games require participants to collaborate and pool their skills to solve puzzles and achieve a shared objective, fostering teamwork and strategic thinking. These tasks emphasize cooperation and the necessity of

[4] https://education.minecraft.net/en-us/discover/what-is-minecraft
[5] https://ringfitadventure.nintendo.com/
[6] https://www.ubisoft.com/en-ca/game/assassins-creed/discovery-tour

leveraging diverse perspectives and abilities to succeed, making them an excellent example of collaboration-focused gamification.

Conclusion

Gamification holds immense potential for transforming education and training, but its success hinges on understanding and addressing individual differences. By considering traits such as competitiveness, emotional stability, and openness to experience, stakeholders can design gamified experiences that resonate with everyone. Personalization, adaptive challenges, and inclusive rewards are key strategies to ensure gamification bridges the gap between those it motivates and those it alienates.

For practical implementation, educators can design course materials that balance competitive and non-competitive elements, fostering inclusivity. Similarly, workplace training programs can offer modular approaches, allowing employees to choose elements that align with their motivations. Incorporating collaborative games, tiered leaderboards, and flexible mechanics ensures gamification provides accessible opportunities for success across diverse populations. Ultimately, the goal is to create gamified systems that are not just engaging but also equitable and effective for all learners.

Chapitre 4
Conclusion

Ce mémoire visait à explorer les interactions complexes entre la complexité des tâches, la charge cognitive et les différences individuelles, en particulier la compétitivité de trait, dans des contextes éducatifs STEM ludifiés. Les objectifs principaux étaient de comprendre comment la complexité des tâches influence la charge cognitive et la performance et d'examiner le rôle modérateur de la compétitivité dans cette relation. Deux questions de recherche guidaient cette étude :

(1) **Dans quelle mesure la complexité des questions influence-t-elle les performances des tâches, par l'intermédiaire de la charge cognitive ?**
(2) **Dans quelle mesure la compétitivité de trait modère-t-elle la relation entre la charge cognitive et la performance des tâches ?**

Pour répondre à ces questions, un design expérimental intra-sujet a été mis en œuvre avec 60 participants réalisant des tâches de complexité variable dans un environnement ludifié. La charge cognitive des participants a été évaluée à l'aide de mesures auto-rapportées (NASA-TLX) et d'indicateurs physiologiques (dilatation pupillaire), tandis que leurs performances étaient mesurées à travers les résultats des tâches. La compétitivité de trait a été évaluée à l'aide d'échelles psychométriques validées. Cette méthodologie rigoureuse a permis d'examiner en détail l'interaction entre la complexité des tâches, la charge cognitive et les différences individuelles dans des contextes d'apprentissage STEM ludifiés.

La rigueur méthodologique de cette étude se distingue par la nature authentique des tâches effectuées, simulant des scénarios réels d'analyse de données dans un contexte éducatif ludifié. En utilisant SAP Analytics Cloud et un prototype haute-fidélité, les participants ont réalisé des tâches reflétant des pratiques professionnelles courantes dans les domaines STEM. De plus, la réalisation de l'étude dans un environnement contrôlé en laboratoire a garanti une cohérence dans l'administration des tâches et la collecte des données, renforçant ainsi la validité interne des résultats. Cette approche constitue une force méthodologique majeure, enrichissant la portée des conclusions.

Les résultats suggèrent que la complexité des tâches influence significativement la charge cognitive, qui à son tour impacte la performance. Plus précisément, des niveaux élevés de complexité des tâches ont été associés à une augmentation de la charge cognitive, entraînant une diminution des performances lorsque les demandes cognitives dépassent la capacité des apprenants. Cependant, une relation non linéaire a été observée entre la charge cognitive et la performance, soutenant l'hypothèse qu'une plage optimale de charge cognitive existe, où la performance atteint un sommet avant de décliner sous des demandes excessives ou insuffisantes.

La compétitivité de trait est apparue comme un modérateur clé dans ces dynamiques. Bien que les individus très compétitifs aient atténué certains des effets négatifs de la charge cognitive sur la performance, l'influence était complexe et variait selon les différentes mesures de charge cognitive. Par exemple, les individus compétitifs ont montré une plus grande résilience face aux demandes cognitives implicites, comme en témoignent les indicateurs physiologiques tels que la dilatation pupillaire, mais cet effet n'a pas été systématiquement reflété dans les mesures auto-rapportées de la charge cognitive.

Ces résultats contribuent à la théorie de la charge cognitive en intégrant des perspectives motivationnelles et en soulignant l'importance des différences individuelles dans les contextes éducatifs ludifiés. Ils mettent en évidence que des stratégies de ludification efficaces nécessitent un équilibre entre la complexité des tâches pour optimiser les demandes cognitives et l'adaptation des éléments de jeu aux traits et besoins des apprenants. En plus d'enrichir la théorie de la charge cognitive en mettant en évidence la relation non linéaire entre charge cognitive et performance, cette recherche élargit les cadres théoriques motivationnels en démontrant le rôle modérateur de la compétitivité de trait dans des contextes éducatifs ludifiés. Les résultats montrent que les individus compétitifs font preuve d'une plus grande résilience face aux charges cognitives élevées et tirent parti des éléments ludifiés, comme les classements, pour maintenir leur engagement et leur performance. Cette intégration des cadres cognitifs et motivationnels approfondit le discours théorique sur l’apprentissage personnalisé et met en lumière l’interaction entre la motivation, les traits de personnalité et la charge cognitive.

D’un point de vue pratique, les résultats de cette étude mettent en évidence l'importance de concevoir des environnements ludifiés qui s’adaptent aux différences individuelles des apprenants, notamment leur niveau de compétitivité. Pour les apprenants très compétitifs, des éléments tels que les classements ou les défis peuvent renforcer l'engagement et la résilience face à des tâches complexes. À l’inverse, pour ceux moins compétitifs, il est essentiel de proposer des mécanismes favorisant la progression personnelle et des récompenses centrées sur l’accomplissement individuel afin de limiter les risques de désengagement. Par ailleurs, l'intégration de tâches collaboratives permet de promouvoir des dynamiques inclusives tout en réduisant la pression de la compétition individuelle. Ces approches soulignent la nécessité de développer des systèmes éducatifs adaptatifs capables d’ajuster la complexité des tâches et les éléments ludiques en temps réel, afin d’optimiser la charge cognitive et de maximiser la réussite des apprenants dans des contextes STEM exigeants.

Malgré ses forces, cette étude présente certaines limites qu’il convient de mentionner. Tout d’abord, le niveau de familiarité des participants avec les systèmes étudiés, comme SAP Analytics Cloud, variait, ce qui a pu influencer leurs performances et leur charge cognitive. Bien que des pré-tests aient été réalisés pour limiter cet effet, de futures recherches pourraient intégrer une évaluation plus approfondie des compétences techniques initiales des participants. Ensuite, la complexité des tâches a été manipulée selon une seule dimension—le nombre d’étapes nécessaires—ce qui limite la généralisation des résultats à d’autres dimensions de la complexité, telles que l’ambiguïté ou la nouveauté des tâches. De plus, le design expérimental s’est concentré sur les réponses immédiates à la complexité et à la charge cognitive, laissant inexplorés les effets à long terme, comme la rétention des connaissances et leur transfert. Enfin, bien que l’environnement contrôlé du laboratoire ait assuré une cohérence méthodologique, il ne reflète pas nécessairement les distractions et la complexité des environnements d’apprentissage réels. Par ailleurs, les mesures auto-rapportées, telles que le NASA-TLX et les échelles de compétitivité de trait, sont sujettes à des biais pouvant affecter l'exactitude des résultats.

Les recherches futures devraient explorer les effets longitudinaux de la ludification dans l'éducation STEM pour évaluer son impact sur la rétention et l'engagement à long terme. L'exploration d'autres traits individuels, tels que la conscience ou l'ouverture, pourrait également mieux éclairer comment divers profils d'apprenants interagissent avec des environnements ludifiés. Par ailleurs, le développement de systèmes adaptatifs capables d'ajuster dynamiquement la complexité des tâches et les éléments de ludification en fonction des données en temps réel des apprenants représenterait une avancée significative dans l'éducation personnalisée.

Ce mémoire contribue à l'enrichissement des recherches sur la ludification et l'éducation STEM en reliant les théories cognitives et motivationnelles à des preuves empiriques. Ses résultats approfondissent notre compréhension de la manière dont la conception des tâches et les différences individuelles façonnent l'engagement et la performance, fournissant ainsi une base pour des environnements d'apprentissage plus efficaces, adaptatifs et inclusifs. En abordant les interactions entre la charge cognitive, la complexité des tâches et les traits de personnalité, cette recherche propose une feuille de route pour aider les éducateurs et les concepteurs à exploiter le potentiel de la ludification pour relever les défis de l'éducation STEM au XXI^{e} siècle.

Bibliographie

Abril, J. M. V., & Trinidad, J. E. (2022). *How competitiveness matters for students: Trait and perceived competitiveness in high- and low-performing contexts*. OSF. https://doi.org/10.31235/osf.io/5ce9n

Brown, S. P., Cron, W. L., & Slocum, J. W. (1998). Effects of Trait Competitiveness and Perceived Intraorganizational Competition on Salesperson Goal Setting and Performance. *Journal of Marketing*, *62*(4), 88–98. https://doi.org/10.2307/1252289

Bybee, R. W. (2010). *The Teaching of Science: 21st Century Perspectives*. NSTA Press.

Crozier, W. R. (1997). *Individual Learners: Personality Differences in Education*. Routledge. https://doi.org/10.4324/9780203130988

Czikszentmihalyi, M. (1990). *Flow: The psychology of optimal experience*. New York: Harper & Row. https://www.academia.edu/download/61507600/Flow_The_Psychology_of_Optimal_Experience20191213-16391-wlbah5.pdf

de Jong, T. (2010). Cognitive load theory, educational research, and instructional design: Some food for thought. *Instructional Science*, *38*(2), 105–134. https://doi.org/10.1007/s11251-009-9110-0

De Raad, B., & Schouwenburg, H. C. (1996). Personality in learning and education: A review. *European Journal of Personality*, *10*(5), 303–336. https://doi.org/10.1002/(SICI)1099-0984(199612)10:5<303::AID-PER262>3.0.CO;2-2

Deterding, S., Dixon, D., Khaled, R., & Nacke, L. (2011). From game design elements to gamefulness: Defining “gamification.” *Proceedings of the 15th International Academic MindTrek Conference: Envisioning Future Media Environments*, 9–15. https://doi.org/10.1145/2181037.2181040

Elliot, A. J., Jury, M., & Murayama, K. (2018). Trait and perceived environmental competitiveness in achievement situations. *Journal of Personality*, *86*(3), 353–367. https://doi.org/10.1111/jopy.12320

ERPsim. (n.d.). *60 Minute Meeting—ERPsim Lab*. Calendly. Retrieved August 30, 2024, from https://calendly.com/erpsimlab/60min

Faust, A. (2021). *The Effects of Gamification on Motivation and Performance*. Springer Fachmedien Wiesbaden. https://doi.org/10.1007/978-3-658-35195-3

Feldon, D. F., Callan, G., Juth, S., & Jeong, S. (2019). Cognitive Load as Motivational Cost. *Educational Psychology Review*, *31*(2), 319–337. https://doi.org/10.1007/s10648-019-09464-6

Festinger, L. (1954). *A Theory of Social Comparison Processes—Leon Festinger, 1954*. https://journals.sagepub.com/doi/abs/10.1177/001872675400700202

Figma: The Collaborative Interface Design Tool. (n.d.). Figma. Retrieved December 1, 2024, from https://www.figma.com/

Fletcher, T. D., & Nusbaum, D. N. (2008). Trait competitiveness as a composite variable: Linkages with facets of the big-five. *Personality and Individual Differences*, *45*(4), 312–317. https://doi.org/10.1016/j.paid.2008.04.020

Hart, S. G., & Staveland, L. E. (1988). Development of NASA-TLX (Task Load Index): Results of Empirical and Theoretical Research. In P. A. Hancock & N. Meshkati

(Eds.), *Advances in Psychology* (Vol. 52, pp. 139–183). North-Holland. https://doi.org/10.1016/S0166-4115(08)62386-9

Heckhausen, J., & Heckhausen, H. (Eds.). (2018). *Motivation and Action*. Springer International Publishing. https://doi.org/10.1007/978-3-319-65094-4

Krath, J., Schuermann, L., & von Korflesch, H. F. O. (2021). Revealing the theoretical basis of gamification: A systematic review and analysis of theory in research on gamification, serious games and game-based learning*. *COMPUTERS IN HUMAN BEHAVIOR*, *125*, 106963. https://doi.org/10.1016/j.chb.2021.106963

Krejtz, K., Duchowski, A. T., Niedzielska, A., Biele, C., & Krejtz, I. (2018). Eye tracking cognitive load using pupil diameter and microsaccades with fixed gaze. *PLOS ONE*, *13*(9), e0203629. https://doi.org/10.1371/journal.pone.0203629

Landers, R. N., Bauer, K. N., Callan, R. C., & Armstrong, M. B. (2015). Psychological Theory and the Gamification of Learning. In T. Reiners & L. C. Wood (Eds.), *Gamification in Education and Business* (pp. 165–186). Springer International Publishing. https://doi.org/10.1007/978-3-319-10208-5_9

Léger, P.-M., Babin, G., Robert, J., Gaudet-Lafontaine, F., Boutin, K.-D., Demazure, T. & Michon, J.-F. (2024). *Business Builders software* (Version 1.0) [Software]. HEC Montréal, Montréal, Québec, Canada.

Leppink, J., Paas, F., van Gog, T., van der Vleuten, C. P. M., & van Merriënboer, J. J. G. (2014). Effects of pairs of problems and examples on task performance and different types of cognitive load. *Learning and Instruction*, *30*, 32–42. https://doi.org/10.1016/j.learninstruc.2013.12.001

Leppink, J., & van den Heuvel, A. (2015). The evolution of cognitive load theory and its application to medical education. *Perspectives on Medical Education*, *4*(3), 119–127. https://doi.org/10.1007/s40037-015-0192-x

Liu, D., Santhanam, R., & Webster, J. (2017). Toward meaningful engagement. *MIS Quarterly*, *41*(4), 1011–1034.

McKendrick, R., & Harwood, A. (2019). Cognitive Workload and Workload Transitions Elicit Curvilinear Hemodynamics During Spatial Working Memory. *Frontiers in Human Neuroscience*, *13*. https://doi.org/10.3389/fnhum.2019.00405

Microsoft Corporation. (2024). *Microsoft Excel* (Version 2407) [Computer software]. Redmond, WA: Microsoft.

Morrison, K. (2006). Complexity theory and education. *APERA Conference, Hong Kong*, 28–30. https://citeseerx.ist.psu.edu/document?repid=rep1&type=pdf&doi=3a45a521a19135943f7c743c2ccaf63242969791

Nacke, L. E., & Deterding, S. (2017). The maturing of gamification research. *Computers in Human Behavior*, *71*, 450–454. https://doi.org/10.1016/j.chb.2016.11.062

Nagano. (n.d.). *hec| Tableau de bord—Nagano*. Retrieved August 30, 2024, from https://cer.hec.ca/

Newby, J. L., & Klein, R. G. (2014). Competitiveness Reconceptualized: Psychometric Development of the Competitiveness Orientation Measure as a Unified Measure of Trait Competitiveness. *The Psychological Record*, *64*(4), 879–895. https://doi.org/10.1007/s40732-014-0083-2

Qualtrics. (n.d.). *Qualtrics XM - Experience Management Software*. Qualtrics. Retrieved December 1, 2024, from https://www.qualtrics.com/

Ryan, R. M., & Deci, E. L. (2000). Self-Determination Theory and the Facilitation of Intrinsic Motivation, Social Development, and Well-Being. *American Psychologist*.

Ryckman, R. M., Hammer, M., Kaczor, L. M., & Gold, J. A. (1990). Construction of a Hypercompetitive Attitude Scale. *Journal of Personality Assessment*, *55*(3–4), 630–639. https://doi.org/10.1080/00223891.1990.9674097

Santhanam, R., Liu, D., & Shen, W.-C. M. (2016). Research Note—Gamification of Technology-Mediated Training: Not All Competitions Are the Same. *Information Systems Research*. https://doi.org/10.1287/isre.2016.0630

SAP. (n.d.). *SAP Analytics Cloud | BI, Planning, and Predictive Analysis Tools*. SAP. Retrieved August 30, 2024, from https://www.sap.com/canada/products/technology-platform/cloud-analytics.html

Sasayama, S. (2016). Is a 'Complex' Task Really Complex? Validating the Assumption of Cognitive Task Complexity. *The Modern Language Journal*, *100*(1), 231–254. https://doi.org/10.1111/modl.12313

Siemens, G., Gašević, D., & Dawson, S. (2015). *Preparing for the digital university: A review of the history and current state of distance, blended and online learning*. https://research.monash.edu/files/256525723/256524746_oa.pdf

Spence, J. T., & Helmreich, R. L. (2014). 11. Relationships with Parental Behavior and Attitudes. In *Masculinity and Femininity: Their Psychological Dimensions,* *Correlates, and Antecedents* (pp. 182–214). University of Texas Press. https://doi.org/10.7560/764439-012

Sugiyo, M., Sunawan, M., & Pranoto, Y. K. S. (2018). *The Role of Achievement Emotions to Cognitive Load*. 499–503. https://doi.org/10.2991/iset-18.2018.101

Sweller, J. (1988). Cognitive load during problem solving: Effects on learning. *Cognitive Science*, *12*(2), 257–285. https://doi.org/10.1016/0364-0213(88)90023-7

Sweller, J. (2020). Cognitive load theory and educational technology. *Educational Technology Research and Development*, *68*(1), 1–16. https://doi.org/10.1007/s11423-019-09701-3

Tobii AB (2024). Tobii Pro Lab (Version 1.241) [Computer software]. Danderyd, Sweden: Tobii AB.

Toda, A. M., Valle, P. H. D., & Isotani, S. (2018). The Dark Side of Gamification: An Overview of Negative Effects of Gamification in Education. In A. I. Cristea, I. I. Bittencourt, & F. Lima (Eds.), *Higher Education for All. From Challenges to Novel Technology-Enhanced Solutions* (pp. 143–156). Springer International Publishing. https://doi.org/10.1007/978-3-319-97934-2_9

Tremblay, M.-L., Rethans, J.-J., & Dolmans, D. (2023). Task complexity and cognitive load in simulation-based education: A randomised trial. *Medical Education*, *57*(2), 161–169. https://doi.org/10.1111/medu.14941

Van Yperen, N. W., & Orehek, E. (2013). Achievement goals in the workplace: Conceptualization, prevalence, profiles, and outcomes. *Journal of Economic Psychology*, *38*, 71–79. https://doi.org/10.1016/j.joep.2012.08.013

Wolfe, R. N., & Johnson, S. D. (1995). Personality as a Predictor of College Performance. *Educational and Psychological Measurement*, *55*(2), 177–185. https://doi.org/10.1177/0013164495055002002

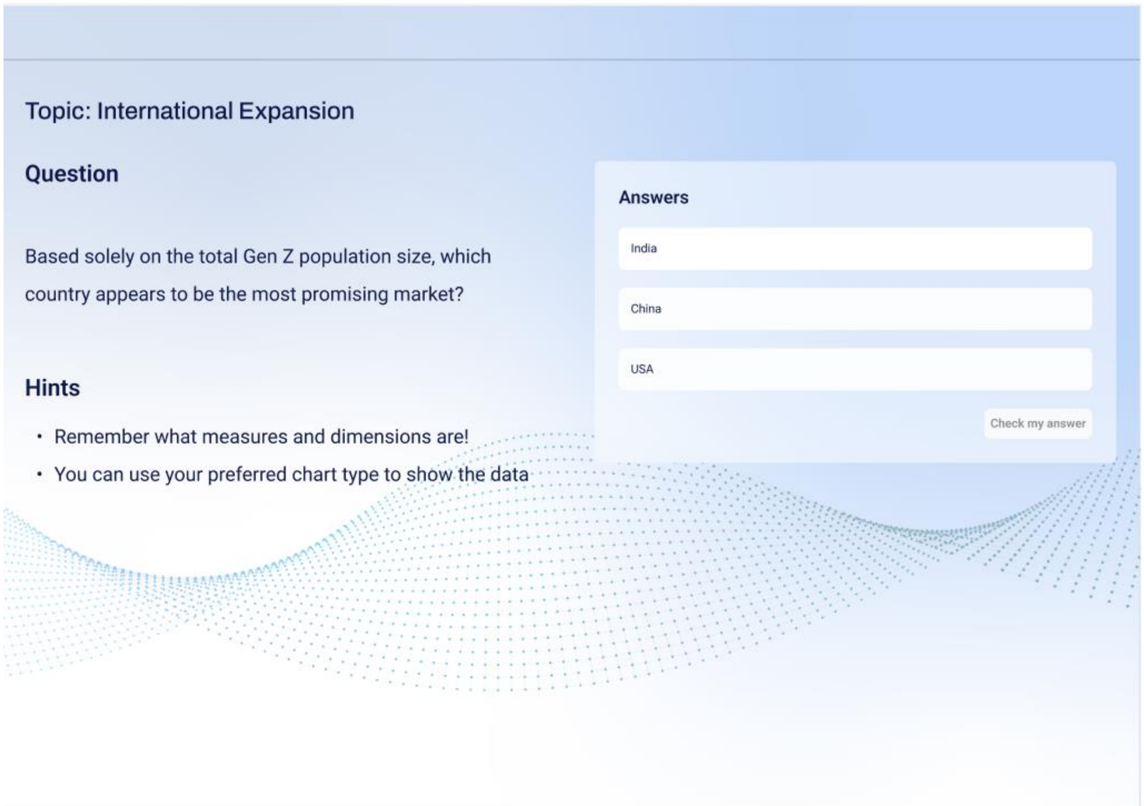
Wood, R. (1986). Task complexity: Definition of the construct. *Organizational Behavior and Human Decision Processes*, *37*, 60–82. https://doi.org/10.1016/0749-5978(86)90044-0

Yerkes, & Dodson. (1908). *Classics in the History of Psychology—Yerkes & Dodson (1908)*. https://psychclassics.yorku.ca/Yerkes/Law/

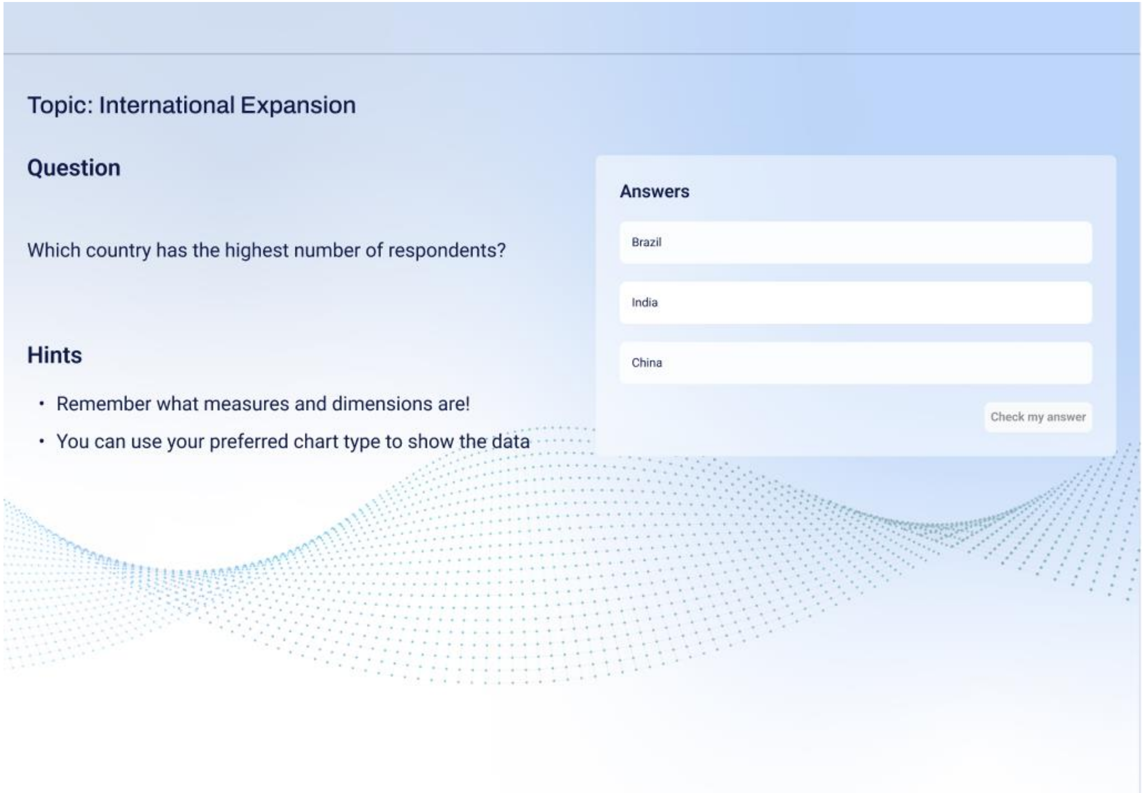
Zainuddin, Z., Chu, S. K. W., Shujahat, M., & Perera, C. J. (2020). The impact of gamification on learning and instruction: A systematic review of empirical evidence. *EDUCATIONAL RESEARCH REVIEW*, *30*, 100326. https://doi.org/10.1016/j.edurev.2020.100326

Annexes

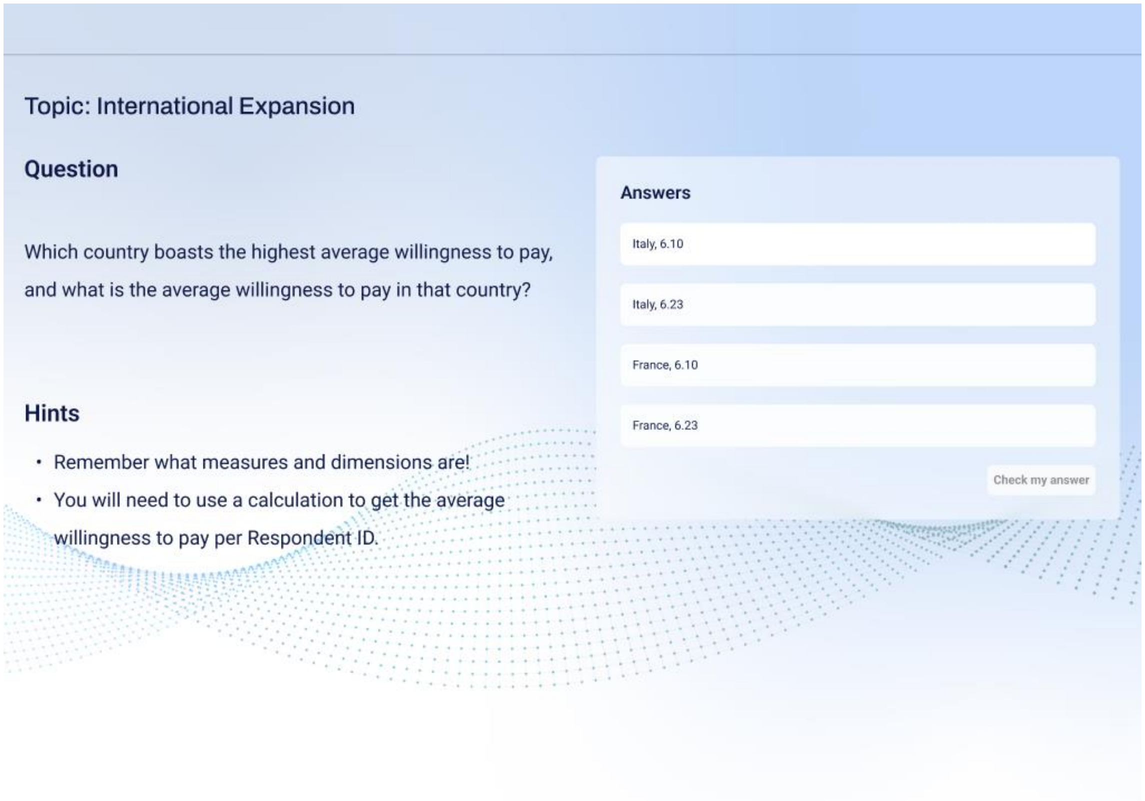
Annexe A : Question 1



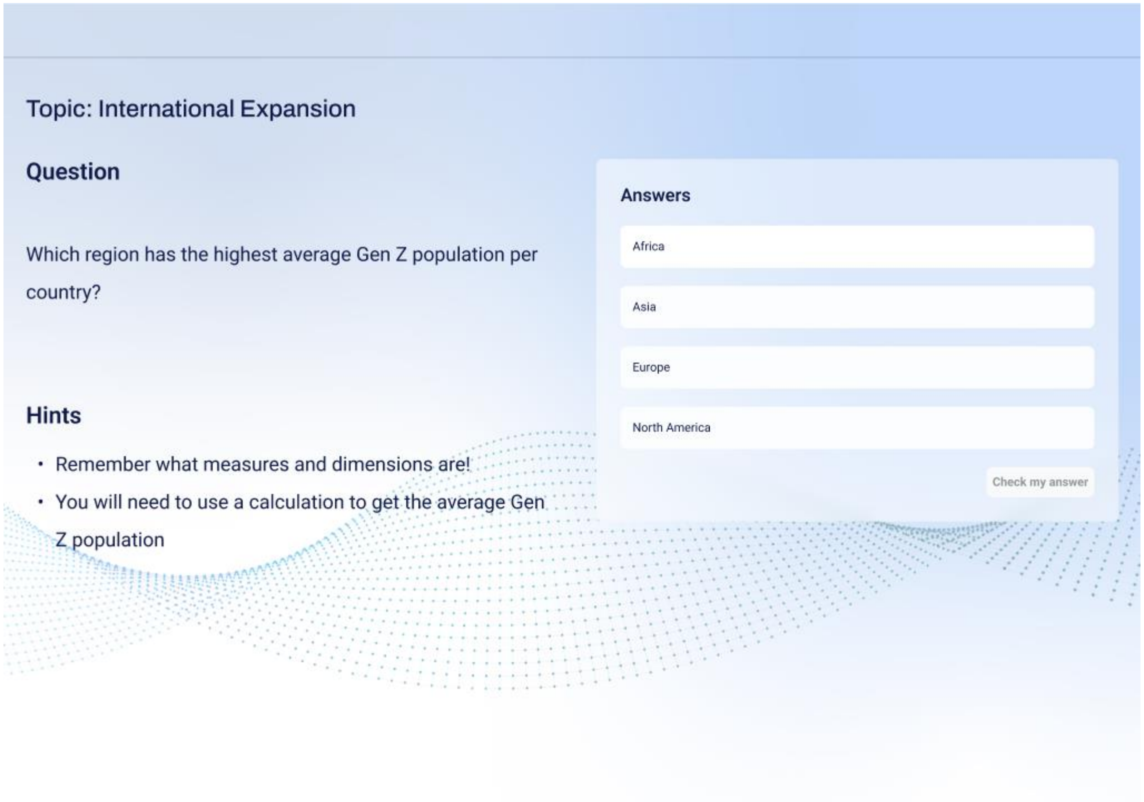
Annexe B : Question 2



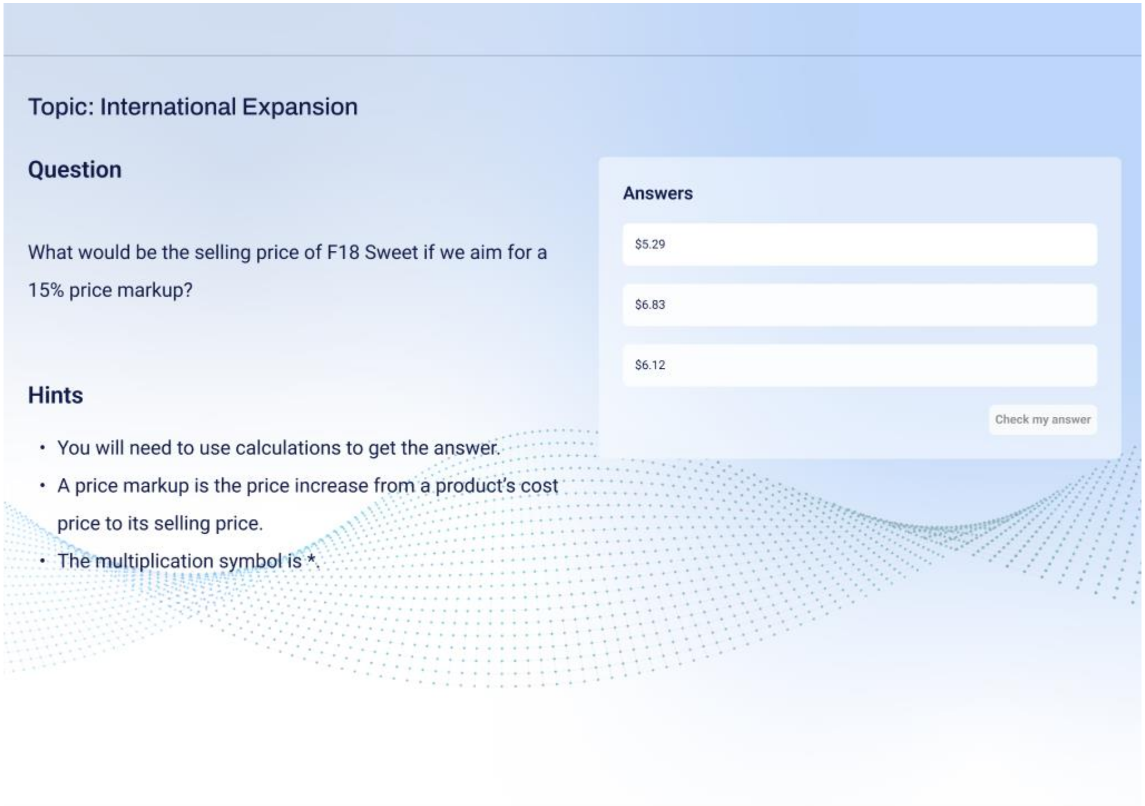
Annexe C : Question 3



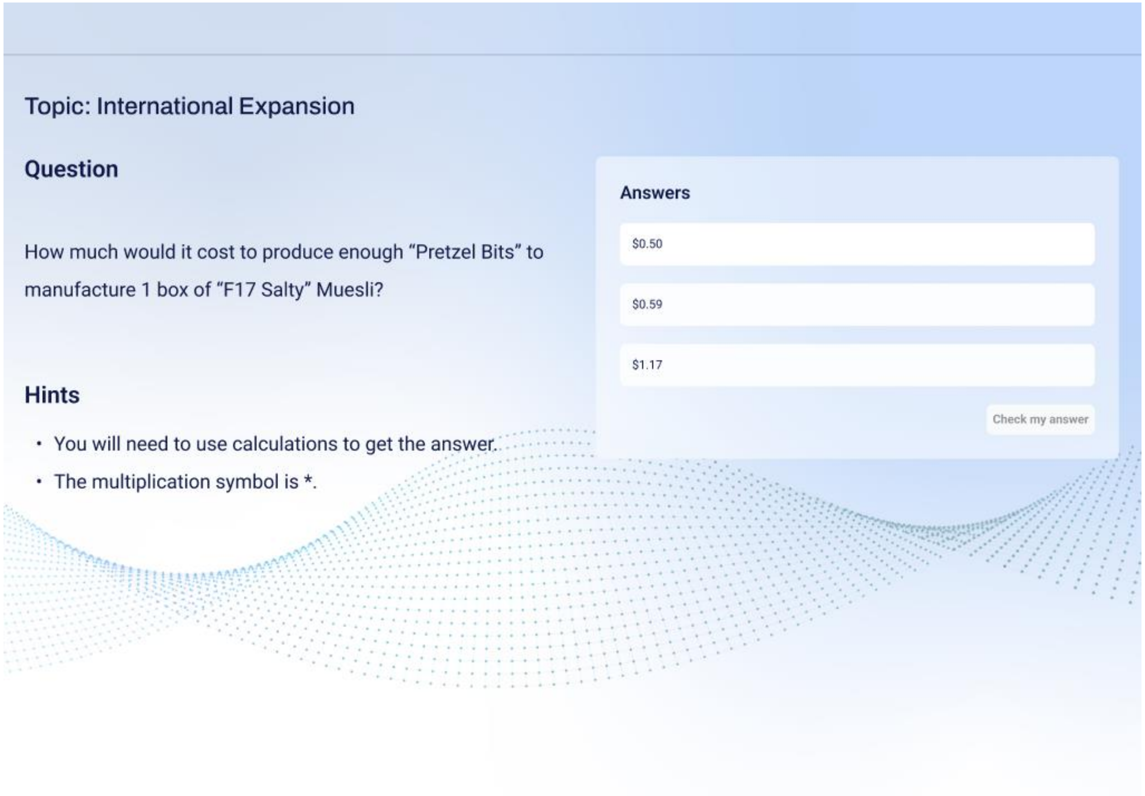
__Annexe D : Question 4__



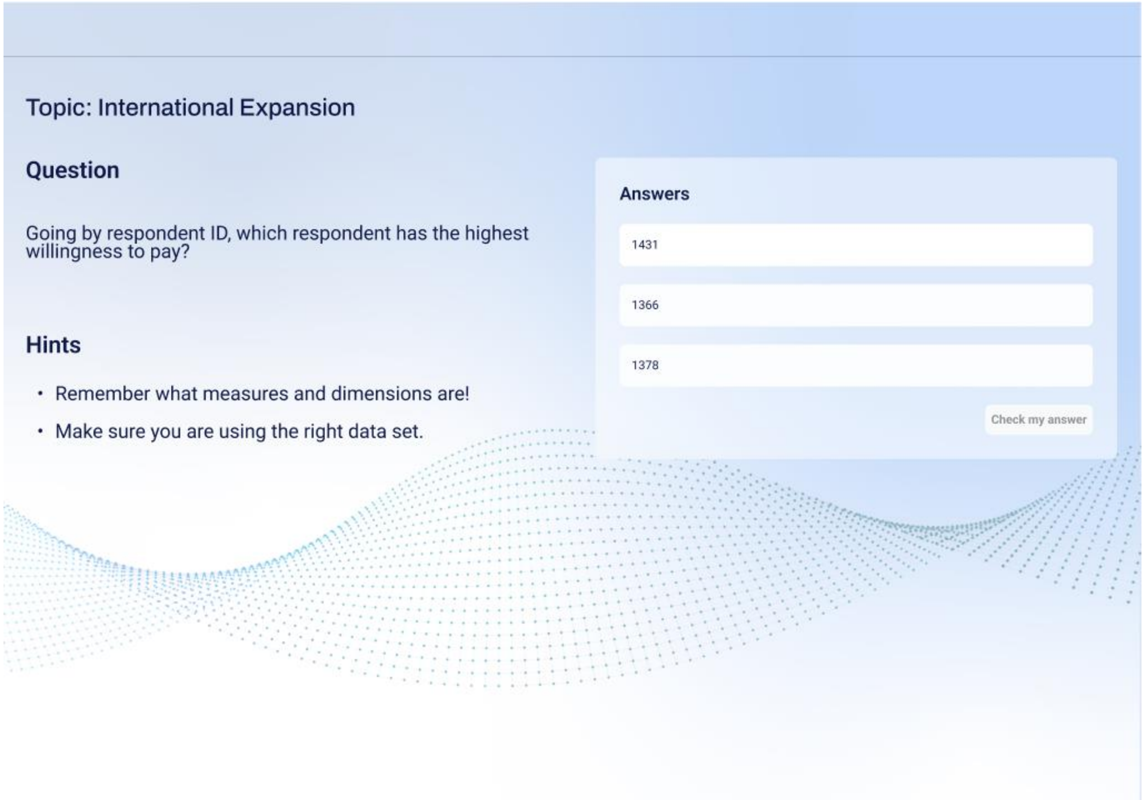
Annexe E : Question 5



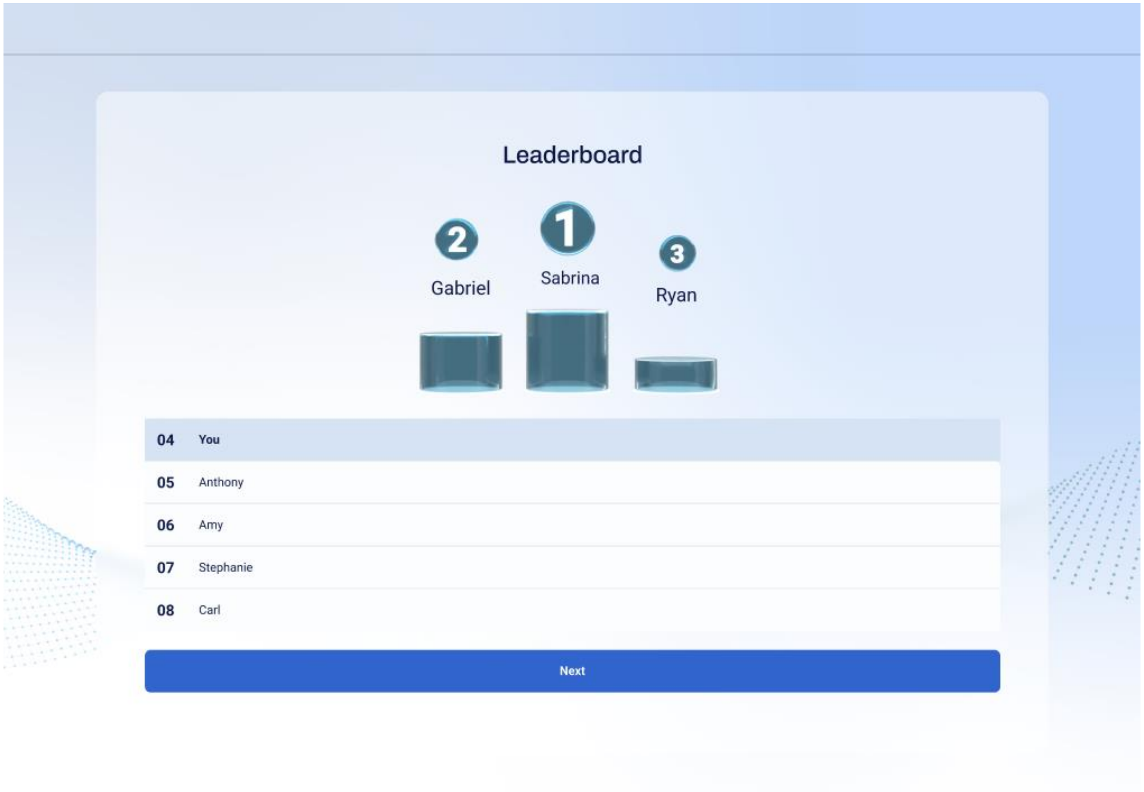
Annexe F : Question 6



Annexe G : Question Tutoriel



Annexe H : Exemple classement



Annexe I : Tableau complet des résultats de médiation pour log_TLX (medium vs low)

Effect	Estimate	95% CI Lower	95% CI Upper	p-value
ACME (control)	-0.124	-0.203	-0.06	< .001 ***
ACME (treated)	-0.237	-0.308	-0.17	< .001 ***
ADE (control)	-0.189	-0.294	-0.1	< .001 ***
ADE (treated)	-0.302	-0.426	-0.19	< .001 ***
Total Effect	-0.426	-0.529	-0.31	< .001 ***
Prop. Mediated (control)	0.287	0.154	0.5	< .001 ***
Prop. Mediated (treated)	0.559	0.42	0.7	< .001 ***
ACME (average)	-0.18	-0.247	-0.12	< .001 ***
ADE (average)	-0.245	-0.36	-0.15	< .001 ***
Prop. Mediated (average)	0.423	0.295	0.59	< .001 ***

Annexe J : Tableau complet des résultats de médiation pour log_TLX (medium vs high)

Effect	Estimate	95% CI Lower	95% CI Upper	p-value
ACME (control)	0.104	0.0518	0.16	< .001 ***
ACME (treated)	0.1065	0.054	0.16	< .001 ***
ADE (control)	0.0398	-0.0462	0.13	0.41
ADE (treated)	0.0424	-0.0485	0.14	0.41
Total Effect	0.1464	0.0439	0.25	0.01 **
Prop. Mediated (control)	0.7098	0.3335	1.77	0.01 **
Prop. Mediated (treated)	0.7309	0.3656	1.75	0.01 **
ACME (average)	0.1053	0.0533	0.16	< .001 ***
ADE (average)	0.0411	-0.0466	0.14	0.41
Prop. Mediated (average)	0.7204	0.354	1.76	0.01 **

Annexe K : Tableau complet des résultats de médiation pour log_TLX (high vs low)

Effect	Estimate	95% CI Lower	95% CI Upper	p-value
ACME (control)	-0.209	-0.307	-0.11	< .001 ***
ACME (treated)	-0.347	-0.419	-0.26	< .001 ***
ADE (control)	-0.227	-0.348	-0.13	< .001 ***
ADE (treated)	-0.365	-0.503	-0.23	< .001 ***
Total Effect	-0.574	-0.675	-0.47	< .001 ***
Prop. Mediated (control)	0.359	0.192	0.55	< .001 ***
Prop. Mediated (treated)	0.612	0.449	0.75	< .001 ***
ACME (average)	-0.278	-0.358	-0.19	< .001 ***
ADE (average)	-0.296	-0.417	-0.18	< .001 ***
Prop. Mediated (average)	0.486	0.329	0.64	< .001 ***

Annexe L : Tableau complet des résultats de médiation pour pupillométrie (medium vs low)

Effect	Estimate	95% CI Lower	95% CI Upper	p-value
ACME (control)	0.003908	0.000137	0.01	0.036 *
ACME (treated)	0.011887	0.000567	0.03	0.036 *
ADE (control)	-0.421615	-0.539249	-0.3	< .001 ***
ADE (treated)	-0.413636	-0.528504	-0.29	< .001 ***
Total Effect	-0.409728	-0.525668	-0.29	< .001 ***
Prop. Mediated (control)	-0.008329	-0.02842	0.0	0.036 *
Prop. Mediated (treated)	-0.026593	-0.076868	0.0	0.036 *
ACME (average)	0.007897	0.000366	0.02	0.036 *
ADE (average)	-0.417626	-0.533489	-0.3	< .001 ***
Prop. Mediated (average)	-0.017461	-0.05148	0.0	0.036 *

Annexe M : Tableau complet des résultats de médiation pour pupillométrie (medium vs high)

Effect	Estimate	95% CI Lower	95% CI Upper	p-value
ACME (control)	0.01671	0.00131	0.04	0.026 *
ACME (treated)	0.01795	0.00144	0.04	0.026 *
ADE (control)	0.14286	0.02625	0.26	0.002 **
ADE (treated)	0.1441	0.02632	0.26	0.002 **
Total Effect	0.16081	0.04563	0.28	< .001 ***
Prop. Mediated (control)	0.10008	0.01052	0.43	0.026 *
Prop. Mediated (treated)	0.1089	0.01175	0.44	0.026 *
ACME (average)	0.01733	0.00138	0.04	0.026 *
ADE (average)	0.14348	0.02628	0.26	0.002 **
Prop. Mediated (average)	0.10449	0.01097	0.43	0.026 *

Annexe N : Tableau complet des résultats de médiation pour pupillométrie (high vs low)

Effect	Estimate	95% CI Lower	95% CI Upper	p-value
ACME (control)	-0.00208	-0.00813	0.0	0.26
ACME (treated)	-0.00554	-0.01878	0.0	0.26
ADE (control)	-0.56805	-0.66943	-0.45	< .001 ***
ADE (treated)	-0.57151	-0.6727	-0.45	< .001 ***
Total Effect	-0.57359	-0.67598	-0.45	< .001 ***
Prop. Mediated (control)	0.00296	-0.00263	0.01	0.26
Prop. Mediated (treated)	0.00826	-0.00771	0.03	0.26
ACME (average)	-0.00381	-0.01328	0.0	0.26
ADE (average)	-0.56978	-0.67051	-0.45	< .001 ***
Prop. Mediated (average)	0.00561	-0.00517	0.02	0.26

Annexe O : Data mapping

Construct Name	Operationalized Name
Task complexity	*Complexity*
NASA TLX Cognitive load	*TLX*
Log Transformed NASA TLX Cognitive load	*log_tlx*
Pupillometry cognitive load	*pupil_adj*
Trait competitiveness	*trait_competi*
Performance	*success_method*

Annexe P : Items questionnaires

Construct name	Measure type	Description	Validity (alpha)	Source Reference
Implicit Cognitive load	Psychophysiological	Cognitive load measured with pupillometry	-	(Krejtz et al., 2018)
Explicit Cognitive load	Self-reported	Nasa TLX 6 items 100 points sliders 1. How mentally demanding was the task? 2. How physically demanding was the task? 3. How hurried or rushed was the pace of the task? 4. How successful were you in accomplishing what you were asked to do? 5. How hard did you have to work to accomplish your level of performance? 6. How insecure, discouraged, irritated, stressed, and annoyed were you?	.92	(Hart & Staveland, 1988)
Trait competitiveness	Self-reported	4 items: 7-point Scale: 1 = Extremely Disagree, to 7 = Extremely Agree 1. I enjoy working in situations involving competition with others. 2. It is important to me to perform better than others on a task. 3. I feel that winning is important in both work and games. 4. I try harder when I am in competition with other people.	.84	(Spence & Helmreich, 2014) (Brown et al., 1998)
Learning Performance	Observed	A score will be attributed to the participants based on the method they used to answer the question asked	-	N/A