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Editorial / Éditorial Volume 50 Issue 3

Martha Cleveland-Innes, *Editor-in-Chief*

Welcome to Volume 50, Issue 3, of The Canadian Journal of Learning and Technology (CJLT). CJLT is a peer-reviewed journal that publishes research focused on technology and learning. This bilingual journal is free of charge to anyone with Internet access, is multi-indexed, and is presented in accessible formats. There are no article submission or publication fees.

Amid threats of a trade war and an imminent federal election in Canada, the editorial team completed and released this issue. Discussions about the decline of civil society and the needs of democracies surround us. We are reminded that education plays a crucial role in fostering informed, engaged, and responsible citizens, which is essential for civil discourse and productive civic participation. More broadly, Canadian and global education remains focused on the development needs of individuals and the socioeconomic world. These development needs are shaped by increased use of artificial intelligence tools and the impact of remote learning and learning losses experienced during the COVID-19 pandemic. CJLT provides research about education in an evolving landscape of contextual and technological change.

This issue covers presentations about current and traditional pedagogies. The Notes Section reviews our opportunities to manage AI application through specific actions, including policy creation and implementation. The remaining five articles present empirical evidence garnered from research about the digital world. Document abstracts are presented in order below.

Policies for Artificial Intelligence in Higher Education: A Call for Action

Mohamed Ally, Athabasca University, Canada; and ***Sanjaya Mishra***, Commonwealth of Learning, Canada

This paper highlights the importance of artificial intelligence (AI) policies in higher education institutions and presents a step-by-step process for adopting institutional policies. Emphasizing the inevitable implications on AI in teaching and learning, this paper also discusses key policy areas for consideration by the stakeholders and lists the competencies that will influence appropriate policy development.

Cet article souligne l'importance des politiques sur l'intelligence artificielle (IA) dans les établissements d'enseignement supérieur et présente un processus étape par étape pour l'adoption de politiques institutionnelles. Soulignant les implications inévitables de l'IA dans l'enseignement et l'apprentissage, ce document aborde également les aspects clés des politiques à prendre en considération par les parties prenantes et énumère les compétences qui influenceront l'élaboration d'une politique appropriée.

Data-Based Decision Making by Teachers in K-12 Schools: A Scoping Review

Areej Tayem and ***Isabelle Bourgeois*** both of the University of Ottawa, Canada

Despite the widespread adoption of data-based decision making (DBDM) policies in schools around the world, there is limited understanding of how teachers use DBDM in K-12 classrooms and the impact of DBDM training on teacher practices and student outcomes. This scoping review aims to provide an overview of the existing literature on the uses of DBDM by teachers globally and identify gaps in the field. The findings (a) highlight a geographical and temporal clustering, with a notable emphasis on studies conducted in the United States and the Netherlands and published in 2016–2017 and 2020–2022; (b) identify a gap in the literature, particularly in the context of online and secondary schools, where the predominant focus has been on elementary and in-person settings; and (c) suggest that although DBDM interventions have been found helpful in altering teacher practices and student outcomes, there is still a need for more sustainable support to enhance DBDM implementation. The study concludes with recommendations for future DBDM research, building on implications from previous interventions.

Malgré l'adoption généralisée des politiques de prise de décision fondée sur les données probantes (PDDP) dans les écoles à travers le monde, peu d'information est disponible au sujet de l'utilisation de la PDDP par les enseignants œuvrant aux paliers primaire et secondaire, ainsi que sur l'impact de la formation en PDDP sur le comportement des enseignants et les résultats scolaires. Cette recension exploratoire vise à fournir un aperçu des écrits actuels sur les usages de la PDDP par les enseignants à l'échelle mondiale et à identifier les lacunes dans le domaine. Les résultats mettent en évidence les points suivants : (a) les études réalisées jusqu'à présent peuvent être groupées de manière géographique et temporelle, et ont surtout été réalisées aux États-Unis et aux Pays-Bas; de plus la majorité des études ont été publiées en 2016-2017 et 2020-2022 ; (b) il existe des lacunes importantes dans les écrits actuels, notamment par rapport au contexte des écoles en ligne et secondaires - les études actuelles reflètent davantage un intérêt pour les écoles élémentaires et les contextes d'études en présentiel ; et (c) les études recensées suggèrent que, bien que les interventions relatives à la PDDP se soient révélées utiles pour modifier les pratiques des enseignants et les résultats scolaires, les enseignants ont besoin d'un soutien plus durable pour améliorer la mise en œuvre de la PDDP. Enfin, l'article fournit des recommandations pour la recherche sur la PDDP, en s'appuyant sur les conclusions des interventions précédentes.

Facteurs qui influencent la conception des tâches de robotique pédagogique soutenant la résolution collaborative de problèmes

Raoul Kamga, Université du Québec à Montréal; ***Sylvie Barma***, Université Laval; ***Frédéric Fournier***, Université du Québec à Montréal; ***Pierre Lachance***, Réseau éducation collaboration innovation technologie; ***Joelle Bérubé-Daigneault***, Université du Québec à Montréal; and ***Sarah Cool-Charest***, Université de Montréal in Canada

La capacité à résoudre des problèmes de manière collaborative constitue une compétence fondamentale pour les élèves du primaire. Les travaux de recherche se sont majoritairement focalisés sur l'analyse et l'évaluation de cette compétence chez les élèves du primaire. Cependant, peu d'attention a été portée au processus de conception des tâches visant à favoriser le développement de la résolution collaborative de problèmes chez ces élèves. Pourtant, la résolution collaborative de problèmes ne peut émerger de manière pertinente que si les tâches sont conçues de manière à encourager les élèves à collaborer. Cette recherche se concentre spécifiquement sur le processus de conception des tâches liées à la robotique pédagogique et utilise, comme cadre théorique, la théorie de l'activité d'Engeström. Les participants, composés d'enseignants du primaire et de conseillers pédagogiques, ont répondu à un questionnaire portant sur leur démarche de conception de tâches et ont participé à deux entrevues de groupes. Les résultats soulignent que la conception des tâches de robotique pédagogique, qui vise à développer la résolution collaborative de problèmes chez les élèves, est tributaire des habiletés technologiques et de conception de tâches en robotique pédagogique de la personne conceptrice. Les règles régissant la conception des tâches de robotique pédagogique incluent le temps nécessaire à leur mise en place et le travail d'équipe.

A fundamental skill for primary school students is the ability to solve problems collaboratively. Most research has focused on the analysis and assessment of this skill in primary school students. However, little attention has been paid to the process of designing tasks to foster the development of collaborative problem-solving in these students. Furthermore, collaborative problem-solving can only emerge in a meaningful way if the tasks are designed in such a way as to encourage students to collaborate. This research focuses specifically on the process of designing tasks related to educational robotics, using the theoretical framework of Engeström's activity theory. Participants, made up of primary school teachers and educational consultants, completed a questionnaire about their task design process and took part in two group interviews. The results highlight that the design of educational robotics tasks, aimed at developing collaborative problem-solving in students, is dependent on the technological and educational robotics task design skills of the designer. The rules governing the design of educational robotics tasks include the time needed to set them up and teamwork.

Adaptive Practicing Design to Facilitate Self-Regulated Learning

Hongxin Yan, University of Eastern Finland; ***Fuhua Lin***, Athabasca University, Canada; and ***Kinshuk***, University of North Texas, USA

Online higher education provides exceptional flexibility in learning but demands high self-regulated learning skills. The deficiency of self-regulated learning skills in many students highlights the need for support. This study introduces a confidence-based adaptive practicing system as an intelligent assessment and tutoring solution to enhance self-regulated learning in STEM disciplines. Unlike conventional intelligent tutoring systems that depend entirely on machine control, confidence-based adaptive practicing integrates learner confidence and control options into the AI-based adaptive mechanism to improve learning autonomy and model efficiency, establishing an AI-learner shared control approach. Based on Vygotsky's zone of proximal development (ZPD) concept, an innovative knowledge-tracing framework and model called ZPD-KT was designed and implemented in the confidence-based adaptive practicing system. To evaluate the effectiveness of the ZPD-KT model, a simulation of confidence-based adaptive practicing was conducted. Findings showed that ZPD-KT significantly improves the accuracy of knowledge tracing compared to the traditional Bayesian knowledge-tracing model. Also, interviews with experts in the field underlined the potential of the confidence-based adaptive practicing system in facilitating self-regulated learning and the interpretability of the ZPD-KT model. This study also sheds light on a new way of keeping humans apprised of adaptive learning implementation.

L'enseignement supérieur en ligne offre une flexibilité exceptionnelle dans l'apprentissage, mais il exige des compétences élevées en termes d'apprentissage autorégulé. Le manque de compétences d'apprentissage autorégulé chez de nombreuses personnes étudiantes met en évidence la nécessité du soutien. Cette étude présente un système de pratique adaptative basé sur la confiance en tant que solution intelligente d'évaluation et de tutorat pour améliorer l'apprentissage autorégulée dans les disciplines STIM. Contrairement aux systèmes de tutorat intelligents conventionnels qui dépendent entièrement du contrôle de la machine, la pratique adaptative basée sur la confiance intègre la confiance de la personne apprenante et les options de contrôle dans le mécanisme adaptatif basé sur l'intelligence artificielle (IA) pour améliorer l'autonomie d'apprentissage et l'efficacité du modèle, établissant ainsi une approche de contrôle partagé entre l'IA et la personne apprenante. Basés sur le concept de zone de développement proximal de Vygotsky (ZPD), un cadre et un modèle innovant de traçage des connaissances appelé ZPD-KT ont été conçus et mis en œuvre dans le système de pratique adaptative basé sur la confiance. Pour évaluer l'efficacité du modèle ZPD-KT, une simulation de pratique adaptative basée sur la confiance a été effectuée. Les résultats ont démontré que le modèle ZPD-KT a considérablement amélioré la précision de la traçabilité des connaissances par rapport au modèle traditionnel de traçage des connaissances bayésiennes. De plus, les entrevues avec des experts dans le domaine ont souligné le potentiel du système de pratique adaptative pour faciliter l'apprentissage autorégulé et l'interprétabilité du modèle ZPD-KT. Cette étude a également mis en lumière une nouvelle façon de tenir les humains informés de la mise en œuvre de l'apprentissage adaptatif.

Student Perceptions of the Athletic Therapy Interactive Concussion Educational (AT-ICE) Tool

***Colin D. King**, Acadia University, Canada;* and ***Loriann M. Hynes**, York University, Canada*

Previous research has identified a considerable amount of variability in how healthcare professionals are taught to recognize, assess, and manage concussions. Responding to these findings, an innovative applied learning technology tool, the Athletic Therapy Interactive Concussion Educational (AT-ICE) Tool, was developed to help teach athletic therapy students how to recognize, assess, and manage concussions. The purpose of this research was to employ an interpretivist conceptual framework to explore athletic therapy students' perceptions of this tool. A questionnaire was used to identify individual factors that impacted student perceptions of AT-ICE and how it could be integrated into the classroom. Overall, participants enjoyed using AT-ICE and felt it helped to stimulate their critical thinking about the entire continuum of concussion care. Several important themes emerged including the importance of detailed scenarios, sharing lived experiences, and integrating anatomy within assessment and management scenarios. Findings suggest that AT-ICE was an effective educational technology that stimulated critical thought throughout the entire continuum of concussion care. Future research could continue to investigate the effectiveness of the tool or explore different ways to implement it in formal athletic therapy educational settings.

> Des recherches antérieures ont identifié une variabilité considérable dans la manière dont les personnes professionnelles de la santé apprennent à reconnaître, évaluer et gérer les commotions cérébrales. En réponse à ces résultats, nous avons développé un outil techno pédagogique d'apprentissage appliqué novateur, l'outil éducatif interactif sur les commotions cérébrales en thérapie sportive (AT-ICE), pour aider à enseigner aux personnes étudiantes en thérapie sportive comment reconnaître, évaluer et gérer les commotions cérébrales. Le but de cette recherche était d'utiliser un cadre conceptuel interprétatif pour explorer les perceptions des personnes étudiantes en thérapie sportive à l'égard de cet outil. Un questionnaire a été utilisé pour identifier les facteurs individuels qui ont eu un impact sur les perceptions des personnes étudiantes à l'égard de l'outil AT-ICE et sur la manière dont il pourrait être intégré dans le cours. Dans l'ensemble, les personnes participantes ont apprécié l'utilisation de l'outil AT-ICE et ont estimé qu'il les aidait à stimuler leur réflexion critique sur l'ensemble du continuum des soins des commotions cérébrales. Plusieurs thèmes importants ont également émergé, notamment l'importance de scénarios détaillés, du partage d'expériences vécues et de l'intégration de l'anatomie dans les scénarios d'évaluation et de gestion. Les résultats suggèrent que l'outil AT-ICE était une technologie éducative efficace qui stimulait la pensée critique tout au long du continuum des soins des commotions cérébrales. Les recherches futures pourraient continuer d'étudier l'efficacité de l'outil tout en explorant différentes façons de le mettre en œuvre dans des contextes éducatifs formels de thérapie sportive.

Mathematics Student Teachers' Behavioural Intention Using ChatGPT

Tang Minh Dung, ***Vo Khoi Nguyen***, ***Doan Cao Minh Tri***, ***Bui Hoang Dieu Ban***, and ***Phu Luong Chi Quoc*** of the Ho Chi Minh City University of Education in Vietnam

The rapid rise of artificial intelligence (AI), exemplified by ChatGPT, has transformed education. However, few studies have examined the factors influencing its adoption in higher education, especially among Mathematics student teachers. This study investigates factors that influence the behavioural intentions of Mathematics student teachers regarding using ChatGPT. Guided by the Unified Theory of Acceptance and Use of Technology (UTAUT) model, data were collected through a questionnaire of 24 items across six factors on a 5-point Likert scale. Using multiple linear regression analysis with RStudio, the findings reveal that Intrinsic Motivation, Performance Expectancy, Social Influence, and Perceived Trust positively affect behavioural intentions to adopt ChatGPT. The study emphasizes implications for developers and educators to enhance AI integration in education, thereby supporting personalized and engaging learning experiences.

L'essor rapide de l'intelligence artificielle (IA), illustré par ChatGPT, a transformé l'éducation. Cependant, peu d'études ont examiné les facteurs influençant son adoption dans l'enseignement supérieur, en particulier parmi les stagiaires en mathématiques. Cette étude examine les facteurs qui influencent les intentions comportementales des stagiaires en mathématiques concernant l'utilisation de ChatGPT. Guidés par le modèle de la théorie unifiée de l'acceptation et de l'utilisation des technologies (UTAUT), les données ont été collectées au moyen d'un questionnaire de 24 éléments portant sur six facteurs sur une échelle de Likert à 5 points. À l'aide d'une analyse de régression linéaire multiple avec RStudio, les résultats révèlent que la motivation intrinsèque, les attentes en matière de performance, l'influence sociale et la confiance perçue affectent positivement les intentions comportementales d'adopter ChatGPT. L'étude met l'accent sur les implications pour les personnes développeuses et enseignantes d'améliorer l'intégration de l'IA dans l'éducation, soutenant ainsi des expériences d'apprentissage personnalisées et engageantes.

Author

Martha Cleveland-Innes is Professor of Open, Digital, and Distance Education at Athabasca University in Canada and Editor-in-Chief of the bilingual *Canadian Journal of Learning and Technology.* She is the co-author of open source publications The Guide to Blended Learning (2018), Participant Experience in an Inquiry-Based Massive Open Online Course (2022), and Principles of Blended Learning (2024). The Design of Digital Learning Environments: Online and Blended Applications of the Community of Inquiry was recently co-edited by Dr. Cleveland-Innes (Taylor& Francis, 2024). Her research interest areas include 1) online and blended learning, 2) artificial intelligence and online communities of inquiry, 3) higher education reform and lifelong learning, and 4) leadership in education. She is currently Visiting Professor of Pedagogy at Mid-Sweden University (2018-present). For more information, see her Athabasca faculty profile.

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Policies for Artificial Intelligence in Higher Education: A Call for Action

Politiques sur l'intelligence artificielle en enseignement supérieur : un appel à l'action

***Mohamed Ally**, Athabasca University, Canada*
***Sanjaya Mishra**, Commonwealth of Learning, Canada*

Abstract

This paper highlights the importance of artificial intelligence (AI) policies in higher education institutions and presents a step-by-step process for adopting institutional policies. Emphasizing the inevitable implications on AI in teaching and learning, this paper also discusses key policy areas for consideration by the stakeholders and lists the competencies that will influence appropriate policy development.

Keywords: artificial intelligence, GenAI, higher education, policies, postsecondary education

Résumé

Cet article souligne l'importance des politiques sur l'intelligence artificielle (IA) dans les établissements d'enseignement supérieur et présente un processus étape par étape pour l'adoption de politiques institutionnelles. Soulignant les implications inévitables de l'IA dans l'enseignement et l'apprentissage, ce document aborde également les aspects clés des politiques à prendre en considération par les parties prenantes et énumère les compétences qui influenceront l'élaboration d'une politique appropriée.

Mots-clés : enseignement postsecondaire, enseignement supérieur, IAg, intelligence artificielle, politiques

Introduction

There is a sense of urgency to develop guidelines, standards, and policies for AI use in higher education as the world approaches the “singularity” era, a blurring between humans and machines. The International Organization for Standardization (in ISO/IEC 22989:2022) defined AI as “a technical and scientific field devoted to the engineered system that generates outputs such as content, forecasts, recommendations or decisions for a given set of human-defined objectives" (International Organization for Standardization, 2022). The Organisation for Economic Co-operation and Development (OECD) defined AI as "a machine-based system that, for explicit or implicit objectives, infers, from the input it receives, how to generate outputs such as predictions, content, recommendations, or decisions that can influence physical or virtual environments" (Russell et al., 2023). As technologies continue to emerge in the fourth industrial revolution, the use of artificial intelligence has expanded to reach all sectors of society, including education (Ally & Perris, 2022) and there is a need for all citizens to be AI literate to benefit from AI (World Economic Forum, 2024).

Both students and teachers in higher education institutions use GenAI (Shaw et al., 2023). Consequently, there are several concerns about the use of AI in teaching, learning, and research. These issues primarily relate to academic integrity (Yusuf et al., 2024) and the originality of student's work for assessment and grading (Lou, 2024). Therefore, it is essential to develop policies related to AI in higher education. This paper discusses in brief the need for such policies, policy areas to consider, and steps to be taken to develop ethical guidelines and policies in higher education.

Benefits of AI

If designed and implemented properly, AI holds immense potential to revolutionise teaching methodologies, personalise learning experiences, and streamline administrative processes. According to UNESCO (2021), AI also has the potential to address some of the biggest challenges in education today and help achieve SDG 4, to "ensure inclusive and equitable quality education and promote lifelong learning opportunities for all." However, innovations bring risks and challenges that must be addressed. AI can be used in a variety of areas in education, including teaching, learning, and assessment. AI can benefit higher education by enabling personalised student support; providing teaching, research, or administrative assistance; conducting learning analytics; and supporting digital literacy training (Jenay, 2024).

There are many benefits to instructors using AI in education. Instructors can use an AI system to adapt learning for individual students, based on each student's preferences and current level of understanding. A knowledge graph can be used to map a student's progress in a course. The Alan Turing Institute suggests that a knowledge graph should "organise data from multiple sources, capture information about entities of interest in a given domain or task (like people, places or events), and forge connections between them" (Alan Turing Institute, n.d., para. 1). The AI system will track the student's progress and create a knowledge graph to show where the student is in the course (Cui & Yu, 2019). As the student interacts with the system, it will learn about the student and update the knowledge graph. For example, in a course, the knowledge graph will show the topics completed, those still to be completed, and the topics in which the student is having problems achieving the learning outcomes and needs help. The intelligence system will prescribe resources and activities for the student to be successful or recommend human intervention to help the student.

The use of AI by students can provide learning flexibility, since students can prompt the GenAI system for resources as they complete their learning. The system can facilitate one-to-one learning by customising the learning experience for individual students. Students who live in remote locations with the required technology can access learning materials and interact with other students and their educational institutions without leaving their community. To receive support while they are learning, the students can access the institution's chatbot, available anytime. This will help reduce the inequalities in education by providing education for all (MacDowell et al., 2024).

AI Policies in Higher Education

Artificial intelligence systems must be developed for humans, since humans will be interacting with the systems. The systems should benefit humans rather than harm or otherwise negatively affect them. The AI systems should be user-centred and not discriminate between individuals based on individual differences. Each system should be transparent so that users—especially non-technical ones—are aware of its capabilities. The data generated by AI systems should be auditable to ensure the data are accurate and non-discriminatory. Individuals should be trained on how to use each AI system, and technical support should be provided for users as they interact with the system. Users provided with technical support and with the correct skills will be able to use the system in the future, ensuring its sustainability. Also, users should be informed about how AI can benefit humanity, so they are motivated to use AI systems (United Nations, 2024). At the same time, users should be informed of the challenges of using AI and the policies they should follow when using these systems.

In a global survey of 450 schools and universities, UNESCO found that fewer than 10% have developed institutional policies and/or formal guidance concerning the use of generative AI applications (UNESCO, 2023). Shaw et al. (2023) in a survey of higher education faculty and students found that 22% of faculty are using GenAI while 49% of students are using GenAI. They also reported that the use of GenAI by faculty and students is increasing. This increasing trend in the use of GenAI in higher education places a sense of urgency for higher education institutions to develop AI policies. A recent report by Ally and Mishra (2024) suggests a procedure for higher education institutions to develop AI policies. In the past AI policies were developed for instructors and students only; however, AI policies also need to provide guidance to other stakeholders such as administrators, learning designers, librarians, researchers, information technology and support staff, and registrar. The report by Ally and Mishra reviewed several institutional AI policies and identified 14 policy areas that stakeholders in higher education should consider while developing institutional policies (Table 1).

In addition to developing AI policies for individual higher education institutions, AI standards should be established that could be applied globally. Marwala (2024) suggested that AI standards should create uniform guidelines for AI design, development, and deployment, focusing on technical quality, ethical considerations, and compatibility. The standard should cover data privacy, algorithmic transparency, security, and bias prevention. The AI standards should be developed by multidisciplinary teams consisting of industry, academia, and regulators, and these guidelines should be regularly updated to ensure global safety, effectiveness, and ethical compliance with AI technologies (Marwala, 2024).

The development of standards for AI use is increasing and educators should be aware of these new standards. In the first half of 2024, 117 AI international standards were developed compared to 3 standards developed in 2018 (United Nations, 2024).

Table 1

Policy Areas for AI in Education

Policy areas		Consideration
1.	Technology access	Provisions for access to AI for all stakeholders; digital divide issues
2.	Data privacy	Concerns related to data privacy discussed
3.	Data security	Issues related to security of data covered
4.	AI ethics	Including diversity, equity, and inclusion
5.	Bias/Stereotypes	Bias and stereotypes related to gender, race, etc. discussed
6.	Teaching and learning	Guidelines for dos and don'ts in teaching and learning
7.	Academic integrity	Concerns related to cheating in assignments, term papers, etc., and guidelines discussed
8.	Transparency	Issues related to lack of transparency of large language models discussed
9.	Training and development	Provision of training for the faculty and staff to use AI tools effectively
10.	Gender	Issues related to gender in the context of AI tools covered
11.	Persons with disabilities	Provisions for persons with disabilities are addressed in the policy for AI in teaching and learning
12.	Copyright and intellectual property	Copyright and intellectual property rights issues related to AI tools are discussed
13.	Environmental concerns	Are there concerns or understanding about the impact of AI tools on the environment?
14.	Cost and sustainability	Can AI be used cost-effectively? Where will the funds come from?

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Stakeholders in higher education institutions have to implement and follow the AI policies. Institutions must implement education and training programs to develop AI skills across the organization, from basic digital literacy to advanced technical expertise, to prepare educators for an AI future (United Nations, 2024). This includes training on AI policies, how to implement the policies, and how to deal with violations of AI policies. As technology emerges and AI policies become outdated, new policies must be developed or existing policies revised. Ally and Mishra (2024) proposed a competency profile (Table 2) that can be used to train or orient stakeholders in higher education on the implementation of AI policies.

Table 2

Competencies for AI Policies

Policy areas		Competencies	
0.	General	0.1	Define policy
		0.2	Describe why it is important to develop AI policies
		0.3	Describe why it is important to follow AI policies
		0.4	Possess basic knowledge of AI
		0.5	Describe how AI is used in your role
		0.6	Determine whether the system you are using has AI capabilities
		0.7	Describe the human role in developing AI systems
1.	Technology access	1.1	Determine what technology you need to use the AI system
		1.2	Determine who to contact if there is a technology issue
		1.3	Use the technology to complete your tasks
2.	Data privacy	2.1	Define data privacy
		2.2	Describe how to keep data private
		2.3	Describe how to tell whether data has been breached
		2.4	Describe the steps to take if data is breached
3.	Data security	3.1	Define data security
		3.2	Describe how to keep data secured
		3.3	Describe how to tell whether data has been accessed illegally
		3.4	Describe the steps to take to keep data secured
4.	AI ethics	4.1	Define AI ethics
		4.2	Describe the AI ethics policies you have to follow in your role
		4.3	Describe why it is important to follow AI ethics policies
		4.4	Describe the consequences of not following AI ethics
		4.5	Describe how you will know whether the AI system you are using is fair and trustworthy

Policy areas		Competencies	
5.	Bias/Stereotypes	5.1	Define bias and stereotypes
		5.2	Describe the AI bias and stereotypes policies to follow in your organisation
		5.3	Describe why it is important to follow policies as you complete your tasks
		5.4	Describe what you would do if you found that the AI system was biased against someone
6.	Teaching and learning	6.1	Determine whether students can use AI software to assist in completing their course work or assignments
		6.2	Describe the policies you have to follow to use AI software for your course
		6.3	Describe how students can use AI to complete course activities
7.	Academic integrity	7.1	Define academic integrity
		7.2	Describe AI academic integrity policies to follow
		7.3	Describe the consequences of not following academic integrity policies
		7.4	Describe actions you will take if academic integrity policies are not followed
8.	Transparency	8.1	Define transparency
		8.2	Describe AI policies related to transparency
		8.3	Describe why it is important to have policies on transparency for AI
9.	Training and development	9.1	Determine how AI is impacting your role
		9.2	Obtain the training you require to use the AI system
		9.3	Determine who to contact if you have questions and need support on the AI system you are using
10.	Gender	10.1	Describe why it is important to have AI policies for gender
		10.2	Describe AI policies for gender
11.	Persons with disabilities	11.1	Describe the different types of disabilities that AI should cater for
		11.2	Describe AI policies to follow for persons with disabilities

Policy areas		Competencies	
12.	Copyright and intellectual property	12.1	Define copyright and intellectual property
		12.2	Describe AI policies for copyright and intellectual property
		12.3	Provide examples of copyright and intellectual property infringement in AI
13.	Environmental concerns	13.1	Describe how AI can contribute to protecting the environment
		13.2	Provide examples of policies that can help to protect the environment
14.	Cost and sustainability	14.1	Describe AI policies related to cost and sustainability
		14.2	Describe whether the AI system you are working with is sustainable
		14.3	Describe why the cost of AI systems should be sustainable

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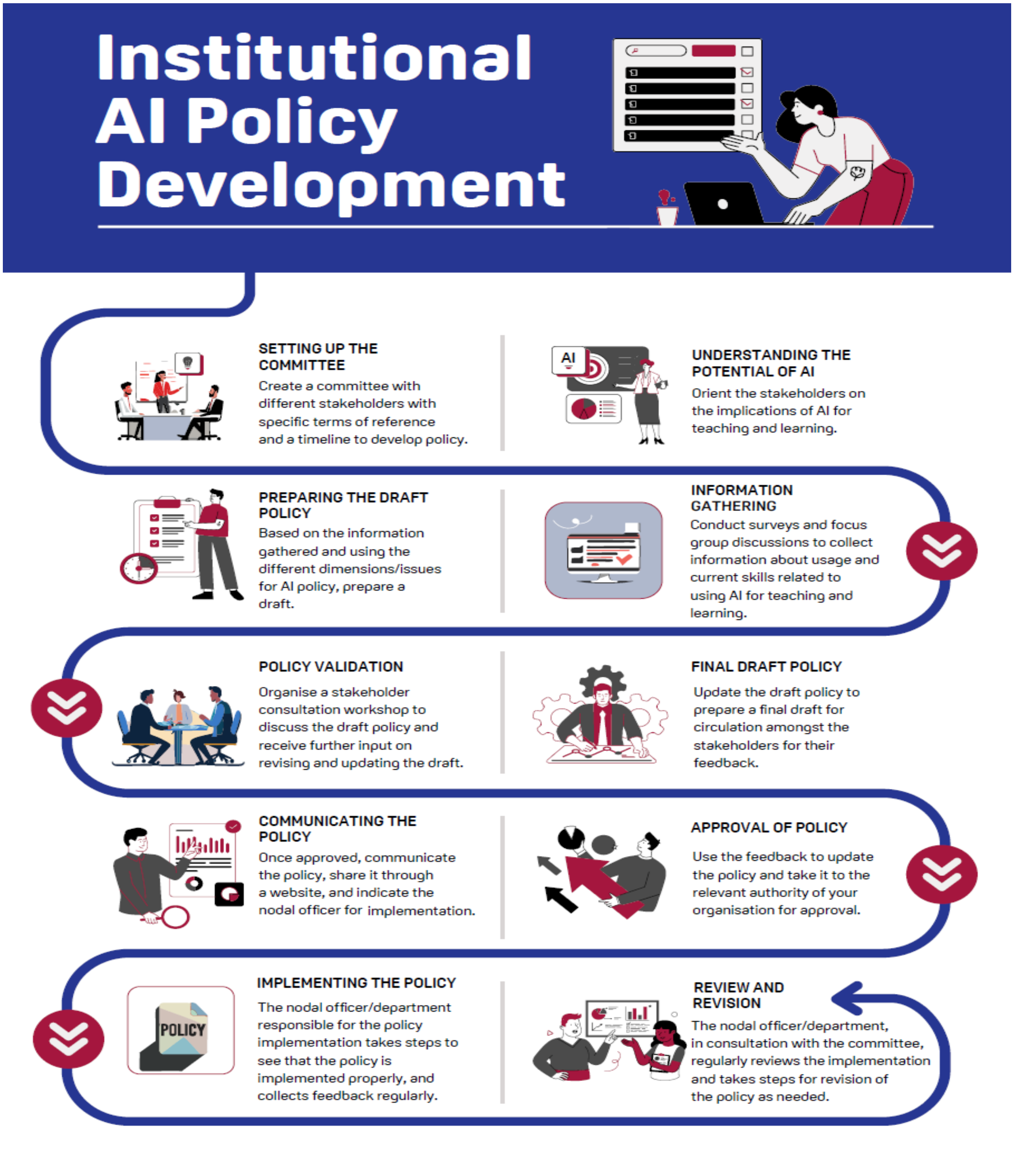
Developing AI Policies in Higher Education

Although AI use in higher education is increasing, a limited number of institutions have policies on the ethical and safe use of AI (Shaw et al., 2023; UNESCO, 2023). Higher education must prioritize AI policy development so that AI is trustworthy and used for good (UNESCO, 2022). Endris et al. (2024) proposed a seven-step process in the context of developing national policies on AI in education. Ally and Mishra (2024) proposed a procedure that can be used to develop AI policies in higher education institutions (Figure 1). The first step is to assemble an institute-wide committee that will develop AI policies for all departments in the institutions. This policy committee must have basic knowledge of AI and must be aware of the need to develop institution-wide AI policies. The committee's first task is to facilitate workshops with all departments to determine how they use AI and what policies should be developed. The committee then use the information from the departments to develop draft policies. The draft policies are then circulated to the different departments to review and provide feedback. The feedback from the different departments is used to finalize the AI policies. This is followed by staff training sessions where staff learn how to implement the AI policies and how to deal with violations of the policies. As AI policies are implemented across the institution, the committee must continue to monitor the implementation to determine if the policies need revision or new policies should be developed as technology emerges.

Figure 1

Institutional AI Policy Development Process



Source. Ally & Mishra (2024). ©Commonwealth of Learning. Available under CCBY-SA.

Conclusion

There will be increasing demands to educate all stakeholders in higher education on how to use emerging technologies efficiently, safely, and ethically (Adel, 2022). Organization leaders will need to be educated to provide leadership on AI development and implementation (Norman et al., 2024). AI is here to stay, and it is developing at a fast pace impacting all sectors of society. The next generation of GenAI will be artificial general intelligence (AGI), which is getting closer to human intelligence and is capable of completing intellectual tasks at a level similar to that of humans (McKinsey & Company, 2024). According to Emmert-Streib (2024), many potential features of AGI will require that new policies be developed, or existing policies be revised to use AGI in higher education. Machine learning will be the main driver of AGI, where the machine will learn from data to develop high-level reasoning to solve problems in complex situations. The AGI system will have features similar to human senses, such as computer vision, speech recognition, natural language processing, and a sense of touch (tactile). With advanced processing, AGI systems can be creative by generating original ideas and applying the ideas in new contexts and situations.

References

Adel, A. (2022). Future of industry 5.0 in society: human-centric solutions, challenges and prospective research areas. *Journal of Cloud Computing, 11*, 40. https://doi.org/10.1186/s13677-022-00314-5

Alan Turing Institute. (n.d.). *Knowledge graphs*. https://www.turing.ac.uk/research/interest-groups/knowledge-graphs

Ally, M., & Mishra, S. (2024). *Developing Policy Guidelines for Artificial Intelligence in Post-secondary Institutions*. Commonwealth of Learning. http://hdl.handle.net/11599/5615

Ally, M., & Perris, K. (2022). Artificial intelligence in the Fourth Industrial Revolution to educate for sustainable development. *Canadian Journal of Learning and Technology, 20*(4), 1–20. https://cjlt.ca/index.php/cjlt/article/view/28287/20625

Cui, J., & Yu, S. (2019). Fostering deeper learning in a flipped classroom: Effects of knowledge graphs versus concept maps. *British Journal of Educational Technology, 50*(5), 2308–2328. https://doi.org/10.1111/bjet.12841

Emmert-Streib, F. (2024). Is ChatGPT the way toward artificial general intelligence? *Discover Artificial Intelligence, 4*, 32. https://doi.org/10.1007/s44163-024-00126-3

Endris, W., Tlili, A., Huang, R., Xu, L., Change, TW, & Mishra. S. (2024). Features, components and processes of developing policy for artificial intelligence in education (AIED): Toward a sustainable AIED development and adoption. *Leadership and Policy in Schools*, 1–9. https://doi.org/10.1080/15700763.2024.2312999

International Organization for Standardization. (2022). Information technology — Artificial intelligence — Artificial intelligence concepts and terminology (ISO/IEC 22989:2022(en)). https://www.iso.org/obp/ui/en/#iso:std:iso-iec:22989:ed-1:v1:en

Jenay, R. (2024). EDUCAUSE AI landscape study. *Research report.* EDUCAUSE. https://www.educause.edu/ecar/research-publications/2024/2024-educause-ai-landscape-study/introduction-and-key-findings

Luo, J. (2024). A critical review of GenAI policies in higher education assessment: A call to reconsider the “originality” of students’ work. *Assessment & Evaluation in Higher Education*, 1–14. https://doi.org/10.1080/02602938.2024.2309963

MacDowell, P., Moskalyk, K., Korchinski, K., & Morrison, D. (2024). Preparing Educators to Teach and Create With Generative Artificial Intelligence. *Canadian Journal of Learning and Technology*, *50*(4), 1–23. https://doi.org/10.21432/cjlt28606

Marwala, T. (2024). “Framework for the Governance of Artificial Intelligence”, UNU Technology Brief 5. United Nations University.

McKinsey & Company. (2024, March 21). *What is artificial general intelligence (AGI)?* https://www.mckinsey.com/featured-insights/mckinsey-explainers/what-is-artificial-general-intelligence-agi

Norman, H., Adnan, N. H., Nordin, N., & Ally, M. (2024). Metaverse and generative artificial intelligence for teaching and learning in higher education. In K. Pushpanadham, N. Nordin, & H. Norman (Eds). *Generative artificial intelligence in higher education: A handbook for educational leaders* (pp. 74–82). Universiti Kebangsaan Malaysia.

Russell Group. (2023). *Russell Group principles on the use of generative AI tools in education.* https://russellgroup.ac.uk/media/6137/rg_ai_principles-final.pdf

Russell, S., Perset, K., & Grobelnik, M. (2023, November 29). *Updates to the OECD's definition of an AI system explained*. OECD.AI Policy Observatory. https://oecd.ai/en/wonk/ai-system-definition-update

Shaw, C., Yuan, L., Brennan, D., Martin, S., Janson, N., Fox, K., & Bryant, G. (2023, October 23). Generative AI In Higher Education. FALL 2023. Tyton Partners. https://tytonpartners.com/app/uploads/2023/10/GenAI-IN-HIGHER-EDUCATION-FALL-2023-UPDATE-TIME-FOR-CLASS-STUDY.pdf

UNESCO. (2021). *AI and education: Guidance for policy-makers*. https://unesdoc.unesco.org/ark:/48223/pf0000376709

UNESCO. (2022). *Recommendation on the ethics of artificial intelligence.* https://unesdoc.unesco.org/ark:/48223/pf0000381137.

UNESCO. (2023, September 6). *UNESCO survey: Less than 10% of schools and universities have formal guidance on AI*. https://www.unesco.org/en/articles/unesco-survey-less-10-schools-and-universities-have-formal-guidance-ai

United Nations. (2024, September). *Governing AI for Humanity*. https://www.un.org/sites/un2.un.org/files/governing_ai_for_humanity_final_report_en.pdf

World Economic Forum. (2024, April 16). *How we can prepare for the future with foundational policy ideas for AI in education*. https://www.weforum.org/agenda/2024/04/prepare-future-policy-ideas-ai-in-education/

Yusuf, A., Pervin, N., & Román-González, M. (2024). Generative AI and the future of higher education: a threat to academic integrity or reformation? Evidence from multicultural perspectives. *International Journal of Educational Technology in Higher Education*, *21*(1), 21. https://doi.org/10.1186/s41239-024-00453-6

Authors

Mohamed Ally is a full Professor of Online and Distance Education at Athabasca University in Alberta, Canada. His current areas of research include mobile learning, e-learning, distance education, augmented reality, virtual reality, mixed reality, and the use of emerging fourth industrial revolution technologies (4IR) in education and training. Dr. Ally is one of the Founding Directors of the International Association of Mobile Learning (IamLearn) and the International Association of Blended Learning (IABL). He recently edited 17 books on the use of emerging technologies in education. His book "Mobile Learning: Transforming the Delivery of Education and Training" won the Charles A. Wedemeyer Award in the United States for significant contribution to distance education. Dr. Ally has presented keynote speeches, papers, and workshops in many countries.
Email: mohameda@athabascau.ca

Sanjaya Mishra is Education Specialist: Technology-Enabled Learning at the Commonwealth of Learning in British Columbia, Canada and one of the leading scholars in open, distance, and online learning with extensive experience in teaching, staff development, research, policy development, innovation, and organisational development. With a multi-disciplinary background in education, information science, communication media, and learning and development, Dr. Mishra has been promoting the use of educational multimedia, eLearning, open educational resources (OER), and open access to scientific information to increase access to quality education and lifelong learning for all.
Email: smishra.col@gmail.com *ORCID*: https://orcid.org/0000-0003-3291-2410

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Data-Based Decision Making by Teachers in K-12 Schools: A Scoping Review

La prise de décision fondée sur les données par les enseignants dans les écoles primaires et secondaires : Examen de la portée

Areej Tayem*, University of Ottawa, Canada*
Isabelle Bourgeois*, University of Ottawa, Canada*

Abstract

Despite the widespread adoption of data-based decision making (DBDM) policies in schools around the world, there is limited understanding of how teachers use DBDM in K-12 classrooms and the impact of DBDM training on teacher practices and student outcomes. This scoping review aims to provide an overview of the existing literature on the uses of DBDM by teachers globally and identify gaps in the field. The findings (a) highlight a geographical and temporal clustering, with a notable emphasis on studies conducted in the United States and the Netherlands and published in 2016–2017 and 2020–2022; (b) identify a gap in the literature, particularly in the context of online and secondary schools, where the predominant focus has been on elementary and in-person settings; and (c) suggest that although DBDM interventions have been found helpful in altering teacher practices and student outcomes, there is still a need for more sustainable support to enhance DBDM implementation. The study concludes with recommendations for future DBDM research, building on implications from previous interventions.

Keywords: data-based decision making, K-12 education, teacher practices, student outcomes

Résumé

Malgré l'adoption généralisée des politiques de prise de décision fondée sur les données probantes (PDDP) dans les écoles à travers le monde, peu d'information est disponible au sujet de l'utilisation de la PDDP par les enseignants œuvrant aux paliers primaire et secondaire, ainsi que sur l'impact de la formation en PDDP sur le comportement des enseignants et les résultats scolaires. Cette recension exploratoire vise à fournir un aperçu des écrits actuels sur les usages de la PDDP par les enseignants à l'échelle mondiale et à identifier les lacunes dans le domaine. Les résultats mettent en évidence les points suivants : (a) les études réalisées jusqu'à présent peuvent être groupées de manière géographique et temporelle, et ont surtout été réalisées aux États-Unis et aux Pays-Bas; de plus la majorité des études ont été publiées en 2016-2017 et 2020-2022 ; (b) il existe des lacunes importantes dans les écrits actuels, notamment par rapport au contexte des écoles en ligne et secondaires - les études actuelles reflètent davantage un intérêt pour les écoles élémentaires et les contextes d'études en présentiel ; et (c) les études recensées suggèrent que, bien que les interventions relatives à la PDDP se soient révélées utiles pour modifier les pratiques des enseignants et les résultats scolaires, les enseignants ont besoin d'un soutien plus durable pour améliorer la mise en œuvre de la PDDP. Enfin, l'article fournit des recommandations pour la recherche sur la PDDP, en s'appuyant sur les conclusions des interventions précédentes.

Mots-clés : prise de décision fondée sur les données probantes , éducation primaire et secondaire , pratiques enseignantes , résultats des élèves

Introduction

Educational technology developments over the past two decades have resulted in increased amounts of data available to decision-makers and innovative ways of utilizing them, particularly in the kindergarten through Grade 12 (K-12) context (Behrens et al., 2018; Datnow & Hubbard, 2015). Edtech tools, such as learning management systems, adaptive learning platforms, and digital assessments, generate vast amounts of data about student learning behaviours, engagement, and performance. These technologies afford educators real-time access to detailed information about student progress, which allows for more personalized instruction and timely interventions (Weller, 2020). In addition, they facilitate the collection of data that can be used not only for student assessment but also for pedagogical decision-making, helping teachers make data-driven improvements to their teaching practices.

In education, data-based decision making (DBDM) refers to the use of empirical evidence to inform educational policies, practices, and decisions (Schildkamp & Ehren, 2013). At its core, DBDM involves the systematic collection, examination, and utilization of various types of educational data (e.g., summative and formative assessments, behavioural data, attendance records, demographic information, to-class and homework assignments, classroom observations, etc.), with a primary objective of enhancing student performance and tailoring educational strategies to meet their individual needs (Marsh, 2012; Marsh et al., 2006). Through the analysis of such data, educators can pinpoint areas where students require additional support, adapt instructional strategies, and implement targeted interventions (Carlson et al., 2011; Faber et al., 2018; Heinrich & Good, 2018; Tsai et al., 2019).

The adoption of DBDM has gained global attention, recognizing its significance in ensuring accountability and driving effective decision-making (Cheng, 1999; Cheng & Curtis, 2004; Maier, 2010). On an international scale, numerous interventions and policies have been implemented to encourage teachers and school leaders to embrace DBDM in conducting well-informed, high-quality decisions. Some of these interventions have focused on specific schools or districts such as the AZiLDR model in Arizona (Ylimaki & Brunderman, 2019), Instructional Coaches in Texas (Rangel et al., 2017), and The Learning Schools Model in New Zealand (Lai et al., 2014). Others have been larger in scope and involved nationwide efforts, such as the Focus Intervention, a 2-year training project in the Netherlands through which all primary school teachers in Dutch public schools were trained on using DBDM to improve their teaching methods (van Geel et al., 2016). The goal of these interventions, regardless of their scope, is to equip teachers with the knowledge and abilities necessary to implement and sustain DBDM. However, due to policies that caused high accountability pressure in some education systems around the world, such as the *No Child Left Behind Act* in the United States (Kempf, 2015), mandatory test-based school accountability policies in Germany (Maier, 2010), Ofsted Inspections and League Tables in the United Kingdom (Schildkamp et al., 2017), and the Education Quality and Accountability Office assessments in Ontario, Canada (Kempf, 2015), the focus of DBDM interventions has mainly been on the use of data from standardised assessments to demonstrate school accountability rather than to enhance the teaching and learning experience (Kempf, 2015).

This scoping review aims to examine comprehensively the landscape of DBDM in the K-12 context for instructional purposes by including studies that assess established interventions targeting the use of data by teachers at the classroom level, as well as how, and the extent to which, teachers use data in their daily practice to inform their instruction. A scoping review was chosen because it is well-suited to mapping a broad and diverse body of literature, offering a comprehensive overview of the topic across various methodologies and contexts. This approach helps identify research gaps and provides a global perspective on the impact of DBDM. However, given that some of the studies included can lack quality and/or methodological rigour, scoping reviews can be challenging. Additionally, although scoping reviews are effective for identifying trends and gaps in the literature, they do not offer in-depth analyses of individual studies, which can limit the researcher's ability to draw detailed conclusions about specific interventions or outcomes. Despite these challenges, a scoping review is ideal for answering the following research questions: 1. How do teachers around the world engage in DBDM for instructional purposes? and 2. To what extent do DBDM interventions influence teachers' instructional practices and student outcomes?

Methods

The review follows PRISMA-ScR guidelines (Tricco et al., 2018) to systematically map evidence, identify key concepts, and uncover knowledge gaps. This framework ensured a rigorous approach to searching, screening, and selecting articles on data use for decision-making in K-12 education.

Article Search and Screening Process

With the assistance of a university librarian, a comprehensive search across four electronic databases was conducted (i.e., *Education Source*, *ERIC*, *Web of Science*, and *Academic Search Complete*). Keywords and controlled vocabulary related to the research question were used as illustrated in Table 1.

Table 1

Keywords and Controlled Vocabulary Used in the Search

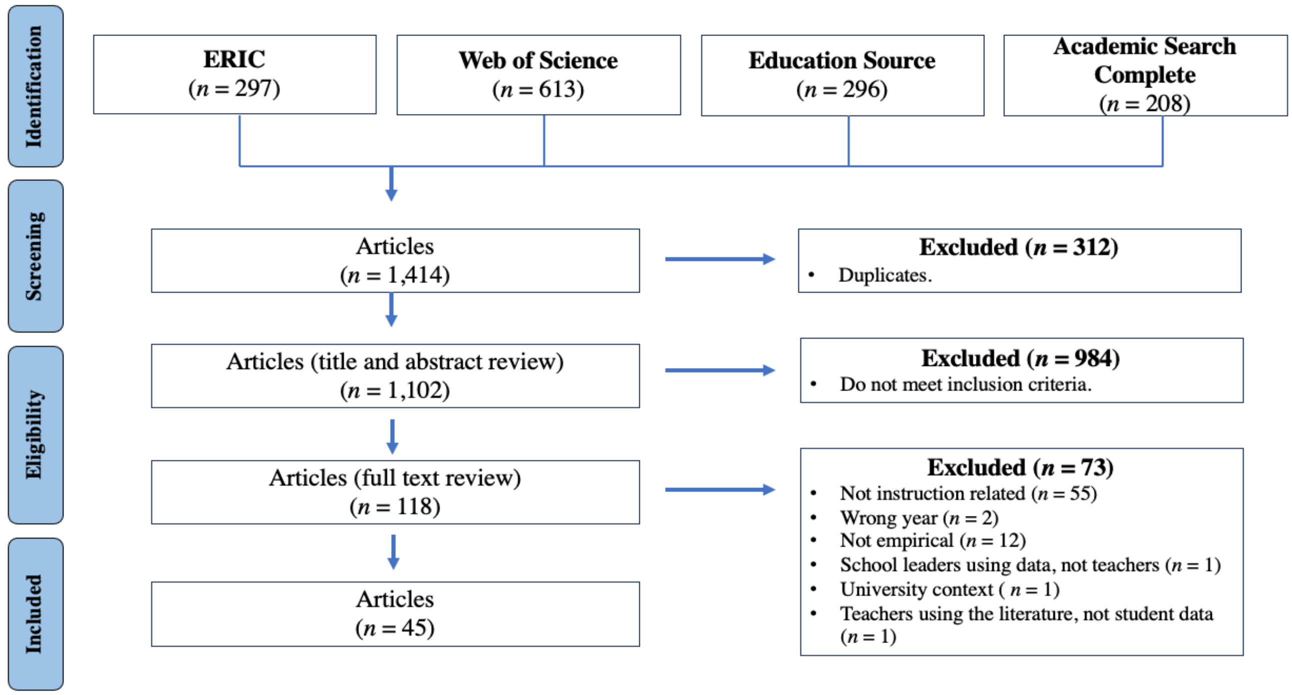
Criteria	Search words
Context 1	Data use/ or data-based decision making/ or data-driven decision making/ or learning analytics
Context 2	K-12/ or schools/ or elementary schools/ or middle schools/ or private schools/ or public schools/ or secondary schools/ elementary school students/ or middle school students/ or secondary school students/ secondary school teachers/ or public school teachers/ or elementary school teachers/ or high school teachers/ or junior high school teachers/ or middle school teachers/ (school* or kindergarten*). ti,ab

Note. Key terms were searched in article titles and abstracts using the ti,ab field code to ensure relevance and precision in the results.

To be included in the review, studies had to be conducted in K-12 settings and published in English between 2013 and 2023. Studies also needed to explore how teachers use data to improve teaching practices and make pedagogical decisions at the classroom level. Studies examining data use by school leaders, districts, or for purposes other than teaching improvement, such as accountability, were excluded. The initial search identified 1,414 articles, with 312 duplicates removed. Interrater reliability was ensured through independent screening of 5% of the articles, showing a 92% agreement. Discrepancies were resolved through follow-up discussions. Following the Search Process Flow diagram (Tricco et al., 2018), 984 articles were excluded as they did not meet the inclusion criteria. Additionally, 73 articles were excluded during the screening process for the following reasons: 55 were not instruction-related, 12 were not empirical, two were published in the wrong year, one focused on school leaders' use of data rather than by teachers, one was set in a university context, and two involved teachers using literature rather than student data. Ultimately, 45 articles were selected for data extraction (Figure 1).

Figure 1

PRISMA-ScR Diagram



Note. Adapted from Tricco et al. (2018).

Data Extraction Process

For a systematic and flexible data extraction process, a template was developed to capture comprehensive information that included article identifiers and overview, context of the study, DBDM intervention details, and outcomes of the intervention (Table 2).

Table 2

Elements in the Data Extraction Template

Variables	Detailed elements
Article identifiers	author, title, journal, year
Context of the study	country, subject matter, teaching environment (i.e., online/in-person), grade level
Aim and research design	aim of the study, number of teachers, number of students, research design

Variables	Detailed elements
DBDM intervention details	intervention type, sources of data used by teachers, previous DBDM professional development, duration of the intervention, reported outcome on teacher practices, reported outcome on student's academic performance, implications regarding training or challenges

This review has several limitations. It includes English-language studies only, potentially missing relevant research published in other languages. Additionally, the review's data, gathered in June 2023, may not cover the most recent studies, particularly those on online learning published after that date. Finally, the focus was primarily on the effects of DBDM interventions on teacher practices and student outcomes, possibly overlooking other variables like school culture and leadership support that might impact intervention effectiveness.

Findings

To provide succinct responses to the two research questions, the findings are organized into two main sections. First, an overview of the research on DBDM will provide key contextual elements that describe the body of studies included as part of the review, and second, a more in-depth analysis of the findings of the included studies will focus on the effects of DBDM interventions on teaching practices.

Geographical and Temporal Concentration of Studies Reviewed

To understand the evolving landscape of DBDM, a critical examination of the included studies reveals a notable concentration of research in the United States (62%) and the Netherlands (25%), clustered around two key periods: 2016–2017 and 2020–2022. Although countries such as Canada, Denmark, Germany, Indonesia, and Spain also contributed to the advancement of research in this field, with almost 13% combined, their collective efforts did not exhibit the same level of magnitude, reflecting a more limited engagement with DBDM in schools. Figure 2 shows the distribution of studies by country and Figure 3 displays their temporal distribution.

As can be seen in Figure 4, the findings demonstrate that during the first period (2016–2017), both the USA and the Netherlands are the leading countries by the number of research studies conducted within this timeframe. However, a notable shift is observed in subsequent years with a significant decline in research efforts in the Netherlands and a small increase in the USA, which retained its lead in this field. The number of research articles in each country could be an indicator of DBDM institutional support, educational priorities, and the integration of DBDM into teaching practices. For example, the higher research output in the USA may suggest a stronger emphasis on studying and implementing DBDM for instructional practices, supported by policies, funding, and professional development. In contrast, the decline in research in the Netherlands could indicate a reduced focus or prioritization of DBDM, possibly pointing to less frequent use or investigation of these practices among teachers.

Figure 2

Geographical Distribution of Studies Reviewed

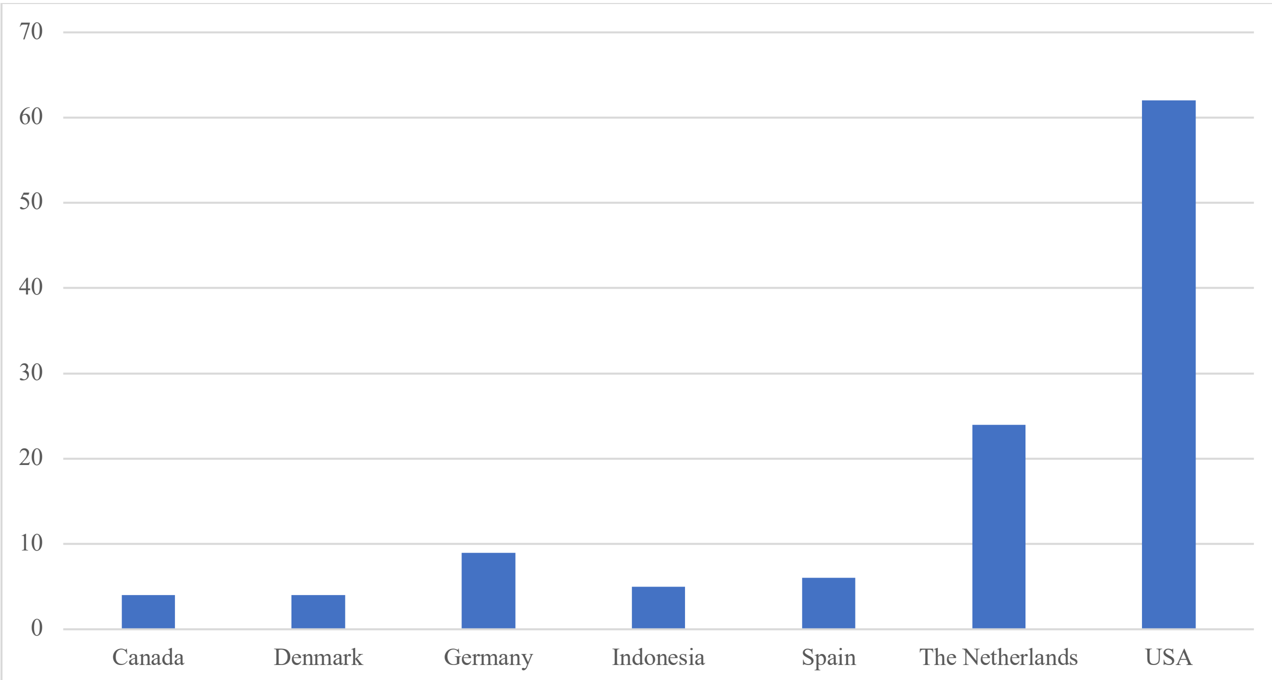


Figure 3

Temporal Concentration of Studies on Teachers' Use of DBDM for Instructional Purposes Published Worldwide (2013–2023)

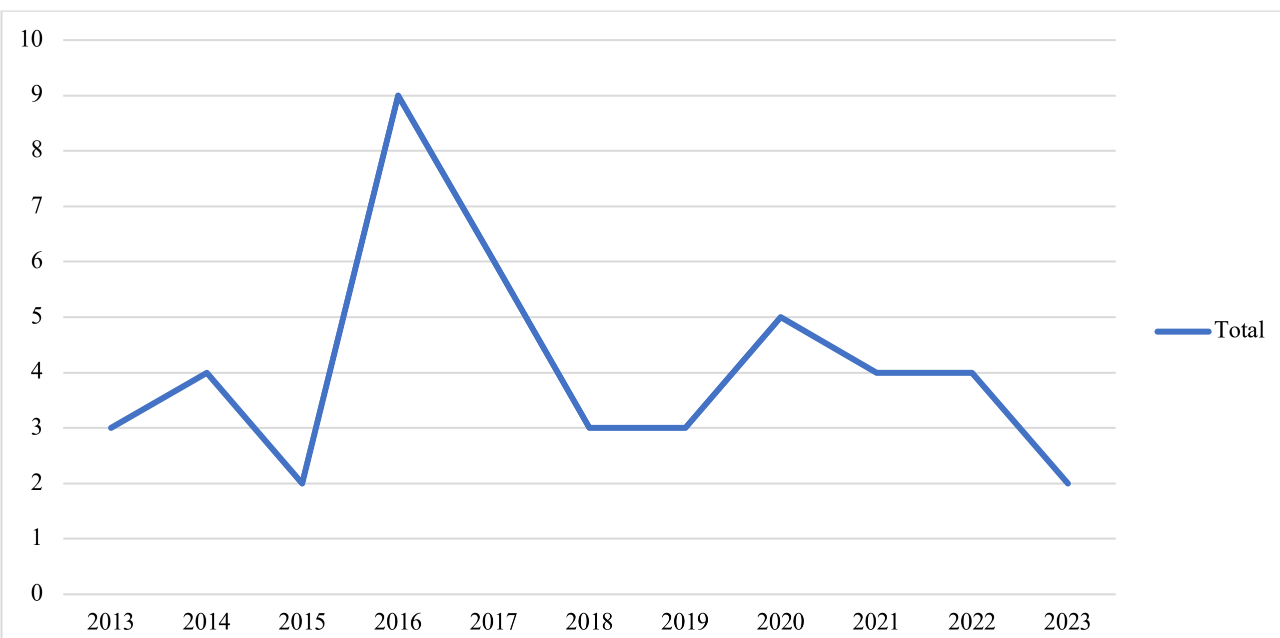
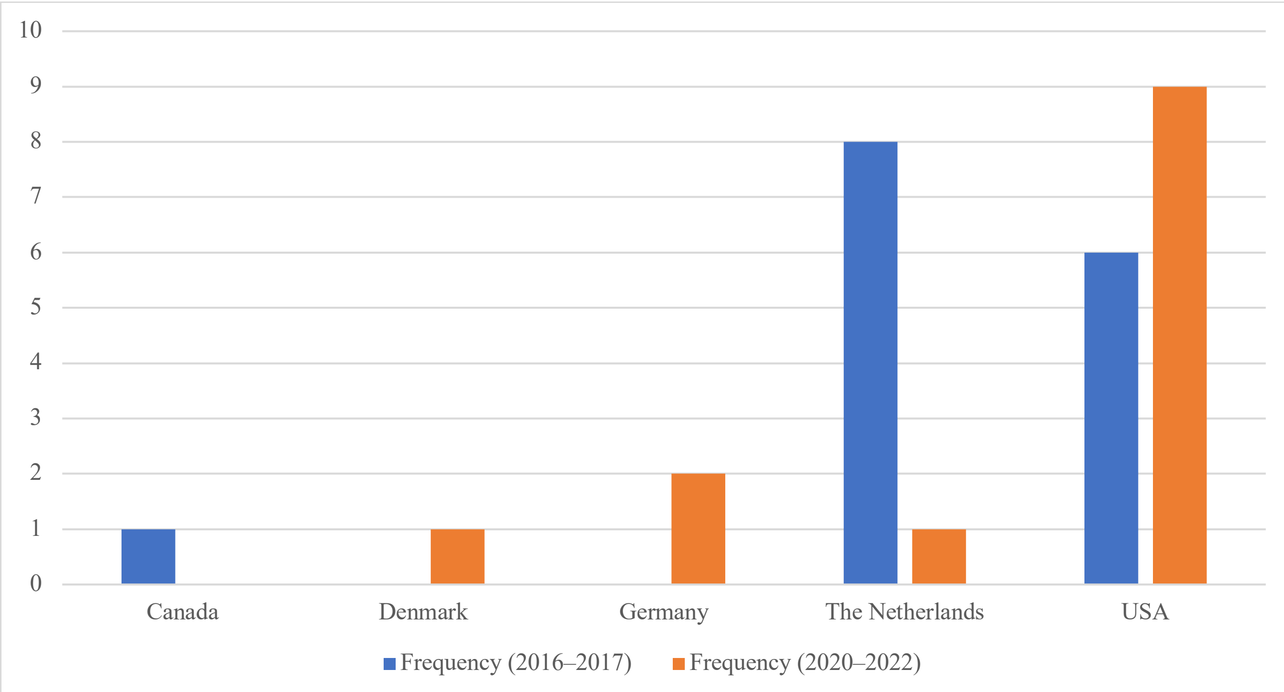


Figure 4

Number of Studies Addressing Teacher Utilization of Data to Improve Teaching Practices in 2016–2017 and 2020–2022



Educational Setting

A number of factors related to the educational setting within which DBDM interventions took place were examined as part of the review; these include the specific grade levels targeted by DBDM initiatives, and the online or in-person contexts that influenced the design and implementation of these initiatives.

Grade Level

Most of the studies reviewed (71%; *n* = 32) were conducted in elementary schools that include Grades 1 to 8. In addition to these, approximately 18% of the studies reviewed (*n* = 8) were conducted in K-12 schools. Although categorized separately, K-12 schools overlap significantly with elementary schools. The focus on the elementary context in the reviewed studies emphasizes the potential role played by DBDM in primary schooling; however, this emphasis also raises questions about the lack of attention given to DBDM interventions conducted in Grades 9 through 12. As seen in Table 3, these studies account for only 11% of the studies reviewed (*n* = 5).

Table 3

Studies Investigating Teacher Data Utilization to Improve Teaching Practices in Each Grade Level

Grade/School level	Frequency	Percentage	Cumulative
Elementary	32	71.11	71.11
K-12	8	17.78	88.89
Secondary/High school	5	11.11	100.00
Total	45	100.00	

In-Person vs. Online Context

This scoping review included studies conducted within traditional, in-person educational settings. While a handful of these studies (i.e., Admiraal et al., 2020; Campos et al., 2021; Peters et al., 2021; Regan et al., 2023; Truckenmiller et al., 2022) included learning analytics and computer-based assessment methods, it should be noted that these advancements were implemented within a conventional classroom environment. Furthermore, these studies are relatively recent, potentially indicating a recent surge in technology-assisted educational data use within traditional in-person classrooms. This focus on in-person contexts underscores a significant gap in understanding how teachers use DBDM in other modalities such as online or hybrid learning environments.

Teacher Engagement with DBDM for Instructional Purposes

More than half of the studies reviewed (n = 25) focused on teacher engagement with DBDM for instructional purposes, highlighting four main themes. Most studies (n = 14) examined teachers' data literacy skills, which showcase varying proficiency levels in using data to inform instruction, directly addressing how teachers engage with DBDM (e.g., Gelderblom et al., 2016, Ho, 2022; Hoover & Abrams, 2013; van den Bosch et al., 2017). Five studies focused on data accessibility and types of data available, which demonstrate that easy access to relevant data enhances instructional decision-making (e.g., Abdusyakur & Poortman, 2019; Admiraal et al., 2020; Farley-Ripple et al., 2019). Three studies explored teachers' perceptions and self-efficacy regarding DBDM, showing that confidence and attitudes influence data use (e.g., De Simone, 2020; Reed, 2015). Lastly, five studies identified factors that facilitate or hinder DBDM, offering insights into the contextual barriers and supports that affect its implementation (e.g., Abdusyakur & Poortman, 2019; Copp, 2017; Schildkamp et al., 2017).

Impacts of DBDM on Instructional Practices and Student Outcomes

The main purposes of DBDM are to support the improvement of instructional practices as well as student outcomes. As shown in Table 4, 20 studies focused on evaluating these potential impacts in a variety of different interventions. The studies can be classified according to the length or duration of the

DBDM intervention evaluated, the extent to which participants had received professional development (PD) related to data use prior to the evaluated interventions, and the sources of data used by teachers.

Table 4

DBDM Interventions Overview

Study	Intervention	PD	Data source	Change in teacher practices	Change in student outcome
Duration: < 1 Year					
Andersen (2020)	Data-Informed Evaluation Culture: Aims to create a data-informed evaluation culture within participating schools in Denmark through comprehensive data training.	Yes	Student assessment	N	NT
Dunn et al. (2013)	Statewide PD Program: Aims to increase teacher use of DBDM in a Pacific Northwestern state. The intervention was evaluated using the Data-Driven Decision Making Efficacy and Anxiety (3D-MEA) inventory.	Yes	Different sources	N	NT
Filderman et al. (2019)	Guidelines for DBDM Implementation: Offers guidelines to support effective DBDM implementation for students with or at risk for reading disabilities in secondary grades.	No	Computer adaptive testing	P	NT
Rodríguez-Martínez et al. (2023)	Personalized Homework Intervention: Assists teachers in using learning analytics to personalize students' homework based on formative assessment results.	No	Computer adaptive testing	NT	H
Schifter et al. (2014)	The Using Data Workshop: Offers a workshop to help teachers interpret and use data from project dashboards, with a focus on PD during summer institutes.	Yes	Learning analytics	P	NT
Duration: 1 Year					
Christman et al. (2016)	The Linking Intervention: Focuses on teacher learning about mathematics instruction and aims to elevate data utilization practices.	Yes	Student assessment	P	NT
Curry et al. (2016)	Data-Informed Instructional Model: Provides K-12 teachers with a model for data-informed instruction, which enhances teaching and learning at the classroom level.	NM	Different sources	P	H

Study	Intervention	PD	Data source	Change in teacher practices	Change in student outcome
Marsh et al. (2015)	Coaching and PLC Intervention: Combines coaching and PLC to support teachers in data utilization.	Yes	Student assessment	P	NT
Peters et al. (2021)	Teacher Training in Differentiated Instruction: Provides teacher training in differentiating instruction using learning progress assessment and reading sportsman materials.	Yes	Computer adaptive testing	NTR	M
Regan et al. (2023)	Technology-Based Graphic Organizer Intervention: Utilizes technology-based graphic organizers, online modules, long-range planning, and virtual PLC activities to support data utilization.	Yes	Computer adaptive testing	P	NT
van der Scheer et al. (2016)	DBDM Intervention for Grade 4 Math Teachers: Focuses on data-based decision making for Grade 4 math teachers.	Yes	Student assessment	P	H
van der Scheer & Visscher (2017)	DBDM Intervention for Grade 4 Math Teachers: Focuses on data-based decision making for Grade 4 math teachers.	Yes	Student assessment	P	NT
Duration: 2 Year					
Campos et al. (2021)	Learning Analytics Dashboard Support Intervention: Focuses on assisting teachers in utilizing data from a learning analytics dashboard designed to facilitate student collaboration and discussion in math. Its goal is to deepen conceptual understanding in math.	Yes	Learning analytics	P	NT
Ebbeler et al. (2016)	Teams Intervention: Forms teams of teachers and teacher leaders to create a community of practice focused on using data to enhance instruction.	Yes	Different sources	P	NT
Faber et al. (2018)	Differentiated Instruction Training: Provides teachers with training to give differentiated instruction to students.	Yes	Student assessment	NT	L
Keuning et al. (2016)	The Focus Intervention: A two-year training course for primary school teams aimed at acquiring knowledge and skills related to DBDM for instructional purposes.	Yes	Student assessment	NT	H

Study	Intervention	PD	Data source	Change in teacher practices	Change in student outcome
Staman et al. (2014)	The Focus Intervention: A two-year training course for primary school teams aimed at acquiring knowledge and skills related to DBDM for instructional purposes.	Yes	Student assessment	P	NT
Staman et al. (2017)	DBDM Training for Differentiated Instruction: Trains teachers in DBDM to provide differentiated instruction.	Yes	Student assessment	P	NT
Duration: 4 Year					
Datnow et al. (2021)	Teacher Collaborative Efforts Intervention: Seeks to promote students' math achievement by fostering collaborative efforts among teachers to improve instruction, including utilizing relevant data.	NM	Student assessment	P	NT
Hebbecker et al. (2022)	DBDM Framework-Based Intervention: Assists teachers in decision making based on data (van Geel et al., 2016)	Yes	Student assessment	P	H

Note. PD = Professional development; PLC = Professional learning communities; NM = Not Mentioned, Teacher behaviour (P = Positive, N = Negative, NTR = Neutral, NT = Not tested); Student outcome (H = High, M = Moderate, L = Low, NT = Not tested).

Duration and Previous Professional Development

The interventions included in the studies reviewed range from a condensed one-session PD workshop (e.g., Schifter et al., 2014) to a 4-year program (e.g., Hebbecker et al., 2022). To gain a clearer understanding of this dimension, interventions were categorized based on their duration (Table 4). Most interventions were conducted within one to two academic years (n = 13). A notable subset of interventions lasted less than one year (n = 5), while only two interventions, one in the Netherlands (Hebbecker et al., 2022) and one in the US (Datnow et al., 2021), took place over a comprehensive 4-year period. The findings also demonstrate that in 16 out of the 20 interventions, teachers had some level of data literacy training prior to the DBDM professional development. For two of the remaining four interventions, it was undetermined whether teachers had prior data literacy training rather than a definitive absence of such training.

Sources of Data Used by Teachers

More than half of the studies reviewed (n = 11) indicated that the main source of data used by teachers as part of the DBDM intervention was generated through student assessment, and four additional studies used assessment data from computer adaptive testing. Other studies also featured learning management systems as a source of data (n = 2) or different sources (n = 3).

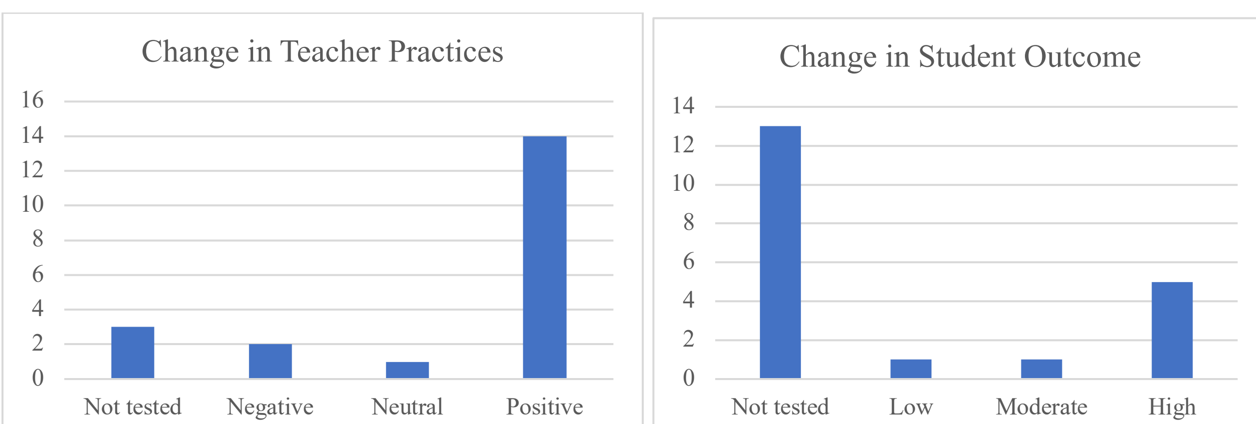
Impact of DBDM Interventions

The impacts of DBDM interventions on instructional practices employed by teachers as well as on student outcomes were assessed in the 20 evaluative studies reviewed. DBDM interventions were assessed as having a "positive" impact on instructional practices if the study findings included one of the following elements: (a) increased emotional, analytical, and/or intentional data sensemaking and data literacy skills; (b) increased or enhanced discussions amongst colleagues on data use and the creation of professional learning communities; (c) instructional adjustments using data; (d) capacity-building for DBDM; (e) increased teacher awareness of data use for school development and instruction; or (f) changes in teacher efficacy related to implementing instructional strategies. The impact of the DBDM interventions on instructional practices was assessed as "neutral" if teachers maintained the same level of data use, and as "negative" if the intervention did not contribute to the development of new skills or positive attitudes related to DBDM. In some studies, no change in teacher practices was measured, as the focus was solely on student outcomes.

The impact of the DBDM interventions on student outcomes was also examined within the 20 evaluative studies. These impacts were considered "high" if the DBDM intervention resulted in: (a) increased student understanding of the learning materials; (b) increased student motivation and engagement; or (c) improved scores on standardized tests. DBDM impacts were considered "moderate" if after the intervention: (a) students recognized the importance of setting challenging learning goals; or (b) there was a small positive effect on student achievement in standardized tests. Lastly, the impact was considered "low" if no significant positive effects were found on student outcomes. In some studies, however, no measurement of student outcomes was included, as the focus was solely on changes in teacher practices.

Figure 5

The Impact of DBDM Interventions on Instructional Practices and Student Outcomes



As illustrated in Figure 5, the number of studies that evaluated the impact of DBDM interventions on instructional practices (n = 17) is higher than those focusing on student outcomes (n = 7). However, in both dimensions, the positive impacts of DBDM on instructional practices and the high impact of the interventions on student outcomes were more commonly found than neutral/moderate or negative/low impacts. Moreover, most of the reviewed studies evaluated the impact of a DBDM intervention on one of the two dimensions; studies that explored the effect of DBDM interventions on both teachers and students were less common (i.e., Curry et al., 2016; Hebbecker et al., 2022; Peters et al., 2021; van der Scheer et al., 2016).

Discussion and Implications

This scoping review offers a comprehensive examination of the landscape of DBDM use by teachers in the K-12 context, which addresses geographical and temporal concentrations, educational settings, and the impact of DBDM interventions. This discussion is based on the review of all 45 articles, providing an in-depth analysis of the current state of the field.

Temporal and Geographical Patterns in Research Distribution

Temporal and geographical patterns in research distribution on DBDM shed light on global variations in how teachers engage with data for instructional purposes. Temporal trends reveal how research on teacher engagement aligns with shifts in policies, technologies, and educational reforms, while geographical patterns highlight disparities driven by contextual factors such as access to resources or institutional support (Christman et al., 2016; Curry et al., 2016; Farrell & Marsh, 2016a, 2016b; Michaud, 2016; Park & Datnow, 2017). By comparing regions and time periods, we can identify factors that contributed to DBDM adoption for instructional purposes by teachers at the classroom level. Additionally, gaps in research across certain areas or periods can guide future studies to explore underrepresented contexts, offering a more comprehensive understanding of DBDM's global impact.

The observed concentration of studies in the United States and the Netherlands found in this review aligns with the existing literature, which highlights these countries' significant efforts in implementing and studying DBDM. The initial surge in articles during 2016–2017 coincides with pivotal policy reforms in the United States (Park & Datnow, 2017) and the Netherlands (Schildkamp et al., 2017), which aimed to reshape the educational landscape, particularly concerning data use and DBDM. Subsequently, a resurgence of research interest appears in the literature during 2020–2022. This period saw an increased focus on technology and computer-based assessment incorporation, which placed DBDM at the forefront of educational change.

First Period (2016–2017)

Signed in 2015, the *Every Student Succeeds Act* marked a shift in US education policy, moving away from high-stakes testing under *No Child Left Behind*. This Act introduced flexible accountability measures, reduced the emphasis on standardized tests, and encouraged data use for instructional improvement (Shirely, 2017). Research from this period focused on how educators utilized diverse data forms to enhance teaching (e.g., Curry et al., 2016; Park & Datnow, 2017). Similarly, declining student performance in international assessments prompted the adoption of DBDM policies in the Netherlands. Initiatives such as the 'Focus' intervention equipped educators with skills to monitor progress and tailor their instruction according to students' needs, which resulted in improvement in teaching practices and student outcomes (Faber et al., 2018; Schildkamp et al., 2017).

Second Period (2020–2022)

Studies published during this period show that teachers started to incorporate technology such as learning analytics and computer-based assessments to collect and analyze data, which reshaped and eased the use of DBDM to support learning (Admiraal et al., 2020; Campos et al., 2021; Truckenmiller et al., 2022). Although the Netherlands saw a decline in research during this period, the DBDM frameworks developed for Dutch schools, such as the Data Teams framework (Schildkamp et al., 2016) and the DBDM process model (van Geel et al., 2016), created the foundation for subsequent studies. These frameworks have been successfully adopted in various international contexts, including Denmark (e.g., Andersen, 2020), the United States (e.g., Datnow et al., 2018; Michaud, 2016; Ylimaki & Brunderman, 2019), New Zealand (e.g., Lai et al., 2014; Lai & McNaughton, 2016), and Germany (e.g., Hebbecker et al., 2022). However, there is notable limited research on teacher use of DBDM at the classroom level in Canada, with only one relevant study (Copp, 2017) addressing policy incentives and data use across Canadian schools.

Educational Settings

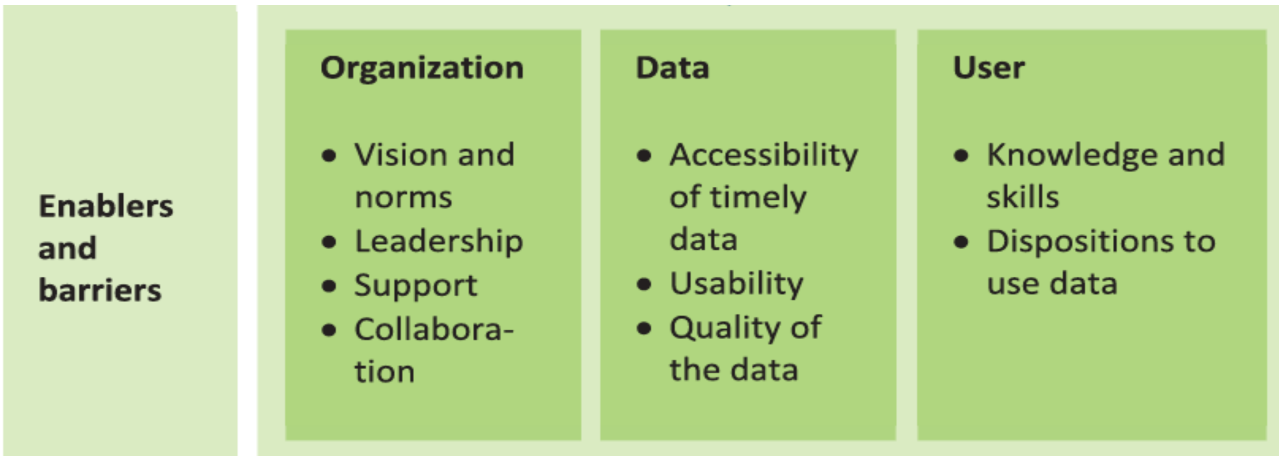
The exploration of educational settings in which DBDM is implemented demonstrates that there is a predominant focus on in-person teaching at the primary/elementary level in the reviewed studies (e.g., Staman et al., 2017; van der Scheer & Visscher, 2017); this raises questions about the extent to which DBDM practices can be adapted to secondary education settings and different learning modalities. Addressing these complexities requires further study to understand the transferability and effectiveness of DBDM strategies at higher grade levels. Moreover, existing literature on online education emphasizes the potential of learning analytics and real-time data to inform personalized instruction (e.g., Behrens et al., 2018; Campos et al., 2021). However, no studies explore how educators can leverage data effectively in an online-learning environment. Thus, there is a need for research that examines the practical integration of DBDM in these educational settings.

Examining the Impact of DBDM Interventions

The findings underscore the importance of tailored interventions and ongoing professional development for effective DBDM implementation. This aligns with Schildkamp et al.'s (2017) DBDM Determinant Model, which highlights three key factors for successful DBDM interventions: organizational context, data characteristics, and user characteristics (Figure 6).

Figure 6

Determinant Model



Note. Schildkamp et al. (2017, p. 244).

Organizational Context: Effective DBDM requires strong leadership support, collaboration, and a clear vision, as Schildkamp et al. (2017) emphasize. Studies in this review address some aspects, such as coaching support (Andersen, 2020), collaboration through communities of practice (Marsh et al., 2015; Keuning et al., 2016), and leadership (Copp, 2017; Ylimaki & Brunderman, 2019). However, they often overlook the 'vision and norms' of institutions.

Data Characteristics: High-quality, timely, and usable data are crucial for DBDM. While many studies focus on assessment and standardized test data, there is a growing recognition of the need for diverse data sources. Researchers such as Curry et al. (2016), Dunn et al. (2013), and Ebbeler et al. (2016) advocate for a multifaceted data approach, emphasizing that diverse data sources enhance the impact on student outcomes. Even studies focusing on assessment data, such as Datnow et al. (2021) and Faber et al. (2018), highlight the importance of incorporating diverse sources of data.

User Characteristics: The predominant focus in the literature is on enhancing teachers' data literacy and positive attitudes toward data use (e.g., Ebbeler et al., 2016; Staman et al., 2014; van der Scheer & Visscher, 2017). Effective training can improve these characteristics, with longitudinal, well-designed professional development showing positive effects on both teacher practices and student achievement (e.g., Andersen, 2020; Campos et al., 2021; Christman et al., 2016). However, Hebbecker et al. (2022) suggest that even short professional development sessions, combined with practical support and resources, can be sufficient for implementing DBDM effectively.

Although DBDM interventions have been found helpful in altering teacher practices and improving student outcomes, there remains a need for more sustainable and ongoing support to enhance DBDM implementation (Abdusyakur & Poortman, 2019; Admiraal et al., 2020; Staman et al., 2017). Short-term interventions or training programs, although effective in the short term, may not fully address the complexities of integrating DBDM into daily teaching practices (Andersen, 2020; van den Bosch et al., 2017). To ensure lasting change, interventions must prioritize building systemic capacity through continued professional learning opportunities, access to high-quality resources, and institutional support structures (Farley-Ripple et al., 2019; Rodríguez-Martínez et al., 2023). These efforts would enable teachers to embed data use more deeply into their instructional practices, thereby fostering sustained improvements in both teaching and learning outcomes.

Conclusion

This scoping review enhances understanding of DBDM in K-12 schools by examining how teachers use student data to guide their pedagogical and instructional practices. It highlights shifts from using DBDM for accountability to improving instruction (Kempf, 2015; Schildkamp & Ehren, 2013), and identifies gaps such as the need for research at the secondary/high school level and in online-learning contexts. The review also explores the impact of DBDM interventions on teacher practices and student outcomes (Hebbecker et al., 2022; Peters et al., 2021; Rodríguez-Martínez et al., 2023). As educational practices evolve, further research is needed to address gaps in secondary education, online learning, and under-represented geographical areas, aiming for a broader, more global understanding of DBDM trends. By addressing existing research gaps and fostering discussions on its implications, future studies can contribute to a more global and nuanced understanding of DBDM. Such efforts are essential for ensuring that data use in education translates into improved instructional practices and better outcomes for students across diverse contexts.

References

Abdusyakur, I., & Poortman, C. L. (2019). Study on data use in Indonesian primary schools. *Journal of Professional Capital and Community*, *4*(3), 198–215. https://doi.org/10.1108/JPCC-11-2018-0029

Admiraal, W., Vermeulen, J., & Bulterman-Bos, J. (2020). Teaching with learning analytics: How to connect computer-based assessment data with classroom instruction? *Technology, Pedagogy and Education*, *29*(5), 577–591. https://doi.org/10.1080/1475939X.2020.1825992

Andersen, I. G. (2020). What went wrong? Examining teachers' data use and instructional decision making through a bottom-up data intervention in Denmark. *International Journal of Educational Research*, *102*, 101585. https://doi.org/10.1016/j.ijer.2020.101585

Behrens, J., Piety, P., DiCerbo, K., & Mislevy, R. (2018). Inferential foundations for learning analytics in the digital ocean. In D. Niemi, R. D. Pea, B. Saxberg, & R. E. Clark (Eds.), *Learning analytics in education* (pp. 1–48). Information Age Publishing Inc.

Campos, F. C., Ahn, J., DiGiacomo, D. K., Nguyen, H., & Hays, M. (2021). Making sense of sensemaking: Understanding how K-12 teachers and coaches react to visual analytics. *Journal of Learning Analytics*, *8*(3), 60–80.

Carlson, D., Borman, G. D., & Robinson, M. (2011). A multistate district-level cluster randomized trial of the impact of data-driven reform on reading and mathematics achievement. *Educational Evaluation and Policy Analysis*, *33*(3), 378–398. https://doi.org/10.3102/0162373711412765

Cheng, L. (1999). Changing assessment: Washback on teacher perspectives and actions. *Teaching and Teacher Education*, *15*(3), 253–271. https://doi.org/10.1016/S0742-051X(98)00046-8

Cheng, L., & Curtis, A. (2004). Washback or backwash: A review of the impact of testing on teaching and learning. In L. Cheng, Y. Watanabe, & A. Curtis (Eds.), *Washback in language testing: Research contexts and methods* (pp. 3–17). Lawrence Erlbaum.

Christman, J. B., Ebby, C. B., & Edmunds, K. A. (2016). Data use practices for improved mathematics teaching and learning: The importance of productive dissonance and recurring feedback cycles. *Teachers College Record*, *118*(11), 1–32. https://doi.org/10.1177/016146811611801101

Copp, D. T. (2017). Policy incentives in Canadian large-scale assessment: How policy levers influence teacher decisions about instructional change. *Education Policy Analysis Archives*, *25*, 115. https://doi.org/10.14507/epaa.25.3299

Curry, K. A., Mwavita, M., Holter, A., & Harris, E. (2016). Getting assessment right at the classroom level: Using formative assessment for decision making. *Educational Assessment, Evaluation and Accountability*, *28*, 89–104. https://doi.org/10.1007/s11092-015-9226-5

Datnow, A., & Hubbard, L. (2015). Teachers' use of assessment data to inform instruction: Lessons from the past and prospects for the future. *Teachers College Record*, *117*(4), 1–26. https://doi.org/10.1177/016146811511700408

Datnow, A., Choi, B., Park, V., & John, E. S. (2018). Teacher talk about student ability and achievement in the era of data-driven decision making. *Teachers College Record*, *120*(4), 1–34. https://doi.org/10.1177/016146811812000408

Datnow, A., Lockton, M., & Weddle, H. (2021). Capacity building to bridge data use and instructional improvement through evidence on student thinking. *Studies in Educational Evaluation*, *69*, 100869. https://doi.org/10.1016/j.stueduc.2020.100869

De Simone, J. J. (2020). The roles of collaborative professional development, self-efficacy, and positive affect in encouraging educator data use to aid student learning. *Teacher Development*, *24*(4), 443–465. https://doi.org/10.1080/13664530.2020.1780302

Dunn, K. E., Airola, D. T., Lo, W. J., & Garrison, M. (2013). What teachers think about what they can do with data: Development and validation of the data driven decision-making efficacy and anxiety inventory. *Contemporary Educational Psychology*, *38*(1), 87–98. https://doi.org/10.1016/j.cedpsych.2012.11.002

Ebbeler, J., Poortman, C. L., Schildkamp, K., & Pieters, J. M. (2016). Effects of a data use intervention on educators' use of knowledge and skills. *Studies in Educational Evaluation*, *48*, 19–31. https://doi.org/10.1016/j.stueduc.2015.11.002

Faber, J., Glas, C., & Visscher, A. J. (2018). Differentiated instruction in a data-based decision-making context. *School Effectiveness and School Improvement*, *29*(1), 43–63. https://doi.org/10.1080/09243453.2017.1366342

Farley-Ripple, E. N., Jennings, A. S., & Buttram, J. (2019). Toward a framework for classifying teachers' use of assessment data. *AERA Open*, *5*(4), 2332858419883571. https://doi.org/10.1177/2332858419883571

Farrell, C. C., & Marsh, J. A. (2016a). Metrics matter: How properties and perceptions of data shape teachers' instructional responses. *Educational Administration Quarterly*, *52*(3), 423–462. https://doi.org/10.1177/0013161X16638429

Farrell, C. C., & Marsh, J. A. (2016b). Contributing conditions: A qualitative comparative analysis of teachers' instructional responses to data. *Teaching and Teacher Education*, *60*, 398–412. https://doi.org/10.1016/j.tate.2016.07.010

Filderman, M. J., Austin, C. R., & Toste, J. R. (2019). Data-based decision making for struggling readers in the secondary grades. *Intervention in School and Clinic*, *55*(1), 3–12. https://doi.org/10.1177/1053451219832991

Gelderblom, G., Schildkamp, K., Pieters, J., & Ehren, M. (2016). Data-based decision making for instructional improvement in primary education. *International Journal of Educational Research*, *80*, 1–14. https://doi.org/10.1016/j.ijer.2016.07.004

Hebbecker, K., Förster, N., Forthmann, B., & Souvignier, E. (2022). Data-based decision-making in schools: Examining the process and effects of teacher support. *Journal of Educational Psychology*, *114*(7), 1695. https://psycnet.apa.org/doi/10.1037/edu0000530

Heinrich, C., & Good, A. (2018). Research-informed practice improvements: Exploring linkages between school district use of research evidence and educational outcomes over time. *School Effectiveness and School Improvement*, *29*(3), 418–445. https://doi.org/10.1080/09243453.2018.1445116

Ho, J. E. (2022). What counts? The critical role of qualitative data in teachers' decision making. *Evaluation and Program Planning*, *91*, 102046. https://doi.org/10.1016/j.evalprogplan.2021.102046

Hoover, N. R., & Abrams, L. M. (2013). Teachers' instructional use of summative student assessment data. *Applied Measurement in Education*, *26*(3), 219–231. https://doi.org/10.1080/08957347.2013.793187

Kempf, A. (2015). The school as factory farm: All testing all the time. In *The pedagogy of standardized testing* (pp. 13–28). Palgrave Macmillan US. https://doi.org/10.1057/9781137486653_2

Keuning, T., Geel, M. V., Visscher, A., Fox, J.-P., & Moolenaar, N. M. (2016). The transformation of schools' social networks during a data-based decision making reform. *Teachers College Record*, *118*(9), 1–33. https://doi.org/10.1177/016146811611800908

Lai, M. K., & McNaughton, S. (2016). The impact of data use professional development on student achievement. *Teaching and Teacher Education*, *60*, 434–443. https://doi.org/10.1016/j.tate.2016.07.005

Lai, M. K., Wilson, A., McNaughton, S., & Hsiao, S. (2014). Improving achievement in secondary schools: Impact of a literacy project on reading comprehension and secondary school qualifications. *Reading Research Quarterly*, *49*(3), 305–334. https://doi.org/10.1002/rrq.73

Maier, U. (2010). Accountability policies and teachers' acceptance and usage of school performance feedback – A comparative study. *School Effectiveness and School Improvement*, *21*(2), 145–165. https://doi.org/10.1080/09243450903354913

Marsh, J. A. (2012). Interventions promoting educators' use of data: Research insights and gaps. *Teachers College Record*, *114*(11), 1–48. https://doi.org/10.1177/016146811211401106

Marsh, J. A., Bertrand, M., & Huguet, A. (2015). Using data to alter instructional practice: The mediating role of coaches and professional learning communities. *Teachers College Record*, *117*(4), 1–40. https://doi.org/10.1177/016146811511700411

Marsh, J. A., Pane, J. F., & Hamilton, L. S. (2006, Nov 7). Making sense of data-driven decision making in education [Occasional Paper]. RAND Corporation.

Michaud, R. (2016). The Nature of Teacher Learning in Collaborative Data Teams. Qualitative Report, 21(3), 529-545. https://doi.org/10.46743/2160-3715/2016.231.

Park, V., & Datnow, A. (2017). Ability grouping and differentiated instruction in an era of data-driven decision making. *American Journal of Education*, *123*(2), 281–306. https://doi.org/10.1086/689930

Peters, M. T., Förster, N., Hebbecker, K., Forthmann, B., & Souvignier, E. (2021). Effects of data-based decision-making on low-performing readers in general education classrooms: Cumulative evidence from six intervention studies. *Journal of Learning Disabilities*, *54*(5), 334–348. https://doi.org/10.1177/00222194211011580

Rangel, V. S., Bell, E. R., & Monroy, C. (2017). A descriptive analysis of instructional coaches' data use in science. *School Effectiveness and School Improvement*, *28*(2), 217–241. https://doi.org/10.1080/09243453.2016.1255232

Reed, D. K. (2015). Middle level teachers' perceptions of interim reading assessments: An exploratory study of data-based decision making. *RMLE Online: Research in Middle Level Education*, *38*(6), 1–13. https://doi.org/10.1080/19404476.2015.11462119

Regan, K., Evmenova, A. S., Mergen, R. L., Verbiest, C., Hutchison, A., Murnan, R., Field, S., & Gafurov, B. (2023). The feasibility of using virtual professional development to support teachers in making data-based decisions to improve students' writing. *Learning Disabilities Research & Practice*, *38*(1), 40–56. https://doi.org/10.1111/ldrp.12301

Rodríguez-Martínez, J. A., González-Calero, J. A., del Olmo-Muñoz, J., Arnau, D., & Tirado-Olivares, S. (2023). Building personalised homework from a learning analytics based formative assessment: Effect on fifth-grade students' understanding of fractions. *British Journal of Educational Technology*, *54*(1), 76–97. https://doi.org/10.1111/bjet.13292

Schifter, C., Natarajan, U., Ketelhut, D. J., & Kirchgessner, A. (2014). Data-driven decision-making: Facilitating teacher use of student data to inform classroom instruction. *Contemporary Issues in Technology and Teacher Education*, *14*(4), 419–432.

Schildkamp, K., & Ehren, M. (2013). From "intuition" to "data"-based decision making in Dutch secondary schools? In K. Schildkamp, M. K. Lai, & L. Earl (Eds.), *Data-based decision making in Education* (pp. 49–67). Springer Netherlands. https://doi.org/10.1007/978-94-007-4816-3_4

Schildkamp, K., Poortman, C., & Handelzalts, A. (2016). Data teams for school improvement. *School Effectiveness and School Improvement*, *27*(2), 228–254. https://doi.org/10.1080/09243453.2015.1056192

Schildkamp, K., Poortman, C., Luyten, H., & Ebbeler, J. (2017). Factors promoting and hindering data-based decision making in schools. *School Effectiveness and School Improvement*, *28*(2), 242–258. https://doi.org/10.1080/09243453.2016.1256901

Shirley, D. (2017). *The new imperatives of educational change: Achievement with integrity*. Routledge. https://doi.org/10.4324/9781315682907

Staman, L., Timmermans, A. C., & Visscher, A. J. (2017). Effects of a data-based decision making intervention on student achievement. *Studies in Educational Evaluation*, *55*, 58–67. https://doi.org/10.1016/j.stueduc.2017.07.002

Staman, L., Visscher, A. J., & Luyten, H. (2014). The effects of professional development on the attitudes, knowledge and skills for data-driven decision making. *Studies in Educational Evaluation*, *42*, 79–90. https://doi.org/10.1016/j.stueduc.2013.11.002

Tricco, A. C., Lillie, E., Zarin, W., O'Brien, K. K., Colquhoun, H., Levac, D., Moher, D., Peters, M. D. J., Horsley, T., Weeks, L., Hempel, S., Akl, E. A., Chang, C., McGowan, J., Stewart, L., Hartling, L., Aldcroft, A., Wilson, M. G., Garritty, C., … Straus, S. E. (2018). PRISMA Extension for Scoping Reviews (PRISMA-ScR): Checklist and explanation. *Annals of Internal Medicine*, *169*(7), 467–485. https://doi.org/10.7326/M18-0850

Tsai, Y., Poquet, O., Gašević, D., Dawson, S., & Pardo, A. (2019). Complexity leadership in learning analytics: Drivers, challenges and opportunities. *British Journal of Educational Technology*, *50*(6), 2839–2854. https://doi.org/10.1111/bjet.12846

Truckenmiller, A. J., Cho, E., & Troia, G. A. (2022). Expanding assessment to instructionally relevant writing components in middle school. *Journal of School Psychology*, *94*, 28–48. https://doi.org/10.1016/j.jsp.2022.07.002

van den Bosch, R. M., Espin, C. A., Chung, S., & Saab, N. (2017). Data-based decision-making: Teachers' comprehension of curriculum-based measurement progress-monitoring graphs. *Learning Disabilities Research & Practice*, *32*(1), 46–60. https://doi.org/10.1111/ldrp.12122

van Geel, M., Keuning, T., Visscher, A. J., & Fox, J.-P. (2016). Assessing the Effects of a School-Wide Data-Based Decision-Making Intervention on Student Achievement Growth in Primary Schools. *American Educational Research Journal*, *53*(2), 360–394. https://doi.org/10.3102/0002831216637346

van der Scheer, E. A., & Visscher, A. J. (2016). Effects of an intensive data-based decision making intervention on teacher efficacy. *Teaching and Teacher Education*, *60*, 34–43. https://doi.org/10.1016/j.tate.2016.07.025

van der Scheer, E. A., Glas, C. A., & Visscher, A. J. (2017). Changes in teachers' instructional skills during an intensive data-based decision making intervention. *Teaching and Teacher Education*, *65*, 171–182. https://doi.org/10.1016/j.tate.2017.02.018

Ylimaki, B., & Brunderman, L., (2019). School development in culturally diverse U.S. schools: Balancing evidence-based policies and education values. *Education Sciences*, *9*(84), 1–15. https://doi.org/10.3390/educsci9020084

Authors

Areej Tayem is a Ph.D. candidate and part-time Professor in the Faculty of Education at the University of Ottawa in Canada. Her research focuses on learning analytics and data-based decision making (DBDM) in K-12 education. *Email*: atayem@uottawa.ca

Isabelle Bourgeois is a full Professor in the Faculty of Education at the University of Ottawa in Canada. Her main research activities focus on program evaluation and evaluation capacity building in public and community organizations. *Email*: isabelle.bourgeois@uottawa.ca

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Facteurs qui influencent la conception des tâches de robotique pédagogique soutenant la résolution collaborative de problèmes

Factors Influencing the Design of Educational Robotics Tasks Supporting Collaborative Problem-Solving

Raoul Kamga, *Université du Québec à Montréal, Canada*

Sylvie Barma, *Université Laval, Canada*

Frédéric Fournier, *Université du Québec à Montréal, Canada*

Pierre Lachance, *Réseau éducation collaboration innovation technologie, Canada*

Joelle Bérubé-Daigneault, *Université du Québec à Montréal, Canada*

Sarah Cool-Charest, *Université de Montréal, Canada*

Résumé

La capacité à résoudre des problèmes de manière collaborative constitue une compétence fondamentale pour les élèves du primaire. Les travaux de recherche se sont majoritairement focalisés sur l'analyse et l'évaluation de cette compétence chez les élèves du primaire. Cependant, peu d'attention a été portée au processus de conception des tâches visant à favoriser le développement de la résolution collaborative de problèmes chez ces élèves. Pourtant, la résolution collaborative de problèmes ne peut émerger de manière pertinente que si les tâches sont conçues de manière à encourager les élèves à collaborer. Cette recherche se concentre spécifiquement sur le processus de conception des tâches liées à la robotique pédagogique et utilise, comme cadre théorique, la théorie de l'activité d'Engeström. Les participants, composés d'enseignants du primaire et de conseillers pédagogiques, ont répondu à un questionnaire portant sur leur démarche de conception de tâches et ont participé à deux entrevues de groupes. Les résultats soulignent que la conception des tâches de robotique pédagogique, qui vise à développer la résolution collaborative de problèmes chez les élèves, est tributaire des habiletés technologiques et de conception de tâches en robotique pédagogique de la personne conceptrice. Les règles régissant la conception des tâches de robotique pédagogique incluent le temps nécessaire à leur mise en place et le travail d'équipe.

Mots-clés : conception des tâches, formation des enseignants, résolution collaborative de problèmes, robotique pédagogique, théorie de l'activité

Abstract

A fundamental skill for primary school students is the ability to solve problems collaboratively. Most research has focused on the analysis and assessment of this skill in primary school students. However, little attention has been paid to the process of designing tasks to foster the development of collaborative problem-solving in these students. Furthermore, collaborative problem-solving can only emerge in a meaningful way if the tasks are designed in such a way as to encourage students to collaborate. This research focuses specifically on the process of designing tasks related to educational robotics, using the theoretical framework of Engeström's activity theory. Participants, made up of primary school teachers and educational consultants, completed a questionnaire about their task design process and took part in two group interviews. The results highlight that the design of educational robotics tasks, aimed at developing collaborative problem-solving in students, is dependent on the technological and educational robotics task design skills of the designer. The rules governing the design of educational robotics tasks include the time needed to set them up and teamwork.

Keywords: activity theory, collaborative problem-solving, educational robotics, task design, teacher education

Introduction

La résolution collaborative de problèmes attire de plus en plus l'attention tant au niveau national qu'international (Bergner et al., 2016; Dindar et al., 2022; Kamga, 2019; OCDE, 2013). Cette compétence revêt une importance cruciale pour les élèves du primaire en les préparant à collaborer efficacement avec leurs pairs ou membres de leur famille pour surmonter des défis quotidiens. Elle revêt également une importance significative dans leur vie quotidienne, afin qu'ils puissent par la suite évoluer dans un monde saturé d'informations, ainsi que sur le plan professionnel, en lien avec de nombreux emplois exigeant la résolution de problèmes complexes au sein d'équipes (Siddiq & Scherer, 2017).

Bien que la recherche se soit penchée sur le développement de la compétence de résolution collaborative de problèmes chez les élèves du primaire (Avry et al., 2018), elle accorde peu d'attention au processus de conception des tâches favorisant cette compétence. De plus, les articles qui décrivent les tâches pouvant développer la résolution collaborative de problèmes se concentrent principalement sur des simulations (Care et al., 2015; Warneken et al., 2014) ou effectuent une analyse théorique des tâches de robotique pédagogique (Kamga et al., 2017). Par ailleurs, les tâches analysées dans les études consultées ne sont pas systématiquement réalisées en classe avec des élèves, mais plutôt en contexte parascolaire (Romero & DeBlois, 2022). Ces recherches n'intègrent pas le point de vue des concepteurs de tâches de robotique pédagogique, ne se penchent pas sur le processus de conception de ces tâches et les facteurs susceptibles de les influencer.

Dans cet article, en nous basant sur le retour d'expérience des concepteurs de tâches de robotique pédagogique, nous présentons les facteurs qui influent sur le processus de conception des tâches visant à développer la résolution collaborative de problèmes chez les élèves du primaire en contexte scolaire.

Résolution collaborative de problèmes

La résolution collaborative de problème est une compétence mobilisant la collaboration et de la résolution de problèmes (Unal & Cakir, 2021). Son développement implique l'engagement d'un groupe d'apprenants dans la résolution d'un problème (OCDE, 2013). Ainsi, la résolution collaborative de problèmes sollicite chez l'individu des habiletés cognitives et sociales (Care et al., 2015; Hesse et al., 2015; Zhang et al., 2022). Selon Hesse et al. (2015), les habiletés cognitives sont celles reliées à la résolution de problèmes tandis que les habiletés sociales sont associées à la collaboration. Les habiletés cognitives sont caractérisées par la construction des connaissances et la régulation de la tâche et de l'apprentissage. Quant aux habiletés sociales, elles sont dimensionnées par la régulation sociale, la participation et la prise de perspective.

Diverses études ont exploré la résolution collaborative de problèmes, certaines la considérant comme une méthode d'apprentissage et d'enseignement (Unal & Cakir, 2021; Yin et al., 2011), d'autres comme une compétence à développer (Dindar et al., 2022; Graesser et al., 2018; Hesse et al., 2015; OCDE, 2013; Song, 2018). Notre étude s'inscrit dans la perspective de la considérer comme une compétence à développer. Les recherches précédentes sur le développement de cette compétence ont exploré sa mesure et son évaluation (Rojas et al., 2021; Zhang et al., 2022), la charge cognitive des participants de l'équipe (Kolfschoten et al., 2014), sa modélisation (Bergner et al., 2016), et les caractéristiques des tâches qui favorisent son développement (Care et al., 2015; Kamga et al., 2017; Nieminen et al., 2022; Warneken et al., 2014). Ainsi, ces études se sont principalement concentrées sur la compréhension de la compétence ou sur les aspects spécifiques des tâches. Les tâches visant à développer la résolution collaborative de problèmes doivent être ouvertes (Nieminen et al., 2022), mal structurées (Unal & Cakir, 2021), complexes (Graesser et al., 2017, 2018) et authentiques, reproduisant ainsi des expériences de la vie réelle (Siddiq & Scherer, 2017).

Conception des tâches et résolution collaborative de problèmes

La conception des tâches d'apprentissage a fait l'objet de plusieurs recherches en éducation (Cevikbas & Kaiser, 2021; De Hei et al., 2016; Oliver & Higgins, 2023). Selon Watson et Ohtani (2015), la conception de la tâche proposée aux élèves peut améliorer leurs apprentissages et la qualité de leur expérience envers la discipline. Il existe plusieurs facteurs qui peuvent influencer la conception des tâches d'apprentissage. Selon Sullivan et al. (2015) dans le cadre des apprentissages de la mathématique, la conception de la tâche peut dépendre de la pédagogie prévue par l'enseignant, de ses connaissances dans l'enseignement de la discipline, de son rôle et de son niveau d'autonomie dans le processus de conception et de réalisation de la tâche, de la culture du milieu et celle de la salle de classe. Ces facteurs abordent soit la dimension « enseignant » ou celle de la classe, mais ne présentent pas les caractéristiques intrinsèques de la tâche. Dans le cadre de la conception des tâches qui impliquent la collaboration, l'étude de De Hei et al. (2016) souligne cinq caractéristiques des tâches à utiliser en classe : significative pour les élèves, utilisant un matériel authentique, stimulante pour les élèves, inciter les élèves à discuter et à échanger des idées et expériences, et favorisant le travail collaboratif. Ces caractéristiques ont été mentionnées par les enseignants et ne concernent que les facteurs liés à l'élève. Bien que plusieurs études aient abordé la conception des tâches, il est pertinent d'accroître les connaissances scientifiques spécifiques à la conception de tâches permettant la résolution collaborative de problèmes. Cependant, la conception des tâches liées à l'utilisation par les élèves d'objets technologiques tels que les robots pédagogiques n'est pas abordée.

Robotique pédagogique et résolution collaborative de problèmes

Introduite par Papert (1980) et ancrée dans le concept de constructionnisme, l'utilisation de la robotique pédagogique représente l'une des premières incursions du numérique dans le domaine éducatif. Depuis son introduction par Papert (1980) dans le contexte éducatif, les usages de la robotique pédagogique ont évolué, car ils étaient initialement axés sur le développement du raisonnement mathématique des élèves. La robotique pédagogique se définit comme la conception ou la programmation d'un robot éducatif dans le but d'atteindre des objectifs d'apprentissage spécifiques ou d'acquérir des compétences particulières (Kamga, 2019). Les robots éducatifs, prenant diverses formes telles que des machines industrielles, des représentations humaines ou animales (Atman Uslu et al., 2022), sont de plus en plus intégrés dans les environnements scolaires. Les tâches de robotique pédagogique offrent la possibilité de mobiliser des concepts issus de plusieurs disciplines, notamment les mathématiques, les sciences, la technologie et l'ingénierie (Atman Uslu et al., 2022; Leroy & Romero, 2022).

Ces tâches sont aussi intégrées dans l'enseignement afin de favoriser le développement de la pensée informatique (Chen et al., 2017; Papadakis & Kalogiannakis, 2022), de stimuler la créativité (Leroy & Romero, 2022), et d'encourager la résolution collaborative de problèmes chez les élèves (Kamga et al., 2017; Socratous & Ioannou, 2022; Taylor & Baek, 2018). Les recherches ont souligné la contribution positive de la robotique pédagogique au développement de la résolution collaborative de problèmes (Atman Uslu et al., 2022). Néanmoins, ces études ne se penchent pas sur la phase de conception des tâches de robotique pédagogique utilisées dans les classes du primaire, et qui ont pour objectif de promouvoir le développement de la résolution collaborative chez les élèves. Notre étude a pour but de contribuer à la compréhension des facteurs qui peuvent influencer la conception des tâches de robotique pédagogique destinées à la résolution collaborative de problèmes par les élèves.

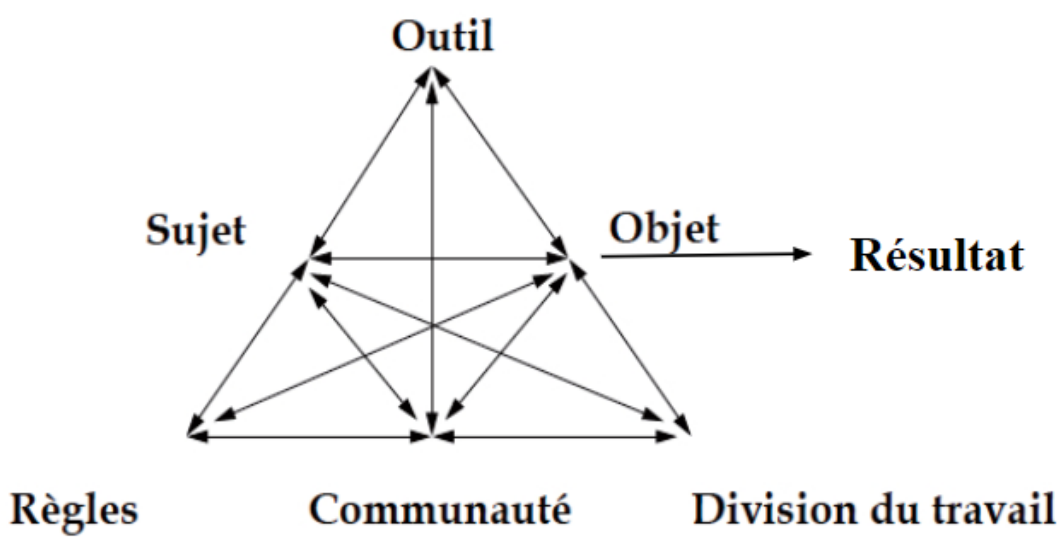
Théorie de l'activité

Le cadre théorique de cette recherche repose sur la théorie de l'activité. Sachant qu'une activité de conception de la tâche pourrait tenir compte de la personne qui conçoit, du contexte culturel et social dans lequel elle va se réaliser et potentiellement de plusieurs autres dimensions, la théorie de l'activité est pertinente pour cette recherche. Cette théorie a été développée dans les travaux d'Engeström et utilisée par plusieurs études en éducation (Engeström, 1999; Engeström & Pyörälä, 2021; Sannino, 2015). De manière générale, cette théorie offre une perspective éclairante sur l'activité humaine, et plus spécifiquement sur notre étude portant sur la conception des tâches de robotique pédagogique. Elle la considère comme ancrée dans un contexte socio-culturel, caractérisé et explicable par un système d'activité (DeVane et Squire, 2012; Engeström & Pyörälä, 2021). Ce système d'activité se compose de sept éléments fondamentaux : le sujet, les outils, l'objet, les règles, la division du travail, la communauté et le résultat.

Le sujet représente une personne ou une collectivité engagée dans l'activité, tandis que l'objet en est l'élément déterminant et orientant, permettant de distinguer une activité d'une autre. Les outils, également appelés artefacts, agissent en tant que médiateurs de l'activité et sont utilisés par le sujet. La communauté désigne l'ensemble des individus impliqués dans l'activité, entre lesquels le travail est réparti. La division du travail offre des indications sur le rôle de chaque membre de la communauté et sur la structure de celle-ci. Le résultat représente l'état désiré de l'objet de l'activité lorsqu'il est transformé par cette dernière. La figure 1 ci-dessous illustre le système d'activité (Engeström, 1987).

Figure 1

Système d'activité



Note. Engeström, 1987.

Ce système d'activité permet une compréhension multidimensionnelle de l'activité en examinant les perspectives du sujet, des outils, de l'objet, de la communauté, des règles et de la division du travail. Cette représentation triangulaire englobe à la fois la médiation individuelle par les outils et les éléments associés à la médiation socio-culturelle, à savoir les règles et la division du travail au sein de la communauté participant à l'activité (Engeström, 1987).

Dans le cadre de la présente recherche, le système d'activité sera mobilisé pour explorer les différentes dimensions mentionnées afin d'identifier les facteurs impliqués dans la conception des tâches de robotique pédagogique permettant le développement de la résolution collaborative de problèmes chez les élèves du primaire.

Questions de recherche

Cette étude est articulée autour de quatre questions de recherche spécifiques (QR), qui se structurent comme suit :

1. Quelles sont les caractéristiques individuelles des concepteurs qui sont susceptibles d'influencer la conception d'une tâche de robotique pédagogique visant le développement de la résolution collaborative de problèmes chez les élèves de l'enseignement primaire (QR1)?
2. Quels sont les outils qui peuvent influencer la conception d'une tâche de robotique pédagogique visant le développement de la résolution collaborative de problèmes par des élèves de l'enseignement primaire (QR2)?
3. Quelles sont les règles qui peuvent influencer la conception d'une tâche de robotique pédagogique visant le développement de la résolution collaborative de problèmes pour des élèves de l'enseignement primaire (QR3)?
4. Quelles sont les caractéristiques propres aux élèves qui peuvent influencer la conception d'une tâche de robotique pédagogique visant le développement de la résolution collaborative de problèmes par des élèves de l'enseignement primaire (QR4)?

Méthodologie de recherche

Participants

Les participants engagés dans cette étude se composent d'enseignants ainsi que de conseillers pédagogiques exerçant dans le domaine de l'enseignement primaire. L'échantillonnage a été déterminé par une condition préalable unique : chaque participant devait avoir préalablement modifié ou conçu une tâche de robotique pédagogique visant à favoriser le développement de la résolution collaborative de problèmes chez les élèves du primaire. Cette condition implique que les participants possèdent une expertise techno-pédagogique spécifique en ce qui concerne l'intégration de la robotique pédagogique dans leur pratique éducative.

Un total de 25 participants ont pris part à notre enquête, dont 8 enseignants et 17 conseillers pédagogiques. Le tableau 1 présente les caractéristiques des participants.

Tableau 1

Caractéristiques des participants

Caractéristiques des participants		Effectif	
Niveau de maîtrise des habiletés technologique d'intégration de la robotique pédagogique	Débutant	5	25
	Intermédiaire	6	
	Avancé	7	

Caractéristiques des participants		Effectif	
	Pas de réponse	7	
Nombre d'années d'expérience en conception ou modification des activités de robotique pédagogique	De 0 à 3ans	7	25
	De 4 à 7 ans	6	
	8 ans et plus	12	
	Pas de réponse	0	

Processus de collecte de données

La collecte de données s'est effectuée au moyen d'un questionnaire élaboré par l'équipe de recherche, complété par deux séances d'entrevue de groupe. Ce questionnaire, majoritairement constitué de questions ouvertes, comportait une section relative à l'expérience des participants dans le domaine de l'enseignement et de la conception des tâches de robotique pédagogique. D'autres sections du questionnaire étaient structurées conformément aux axes du système d'activité (sujet, outils, objet de l'activité, division du travail, communauté et règles). Par exemple, il y avait des questions qui demandaient aux participants de décrire les caractéristiques des robots, des élèves, de la salle de classe, de la communauté, qui étaient susceptibles d'influencer leur conception des tâches de robotique pédagogique. L'équipe de recherche estimait que le temps nécessaire pour y répondre était d'environ 30 minutes. Les participants avaient accès au questionnaire *via* la plateforme LimeSurvey. Parmi les 17 conseillers pédagogiques, 9 ont répondu à l'intégralité des questions posées, tandis que parmi les 8 enseignants, seuls 2 l'ont fait.

À l'issue de la phase du questionnaire, deux enseignantes et trois conseillères pédagogiques ont consenti à poursuivre leur participation au projet en s'engageant dans une série de deux entretiens de groupe. Les résultats de l'analyse des réponses au questionnaire ont été exploités et présentés aux participants afin de diriger les discussions lors de la première séance d'entretien de groupe. Quant à la seconde séance d'entretien de groupe, elle a été orientée par les résultats issus de l'analyse des transcriptions vidéo de la première séance.

Méthodologie d'analyse de données

La méthodologie d'analyse de données adoptée dans cette étude repose sur l'analyse de contenu, conformément aux principes énoncés par Barma (2008) et L'Écuyer (1990). Bien que les grandes catégories aient été préalablement déterminées en tant que pôles du système d'activité, les éléments constitutifs de ces catégories ont été obtenus par une analyse émergente. Cette dernière a consisté en l'organisation des éléments caractérisant chaque catégorie, réalisée par un membre expérimenté de l'équipe de recherche (C1).

Dans un second temps, un autre membre de l'équipe (C2) a été chargé de confirmer ou d'infirmer les résultats obtenus lors de la première analyse. Ceci a conduit à une deuxième version des résultats. Une réunion entre ces deux membres de l'équipe (C1 & C2) et un troisième membre plus expérimenté (C3) a permis d'obtenir la troisième version des résultats. La quatrième version des résultats a été établie au cours d'une ultime réunion impliquant C3 et trois autres membres de l'équipe (C4, C5, & C6). Cette quatrième version a fait l'objet d'une confrontation auprès des participants lors de la première séance d'entretien de groupe. L'analyse des données issues de la transcription de cette première séance d'entretien de groupe a conduit à l'obtention d'une cinquième version des systèmes d'activité. Cette cinquième version a été soumise aux mêmes participants lors de la deuxième séance d'entretien de groupe. L'analyse des transcriptions de la deuxième séance d'entretien de groupe a permis d'obtenir la sixième et dernière version des résultats. C'est cette dernière version des résultats qui est présentée dans cet article.

Résultats

Nous présentons les résultats conformément aux questions de recherche spécifiques énoncées dans la section prévue à cet effet.

Résultats 1 : caractéristiques individuelles des concepteurs

Nous débutons en réitérant la question de recherche QR1 : « Quelles sont les "caractéristiques individuelles des concepteurs" susceptibles d'influencer la conception d'une tâche de robotique pédagogique visant le développement de la résolution collaborative de problèmes chez les élèves de l'enseignement primaire (QR1)? »

Les résultats à cette question indiquent deux caractéristiques individuelles susceptibles d'exercer une influence sur la conception d'une tâche de robotique pédagogique visant le développement de la résolution collaborative de problèmes chez les élèves du primaire : 1) habileté à créer les tâches et 2) niveaux de connaissances en robotique (habiletés technologiques en robotique pédagogique).

Habiletés à créer les tâches

Cette caractéristique a été exclusivement relevée par les enseignants. En effet, d'après leur perspective, leur compétence à concevoir des tâches influence la manière dont ils créent celles liées à la robotique pédagogique. Selon leur témoignage, « *cette aptitude s'accroît avec les années et joue un rôle crucial dans le degré d'ouverture des tâches élaborées* ». Cette observation peut s'expliquer par le fait que plusieurs enseignants, au début de leur carrière ou lors de l'intégration initiale d'un nouvel outil pédagogique, optent pour l'utilisation de tâches déjà existantes.

Niveau de connaissances en robotique (habileté technologique en robotique pédagogique)

Les conseillers pédagogiques ont mis en exergue l'importance de leur niveau de connaissances spécifiques à la robotique. En d'autres termes, leurs compétences technologiques dans le domaine de la robotique pédagogique guideront le processus de conception des tâches visant à développer la résolution collaborative de problèmes chez les élèves du primaire. Selon les conseillers pédagogiques, leur niveau de connaissances du robot leur confère la capacité de concevoir des tâches plus variées, voire nécessitant des programmes informatiques plus complexes, comme en témoigne l'extrait suivant : « […] *le niveau de maîtrise permet de créer des tâches plus variées* ».

Résultats 2 : artefacts ou outils qui peuvent influencer la conception d'une tâche de robotique pédagogique

La seconde question spécifique de recherche (QR2) porte sur les « artefacts » qui peuvent influencer la conception d'une tâche de robotique pédagogique visant le développement de la résolution collaborative de problèmes chez les élèves du primaire. Les résultats de l'étude mettent en lumière cinq artefacts qui peuvent influencer la conception de ces tâches : le curriculum scolaire, le robot pédagogique, l'espace physique de la classe, le logiciel de programmation, ainsi que la pédagogie prévue par le concepteur de la tâche.

Le curriculum scolaire

La conception d'une tâche de robotique pédagogique visant à favoriser le développement de la résolution collaborative de problèmes au sein d'un contexte de classe requiert l'intégration des éléments du curriculum scolaire. En effet, ces éléments offrent une orientation précieuse au concepteur de la tâche en identifiant les notions disciplinaires à mobiliser par les élèves, ainsi que le niveau de difficulté qu'ils peuvent rencontrer. De plus, le curriculum permet d'assurer que la tâche proposée est en cohérence avec les attentes scolaires. L'extrait du verbatim de la deuxième séance d'entretien de groupes le souligne :

> *Et on juge que plus l'activité est bien planifiée, plus on a anticipé les différents obstacles, plus on va être capable de bien répondre à notre intention pédagogique, car on a vraiment ciblé quelque chose de précis. Donc au lieu d'aller essayer d'intégrer tout le multidisciplinaire* […].

Le robot pédagogique

Les enseignants et les conseillers pédagogiques ont mis en exergue que le choix du robot pédagogique à utiliser dans une tâche de robotique exerce une influence sur la conception de ladite tâche. Lors du processus de conception, ils veillent à ce que le robot envisagé soit disponible au sein des écoles ou qu'il présente un coût raisonnable. Outre le prix et la disponibilité du robot à intégrer dans la tâche à concevoir, ils tiennent compte de la facilité d'utilisation du robot, ainsi que de ses caractéristiques physiques et technologiques. Ces dernières englobent des aspects tels que la taille et la robustesse des composants du robot, l'autonomie et l'accessibilité de la batterie, la solidité et les possibilités d'utilisation offertes par le robot. Les deux extraits ci-dessous du verbatim de la première séance d'entretien de groupe le soulignent.

> *Je pense que ça ressort en pensant à ce qu'il faut que je connaisse quelles sont les caractéristiques du robot pour pouvoir me positionner avec mon intention pédagogique* […].
>
> […] *bien quand on ne sait pas ce que le robot est en mesure de faire, c'est extrêmement difficile d'aller concevoir des problèmes qui vont aller chercher différentes options* […].

L'espace physique

Les tâches de robotique pédagogique visant le développement de la compétence de résolution collaborative de problèmes des élèves du primaire qui sont conçues pour être réalisées en classe dépendent de l'espace physique disponible. Les participants à cette recherche mettent en exergue la relation entre la taille du robot, la tâche conçue et l'espace physique disponible en classe pour la réalisation de la tâche. Cet extrait de la première séance de l'entrevue en témoigne :

> *Puis, j'ajouterai également l'environnement physique. Est-ce que notre classe est assez spacieuse pour qu'on puisse mettre en place des activités? Des fois on a une toute petite classe, beaucoup d'élèves et juste pas possible. Alors ça, c'est quelque chose que j'ajouterai pour les enseignants.*

En fait, pour pallier la limite de l'espace physique disponible dans la salle de classe, les participants soulignent la possibilité de considérer le corridor et les gymnases de l'école dans la conception de la tâche ou alors d'avoir recours à des robots de petite taille. Ce qui peut influencer la tâche de robotique pédagogique à concevoir.

Le logiciel de programmation

Le logiciel de programmation qui sera utilisé pour donner des instructions au robot joue un rôle important lors de la conception des tâches de robotique pédagogique. Le langage de programmation du logiciel (environnement de programmation) peut permettre de complexifier la tâche de robotique pédagogique. La langue utilisée par le logiciel de programmation est considérée par les participants comme étant une caractéristique du logiciel qui influence la conception de la tâche. Par exemple, dans un contexte francophone, l'utilisation d'un logiciel de programmation de langue anglaise augmenterait la complexité de la tâche pour les élèves. En plus de toutes ces caractéristiques du logiciel de programmation, les participants ont souligné les aspects éthiques relatifs au logiciel de programmation du robot. Ce dernier élément est pertinent pour les concepteurs, car la tâche proposée doit tenir compte de la protection des données des élèves telles que les adresses courriel, noms et âges. L'extrait de la première séance des entrevues de groupe souligne ces aspects éthiques.

> *Concernant les enseignants, je suis vraiment d'accord avec ça.* […] *on a vraiment été sensibilisé également aux enjeux éthiques, à la protection des données des élèves.* […] *Donc je pense que c'est un élément important à ajouter; enjeux éthiques des logiciels de programmation.*

La pédagogie prévue du concepteur de la tâche de robotique pédagogique

La pédagogie prévue par les conseillers pédagogiques ou par les enseignants influence la conception de la tâche de robotique pédagogique visant le développement de la résolution collaborative de problèmes. Elle permet à l'enseignant de structurer la tâche de robotique pédagogique pour faciliter la résolution collaborative de problèmes par les élèves. En effet, dans l'exemple d'une pédagogie mettant en avant la différenciation pédagogique, les participants soulignent qu'ils créent des tâches avec plusieurs niveaux de complexités croissantes. Dans le cas où la pédagogie intègre l'interdisciplinarité, la tâche créée mobilisera les notions de plusieurs disciplines comme en témoigne cet extrait de la première séance de l'entrevue : « *Puis je crois beaucoup à la pédagogie STEAM comme science, technologie,* *ingénierie, mathématiques. Je pense que ça nous permet d'aborder la résolution des problèmes en intégrant différentes matières*. »

Résultats 3 : Règles qui peuvent influencer la conception d'une tâche de robotique pédagogique

La troisième question spécifique de recherche porte sur « les règles » qui peuvent influencer la conception d'une tâche de robotique pédagogique visant le développement de la résolution collaborative de problèmes chez les élèves de l'enseignement primaire (QR3)?

L'analyse des données a révélé deux règles pouvant exercer une influence sur la conception des tâches de robotique pédagogique visant à développer la résolution collaborative de problèmes chez les élèves du primaire. Les enseignants et les conseillers pédagogiques ont tous deux souligné ces deux règles : le travail en équipe et la durée de l'activité.

Travail d'équipe

Lors de la conception des tâches de robotique pédagogique visant le développement de la résolution collaborative de problèmes chez les élèves du primaire, les enseignants et les conseillers pédagogiques établissent comme règle que la tâche doit être réalisée en équipe d'élèves. La structuration ou la modification des rôles des élèves dépendrait donc de la complexité des tâches. L'extrait suivant de la deuxième séance d'entrevue le démontre :

> *Lorsque je conçois une activité d'apprentissage, la formation de mes équipes va être drôlement importante.* […] *le fait de former les équipes avec des profils d'élèves qui sont homogènes, va favoriser beaucoup au niveau de la collaboration et le travail dans la zone proximale de développement* […].

Durée de l'activité

Le développement de la compétence de résolution collaborative de problèmes requiert du temps. Les enseignants et les conseillers pédagogiques reconnaissent l'importance de la durée allouée à la réalisation de la tâche en classe. En effet, la conception de la tâche de robotique pédagogique doit prendre en considération le temps nécessaire pour le rangement, la mise en place, et la gestion des outils robotiques, ainsi que celui accordé à sa réalisation effective. Il est important de considérer la durée de l'activité de robotique pédagogique à réaliser. L'extrait de la première séance d'entrevue le mentionne : « […] *donc lorsqu'on planifie l'activité, on devrait vraiment s'assurer d'avoir un temps de réserver à chacune des étapes. Donc, à l'étape de la préparation,* […] *un moment pour vivre l'activité, mais vraiment de se réserver une période de qualité* […] ».

Résultats 4 : caractéristiques propres aux élèves qui peuvent influencer la conception d'une tâche de robotique pédagogique

La quatrième question spécifique de recherche aborde les « caractéristiques propres aux élèves » qui peuvent influencer la conception d'une tâche de robotique pédagogique visant le développement de la résolution collaborative de problèmes des élèves de l'enseignement primaire (QR4)?

Les enseignants et les conseillers pédagogiques ont souligné que la conception des tâches de robotique pédagogique peut être influencée par deux caractéristiques propres aux élèves : la zone proximale de développement et l'intérêt des élèves.

Zone proximale de développement des élèves

Les conseillers pédagogiques et les enseignants ont souligné la zone proximale de développement des élèves comme étant importante pour cibler la complexité adéquate de la tâche à concevoir. La différence d'approche entre enseignants et conseillers pédagogiques réside dans la méthode d'identification de cette zone proximale de développement. Lors de la conception de l'activité, les conseillers pédagogiques se fondent sur leur expérience pour déterminer ce qui pourrait constituer la zone proximale de développement des élèves, sans cibler spécifiquement un groupe d'élèves dans un contexte bien défini. Par exemple, la tâche sera destinée aux élèves de troisième année du primaire en général plutôt qu'à ceux de troisième année d'une classe en particulier. À l'inverse, lorsqu'ils conçoivent la tâche, les enseignants tiennent compte de la zone proximale de développement des élèves auxquels ils enseignent. Ainsi, la tâche est davantage adaptée aux élèves spécifiques de la classe de l'enseignant. L'extrait suivant, tiré du verbatim de la séance 2, souligne l'importance de la zone proximale de développement des élèves lors de la conception des tâches de robotique pédagogique :

> *Donc par rapport à ces capacités, par rapport à son bagage. Je ne sais pas, à mon sens à moi, le fait ce qu'il va devoir apprendre nécessite la collaboration ou si c'est carrément là-dessus qu'on mise. Bien oui il faut en tenir compte de sa zone proximale de développement.*

Intérêt des élèves

Cette caractéristique est exclusivement mise en avant par les enseignants. Du fait de leur proximité et de leurs interactions fréquentes avec leurs élèves, les enseignants ont une connaissance approfondie des centres d'intérêt de ces derniers. En conséquence, ils sont en mesure de concevoir des tâches qui résonnent de manière significative avec leurs élèves. Comme le dit l'enseignante dans cet extrait de verbatim de la première séance d'entrevue, « *premièrement déjà quand on conçoit une tâche, on regarde aussi les intérêts,* […] *donc on y va avec les intérêts des élèves.* […] *Donc je dois mettre des éléments pour susciter leur intérêt.* » Le tableau 2 présente la synthèse des résultats.

Tableau 2

Synthèse des résultats

Questions de recherche	Résultats
Quelles sont les caractéristiques individuelles des concepteurs qui sont susceptibles d'influencer la conception d'une tâche de robotique pédagogique (QR1)?	• Habiletés à créer les tâches • Niveau de connaissances du robot (habileté technologique en robotique pédagogique)

Questions de recherche	Résultats
Quels sont les outils qui peuvent influencer la conception d'une tâche de robotique pédagogique (QR2)?	• Curriculum scolaire • Robot pédagogique • Espace physique de la classe • Logiciel de programmation • Pédagogie prévue par le concepteur
Quelles sont les règles qui peuvent influencer la conception d'une tâche de robotique pédagogique (QR3)?	• Travail en équipe • Durée de l'activité
Quelles sont les caractéristiques propres aux élèves qui peuvent influencer la conception d'une tâche de robotique pédagogique (QR4)?	• Zone proximale de développement • Intérêt des élèves

Discussion

Cette section est structurée autour des différentes questions de recherche abordées dans ce texte et interprète les résultats à la lumière de la théorie de l'activité (Engeström, 1987, 1999) et des études précédentes.

Caractéristiques individuelles des concepteurs

Selon la théorie de l'activité, les caractéristiques individuelles du sujet sont importantes dans la réalisation d'une activité (Engeström, 1987, 1999). Nos sujets dans cette étude sont les enseignants et les conseillers pédagogiques. Les résultats de recherche soulignent que les caractéristiques individuelles des enseignants susceptibles d'influencer la conception des tâches de robotique pédagogiques visant la résolution collaborative de problèmes par les élèves sont différentes de celles des conseillers pédagogiques. Dans le cas des enseignants, il faut considérer les habiletés à créer les tâches de robotique pédagogique, alors que dans celui des conseillers pédagogiques, ce sont les habiletés technologiques. La caractéristique identifiée chez les enseignants est en accord avec les études de Sullivan et al. (2015) dans le cadre des tâches de mathématiques. Quant à celle décelée chez les conseillers pédagogiques, elles sont une contribution de notre étude. L'aisance à créer les tâches demandées dans le cas des enseignants s'expliquerait par leurs années d'expérience en enseignement. Quant aux conseillers pédagogiques mobilisés dans cette étude, ils possèdent de nombreuses années d'expérience en enseignement, et la nature de leur rôle à l'école les positionne comme des experts en mobilisation pédagogique du numérique auprès des enseignants.

Pour une meilleure conception des tâches de robotique pédagogique visant la résolution collaborative de problèmes, il serait pertinent de mobiliser les enseignants et les conseillers pédagogiques pour faire la co-conception ou d'améliorer les habiletés des enseignants à créer des tâches de robotique pédagogique.

Artefacts qui peuvent influencer la conception d'une tâche

L'activité du sujet est médiatisée par les artefacts (Engeström & Pyörälä, 2021). Les résultats de cette étude présentent plusieurs artefacts dont certains sont directement liés au robot : les caractéristiques du robot pédagogique et son logiciel de programmation. Les autres artefacts identifiés sont propres à l'enseignement (la pédagogique mise en place et le curriculum scolaire) et à l'environnement physique de l'enseignant (espace physique de la classe). Les études de Sullivan et al. (2015) ont aussi souligné la pertinence de considérer les outils dans la conception des tâches. En fait, comme le mentionne l'étude de Sullivan et al. (2015), il n'est pas possible de séparer la conception de la tâche de la pédagogie de l'enseignant. Selon ces auteurs, la prise de décision concernant la pédagogie à implémenter constitue un élément central dans la conception de la tâche. En effet, en fonction de la pédagogie que le concepteur prévoit de mettre en œuvre, il va anticiper la réaction des élèves relative à la tâche. L'étude de Tissenbaum et al. (2012) mentionne la pertinence de considérer les caractéristiques de l'environnement de la classe. En fait, l'environnement de la classe peut encourager les interactions entre les élèves, notamment par l'organisation de l'espace et des outils pédagogiques tels que des tables, la présence d'écrans ou d'autres technologies visant à faciliter l'orchestration de l'activité. Les résultats de cette étude, en plus d'être en accord avec celles de Sullivan et al. (2015) et de Tissenbaum et al. (2012), soulignent qu'il n'est pas non plus possible de séparer la conception d'une tâche de robotique pédagogique du robot pédagogique et du curriculum scolaire, dans le cadre de la résolution collaborative de problèmes.

Règles qui peuvent influencer la conception d'une tâche

Les résultats de cette étude ont permis de définir les deux règles que sont le travail d'équipe et la durée de l'activité. Par définition, la résolution collaborative de problèmes implique que plusieurs personnes doivent travailler ensemble pour proposer des solutions (Hesse et al., 2015; OCDE, 2013; Zhang et al., 2022). Ainsi, les résultats de cette étude ont souligné la pertinence de considérer l'organisation de la classe en équipe. En particulier, il s'agit de déterminer le nombre d'équipes, la structuration de chacune d'elles et le rôle de chaque élève dans celles-ci, qui pourraient dépendre de la complexité de la tâche. Ces résultats corroborent ceux de l'étude menée par Hall (2014). Cette dernière met l'accent sur le fait que les rôles doivent être clairement définis pour offrir aux élèves la possibilité de permuter durant la réalisation de la tâche.

La durée prévue pour la réalisation de la tâche est un facteur pertinent pour permettre le développement de la résolution collaborative de problèmes par les élèves. Ainsi, lors de la conception de la tâche, en plus de considérer cette durée, il faudrait prévoir la durée de gestion et d'installation du matériel.

Caractéristiques propres aux élèves

Les résultats de cette étude soulignent que deux caractéristiques des élèves sont à considérer : leur zone proximale de développement et leur intérêt vis-à-vis de la tâche. Ces résultats sont en accord avec ceux des travaux de Watson et Ohtani (2015). Toutefois, il n'est pas aisé pour les enseignants d'évaluer la zone proximale de développement de chaque élève. Ceci est encore plus difficile pour les conseillers pédagogiques qui conçoivent des tâches qui ne sont pas destinées à des élèves en particulier.

Conclusion

L'objectif de cette étude était de définir les facteurs influençant la conception des tâches de robotique pédagogique visant le développement de la compétence de résolution collaborative de problèmes chez les élèves du primaire.

Cette étude a mis au jour plusieurs facteurs influençant la conception d'une tâche de robotique pédagogique, notamment les habiletés technologiques et pédagogiques du concepteur, les caractéristiques des robots et logiciels utilisés, la pédagogie prévue, ainsi que les spécificités des élèves ciblés par la tâche. Toute comme l'étude de Sullivan et al. (2015) qui a été réalisée dans le cadre de la conception des tâches de mathématique, notre étude souligne que la conception d'une tâche de robotique pédagogique visant la résolution collaborative de problèmes est multidimensionnelle. Les résultats de cette étude nous amènent à recommander une co-conception de tâche de robotique pédagogique impliquant personnes enseignantes et personnes conseillères pédagogiques pour améliorer la qualité des tâches qui visent à développer la résolution collaborative de problèmes chez les élèves du primaire. En fait, les personnes enseignantes possèdent une meilleure connaissance des spécificités de leurs élèves, de leurs besoins et des contraintes réelles en classe alors que les conseillères pédagogiques apportent une vision plus large des stratégies pédagogiques de mobilisation des robots en classe.

La principale limite de cette étude est le nombre limité des participants et dans le fait qu'elle repose sur les pratiques déclarées par ces derniers. Toutefois, cette étude ouvre de nouvelles perspectives de recherche en suggérant de mobiliser des approches telles que l'observation directe des participants pendant la conception des tâches de robotique pédagogique. Il serait également pertinent d'explorer l'effet de la co-conception des tâches par des binômes personne enseignante/personne conseillère pédagogique sur la qualité et l'efficacité de la résolution collaborative de problèmes.

Références

Atman Uslu, N., Yavuz, G. Ö., & Koçak Usluel, Y. (2022). A systematic review study on educational robotics and robots. *Interactive Learning Environments*, 1–25. https://doi.org/10.1080/10494820.2021.2023890

Avry, S., Chanel, G., Betrancourt, M., & Molinari, G. (2018). Effet des antécédents émotionnels de contrôle et de valeur sur la résolution de problème dans un jeu vidéo collaboratif. *Revue des sciences et techniques de l'information et de la communication pour l'éducation et la formation, 25*(1). https://doi.org/10.23709/STICEF.25.1.3

Barma, S. (2008). Un contexte de renouvellement de pratiques en éducation aux sciences et aux technologies : une étude de cas réalisée sous l'angle de la théorie de l'activité [thèse]. Université Laval. http://hdl.handle.net/20.500.11794/20215

Bergner, Y., Andrews, J. J., Zhu, M., & Gonzales, J. E. (2016). Agent-based modeling of collaborative problem solving : Agent-based modeling of collaborative problem solving. *ETS Research Report Series, 2016*(2), 1–14. https://doi.org/10.1002/ets2.12113

Care, E., Griffin, P., Scoular, C., Awwal, N., & Zoanetti, N. (2015). Collaborative problem solving tasks. Dans P. Griffin et E. Care (dir.), *Assessment and teaching of 21st century skills* (pp. 85–104). Springer Netherlands. https://doi.org/10.1007/978-94-017-9395-7_4

Cevikbas, M., & Kaiser, G. (2021). A systematic review on task design in dynamic and interactive mathematics learning environments (DIMLEs). *Mathematics, 9*(4), 399. https://doi.org/10.3390/math9040399

Chen, G., Shen, J., Barth-Cohen, L., Jiang, S., Huang, X., & Eltoukhy, M. (2017). Assessing elementary students' computational thinking in everyday reasoning and robotics programming. *Computers & Education, 109*, 162–175. https://doi.org/10.1016/j.compedu.2017.03.001

De Hei, M. S. A., Sjoer, E., Admiraal, W., & Strijbos, J.-W. (2016). Teacher educators' design and implementation of group learning activities. *Educational Studies, 42*(4), 394–409. https://doi.org/10.1080/03055698.2016.1206461

DeVane, B., & Squire, K. D. (2012). Activity theory in the learning technologies. Dans *Theoretical foundations of learning environments* (2e éd., pp. 242–267). Routledge. https://www.taylorfrancis.com/chapters/edit/10.4324/9780203813799-12/activity-theory-learning-technologies-benjamin-devane-kurt-squire

Dindar, M., Järvelä, S., Nguyen, A., Haataja, E., & Çini, A. (2022). Detecting shared physiological arousal events in collaborative problem solving. *Contemporary Educational Psychology, 69*, 102050. https://doi.org/10.1016/j.cedpsych.2022.102050

Engeström, Y. (1987). Learning by expanding: An activity-theoretical approach to developmental research. https://lchc.ucsd.edu/mca/Paper/Engestrom/Learning-by-Expanding.pdf

Engeström, Y. (1999). Activity theory and individual and social transformation. Dans Y. Engeström, R. Miettinen et R.-L. Punamäki-Gitai (dir.), *Perspectives on activity theory* (pp. 19–38). Cambridge University Press.

Engeström, Y., & Pyörälä, E. (2021). Using activity theory to transform medical work and learning. *Medical Teacher, 43*(1), 7–13. https://doi.org/10.1080/0142159X.2020.1795105

Graesser, A., Fiore, S. M., Greiff, S., Andrews-Todd, J., Foltz, P. W., & Hesse, F. W. (2018). Advancing the science of collaborative problem solving. *Psychological Science in the Public Interest, 19*(2), 59–92. https://doi.org/10.1177/1529100618808244

Graesser, A., Kuo, B.-C., & Liao, C.-H. (2017). Complex problem solving in assessments of collaborative problem solving. *Journal of Intelligence, 5*(2), 10. https://doi.org/10.3390/jintelligence5020010

Hall, B. M. (2014). Designing collaborative activities to promote understanding and problem-solving. *International Journal of e-Collaboration, 10*(2), 55–71.

Hesse, F., Care, E., Buder, J., Sassenberg, K., & Griffin, P. (2015). A framework for teachable collaborative problem solving skills. Dans P. Griffin et E. Care (dir.), *Assessment and teaching of 21st century skills* (pp. 37–56). Springer Netherlands. https://doi.org/10.1007/978-94-017-9395-7_2

Kamga, R. (2019). Analyse de la compétence de résolution collaborative de problèmes des futur(e)s enseignant(e)s de l'enseignement primaire. Université Laval. https://corpus.ulaval.ca/jspui/handle/20.500.11794/36794

Kamga, R., Romero, M., Komis, V., & Mirsili, A. (2017). Design requirements for educational robotics activities for sustaining collaborative problem solving. Dans D. Alimisis, M. Moro et E. Menegatti (dir.), *Educational robotics in the makers era* (vol. 560, pp. 225–228). Springer International Publishing. https://doi.org/10.1007/978-3-319-55553-9_18

Kolfschoten, G., French, S., & Brazier, F. (2014). A discussion of the cognitive load in collaborative problem-solving: The decision-making phase. *EURO Journal on Decision Processes, 2*(3–4), 257–280. https://doi.org/10.1007/s40070-014-0034-9

L'Écuyer, R. (1990). Méthodologie de l'analyse développementale de contenu. Méthode GPS et concept de soi. Presses de l'Université du Québec. http://www.deslibris.ca/ID/422680

Leroy, A., & Romero, M. (2022). Creative intention and persistence in educational robotic. *Educational Technology Research and Development*, 70. https://doi.org/10.1007/s11423-022-10128-6

Nieminen, J. H., Chan, M. C. E., & Clarke, D. (2022). What affordances do open-ended real-life tasks offer for sharing student agency in collaborative problem-solving? *Educational Studies in Mathematics, 109*(1), 115–136. https://doi.org/10.1007/s10649-021-10074-9

OCDE. (2013). Pisa 2015: draft collaborative problem solving framework. Organization for Economic Cooperation & Development. https://www.oecd.org/pisa/pisaproducts/Draft%20PISA%202015%20Collaborative%20Problem%20Solving%20Framework%20.pdf

Oliver, M., & Higgins, S. (2023). Exploring task design to promote discipline-specific reasoning in primary English. *Thinking Skills and Creativity, 47*, 101230. https://doi.org/10.1016/j.tsc.2022.101230

Papadakis, S., & Kalogiannakis, M. (2022). Learning computational thinking development in young children with bee-bot educational robotics. Dans I. R. Management Association (dir.), *Research anthology on computational thinking, programming, and robotics in the classroom* (pp. 926–947). IGI Global. https://doi.org/10.4018/978-1-6684-2411-7.ch040

Papert, S. (1980). *Turtle geometry: A mathematics made for learning. Dans Mindstorms. Children, computers and powerful ideas* (pp. 55–94). Basic Books. http://worrydream.com/refs/Papert%20-%20Mindstorms%201st%20ed.pdf

Rojas, M., Nussbaum, M., Chiuminatto, P., Guerrero, O., Greiff, S., Krieger, F., & Van Der Westhuizen, L. (2021). Assessing collaborative problem-solving skills among elementary school students. *Computers & Education, 175*, 104313. https://doi.org/10.1016/j.compedu.2021.104313

Romero, M., & DeBlois, L. (2022). Analyse du processus de construction de connaissances dans des activités de programmation à l'école. *Canadian Journal of Science, Mathematics and Technology Education, 22*(2), 405–421. https://doi.org/10.1007/s42330-022-00210-9

Sannino, A. (2015). The emergence of transformative agency and double stimulation: Activity-based studies in the Vygotskian tradition. *Learning, Culture and Social Interaction, 4*, 1–3. https://doi.org/10.1016/j.lcsi.2014.07.001

Siddiq, F., & Scherer, R. (2017). Revealing the processes of students' interaction with a novel collaborative problem solving task: An in-depth analysis of think-aloud protocols. *Computers in Human Behavior, 76*, 509–525. https://doi.org/10.1016/j.chb.2017.08.007

Socratous, C., & Ioannou, A. (2022). Evaluating the impact of the curriculum structure on group metacognition during collaborative problem-solving using educational robotics. *TechTrends, 66*. https://doi.org/10.1007/s11528-022-00738-5

Song, Y. (2018). Improving primary students' collaborative problem solving competency in project-based science learning with productive failure instructional design in a seamless learning environment. *Educational Technology Research and Development, 66*(4), 979–1008. https://doi.org/10.1007/s11423-018-9600-3

Sullivan, P., Knott, L., & Yang, Y. (2015). The relationships between task design, anticipated pedagogies, and student learning. Task design in mathematics education. An ICMI Study 22, (pp. 8–114). Springer Nature.

Taylor, K., & Baek, Y. (2018). Collaborative robotics, more than just working in groups. *Journal of Educational Computing Research, 56*(7), 979–1004. https://doi.org/10.1177/0735633117731382

Tissenbaum, M., Lui, M., & Slotta, J. (2012). Co-designing collaborative smart classroom curriculum for secondary school science. *Journal of Universal Computer Science, 18*(3), 327–352.

Unal, E., & Cakir, H. (2021). The effect of technology-supported collaborative problem solving method on students' achievement and engagement. *Education and Information Technologies, 26*(4), 4127–4150. https://doi.org/10.1007/s10639-021-10463-w

Warneken, F., Steinwender, J., Hamann, K., & Tomasello, M. (2014). Young children's planning in a collaborative problem-solving task. *Cognitive Development, 31*, 48–58. https://doi.org/10.1016/j.cogdev.2014.02.003

Watson, A. & Ohtani, M. (2015). Task design in mathematics education. An ICMI Study 22. Springer Nature.

Yin, K. Y., Abdullah, A. G. K., & Alazidiyeen, N. J. (2011). Collaborative problem solving methods towards critical thinking. *International Education Studies, 4*(2), 58–62. https://doi.org/10.5539/ies.v4n2p58

Zhang, S., Gao, Q., Sun, M., Cai, Z., Li, H., Tang, Y., & Liu, Q. (2022). Understanding student teachers' collaborative problem solving: Insights from an epistemic network analysis (ENA). C*omputers & Education, 183*, 104485. https://doi.org/10.1016/j.compedu.2022.104485

Auteurs

Raoul Kamga est professeur au département de didactique de l'Université du Québec à Montréal, Canada. Il détient un doctorat en technologie éducative et est coresponsable du groupe de recherche sur le numérique en éducation (ENUMED). Ses domaines d'expertise incluent l'intelligence artificielle en éducation, la résolution collaborative de problèmes et la robotique pédagogique.
Courriel : kamga_kouamkam.raoul@uqam.ca

Sylvie Barma, professeure titulaire à l'Université Laval, Canada, se focalise sur les enseignants cherchant à innover dans leur pratique. Elle a dirigé le Centre de recherche sur la réussite scolaire et a été professeure invitée dans diverses universités mondiales. Elle a mené ses recherches en innovation éducative dans une perspective socioculturelle. *Courriel* : Sylvie.Barma@fse.ulaval.ca

Frédéric Fournier est professeur au département de didactique de l'Université du Québec à Montréal, Canada. Il a enseigné des cours sur le design d'activités numériques innovantes et sur l'apprentissage en laboratoire de sciences et technologie. Ses recherches portent sur la didactique des sciences, en s'appuyant notamment sur les laboratoires créatifs et la robotique pédagogique.
Courriel : fournier.frederic@uqam.ca

Pierre Lachance a été enseignant de sciences au secondaire. Il est désormais une personne-ressource au service national du Réseau Éducation Collaboration Innovation et Technologie, où il accompagne les enseignants de sciences dans l'intégration pédagogique du numérique, en leur proposant des formations en présence ou à distance. *Courriel* : pierre.lachance@recit.qc.ca

Joelle Bérubé-Daigneault, titulaire d'une maîtrise en éducation et d'un baccalauréat en études littéraires, enseigne le français au secondaire. Dynamique et créative, elle transmet sa passion de l'apprentissage à ses élèves. Curieuse de voyages et d'éducation, elle a enseigné en Afrique du Sud et explore l'usage du numérique en éducation. *Courriel* : berube-daigneault.joelle@uqam.ca

Sarah Cool-Charest a fait une maîtrise en éducation, option éducation préscolaire et enseignement primaire, à l'Université de Montréal, Canada. Auparavant, elle a suivi des études supérieures en études littéraires ainsi qu'en enseignement du français, langue première, au secondaire, à l'UQAM.
Courriel : sarah.cool.charest@umontreal.ca

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Adaptive Practicing Design to Facilitate Self-Regulated Learning

Conception d'une pratique adaptative pour faciliter l'apprentissage autorégulé

Hongxin Yan, *University of Eastern Finland*
Fuhua Lin, *Athabasca University, Canada*
Kinshuk, *University of North Texas, USA*

Abstract

Online higher education provides exceptional flexibility in learning but demands high self-regulated learning skills. The deficiency of self-regulated learning skills in many students highlights the need for support. This study introduces a confidence-based adaptive practicing system as an intelligent assessment and tutoring solution to enhance self-regulated learning in STEM disciplines. Unlike conventional intelligent tutoring systems that depend entirely on machine control, confidence-based adaptive practicing integrates learner confidence and control options into the AI-based adaptive mechanism to improve learning autonomy and model efficiency, establishing an AI-learner shared control approach. Based on Vygotsky's zone of proximal development (ZPD) concept, an innovative knowledge tracing framework and model called ZPD-KT was designed and implemented in the confidence-based adaptive practicing system. To evaluate the effectiveness of the ZPD-KT model, a simulation of confidence-based adaptive practicing was conducted. Findings showed that ZPD-KT significantly improves the accuracy of knowledge tracing compared to the standard Bayesian Knowledge Tracing model. Also, interviews with experts in the field underlined the potential of the confidence-based adaptive practicing system in facilitating self-regulated learning and the interpretability of the ZPD-KT model. This study also sheds light on a new way of keeping humans apprised of adaptive learning implementation.

Keywords: adaptive practicing, confidence-based assessment, knowledge tracing, question sequencing, self-regulated learning, wheel-spinning

Résumé

L'enseignement supérieur en ligne offre une flexibilité exceptionnelle dans l'apprentissage, mais il exige des compétences élevées en termes d'apprentissage autorégulé. Le manque de compétences d'apprentissage autorégulé chez de nombreuses personnes étudiantes met en évidence la nécessité du soutien. Cette étude présente un système de pratique adaptative basé sur la confiance en tant que solution intelligente d'évaluation et de tutorat pour améliorer l'apprentissage autorégulée dans les disciplines STIM. Contrairement aux systèmes de tutorat intelligents conventionnels qui dépendent entièrement du contrôle de la machine, la pratique adaptative basée sur la confiance intègre la confiance de la personne apprenante et les options de contrôle dans le mécanisme adaptatif basé sur l'intelligence artificielle (IA) pour améliorer l'autonomie d'apprentissage et l'efficacité du modèle, établissant ainsi une approche de contrôle partagé entre l'IA et la personne apprenante. Basés sur le concept de zone de développement proximal de Vygotsky (ZPD), un cadre et un modèle innovant de traçage des connaissances appelé ZPD-KT ont été conçus et mis en œuvre dans le système de pratique adaptative basé sur la confiance. Pour évaluer l'efficacité du modèle ZPD-KT, une simulation de pratique adaptative basée sur la confiance a été effectuée. Les résultats ont démontré que le modèle ZPD-KT a considérablement amélioré la précision de la traçabilité des connaissances par rapport au modèle traditionnel de traçage des connaissances bayésiennes. De plus, les entrevues avec des experts dans le domaine ont souligné le potentiel du système de pratique adaptative pour faciliter l'apprentissage autorégulé et l'interprétabilité du modèle ZPD-KT. Cette étude a également mis en lumière une nouvelle façon de tenir les humains informés de la mise en œuvre de l'apprentissage adaptatif.

Mots-clés : apprentissage autorégulé, évaluation basée sur la confiance, pratique adaptative, rouet, séquence de questions, traçage des connaissances

Introduction

Online education has become an important educational paradigm in the field of higher education. Self-paced online learning provides increased flexibility because learners can study anywhere, anytime, and at their own pace. Yet, self-paced online learning faces inherent challenges due to reduced synchronous interaction when learners study independently and asynchronously (Yan et al., 2020). Disciplines such as science, technology, engineering, and mathematics (STEM) demand high self-regulated learning (SRL) skills so that learners are able to self-monitor their learning progress, evaluate their knowledge proficiency, identify learning gaps, regulate learning efforts, and seek targeted support (Nuryadin et al., 2024; Schunk & DiBenedetto, 2020).

Previous research has identified a significant positive relationship between SRL strategies and online academic success (Broadbent & Poon, 2015; Nuryadin et al., 2024; Wong et al., 2019). Self-regulated learning skills become even more critical for self-paced online learning, which requires high levels of learner autonomy and has low levels of teacher presence (Lehmann et al., 2014). However, not every learner has adequate SRL skills. Learners are generally inaccurate when monitoring their learning without additional instruction (Viberg et al., 2020). In higher education, researchers have found that instructors tend to focus on course content, providing limited opportunities for scaffolding SRL (Broadbent, 2017; Jansen et al., 2019; Zimmerman, 2020). Hence, it is imperative to provide learners with a means to facilitate their SRL in self-paced online STEM higher education. Yan et al. (2022) argued that adaptive practicing could be an effective tool to meet this need. As a type of formative assessment, adaptive practicing selects exercise questions based on individuals' knowledge states. Hence, it can assess learners' knowledge levels, identify learning weaknesses, and provide instructive feedback and remedial materials for learning.

Adaptive practicing can use computed algorithms (Manouselis et al., 2011) to realize two core functions: knowledge tracing and question sequencing. Knowledge tracing estimates and tracks learners' knowledge proficiency based on their responses to questions. Question sequencing decides the optimal knowledge component and the exercise to practice with each time to obtain the maximum learning gain.

One limitation of previous knowledge tracing models is that they mainly rely on the answer correctness collected during the assessment (Clement et al., 2015; Pelánek, 2017). However, if certain question types such as multiple-choice are used for assessment, it is hard to discern learners who guess correctly from those who actually know the answer (Novacek, 2013). As Clement et al. (2015) pointed out, answer correctness alone may not tell whether an exercise is effective, but with certain side information, it could. Regarding side information, Holstein et al. (2020) stated that humans may have relevant information to which adaptive learning systems are likely blind. Thus, these researchers have posited that considering learners' subjective feelings of knowledge in adaptive learning systems can more efficiently determine whether their answers reflect actual knowledge levels. For example, Novacek (2013) suggested a confidence-based assessment in which learners select the answers they believe are correct and indicate their confidence in their selections.

Another limitation of previous adaptive learning systems is that instructional sequencing usually assumes exclusive machine control but seldom considers learner control. In the context of adaptive practicing, learners usually do not have any control over which knowledge component or question they should practice with next time. Learner control is related to the earlier conceptual development of self-directed learning in distance education, stressing learning autonomy and personal responsibility for the learning process (Sorgenfrei & Smolnik, 2016). According to self-determination theory (Deci et al., 1991), learner control can enhance learning motivation by strengthening the human need for autonomy—the desire to self-initiate, self-control one's behaviour, control activities, and freely pursue one's decisions. Research has demonstrated the importance of learners' perceived autonomy to their motivation and academic performance (Hsu et al., 2019; Luo et al., 2021; Sorgenfrei & Smolnik, 2016).

Thus, considering learner inputs on knowledge judgement and question sequencing in the adaptive practicing model could increase model effectiveness and promote learning autonomy and engagement. Despite these potential advantages, few studies have explored how these learner inputs are factored into the AI agent's decision-making. To the best of our knowledge, studies have not sufficiently investigated how learner control could be considered in an adaptive practicing model design. As noted by Doroudi et al. (2019) in a review paper, AI agents could consider learner judgements and control during decision-making, but such a form of shared control has not been investigated in the context of instructional sequencing because it is challenging to address the subjectivity of learner judgement and control. To fill this research gap, our study investigated how to incorporate learner confidence in the adaptive practicing mechanism to design an AI-learner shared control model. Through simulation, significant improvement was found in the effectiveness of such an AI-learner shared control model compared to the standard Bayesian Knowledge Tracing (BKT) model (Corbett & Anderson, 1994).

This paper begins by reviewing previous work related to human-AI collaboration approaches and confidence-based assessment. Then we discuss how we designed a confidence-based adaptive practicing system and a ZPD-based knowledge tracing framework and model which were built in response to the research gaps identified by our literature review. We then present the findings of the evaluation of our model which was conducted through a simulation exploring the effectiveness of the model. Finally, the advantages and limitations of the model design are discussed.

Related Work

First, we reviewed what has been done regarding human-AI collaboration approaches designed for adaptive learning. Then, past studies investigating how learners' confidence is incorporated into assessment were examined.

Human-AI Collaboration Approaches

Human-AI collaboration stresses that humans and AI are partners in achieving the overall goal, and each party contributes according to its strengths and weaknesses (Brusilovsky, 2024). The general ideas of learner control have been extensively explored in the educational field and have formed one of the foundations of SRL (Bjork et al., 2013). In the context of online learning system design, learner control refers to certain learning process features, such as control over the path, sequence, flow, and so forth (Sorgenfrei & Smolnik, 2016). Sorgenfrei and Smolnik's analysis demonstrated that learner control over variables such as time, pace, navigation, and design is associated with improved learning outcomes.

Some studies have considered how to keep humans in the loop of AI-based adaptive learning. Brusilovsky (2024) summarized four approaches of AI-learner shared control for adaptive content selection. One approach is through the editable learner model (Weber & Brusilovsky, 2001). In Weber and Brusilovsky's ELM-ART system, the AI determines the state of learner knowledge and displays it to the learner, while the learner has a chance to correct obvious errors. The second approach is called ranking-based human-AI collaboration (Rahdari et al., 2022), whereby AI does the work of careful selection and ranking, but the learner has the final say in selecting the most relevant content item. A third approach is adaptive navigation support (Brusilovsky, 2007) where AI works in the background to decide the best links to appropriate content, but AI advice is provided in a less direct form, and the final control is in learners' hands. The fourth approach is that learner control is enabled during the decision-making process. For example, the system can allow the user to choose one of the available content selection algorithms (Ekstrand, 2015) or let the learner control some parameters of the recommendation process (Papoušek & Pelánek, 2017).

These approaches show some possibilities of how AI-learner shared control can be realized in adaptive learning. However, as Brusilovsky (2024) pointed out, content selection in the first three approaches is mainly done by AI agents alone, while learners are only involved at the beginning for learner model adjustment or at the end for selecting content from what is recommended by AI agents. The fourth approach requires extensive knowledge of learners in computing algorithms and adds extraneous cognitive load for learning. The limitations of previous approaches call for a more straightforward and effective AI-learner shared control model for adaptive practicing.

Confidence-Based Assessment

Multiple-choice questions remain prevalent in traditional assessments, but their reliance on binary scoring (correct/incorrect) fails to distinguish between mastered knowledge and guesswork, a limitation widely acknowledged in current pedagogical research (Preheim et al., 2023). To address this, confidence-based assessment techniques combine the answer selection with learners' perceived certainty levels (e.g., *not sure*, *partly sure*, and *sure*), enabling a nuanced evaluation of knowledge mastery (Gardner-Medwin & Curtin, 2007; Remesal et al., 2023). For instance, Smrkolj et al. (2022) demonstrated that this approach improves the reliability of assessments by penalizing confidence errors and rewarding accurate self-awareness. Inspired by this confidence-based assessment technique, we proposed integrating learners' confidence in the adaptive practicing model to improve the knowledge tracing efficiency.

Our Approach to an AI-Learner Shared Control Model Design

To design an AI-learner shared control model, we first determined what learner inputs should be considered in the adaptive practicing model. We then describe the theories that supported our model design.

Learner Input

The idea of increasing interaction between humans and machine-learning algorithms is to make machine learning more accurate or to obtain the desired accuracy faster through learning with humans (Mosqueira-Rey et al., 2023). Inspired by confidence-based assessment techniques, we realized that answer responses combined with learners' perception of their knowledge levels (e.g., confidence or difficulty rating) could potentially make knowledge tracing more efficient. For example, if learners skip a question and indicate it is too easy, or if a learner answers a question correctly and indicates full confidence, this learner likely has mastered the knowledge. The integration of such learner inputs could be an algorithmic advantage compared to the traditional knowledge tracing models, such as the BKT model (Corbett & Anderson, 1994), which typically needs many questions to train the model because of the parameters of guessing and slipping (careless mistakes) considerations. Therefore, we included confidence rating and question skipping as learner inputs in the adaptive practicing model.

Confidence Rating

After learners selected an answer to a multiple-choice question, they could indicate their confidence level on a scale ranging from *no confidence* to *full confidence*, with intermediate levels of low, moderate, and high confidence.

Question Skipping

Our model gave learners the option to skip a question if they felt it was too easy or too hard. Learners' question-skipping choice could override the system's decision on question selection to avoid boredom or frustration. Also, time would be saved by skipping ineffective exercises. We argue that question-skipping is also based on learner confidence in the knowledge tested by the question.

Supporting Theories for the Model Design

The design of our adaptive practicing model was based on the following learning theories.

Knowledge Space Theory

Knowledge space theory (Doignon & Falmagne, 1999) is a theoretical framework which proposes that every knowledge domain can be represented in terms of a set of knowledge components (KCs). Knowledge states represent the subset of KCs a learner has mastered or learned. Each KC is assessed by a set of questions. The KCs in a knowledge domain usually are interrelated or have prerequisite relationships. Our study treated course learning outcomes as the KCs. So, the adaptive practicing model considered the prerequisite relationships among learning outcomes when selecting the optimal questions for practicing.

Zone of Proximal Development

The concept of zone of proximal development (ZPD) by Lev Vygotsky refers to a zone where a learner can complete tasks with assistance but not independently (Vygotsky, 1978). According to Vygotsky, concrete growth can only occur in the ZPD, and learning is most effective when timely support is provided. Traditional self-assessment usually contains a set of exercises without any adaptive mechanism. With such a one-size-fits-all assessment approach, some learners may feel under-challenged or bored, while others may feel over-challenged or frustrated. According to Vygotsky's theory, this problem stems from the fact that each learner has a different ZPD at any given time (Vainas et al., 2019). The adaptive practicing model in this study attempted to mitigate this problem by tracking learners' ZPD and keep them practicing in their ZPD. As a well-known and vastly researched concept in educational psychology, ZPD has laid the foundation for personalized learning, and some ZPD-based learning tools have been developed to sequence instructional content (Vainas et al., 2019).

Dynamic Difficulty Adjustment

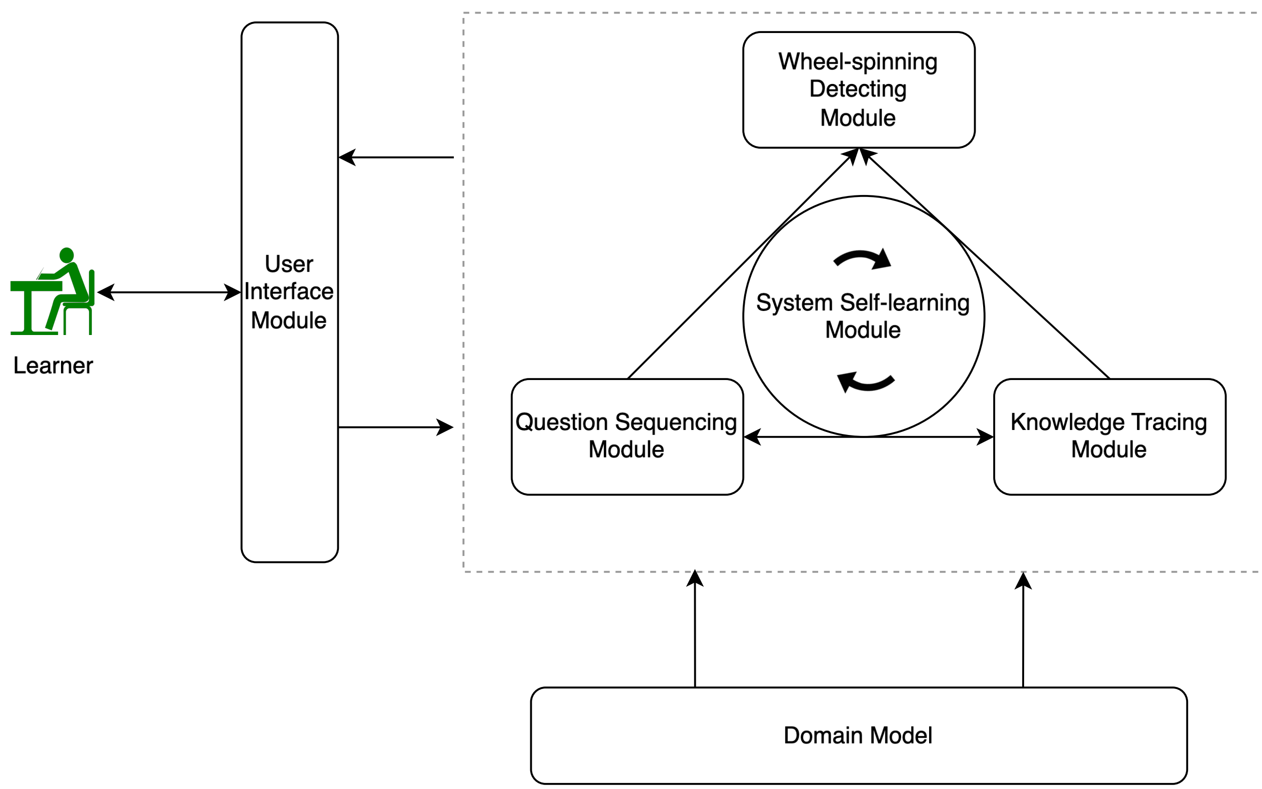
Dynamic difficulty adjustment is a technique often used in video games to automatically adjust the game's difficulty level in real time based on the player's ability (Zohaib, 2018). In the field of education, this technique can be borrowed to adjust the difficulty of learning materials based on learners' skill levels to keep them engaged. This technique can be instrumental in online environments where it is difficult to provide personalized feedback and support to individual learners. Inspired by this technique, adaptive practicing can be realized through different adaptive methods such as modifying the difficulty level of the exercises, changing the sequence of the questions, or adjusting the pace of the practice.

A New Adaptive Practicing System and Its Model Design

This study investigated a confidence-based adaptive practicing (CAP) system and a ZPD Knowledge Tracing (ZPD-KT) model design. Inspired by the Intelligent Tutoring System's four-component structure (Nkambou et al., 2010), a six-module architecture for CAP design was developed (Figure 1). The six modules included the user interface, domain model, knowledge tracing, question sequencing, wheel-spinning detection, and system self-learning.

Figure 1

The Architecture of the Confidence-Based Adaptive Practicing System

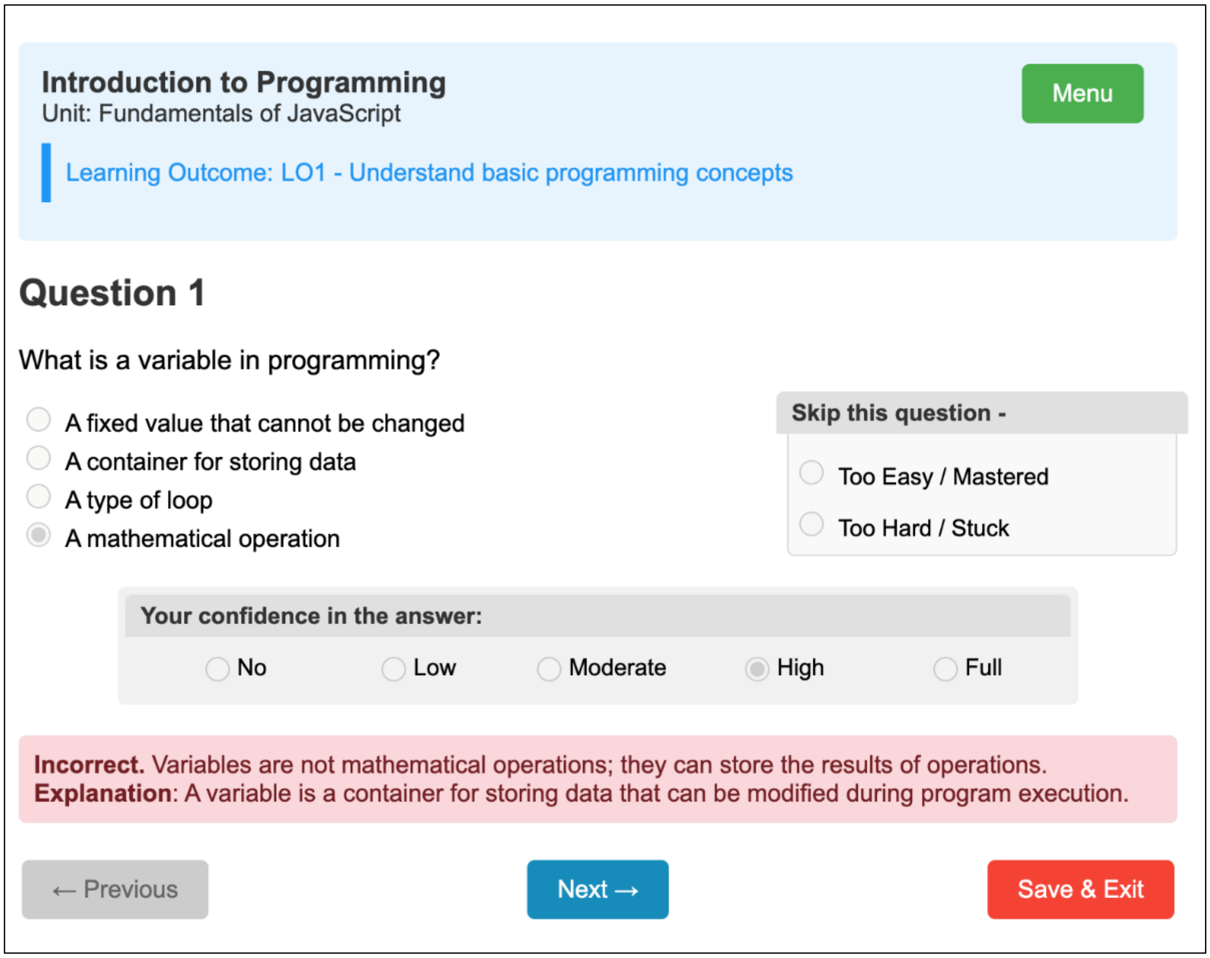


User Interface Module

The user interface of CAP consists of essential components such as question body, options, feedback, and buttons for navigation and responding (Figure 2). Unlike conventional practicing systems, the CAP interface includes two unique components: (a) a question skip option, along with answer options whereby if a question is too hard or too easy, a learner could choose to skip it, and (b) a learner confidence rating, which allows learners to select their confidence level in the answer. After selecting an answer, learners are asked to rate their confidence using a Likert scale (1 = *no confidence* to 5 = *full confidence*).

Figure 2

Example of the Learner Interface of the Confidence-Based Adaptive Practicing System



Domain Model

As illustrated in Figure 1, the CAP system was built on the domain model which describes four types of information: (a) the KCs covered by the practicing, (b) the knowledge learning paths from the initial state to the final state (Figure 3), (c) the dependencies among those KCs, and (d) the exercises (including question item, options, correct answer, and feedback) corresponding to each KC. In higher education, learning outcomes are generally the competencies that learners should master, typically expressed in Bloom's taxonomy. For the purposes of this study, learning outcomes were regarded as KCs.

Knowledge Tracing Module

The knowledge tracing module detects a learner's knowledge state and tracks their changes during practicing. Relative to the ZPD, four cognitive statuses on a KC were defined in this study:

- *mastered*: a KC has been learned (above the ZPD)

- *in-learning*: a KC is being learned (in the ZPD)
- *unlearnable*: beyond a learner's ability (below the ZPD)
- *wheel-spinning:* stuck or unproductive struggle

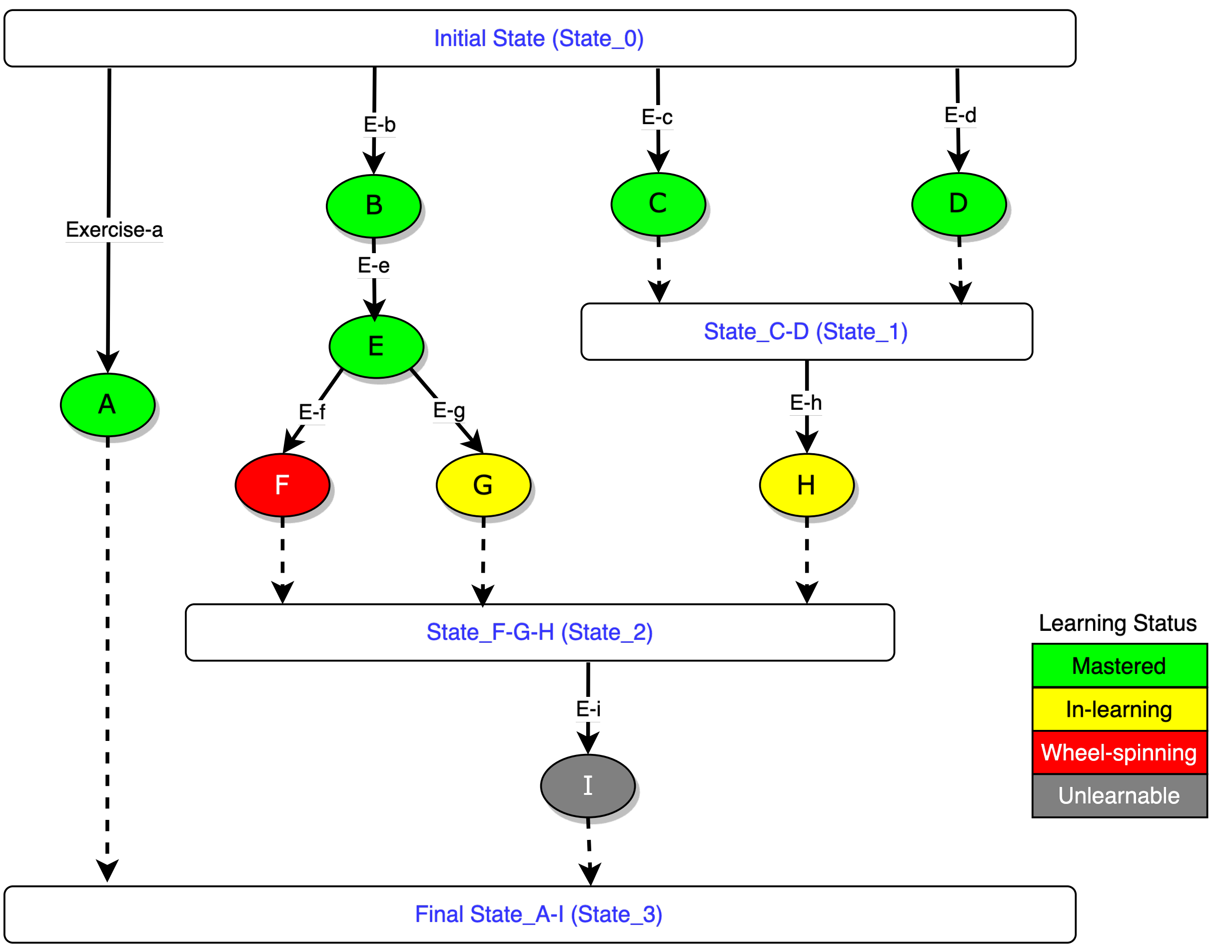
Wheel-spinning is a learning phenomenon analogic to a car stuck in snow or mud—the wheels will spin without getting anywhere despite devoting effort to moving (Beck & Gong, 2013).

Figure 3 shows one example of a learner's knowledge states at a given time during practice for learning a topic. There are nine learning outcomes (LOs) in this topic: A, B, C, D, E, F, G, H, and I, each mapping to an exercise set (i.e., exercises a, b, c, d, e, f, g, h, and i). Some prerequisite relationships exit. For example, LO-B is a prerequisite for LO-E, which is a prerequisite for LO-F and LO-G.

In Figure 3, the KCs in green (A, B, C, D, and E) are mastered; KCs in yellow (G and H) are in-learning; the KC in grey (I) is unlearnable; and the KC in red (F) indicates wheel-spinning.

Figure 3

An Example of a Learner's Knowledge States

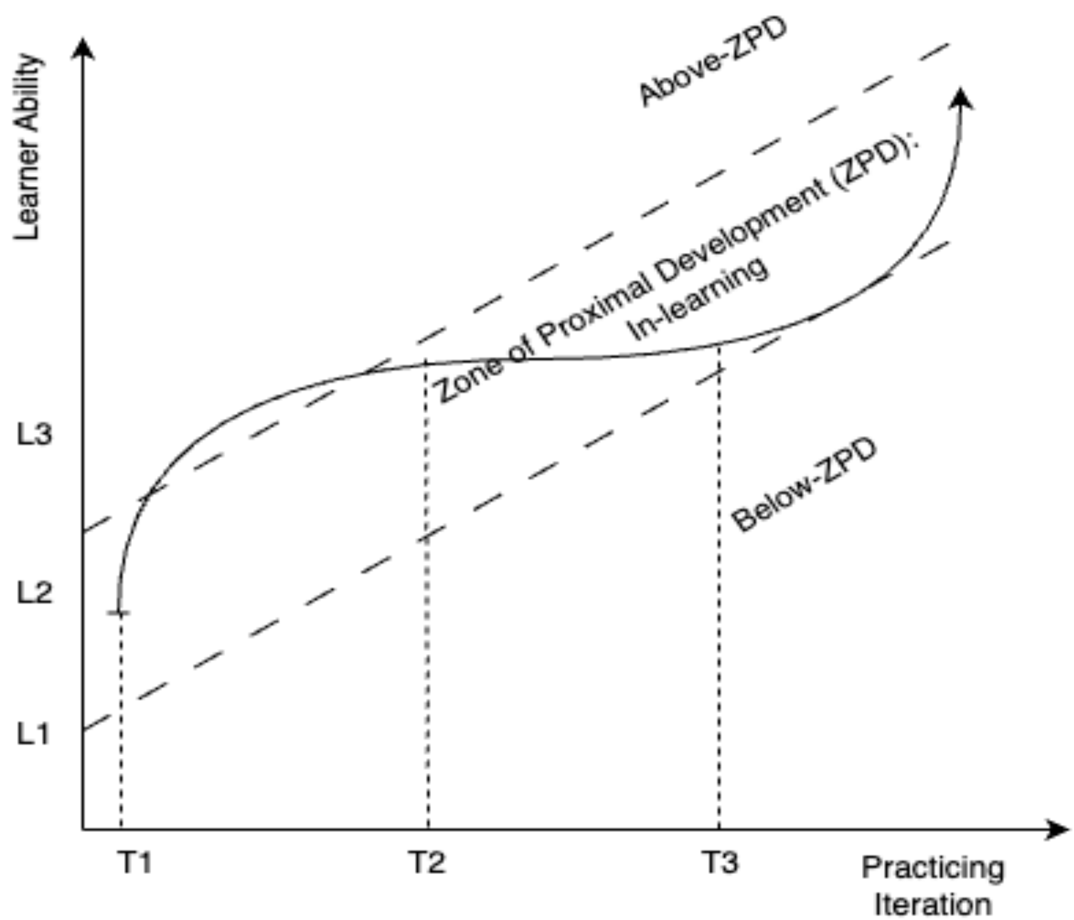


Note. Letters A through I in the figure indicate learning outcomes for this topic. Letters E-a through E-i indicate the sets of exercises that map to the respective learning outcomes.

Learners' ZPD usually move to higher levels as they learn or practice. Figure 4 shows an example of how a learner's ZPD moved from one level to the next, demonstrating an increase in ability. Since learning is a dynamic process, the knowledge tracing module needed to track learners' ZPD based on their responses in order to present optimal questions for maximum practice effectiveness. That is why we chose a ZPD-KT framework and model.

Figure 4

Example of a Learner's Changing Zones of Proximal Development as Determined by Practice Iteration



Note. L1 is Level-1; L2 is Level-2; L3 is Level-3; T1 is Time-1, T2 is Time-2; T3 is Time-3.

Zone of Proximal Development Knowledge Tracing Framework

To use the ZPD concept for knowledge tracing purposes, nine ZPD levels corresponding to learners' answer correctness and confidence rating were defined. These nine ZPD levels include: above, ceiling, upper, mid-upper, mid, mid-lower, lower, flooring, and below. Each ZPD level is associated with a range of mastery values. Table 1 depicts the mapping relationships between learner responses and the ZPD levels. For example, if the answer was correct and the confidence was rated high, the learner's

ZPD level would fall under ceiling and the mastery value would be in the high range [0.80–0.95]. It is important to note that the ZPD level determined by learners' responses and confidence rating comes with some subjectivity due to reliance on learners' reported perceptions rather than objective measures.

Table 1

Learner ZPD Categorized by Correct Answers, Confidence Rating, and Mastery

Zone	Answer correctness	Confidence rating	Mastery range	Midpoint mastery
Above ZPD[1]	True	Full	0.95–1.00	0.975
Ceiling ZPD	True	High	0.80–0.94	0.875
Upper ZPD	True	Moderate	0.65–0.79	0.725
Mid-upper ZPD	True	Low	0.55–0.64	0.600
Mid ZPD	True/False	No	0.45–0.54	0.500
Mid-lower ZPD	False	Low	0.35–0.44	0.400
Lower ZPD	False	Moderate	0.20–0.34	0.275
Floor ZPD	False	High	0.05–0.19	0.125
Below ZPD[2]	False	Full	0.00–0.04	0.025

Note. ZPD = zone of proximal development. [1]If a question was skipped because it was too easy or mastered, the question also fell into the category of above ZPD. [2]If a question was skipped because it was too hard or the learner got stuck, the question also fell into the category of below ZPD.

Zone of Proximal Development Knowledge Tracing Algorithm

Based on the ZPD-KT framework, a ZPD-based knowledge tracing algorithm was created. The algorithm first examines a learner's response to a question (answer correctness and confidence rating), and then determines the ZPD level (Table 1). The midpoint of the mastery range of that ZPD level is then used as the newly observed mastery value (denoted in Equation 1 as *masteryZPD*). Because of the subjectivity of the confidence rating, we decided it would be more reliable to consider the historical trend of the mastery values. Therefore, the current estimated mastery value is calculated as shown in Equation 1: the average of the previously predicted mastery value and the current observed mastery value. Then, since the practicing system provides learners with feedback or remedial materials, a learner's mastery value is predicted to increase by a learning rate (LR), as formulated in Equation 2.

$$\text{masteryEstimated}[t] = (\text{masteryPredicted}[t\text{-}1] + \text{masteryZPD}[t]) / 2 \quad (1)$$

$$\text{masteryPredicted}[t] = \text{masteryEstimated}[t] + (1 - \text{masteryEstimated}[t]) \times \text{LR} \quad (2)$$

The ZPD-KT model is more transparent and interpretable to educators than some machine learning-based knowledge tracing models (e.g., BKT). Therefore, there would be a higher likelihood of it being adopted in a real-world teaching context.

Wheel-Spinning Detecting Module

The wheel-spinning detecting module was designed to detect a learning situation where learners struggled unproductively with a KC. When feedback and remedial materials provided in the adaptive practicing could not help learners move forward, this module would alert the learners of wheel-spinning and suggest they ask for help from other sources, such as academic experts. Wheel-spinning happens when a learner keeps spending time on an unlearnable KC. Given that prerequisite relationships among KCs exist, a KC may be unlearnable because its prerequisite KCs have not yet been mastered. In such cases, the learner should be directed to the prerequisite KCs for practicing first. A learner is wheel-spinning on a KC if the following two conditions are met: (a) a KC is detected unlearnable; and, (b) all its prerequisite KCs have been mastered.

Question Sequencing Module

The question sequencing module provides individual learners with the optimal question sequence to obtain the maximum learning gain at each practice opportunity. The optimal question presented to a learner is based on the learner's knowledge state predicted in the knowledge tracing module. In the CAP system, question sequencing consists of two steps: (a) select the optimal KC from all KCs that are not mastered yet for practicing, and (b) select the optimal question from a question pool corresponding to the KC. The optimal KC selection is determined by three factors: (a) prerequisite relationships among KCs (the prerequisite KC should be practiced first); (b) the mastery level of each KC (the KC with a mastery level closer to upper ZPD should be practiced first in the CAP system); and (c) the Bloom's taxonomy level of each KC (the KC with lower level should be practiced first). Equation 3 formulates the optimal score calculation for KCs by summing the score of each factor with a certain weight, expressed in the equations as kcScore. After a KC is selected, a question is chosen from a question pool corresponding to the selected KC by checking their difficulties against the KC mastery level and their practice history (as shown in Equation 4). The weights were initially set based on experts' experience.

$$\text{kcScore} = \text{w1 x prerequisteScore} + \text{w2 x masteryLevelScore} + \text{w3 x BloomScore} \quad (3)$$

$$\text{questionScore} = \text{w4 x difficultyMatchScore} + \text{w5 x practiceHistoryScore} \quad (4)$$

System Self-Learning Module

Learning is a complex process. In the environment of adaptive practicing, there are many additional uncertainties. First, the learner confidence rating is somewhat subjective. For example, learners may be overconfident or underconfident in their knowledge level. Second, the prerequisite relationships among KCs could be hard or soft and sometimes challenging to quantify. In addition, the effectiveness of exercise questions for a particular KC can vary widely. Therefore, the cognitive status deduced by learners' responses reflects a likelihood rather than certainty. For example, if learners answer a question correctly and indicate full confidence, it is likely that learners have mastered the knowledge, but it is still possible that this is not the case. To avert the subjectivity of learner confidence and improve the accuracy of knowledge tracing in the CAP, a system self-learning module was designed. This module aimed to optimize the LR (as shown in Equation 2) by analyzing learning data continuously collected from the system. The expectation-maximization technique was used in the system self-learning module to find the maximum likelihood of the parameter, in this case, the LR.

Module Evaluation

It is crucial to evaluate the CAP system and the ZPD-KT model design for their effectiveness in tracing learners' knowledge, selecting optimal exercise questions, and detecting wheel-spinning. Two evaluation phases were conducted: (a) interviews with experts to gain insights into the strengths and weaknesses of the model design, and (b) simulation of the model to test its effectiveness.

Interview

In the first phase, feedback was gathered by interviewing four experts: three in the field of computing for education and one in physics. These experts work at an online university and teach self-paced courses in STEM disciplines. During the interview, we explained the purpose of this research project, demonstrated the CAP system, and explained the ZPD-KT model. All interviewees indicated they had already realized the SRL-related challenges in self-paced online education, and agreed that: (a) embedding such adaptive practicing activities in courses could be an effective solution to address this challenge for STEM disciplines; (b) the ZPD-based knowledge tracing framework and algorithm are easy to understand and make sense; and (c) incorporating learner confidence and learner control could help improve learner engagement and learning autonomy. The experts also offered some suggestions for design improvement. For example, some wondered whether the large language model AI technology could help instructors create exercise questions to reduce their workload, whether different question difficulty levels should be considered, whether the learning rates should be personalized for individual learners, and so forth. Based on this feedback, the model design was refined.

Simulation

In the second phase, a simulation of the CAP system and the ZPD-KT model was conducted. Running a simulation allows for thorough testing of its functionality before implementation. Simulating various scenarios allows potential flaws and issues to be identified and addressed in the design stage. By testing the system with different data inputs and user behaviours, it is possible to optimize the algorithms to make the design more effective, accurate, and robust.

Simulation Setup

The simulation was created in JavaScript for a web application. We simulated a computer science course with five learning outcomes (KCs) at different Bloom's taxonomy levels (i.e., remember, understand, apply, analyze, evaluate, or create). Certain prerequisite relationships were set up for these learning outcomes. Each learning outcome mapped to a pool of exercise questions with different difficulty levels. A total of 8,000 learners were simulated. The main goal of the simulation was to find out how well the ZPD-KT predicted the mastery value at each practicing opportunity, or how much the prediction error would be. Therefore, these learners were randomly assigned an initial estimated mastery value for each learning outcome following a normal distribution. A learning rate was specified for predicting the new mastery value. Also, these learners were randomly assigned an initial actual mastery value for each learning outcome. A random value between 0.1 and 0.3 was drawn as the actual learning increment at each practice opportunity. The ZPD-KT model needed to track the changing knowledge levels of all learners who had different initial actual mastery values and learning increments. To do this, we also simulated the standard Bayesian Knowledge Tracing (stdBKT) model as the baseline for comparison.

Findings

First, the simulation helped refine the ZPD-based knowledge tracing algorithm. Also, it showed that the ZPD-KT model has significantly higher prediction accuracy than the stdBKT model.

Zone of Proximal Development Knowledge Tracing Algorithm Improvement

By experimenting through simulation, we discovered that the prediction accuracy could be improved significantly if the learning rate was adjusted for each practicing opportunity based on their mastery values (Equation 5).

$$\text{LR} = \text{baseLR x masteryZPD}[t] \text{ x } [1 + (\text{masteryZPD}[t] - \text{masteryPredicted}[t\text{-}1])] \tag{5}$$

By running the system self-learning module, we identified that the optimal base learning rate (baseLR) is 0.517.

Prediction Accuracy

The simulated practicing data for both ZPD-KT and stdBKT models were compared for prediction accuracy. Figure 5 shows each model's average prediction deviation for each learning outcome. Figure 6 shows an example of the knowledge tracing progression on a learning outcome for a student comparing the two models.

The average prediction deviation is calculated as shown in Equation 6:

$$\frac{\sum_{t=1}^{T}(P_t - A_t)}{T} \tag{6}$$

t = practice time

T = the total number of practices

P_t = the predicted mastery value at time t

A_t = the actual mastery value at time t

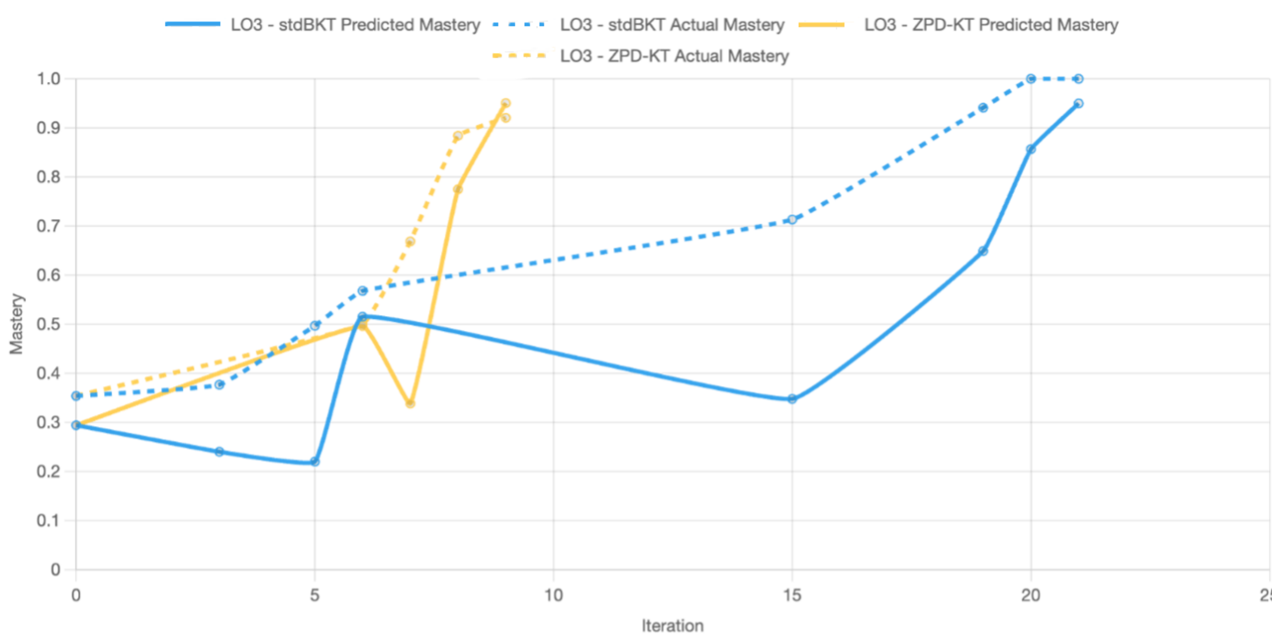
Figure 5

Prediction Deviation Comparison Between the Two Research Models

Note. stdBKT = standard Bayesian Knowledge Tracing; ZPD-KT = zone of proximal development knowledge tracing; LO = learning outcome.

Figure 6

An Example of Knowledge Tracing Progression of ZPD-KT vs. stdBKT



Note. stdBKT = standard Bayesian Knowledge Tracing; ZPD-KT = zone of proximal development knowledge tracing; LO = learning outcome.

Table 2 shows two comparison metrics for all learning outcomes and all students: (a) the average prediction deviation from the actual mastery value and (b) the accuracy of predicted mastered status.

Table 2

Overall Comparison Between ZPD-KT and stdBKT Model

Metric	stdBKT	ZPD-KT	stdBKT vs. ZPD-KT *t*	*p*
Average prediction deviation	0.174999	0.116735	26.05	< .0001
Accuracy of predicted mastered	82.83%	88.29%	-24.41	< .0001

Note. stdBKT = standard Bayesian Knowledge Tracing; ZPD-KT = zone of proximal development knowledge tracing.

With a learner sample size of 8,000 and total trials of around 20,000, the statistical comparison between stdBKT and ZPD-KT reveals significant differences in both metrics. For average prediction deviation, the *t*-statistic is 26.05, indicating a highly significant difference favouring ZPD-KT's lower deviation. The accuracy of predicted mastered again shows a significant difference in favour of ZPD-KT's higher accuracy. These results strongly suggest that ZPD-KT outperforms stdBKT in both prediction accuracy and mastery identification, with the large sample size providing robust statistical evidence for these conclusions.

Discussion

Traditionally, higher education courses mainly focus on instructional content. As more educators realize that SRL can be a critical factor for online learning success, they are using formative assessment to permit learners to self-check their knowledge proficiencies and weaknesses. Nevertheless, Ebbinghaus' (1913) *forgetting curve* reminds us that retrieval practice is essential. Also, learners need to consolidate interrelated concepts and skills covered across units or entire courses. In some cases, learners may need to identify the root cause of the academic difficulties they are experiencing, such as struggling with a concept or skill.

Unlike traditional self-assessments that rely on predetermined questions, adaptive practicing systems trace learners' knowledge levels as they keep changing. This study designed a CAP system for learning autonomy and efficient adaptivity. As an AI-learner shared control model, ZPD-KT effectively embeds learner confidence and learner control in the model design.

The ZPD-KT model tested significantly increased prediction accuracy compared to the stdBKT model through simulation, but it still has great potential for improvement. For example, the mastery ranges specified in the ZPD-KT framework shown in Table 1 and the weights used for question sequencing as shown in Equations 3 and 4 are all based on educators' experience and therefore are somewhat arbitrary. They could be further optimized by analyzing learners' practicing data through machine learning technology. This optimization process could be integrated into the system self-learning module.

Although the CAP system is designed with STEM courses in mind, it could be used for any discipline. Since CAP carefully considers the prerequisite relationships among KCs, it has a tremendous advantage when dealing with subjects that have complex learning topics and hierarchical structures. However, the CAP system does not consider the forgetting factor during the practicing process. To address this issue, we plan to embed the spaced practice principle in the future, which could especially benefit learning outcomes at the lower levels of Bloom's taxonomy.

Additionally, the ZPD-KT model does not require training with massive historical data, so it eliminates the cold start problem and reduces potential biases caused by training data. While initially designed for self-paced online higher education, CAP could be used in many other online learning environments. However, further research and experiments are needed to validate such hypotheses.

Conclusion

Facilitating self-regulated learning skills is critical for success in education. To do this, an AI-learner shared control model (ZPD-KT) for a confidence-based adaptive practicing (CAP) system for self-paced online STEM courses was designed. Through a simulation, the model design was refined and its effectiveness was tested. In practical terms, the comparison shown in Table 2 suggests that ZPD-KT is substantially more effective than the stdBKT model. This improvement could lead to more personalized and efficient experiences for learners when implemented in educational technology systems.

Although designed to facilitate self-regulated learning, adaptive practicing could also reduce instructor workload for academic support in self-paced online learning. By exploring integrating learner confidence and control in the adaptive practicing system, this study can shed light on researching a new way of keeping human learners in the loop of AI-based adaptive learning.

So far, this study has only investigated confidence rating and question skipping in the AI-learner shared control model. Future research could investigate how other side information is included in the model. For example, learners' affective states (e.g., confusion, engagement, frustration, and distraction) also indicate learning performance and could be considered in the adaptive practicing model design. At this stage, a simulation was conducted to evaluate the effectiveness of the CAP system and the ZPD-KT model. However, an experiment with real-world courses is planned to evaluate how learners react to the interaction design of the CAP, such as how they feel about the options provided for the confidence rating and question skipping.

References

Beck, J. E., & Gong, Y. (2013). Wheel-spinning: Students who fail to master a skill. In H. C. Lane, K. Yacef, J. Mostow, & P. Pavlik (Eds.), *Artificial intelligence in education. AIED2013* (pp. 431–440). Springer. https://doi.org/10.1007/978-3-642-39112-5_44

Bjork, R. A., Dunlosky, J., & Kornell, N. (2013). Self-regulated learning: Beliefs, techniques, and illusions. *Annual Review of Psychology*, *64*, 417–444. https://doi.org/10.1146/annurev-psych-113011-143823

Broadbent, J., & Poon, W. L. (2015). Self-regulated learning strategies and academic achievement in online higher education learning environments: A systematic review. *The Internet and Higher Education*, *27*, 1–13. https://doi.org/10.1016/j.iheduc.2015.04.007

Broadbent, J. (2017). Comparing online and blended learners' self-regulated learning strategies and academic performance. *The Internet and Higher Education*, *33*, 24–32. https://doi.org/10.1016/j.iheduc.2017.01.004

Brusilovsky, P. (2007). Adaptive navigation support. In P. Brusilovsky, A. Kobsa, & W. Nejdl (Eds.), *The adaptive web* (pp. 263–290). Springer. https://doi.org/10.1007/978-3-540-72079-9_8

Brusilovsky, P. (2024). AI in education, learner control, and human-AI collaboration. *International Journal of Artificial Intelligence in Education*, *34*, 122–135. https://doi.org/10.1007/s40593-023-00356-z

Clement, B., Roy, D., Oudeyer, P.-Y., & Lopes, M. (2015). Multi-armed bandits for intelligent tutoring systems. *Journal of Educational Data Mining*, *7*(2), 20–48. https://doi.org/10.48550/arXiv.1310.3174

Corbett, A. T., & Anderson, J. R. (1994). Knowledge tracing: Modeling the acquisition of procedural knowledge. *User Modeling and User-Adapted Interaction*, *4*, 253–278. https://doi.org/10.1007/BF01099821

Deci, E. L., Vallerand, R. J., Pelletier, L. G., & Ryan, R. M. (1991). Motivation and education: The self-determination perspective. *Educational Psychologist*, *26*(3-4), 325–346. https://doi.org/10.1080/00461520.1991.9653137

Doignon, J.-P., & Falmagne, J.-C. (1999). *Knowledge spaces*. Springer-Verlag. https://doi.org/10.1007/978-3-642-58625-5

Doroudi, S., Aleven, V., & Brunskill, E. (2019). Where's the reward? *International Journal of Artificial Intelligence in Education*, *29*, 568–620. https://doi.org/10.1007/s40593-019-00187-x

Ebbinghaus, H. (1913). Memory: A contribution to experimental psychology. *Annals of Neurosciences, 20*(4), 155–156. https://www.doi.org/10.5214/ans.0972.7531.200408

Ekstrand, B. (2015). What it takes to keep children in school: A research review. *Educational Review*, *67*(4), 459–482. https://doi.org/10.1080/00131911.2015.1008406

Gardner-Medwin, T., & Curtin, N. (2007, May 29–31). Certainty-based marking (CBM) for reflective learning and proper knowledge assessment. In *REAP International Online Conference on Assessment Design for Learner Responsibility* (pp. 1–7). REAP. https://www.ucl.ac.uk/lapt/REAP_cbm.pdf

Holstein, K., Aleven, V., & Rummel, N. (2020). A conceptual framework for human–AI hybrid adaptivity in education. In I. Bittencourt, M. Cukurova, K. Muldner, R. Luckin, & E. Millán (Eds.), *Artificial intelligence in education. AIED 2020* (pp. 240–254). Springer. https://doi.org/10.1007/978-3-030-52237-7_20

Hsu, H. C. K., Wang, C. V., & Levesque-Bristol, C. (2019). Re-examining the impact of self-determination theory on learning outcomes in the online learning environment. *Education and Information Technologies*, *24*, 2159–2174. https://doi.org/10.1007/s10639-019-09863-w

Jansen, R. S., van Leeuwen, A., Janssen, J., & Kester, L. (2019). Supporting learners' self-regulated learning in Massive Open Online Courses. *Computers & Education, 146*, 103771. https://doi.org/10.1016/j.compedu.2019.103771

Lehmann, T., Hähnlein, I., & Ifenthaler, D. (2014). Cognitive, metacognitive and motivational perspectives on preflection in self-regulated online learning. *Computers in Human Behavior*, *32*, 313–323. https://doi.org/10.1016/j.chb.2013.07.051

Luo, Y., Lin, J., & Yang, Y. (2021). Students' motivation and continued intention with online self-regulated learning: A self-determination theory perspective. *Zeitschrift für Erziehungswissenschaft*, *24*, 1379–1399. https://doi.org/10.1007/s11618-021-01042-3

Manouselis, N., Drachsler, H., Vuorikari, R., Hummel, H., & Koper, R. (2011). Recommender systems in technology-enhanced learning. In F. Ricci, L. Rokach, B. Shapira, & P. Kantor (Eds.), *Recommender systems handbook* (pp. 387–415). Springer. https://doi.org/10.1007/978-0-387-85820-3_12

Mosqueira-Rey, E., Hernández-Pereira, E., Alonso-Ríos, D., Bobes-Bascarán, J., & Fernández-Leal, A. (2023). Human-in-the-loop machine learning: A state of the art. *Artificial Intelligence Review*, *56*(4), 3005–3054. https://doi.org/10.1007/s10462-022-10246-w

Nkambou, R., Bourdeau, J., & Mizoguchi, R. (Eds.). (2010). *Advances in intelligent tutoring systems*. Springer. https://doi.org/10.1007/978-3-642-14363-2

Novacek, P. (2013). Confidence-based assessments within an adult learning environment. In G. Demetrios, J. Sampson, M. Spector, D. Ifenthaler, & P. Isaías (Eds.), *IADIS International Conference on Cognition and Exploratory Learning in Digital Age (CELDA 2013)* (pp. 403–406). International Association for Development of the Information Society. https://eric.ed.gov/?id=ED562245

Nuryadin, A., Lidinillah, D. A. M., Prehanto, A., Maesaroh, S. S., Putri, I. R., & Desmawati, S. A. (2024). Self-regulated learning in STEM education: A bibliometric mapping analysis of research using Scopus database. *International Journal of Education in Mathematics, Science and Technology*, *12*(4), 919–941. https://doi.org/10.46328/ijemst.4015

Papoušek, J., & Pelánek, R. (2017). Should we give learners control over item difficulty? In M. Tkalcic, D. Thakker, P. Germanakos, K. Yacef, C. Paris, & O. Santos (Eds.), *UMAP '17: Adjunct publication of the 25th Conference on User Modeling, Adaptation and Personalization* (pp. 299–303). ACM. https://doi.org/10.1145/3099023.3099080

Pelánek, R. (2017). Bayesian knowledge tracing, logistic models, and beyond: An overview of learner modeling techniques. *User Modeling and User-Adapted Interaction*, *27*(3), 313–350. https://doi.org/10.1007/s11257-017-9193-2

Preheim, M., Dorfmeister, J., & Snow, E. (2023). Assessing confidence and certainty of students in an undergraduate linear algebra course. *Journal for STEM Education Research*, *6*, 159–180. https://doi.org/10.1007/s41979-022-00082-6

Rahdari, B., Brusilovsky, P., He, D., Thaker, K. M., Luo, Z., & Lee, Y. J. (2022). HELPeR: An interactive recommender system for ovarian cancer patients and caregivers. In J. Golbeck, F. M. Harper, V. Murdock, M. Ekstrand, B. Shapira, J. Basilico, K. Lundgaard, & E. Oldridge (Eds.), *RecSys '22: Proceedings of the 16th ACM Conference on Recommender Systems* (pp. 644–647). https://doi.org/10.1145/3523227.3551471

Remesal, A., Corral, M. J., García-Mínguez, P., Domínguez, J., SanMiguel, I., Macsotay, T., & Suárez, E. (2023). Certainty-based self-assessment: A chance for enhanced learning engagement in higher education. An experience at the University of Barcelona. In D. Guralnick, M. E. Auer, & A. Poce (Eds.), *Creative approaches to technology-enhanced learning for the workplace and higher education. TLIC 2023* (pp. 689–700). Springer. https://doi.org/10.1007/978-3-031-41637-8_56

Schunk, D. H., & DiBenedetto, M. K. (2020). Motivation and social cognitive theory. *Contemporary Educational Psychology*, *60*, Article 101832. https://doi.org/10.1016/j.cedpsych.2019.101832

Smrkolj, Š., Bančov, E., & Smrkolj, V. (2022). The reliability and medical students' appreciation of certainty-based marking. *International Journal of Environmental Research and Public Health*, *19*(3), Article 1706. https://doi.org/10.3390/ijerph19031706

Sorgenfrei, C., & Smolnik, S. (2016). The effectiveness of e-learning systems: A review of the empirical literature on learner control. *Decision Sciences Journal of Innovative Education*, *14*(2), 154–184. https://doi.org/10.1111/dsji.12095

Vainas, O., Bar-Ilan, O., Ben-David, Y., Gilad-Bachrach, R., Lukin, G., Ronen, M., & Sitton, D. (2019). *E-Gotsky: Sequencing content using the zone of proximal development*. ArXiv. https://doi.org/10.48550/arXiv.1904.12268

Viberg, O., Khalil, M., & Baars, M. (2020). Self-regulated learning and learning analytics in online learning environments: A review of empirical research. In C. Rensing & H. Drachsler (Chairs), *LAK '20: Proceedings of the Tenth International Conference on Learning Analytics & Knowledge* (pp. 524–533). ACM. https://doi.org/10.1145/3375462.3375483

Vygotsky, L. S. (1978). *Mind in society: The development of higher psychological processes* (M. Cole, V. John-Steiner, S. Scribner, & E. Souberman, Eds.). Harvard University Press.

Weber, G., & Brusilovsky, P. (2001). ELM-ART: An adaptive versatile system for Web-based instruction. *International Journal of Artificial Intelligence in Education*, *12*, 351–384. https://telearn.hal.science/hal-00197328v1

Wong, J., Baars, M., Davis, D., Van Der Zee, T., Houben, G. J., & Paas, F. (2019). Supporting self-regulated learning in online learning environments and MOOCs: A systematic review. *International Journal of Human–Computer Interaction*, *35*(4-5), 356–373. https://doi.org/10.1080/10447318.2018.1543084

Yan, H., Lin, F., & Kinshuk. (2021). Including learning analytics in the loop of self-paced online course learning design. *International Journal of Artificial Intelligence in Education*, *31*, 878–895. https://doi.org/10.1007/s40593-020-00225-z

Yan, H., Lin, F., & Kinshuk. (2022). Removing learning barriers in self-paced online STEM education. *Canadian Journal of Learning and Technology*, *48*(4), 1–18. https://doi.org/10.21432/cjlt28264

Zimmerman, B. J. (2020). Attaining self-regulation: A social cognitive perspective. In *Handbook of Self-Regulation* (3rd ed., pp. 13–39). Elsevier.

Zohaib, M. (2018). Dynamic difficulty adjustment (DDA) in computer games: A review. *Advances in Human-Computer Interaction*, *2018*, Article 5681652. https://doi.org/10.1155/2018/5681652

Authors

Hongxin Yan is a Learning Designer at Athabasca University in Alberta, Canada and a Doctoral Student at the University of Eastern Finland (UEF). His research interests include adaptive and personalized learning, artificial intelligence (AI) in education, learning analytics, and related fields. *Email*: hongya@student.uef.fi *ORCID*: 0000-0002-3729-0844

Fuhua Lin is a Professor in the Faculty of Science and Technology at Athabasca University in Alberta, Canada. His research focuses on adaptive learning systems, artificial intelligence in education, and virtual reality applications for training. He has led multiple NSERC/CFI/Alberta Innovates-funded projects to advance personalized learning technologies. *Email*: oscarl@athabascau.ca

Kinshuk is a full Professor and the Dean of the College of Information at the University of North Texas, USA. His research interests include learning analytics, mobile learning, ubiquitous learning, personalized learning, and adaptivity. *Email*: kinshuk@ieee.org

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Student Perceptions of the Athletic Therapy Interactive Concussion Educational (AT-ICE) Tool

Perceptions des personnes étudiantes sur l'outil éducatif interactif sur les commotions cérébrales en thérapie sportive (AT-ICE)

***Colin D. King**, Acadia University, Canada*
***Loriann M. Hynes**, York University, Canada*

Abstract

Previous research has identified a considerable amount of variability in how healthcare professionals are taught to recognize, assess, and manage concussions. Responding to these findings, an innovative applied learning technology tool, the Athletic Therapy Interactive Concussion Educational (AT-ICE) Tool, was developed to help teach athletic therapy students how to recognize, assess, and manage concussions. The purpose of this research was to employ an interpretivist conceptual framework to explore athletic therapy students' perceptions of this tool. A questionnaire was used to identify individual factors that impacted student perceptions of AT-ICE and how it could be integrated into the classroom. Overall, participants enjoyed using AT-ICE and felt it helped to stimulate their critical thinking about the entire continuum of concussion care. Several important themes emerged including the importance of detailed scenarios, sharing lived experiences, and integrating anatomy within assessment and management scenarios. Findings suggest that AT-ICE was an effective educational technology that stimulated critical thought throughout the entire continuum of concussion care. Future research could continue to investigate the effectiveness of the tool or explore different ways to implement it in formal athletic therapy educational settings.

Keywords: applied learning technology, athletic therapy education, concussion care

Résumé

Des recherches antérieures ont identifié une variabilité considérable dans la manière dont les personnes professionnelles de la santé apprennent à reconnaître, évaluer et gérer les commotions cérébrales. En réponse à ces résultats, nous avons développé un outil techno pédagogique d'apprentissage appliqué novateur, l'outil éducatif interactif sur les commotions cérébrales en thérapie sportive (AT-ICE), pour aider à enseigner aux personnes étudiantes en thérapie sportive comment reconnaître, évaluer et gérer les commotions cérébrales. Le but de cette recherche était d'utiliser un cadre conceptuel interprétatif pour explorer les perceptions des personnes étudiantes en thérapie sportive à l'égard de cet outil. Un questionnaire a été utilisé pour identifier les facteurs individuels qui ont eu un impact sur les perceptions des personnes étudiantes à l'égard de l'outil AT-ICE et sur la manière dont il pourrait être intégré dans le cours. Dans l'ensemble, les personnes participantes ont apprécié l'utilisation de l'outil AT-ICE et ont estimé qu'il les aidait à stimuler leur réflexion critique sur l'ensemble du continuum des soins des commotions cérébrales. Plusieurs thèmes importants ont également émergé, notamment l'importance de scénarios détaillés, du partage d'expériences vécues et de l'intégration de l'anatomie dans les scénarios d'évaluation et de gestion. Les résultats suggèrent que l'outil AT-ICE était une technologie éducative efficace qui stimulait la pensée critique tout au long du continuum des soins des commotions cérébrales. Les recherches futures pourraient continuer d'étudier l'efficacité de l'outil tout en explorant différentes façons de le mettre en œuvre dans des contextes éducatifs formels de thérapie sportive.

Mots-clés : éducation en thérapie sportive, soins des commotions cérébrales, technologie d'apprentissage appliqué

Introduction

Concussions have the potential to become a burden for the public health care system when not immediately recognized (Damji & Babul, 2018). Previous research has identified a considerable amount of variability within healthcare professional education regarding the recognition, assessment, and management of concussions (Haider et al., 2018; Mann et al., 2017; Yorke et al., 2016), which has the potential to contribute to challenges in consistently identifying such injuries. Youth and adolescent concussions reported to hospital emergency departments saw a four-fold increase over the 11-year period of 2003–2013 (Zemek et al., 2017) with sport participation being the most common mechanism of injury (Iverson et al., 2023; Zemek at al., 2017). Certified athletic therapists/trainers (ATs) are unique in that they are typically one of the only health care providers managing concussions from initial injury identification through full recovery. In many sporting environments, ATs are the first responders on site to recognize and identify athletes with suspected concussions (Broglio et al., 2014). With a growing need to recognize potential concussions early and prevent long term sequalae (D. King et al., 2014), it is critical for ATs to have training and a comprehensive background in concussion recognition, assessment, and management.

The Sport Concussion Assessment Tool™ 6 (SCAT6) recognizes ATs as members of the sport-related concussion network with expertise in diagnostic assessments, clinical evaluations, and treatment interventions for sport-related concussions (Echemendia et al., 2023). While many ATs have used the evolving SCAT tools since the first International Conference on Concussion in Sport in 2001, a study by Lempke et al. (2020) showed that 40.1% of AT participants were not familiar with the SCAT5. SCAT5 was the most current protocol at the time of their publication, as recommended by the consensus statement on concussion in sport (McCrory et al., 2017). The Lempke et al. (2020) finding may be because there was and continues to be no defined minimum standard for concussion recognition, assessment, and management within the AT profession. Despite the unique healthcare training of ATs, variability exists in the educational approaches to concussions (Lempke et al., 2020).

In addition to the availability of concussion assessment tools and consensus statements related to concussion management and best-practice guidelines, there is a need for educators of aspiring ATs to provide more consistent training and greater opportunities for learning the entire continuum of concussion care, being recognition, assessment, and management. While variability exists within each accredited institution for teaching AT in Canada, current concussion education about the recognition, assessment, and management of concussions is delivered through didactic theory in the traditional classroom setting, skill practice during guided laboratory settings, and experientially through various placements with teams and in clinical settings throughout students' respective programs (C. D. King & Hynes, 2021). However, due to the nature of student placements in most healthcare professions, each student is not guaranteed to follow concussions across the entire continuum from point of injury to return to sport. While theoretical and practical education are valuable, they do not guarantee that students will obtain the confidence to manage concussions upon graduation (Yorke et al., 2016). Hunt et al. (2017) discovered unique perspectives from students about effective concussion education and concluded that AT educators should explore different educational techniques that encourage higher-level thinking and implementation, instead of focusing on traditional didactic education. Simulation education is one method that can help foster higher order thinking with physical skill response and has been shown to improve the learners' confidence in the absence of lived experience in student placements (Miller et al., 2018). Unfortunately, this method of learning and skill development is not always accessible to students across all academic institutions due to the cost and space availability to house such equipment.

To provide the most optimal educational experience that imparts strong foundational knowledge coupled with confidence in the execution of practical skills, educators are encouraged to reflect on the scope of practice of their respective profession, the unique characteristics of their educational context, and effective pedagogical strategies for improving the ways that health professionals learn about recognizing, assessing, and managing concussions. In response to this need, we have developed the Athletic Therapy Interactive Concussion Educational (AT-ICE) Tool, an online applied learning technology designed to engage students in realistic and interactive concussion scenarios to help to bridge the gap between classroom activities and real-world situations.

Method

Conceptual Theoretical Framework

The purpose of this project was to explore student perceptions of the learning technology tool called AT-ICE. The decision was made to employ an interpretivist conceptual framework to guide the design of this study instead of exploring the tool's effectiveness solely through a statistical positivist lens (Ashley & Orenstein, 2005). Following this interpretivist epistemology allowed us to explore some of the individual factors that impacted students' perceptions of AT-ICE and how it could be integrated into the classroom, an important aspect to consider when designing educational interventions (Dean, 2018). Generalizability of findings is not a tenet of interpretivist inquiry (Stenfors-Hayes et al., 2013). Readers can compare their unique educational contexts to those described in this study, before determining if this or a similar tool would be beneficial to use within their specific context.

Participants

University research ethics approval was granted by each of the Canadian Athletic Therapists Association (CATA) accredited institutions prior to data collection. There were nine CATA institutions at the time of the study. Recruitment emails were sent through the program directors to the graduating student cohorts from each institution. A total of 35 students responded, although 13 responses were removed from the sample due to being incomplete. Complete responses were provided by 22 participants (20.7±1.2 years; 14 females, 8 males), representing five CATA accredited institutions.

Instrumentation

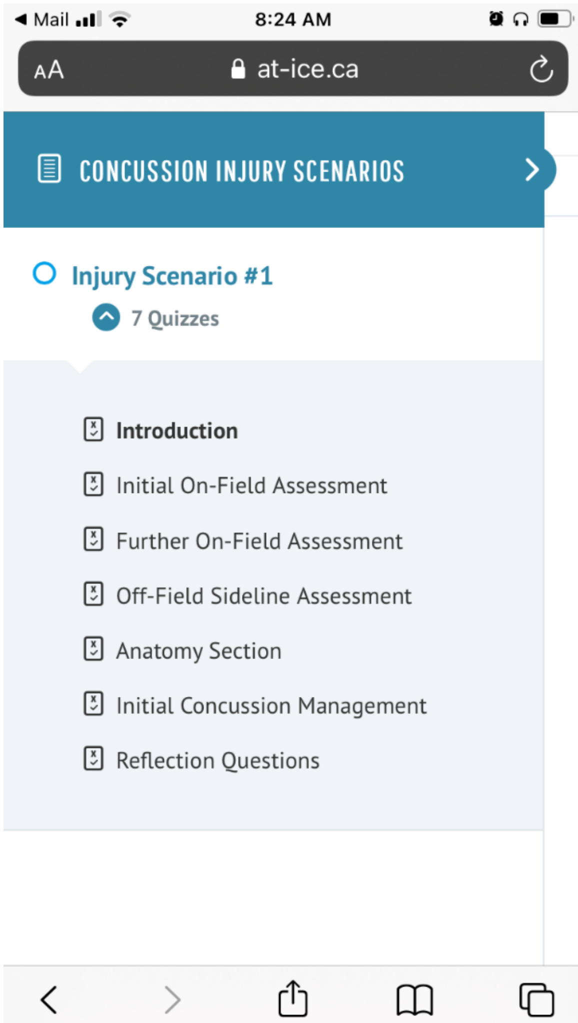
Athletic Therapy Interactive Concussion Educational Tool

Prior to completing the questionnaire, participants were first asked to independently review AT-ICE. It is an online learning technology tool designed to engage students in realistic, contextually authentic concussion scenarios by integrating the knowledge and practical skills required to effectively recognize, assess, and manage concussions (C. D. King & Hynes, 2022). The AT-ICE guides students through complete situational experiences covering the entire continuum of concussion care, starting with on-field recognition of a potential injury, all the way through the concussion management process. During the development process, AT experts were engaged to help define the minimum standard/level of competence that should be expected of entry-level ATs (C. D. King & Hynes, 2022). Various technologies and pedagogical strategies were incorporated into each component of the online tool to engage students in the various types of knowledge, skills, and reflection required for effective concussion care.

Figure 1 shows AT-ICE Injury Scenario #1 as an exemplar of the template used for each concussion scenario within AT-ICE. The template consists of: 1) an introductory section that sets up the initial scenario; 2) the initial on-field assessment; 3) further on-field assessment; 4) off-field sideline assessment; 5) anatomy section; 6) initial concussion management; and 7) reflection questions section. To organize the different types of questions, each section in the template was further divided into three subsections, incorporating different pedagogical strategies, activities, and technologies.

Figure 1

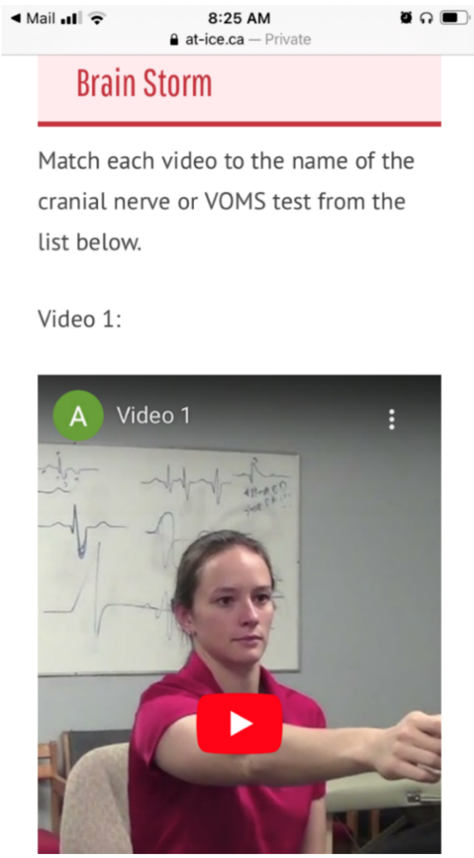
AT-ICE Injury Scenario #1



The first subsection labeled *Brain Storm* (Figure 2) included content knowledge questions using multiple-choice, matching, and open-ended questions, which provided further critical thinking opportunities for students. The second subsection, *Brain Share*, involved structured peer activities that engaged students in essential physical assessment psychomotor skills required to demonstrate competence in concussion care. This subsection encouraged the use of technology by asking students to video themselves performing specific concussion tests and uploading them with their submission. By videoing their skills, each student could critically reflect on their performance, retake the video until it met their satisfaction, and then they could upload a final version to be evaluated by their instructor. Brain Share activities helped to structure peer-assisted learning by prompting students to discuss with a partner their experiences about a particular situation (such as "With a partner, discuss how you would rule out each of the injuries included in the answer above"). The final subsection, *Brain Tease*, included critical thinking questions that asked students to think about how they would respond to a particular situation (such as, "You are completing your on-field assessment and a referee comes over asking you to hurry up and get the athlete off the field. How would you handle this situation?").

Figure 2

Brain Storm Section Example



Questionnaire

A custom questionnaire was designed using the Acadia University Online Survey system, to explore student perceptions about using technology for learning, and about using AT-ICE (Appendix). The questionnaire statements about using technology for learning were important to gauge participants' initial predisposition to technology, because, as Hart and Sutcliffe (2019) wrote, if students were intimidated by, or had initial negative attitudes towards using technology for learning, then those perceptions could impact the overall findings of the study. The questionnaire also included open-ended questions asking students to reflect on improvements for the tool and potential ways to implement such a tool within formal academic settings. The questionnaire was initially field-tested with two teachers from CATA accredited programs, and with two AT students who were not eligible to participate in the study, because they were not in the graduating year of their program. During this review process, the questionnaire was reorganized and grammar was corrected.

Procedure

A recruitment email was sent to all program directors of the nine CATA accredited institutions (Acadia University, Camosun College, Concordia University, Mount Royal University, Sheridan College, Université du Québec à Trois-Rivières, University of Manitoba, University of Winnipeg, and York University) and asked to be distributed to the graduating student cohorts from each institution. The recruitment email included the links for the consent form, AT-ICE (www.at-ice.ca), and the online questionnaire. After providing consent, participants were instructed to review AT-ICE first, before responding to the online questionnaire. Program directors were sent a reminder email two weeks after the initial communication. It was explained to all students that participation was voluntary and not a mandated part of their academic program. Additionally, program directors were not provided information as to who decided to participate in the research project.

Data Analysis and Trustworthiness

As seen in Appendix, the questionnaire asked participants to report their level of agreement with 16 statements by selecting a single response on a 5-point Likert scale ranging from 1 = *strongly disagree* with the statement to 5 = *strongly agree* with the statement. Since there were 22 completed questionnaires, each descriptive statistic reported in Table 1 has an N-value of 22. These responses were aggregated, and descriptive statistics (means ± standard deviations) were calculated in Microsoft Excel®. The three open-ended responses were analyzed for emergent themes by the two researchers. After separate analyses were conducted, the researchers met to discuss any themes until consensus was reached.

Results

Descriptive Statistical Analysis

Table 1

Responses to Questionnaire Statements 5 to 20

Questionnaire Statement	*M*	*SD*
5. I enjoyed using this educational tool	4.67	0.49
6. I feel that technology, when used the right way, can empower student learning	4.67	0.49
7. The educational tool came with clear instructions about how to follow the scenarios	4.40	0.51
8. The concussion scenarios were presented in an understandable format	4.73	0.46
9. The concussion scenarios were easy to navigate	4.27	0.88
10. The concussion scenarios helped to stimulate student critical thinking	4.80	0.41
11. I have used text-based cases while studying before	4.67	0.62

Questionnaire Statement	*M*	*SD*
12. The anatomy animation clips were difficult to use	3.20	1.26
13. The detail of the anatomy animations allowed me to accurately give additional context to the scenarios	2.07	0.96
14. The anatomy animations were an adequate substitute for hands-on anatomy models	4.47	0.52
15. The concussion scenarios did not provide enough information to carry out an accurate assessment	2.13	1.16
16. The concussion scenarios did not provide enough information to make a decision regarding the most appropriate management plan	2.07	0.96
17. The concussion scenarios were too difficult for my current knowledge base	2.13	0.83
18. I think that using technology to present scenarios is more motivational than using text-based cases	4.27	0.70
19. The level of analysis required in the scenarios was too difficult	2.00	0.76
20. Using technology to learn is distracting	1.80	0.77

Using Technology for Learning

When exploring the impact of any form of educational technology, it is important to consider participants' initial predispositions to technology use. This is important because if an individual has negative attitudes about using technology for education, then these negative attitudes may be reflected in their responses to any form of educational technology, regardless of differences in design (Asscher & Glikson, 2023). Negative predispositions towards technology would make it difficult to interpret if negative responses were about a specific educational technology or general negative attitudes about technology use (Hart & Stufcliffe, 2019).

The findings from this study suggest that the participants enjoyed using technology for their learning and were not intimidated by its use. Participants reported a strong level of agreement with the questionnaire statement: I feel that technology, when used the right way, can empower student learning (4.67±0.49). Additionally, participants disagreed with the statement: using technology to learn is distracting (1.80±0.77). Based on these findings, there were no initial negative predispositions to using technology found in the sample.

General Perception of AT-ICE

Overall, the participants felt that AT-ICE was easy to use and was more motivational to their learning than using text-based cases (4.27±0.70). This finding was further supported by the participants agreeing with the following questionnaire statements: the educational tool came with clear instructions about how to follow the scenario (4.40±0.51), the concussion scenarios were presented in an understandable format (4.73±0.46), and the concussion scenarios were easy to navigate (4.27±0.88). A more neutral response (3.20±1.26) emerged for the statement: the anatomy animation clips were difficult to use. This finding made sense since the anatomy animations were not embedded directly into the tool, as students were provided with a specific list of YouTube links to watch anatomy animations from different content areas (e.g., cranial nerves and vascular anatomy).

Perception of Impact of AT-ICE on Learning

The main purpose of this project was to explore the students' perception of impact of AT-ICE on learning. Participants appeared to enjoy using AT-ICE, strongly agreeing with statement number 5 from the questionnaire (4.67±0.49). Participants felt that the tool helped to simulate their critical thinking (4.80±0.41), while helping them to learn and guide the practice of skills required to carry out appropriate concussion recognition, assessment, and management plan selection. To ensure that participants were reading statements and not selecting all the same responses on the Likert scale, ten of the statements were written in the affirmative and six in the negative. The negative statements were numbered 12, 15, 16, 17, 19, and 20. Participants disagreed with the following negative questionnaire statements: the concussion scenarios did not provide enough information to carry out an accurate assessment (2.13±1.16), the concussion scenarios did not provide enough information to make a decision regarding the most appropriate management plan (2.07±0.96), and the level of analysis required in the scenarios was too difficult (2.00±0.76).

Thematic Analysis of Open-Ended Questions

Within the open-ended questions, participants were asked to reflect and explore the individual factors that impacted their perceptions of AT-ICE. When asked to describe the areas that they enjoyed most about AT-ICE, several themes emerged from the participant responses: the importance of detailed scenarios, sharing lived experiences, and integrating anatomy within assessment and management scenarios.

Detailed Scenarios

The first theme was described as the importance of having organized scenarios with sufficient details to be able to have a better appreciation for what is being asked. Fifteen participants described the importance of having structured scenarios that included real-time videos to demonstrate the mechanisms of injury. These participants commented that oftentimes during simulated practical scenarios, they needed to make assumptions about what actually happened to the athlete based on using only a written text description. The mechanism of injury videos in AT-ICE scenarios ensured that all students were evaluating the exact same situation and able to observe what happened, how the athlete responded to the injury, what the therapist saw when they arrived on scene, etc. As one participant described:

> I liked how there were real sport videos to analyze instead of reading a block of text. I think it's better to practice watching videos because it helps me practice looking for differential diagnoses while watching the injury happening in real time. (AT-Stu 2)

Sharing Lived Experiences

Another theme that emerged was related to participants' personal experiences during structured peer activities within the Brain Share sections. Twelve participants provided comments about the importance of embedding these types of questions into educational tools so that the students have the opportunity to learn from one another. This was illustrated by one participant who said:

> Asking for our personal experiences is important because we may have specific examples that can help each other. Maybe I saw more incidents in my sport (rugby) and can help others with what I saw, how the athlete appeared, what they complained about, etc. We all don't get to see the same number of concussions in our placements and if we do, they are not always the same. (AT-Stu 12)

Integrating Anatomy Within Assessment and Management Scenarios

The third theme that emerged was related to the integration of anatomy knowledge into the assessment and management scenario. Seven participants provided commentary about the anatomy sections and thought it was an important area that is often forgotten about in these types of educational tools. As one participant described:

> Usually when we work through case scenarios in class, we are not asked much about the anatomy. We often just focus on the assessment piece or the rehab piece and not really get back in-depth to the anatomy we covered. I liked how the tool had all aspects of it. The assessment, the anatomy, and the management. (AT-Stu 3)

Another participant added:

> I had confidence that the anatomy videos provided were accepted by an academic institute and can be trusted- there are so many YouTube videos for anatomy and assessment skills that it is difficult to know if you are getting the right information on your own. (AT-Stu 7)

Improvements for AT-ICE

Participants were asked to suggest any improvements to AT-ICE. Most of the feedback provided was related to the technical functions of the tool itself. For example, seven participants described the desire to have the ability to edit their responses before submitting the final version, and five participants suggested having correct answers show up after the final submission with explanations and rationale for the correct responses. The only other theme that emerged from this question was to have more scenarios built within the tool with differing levels of complexity for each scenario. As one participant said, "More scenarios would be useful so we can practice the easier straight forward ones but also to challenge ourselves with something more complex that we often see in concussion cases" (AT-Stu 21). Another participant added, "The management piece was pretty easy. I would suggest adding more complicated scenarios that have us making decisions based on what symptoms someone reports. That would be very useful and interesting to work through" (AT-Stu 14).

Implementing AT-ICE Within Teaching and Learning

The final question on the questionnaire asked participants to describe how they could use AT-ICE as part of their learning about concussion care. Originally, AT-ICE was designed to be used as a supplementary tool for AT educators, and not as a standalone tool that replaces in-person learning about concussions (C. D. King & Hynes, 2022). Participant responses overwhelmingly supported the notion of using this tool as a supplement to help guide their learning about concussion care. Within the responses, 10 participants described a form of flipped classroom (Akçayır & Akçayır, 2018), without actually using the specific term. As one participant suggested:

> This would be useful to educators as a small homework assignment to do before the on-hands lab time. The students do one section, such as on-field management, before coming to class and the instructor then goes through the entire section with them to demonstrate the new skills and provide corrections and answer questions. This way, the students can apply their skills to each new case in a self-directed way with guidelines to keep them on task, and the instructor does not simply give the answers away. (AT-Stu 12)

Similarly, another participant replied:

> Our professors have so much to add to this topic that we don't get in a textbook. They can provide us with their real-world experiences as to what to expect. How difficult it is to actually assess concussions a lot of the time. To share with us what they saw, what they experienced because as we know, not every concussion injury follows the textbook case. (AT-Stu 1)

Seven participants felt that AT-ICE could be used by their teacher to guide their learning in a classroom setting, by completing sections individually and then taking part in a wider class discussion. According to AT-Stu 10, AT-ICE "could be presented to complete individually/in pairs and then open a classroom discussion afterwards in which students can ask questions/share stories to facilitate a more in-depth learning experience from peers and professors."

Discussion

Proposed Teaching Plan for AT-ICE

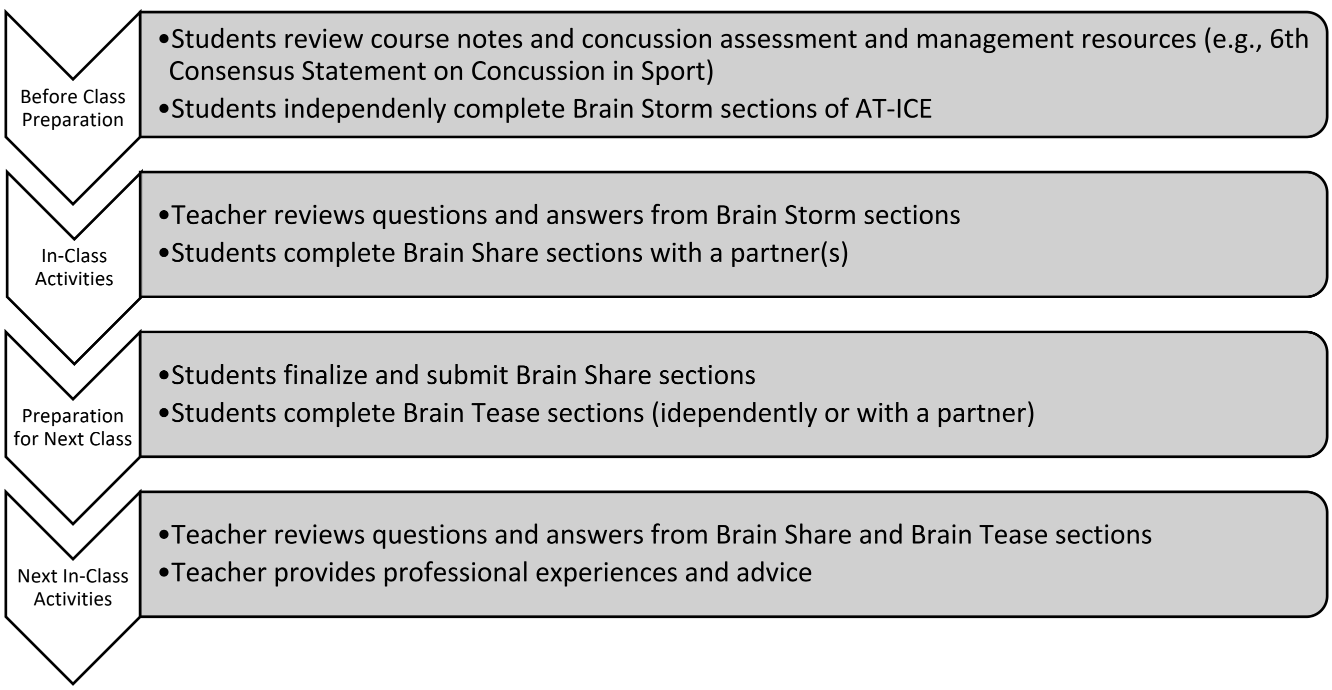
When implementing any form of educational technology into the classroom, educators need to think about how to use that particular technology in pedagogically meaningful ways (Mishra & Koehler, 2006). By following this approach, research has shown that educators can improve their delivery of instruction by using diverse pedagogical strategies to provide more valuable learning experiences (Fawns, 2022; Rapanta et al., 2021). As described by participants in the current study, we propose that AT educators consider using the flipped classroom model when using AT-ICE.

The flipped classroom model has long been recognized as an innovative and effective instructional approach in higher education, especially when integrating educational technologies (Baytiyeh, 2017; Hwang et al., 2015; Lo, 2018). This instructional approach allows for more in-class time being spent on interactive learning activities, as the traditional content delivery component (e.g., lecturing) is shifted outside of the classroom through instructional videos and directed readings (Lo, 2018). However, effective use of this method requires purposeful in-class learning designs and activities that help connect student learning across at-home and in-school contexts (Hwang et al., 2015).

Study participants described examples of how their teachers could use AT-ICE in pedagogically meaningful ways, by guiding students to actively think and discuss the different aspects of concussion care as they work through the various sections of the tool. Figure 3 provides a proposed teaching plan of how an AT educator could use the flipped classroom model to structure their use of AT-ICE. Additionally, educators could allow for time to provide professional feedback, share their experiences, and provide advice of what they would do in a similar situation (Hwang et al., 2015). In these types of interactions, the student plays the role of the active learner, whereas the teacher plays the role of the facilitator as opposed to the traditional lecturer or instructor (Baytiyeh, 2017).

Figure 3

Proposed Teaching Plan for AT-ICE



Additional pedagogical approaches could be beneficial when implementing AT-ICE, as we are not advocating for a rigid teaching model that must be adapted by all educators in the exact same manner. Effective learning technology integration does not advocate for or against a particular technology or pedagogy because what has been shown to be effective and innovative today can quickly become outdated (Kopcha et al., 2020). Instead, we are advocating for educators to take a critical stance when deciding to use an educational tool like AT-ICE, and with the position of Väätäjä and Ruokamo (2021), to think about how a tool can be implemented in pedagogically meaningful ways within a unique educational context.

Limitations

Two limitations within this study were noted. One limitation was related to the academic level of students who volunteered for this study. Since we did not ask about grade point averages, we do not know the academic level of students who responded. Acknowledging that the participants self-selected, it is possible that the sample may be composed of predominantly academically strong students, because top students often like to be challenged and may prefer these learner-centred, self-directed approaches whereas other students may share different opinions. Future research could consider these potential differences and explore whether these tools are beneficial to an academically wide range of students, not just those who are engaged, motivated, and active learners. Another limitation was that we were successful in recruiting participants from only five of the nine CATA accredited institutions, meaning our sample is not representational of all nine accredited institutions.

Future Research Directions

The findings described herein highlight the potential for the online applied learning technology tool AT-ICE to enhance concussion care education for AT students. Future research could explore both student and teacher perspectives of these types of innovative educational tools. Formal pre and post learning assessments could be completed to explore the effectiveness of the tool. Future studies could explore the impact of AT-ICE on student self-efficacy and confidence in their abilities to recognize, assess, and manage concussions. Additionally, a follow-up study could investigate AT teachers' perceptions of AT-ICE, the proposed teaching plan, and other ways that these types of applied learning technologies can be integrated in pedagogically meaningful ways within AT classrooms.

Conclusion

The findings from this study demonstrated that AT-ICE was perceived positively by AT student participants as a learning technology tool that can be used to teach AT students about all aspects of concussion care. The tool was designed to stimulate student critical thinking, provide structured independent critical reflection opportunities, and guide peer-assisted learning to practice the skills required to carry out comprehensive concussion recognition, assessment, and management plans. Feedback from the participants was used to design a flipped classroom teaching plan that could be used by Athletic Therapy educators to implement the Athletic Therapy Interactive Concussion Educational tool in a pedagogically meaningful way.

Acknowledgements

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References

Akçayır, G., & Akçayır, M. (2018). The flipped classroom: A review of its advantages and challenges. *Computers & Education*, *126*, 334–335. https://doi.org/10.1016/j.compedu.2018.07.021

Ashley, D., & Orenstein, D. M. (2005). *Sociological theory: Classical statements* (6th ed.). Pearson Education.

Asscher, O., & Glikson, E. (2023). Human evaluations of machine translation in an ethically charged situation. *New Media & Society*, *25*(5), 1087–1107. https://doi.org/10.1177/14614448211018833

Baytiyeh, H. (2017). The flipped classroom model: When technology enhances professional skills. *The International Journal of Information and Learning Technology*, *34*(1), 51–62. https://doi.org/10.1108/IJILT-07-2016-0025

Broglio, S. P., Cantu, R. C., Gioia, G. A., Guskiewicz, K. M., Kutcher, J., Palm, M., & Valovich McLeod, T. C. (2014). National Athletic Trainers' Association position statement: Management of sport concussion. *Journal of Athletic Training*, *49*(2), 245–265. https://doi.org/10.4085/1062-6050-49.1.07

Damji, F., & Babul, S. (2018). Improving and standardizing concussion education and care: A Canadian experience. *Concussion*, *3*(4). https://doi.org/10.2217/cnc-2018-0007

Dean, B. A. (2018). The Interpretivist and the Learner. *International Journal of Doctoral Studies*, *13*, 1–8. https://doi.org/10.28945/3936

Echemendia, R. J., Brett, B. L., Broglio, S., Davis, G. A., Giza, C. C., Guskiewicz, K. M., Harmon, K. G., Herring, S., Howell, D. R., Master, C. L., Valovich McLeod, T. C., McCrea, M., Naidu, D., Patricios, J., Putukian, M., Walton, S. R., Schneider, K. J., Burma, J. S., & Bruce, J. M. (2023). Introducing the Sport Concussion Assessment Tool 6 (SCAT6). *British Journal of Sports Medicine*, *57*(11), 619–621. https://doi.org/10.1136/bjsports-2023-106849

Fawns, T. (2022). An entangled pedagogy: Looking beyond the pedagogy–technology dichotomy. *Postdigital Science and Education*, *4*, 711–728. https://doi.org/10.1007/s42438-022-00302-7

Haider, M. N., Leddy, J. J., Pavlesen, S., Kluczynski, M., Baker, J. G., Miecznikowski, J. C., & Wiler, B. S. (2018). A systematic review of criteria used to define recovery from sport-related concussion in youth athletes. *British Journal of Sports Medicine*, *52*(18), 1179-1190. https://doi.org/10.1136/bjsports-2016-096551

Hart, J., & Sutcliffe, A. (2019). Is it all about the apps or the device? User experience and technology acceptance among iPad users. *International Journal of Human-Computer Studies*, *130*, 93–112. https://doi.org/10.1016/j.ijhcs.2019.05.002

Hunt, T. N., Harris, L., & Way, D. (2017). The impact of concussion education on the knowledge and perceived expertise of novice health care professionals. *Athletic Training Education Journal*, *12*(1), 26–38. https://doi.org/10.4085/120126

Hwang, G. J., Lai, C. L., & Wang, S. Y. (2015). Seamless flipped learning: A mobile technology-enhanced flipped classroom with effective learning strategies. *Journal of Computers in Education*, *2*, 449–473. https://doi.org/10.1007/s40692-015-0043-0

Iverson, G. L., Castellani, R. J., Cassidy, J. D., Schneider, G. M., Schneider, K. J., Echemendia, R. J., Bailes, J. E., Hayden, K. A., Koerte, I. K., Manley, G. T., McNamee, M., Patricios, J. S., Tator, C. H., Cantu, R. C., & Dvorak, J. (2023). Examining later-in-life health risks associated with sport-related concussion and repetitive head impacts: A systematic review of case-control and cohort studies. *British Journal of Sports Medicine*, *57*(12) 810–824. https://doi.org/10.1136/bjsports-2023-106890

King, C. D., & Hynes, L. M. (2021). An exploration of concussion assessment and management knowledge in athletic therapy students. *International Journal for the Scholarship of Teaching and Learning, 15*(2), Article 11. https://doi.org/10.20429/ijsotl.2021.150211

King, C. D., & Hynes, L. M. (2022). An action research approach to designing the athletic therapy interactive concussion educational tool. *International Journal of Technology, Knowledge and Society*. *18*(2), 19–34. https://doi.org/10.18848/1832-3669/CGP/v18i02

King, D., Brughelli, M., Hume, P., & Gissane, C. (2014). Assessment, management and knowledge of sport-related concussion: Systematic review. *Sports Medicine*, *44*, 449–471. https://doi.org/10.1007/s40279-013-0134-x

Kopcha, T. J., Neumann, K. L., Ottenbreit-Leftwich, A., & Pitman, E. (2020). Process over product: The next evolution of our quest for technology integration. *Educational Technology Research and Development*, *68*, 729–749. https://doi.org/10.1007/s11423-020-09735-y

Lempke, L. B., Schmidt, J. D., & Lynall, R. C. (2020). Athletic trainers' concussion-assessment and concussion-management practices: An update. *Journal of Athletic Training*, *55*(1), 17–26. https://doi.org/10.4085/1062-6050-322-18

Lo, C. K. (2018). Grounding the flipped classroom approach in the foundations of educational technology. *Educational Technology Research and Development*, *66*, 793–811. https://doi.org/10.1007/s11423-018-9578-x

Mann, A., Tator, C. H., & Carson, J. D. (2017). Concussion diagnosis and management: Knowledge and attitudes of family medicine residents. *Canadian Family Physician, 63*(6), 460–466.

McCrory, P., Meeuwisse, W., Dvorak, J., Aubry, M., Bailes, J., Broglio, S., Cantu, R. C., Cassidy, D., Echemendia, R. J., Castellani, R. J., Davis, G. A., Ellenbogen, R., Emery, C., Engebretsen, L., Feddermann-Demont, N., Giza, C. C., Guskiewicz, K. M., Herring, S., Iverson, G. L., … & Vos, P. E. (2017). Consensus statement on concussion in sport – the 5th international conference on concussion in sport held in Berlin, October 2016. *British Journal of Sports Medicine*, *51*(11), 838–847. https://doi.org/10.1136/bjsports-2017-097699

Miller, M. B., Macpherson, A. K., & Hynes, L. M. (2018). Athletic therapy students' perceptions of high-fidelity manikin simulation: A pilot study. *Athletic Training Education Journal*, *13*(2), 158–167. https://doi.org/10.4085/1302158

Mishra, P., & Koehler, M. (2006). Technological pedagogical content knowledge: A framework for teacher knowledge. *Teachers College Record*, *108*(6), 1017–1054. https://doi.org/10.1111/j.1467-9620.2006.00684.x

Rapanta, C., Botturi, L., Goodyear, P., Guàrdia, L., & Koole, M. (2021). Balancing technology, pedagogy and the new normal: Post-pandemic challenges for higher education. *Postdigital Science and Education*, *3*, 715–742. https://doi.org/10.1007/s42438-021-00249-1

Stenfors-Hayes, T., Hult, H., & Dahlgren, M. A. (2013). A phenomenographic approach to research in medical education. *Medical Education*, *47*(3), 261–270. https://doi.org/10.1111/medu.12101

Väätäjä, J. O., & Ruokamo, H. (2021). Conceptualizing dimensions and a model for digital pedagogy. *Journal of Pacific Rim Psychology*, *15,* 1–12. https://doi.org/10.1177/1834490921995395

Yorke, A. M., Littleton, S., & Alsalaheen, B. A. (2016). Concussion attitudes and beliefs, knowledge, and clinical practice: Survey of physical therapists. *Physical Therapy & Rehabilitation Journal*, *96*(7), 1018–1028. https://doi.org/10.2522/ptj.20140598

Zemek, R. L., Grool, A. M., Rodriguez Duque, D., DeMatteo, C., Rothman, L., Benchimol, E. I., Guttmann, A., & Macpherson, A. K. (2017). Annual and seasonal trends in ambulatory visits for pediatric concussion in Ontario between 2003 and 2013. *The Journal of Pediatrics*, *181*, 222–228.e2. https://doi.org/10.1016/j.jpeds.2016.10.067

Appendix

Student Questionnaire

The following questionnaire has been designed in an effort to collect valuable feedback while exploring the effectiveness of using the Athletic Therapy Interactive Concussion Educational Tool in athletic therapy accredited institutions.

Thank you for your participation.

---

1. Gender
    a. Female
    b. Male
    c. Other _______
    d. Wish Not to Disclose
2. Age
3. Year in Athletic Therapy Program _________
4. Accredited Institution
    a. Sheridan College
    b. York University
    c. Concordia University
    d. University of Winnipeg
    e. University of Manitoba
    f. Mount Royal University
    g. Camosun College
    h. UQTR
    i. Acadia University

After reviewing the **Athletic Therapy Interactive Concussion Educational Tool,** please answer the following questions by placing an "x" by a single number on the Likert Scale that best represents your answers. Answers will be scored on a scale with a value of 1 assigned to strongly disagree, all the way to 5 for strongly agree.

5. I enjoyed using this educational tool.

   ( ) 1 Strongly Disagree ( ) 2 Disagree ( ) 3 Neutral ( ) 4 Agree Strongly ( ) 5 Agree

6. I feel that technology, when used the right way, can empower student learning.

   ( ) 1 Strongly Disagree ( ) 2 Disagree ( ) 3 Neutral ( ) 4 Agree Strongly ( ) 5 Agree

7. The educational tool came with clear instructions about how to follow the scenario.

   ( ) 1 Strongly Disagree ( ) 2 Disagree ( ) 3 Neutral ( ) 4 Agree Strongly ( ) 5 Agree

8. The concussion scenarios were presented in an understandable format.

   ( ) 1 Strongly Disagree ( ) 2 Disagree ( ) 3 Neutral ( ) 4 Agree Strongly ( ) 5 Agree

9. The concussion scenarios were easy to navigate.

   ( ) 1 Strongly Disagree ( ) 2 Disagree ( ) 3 Neutral ( ) 4 Agree Strongly ( ) 5 Agree 5

10. The concussion scenarios helped to stimulate student critical thinking.

    ( ) 1 Strongly Disagree ( ) 2 Disagree ( ) 3 Neutral ( ) 4 Agree Strongly ( ) 5 Agree

11. I have used text-based cases while studying before.

    ( ) 1 Strongly Disagree ( ) 2 Disagree ( ) 3 Neutral ( ) 4 Agree Strongly ( ) 5 Agree

12. The anatomy animation clips were difficult to use.

    ( ) 1 Strongly Disagree ( ) 2 Disagree ( ) 3 Neutral ( ) 4 Agree Strongly ( ) 5 Agree

13. The detail of the anatomy animations allowed me to accurately give additional context to the scenarios.

    ( ) 1 Strongly Disagree ( ) 2 Disagree ( ) 3 Neutral ( ) 4 Agree Strongly ( ) 5 Agree

14. The anatomy animations were an adequate substitute for hands-on anatomy models.

    ( ) 1 Strongly Disagree ( ) 2 Disagree ( ) 3 Neutral ( ) 4 Agree Strongly ( ) 5 Agree

15. The concussion scenarios did not provide enough information to carry out an accurate assessment.

    ( ) 1 Strongly Disagree ( ) 2 Disagree ( ) 3 Neutral ( ) 4 Agree Strongly ( ) 5 Agree

16. The concussion scenarios did not provide enough information to make a decision regarding the most appropriate management plan.

    ( ) 1 Strongly Disagree ( ) 2 Disagree ( ) 3 Neutral ( ) 4 Agree Strongly ( ) 5 Agree

17. The concussion scenarios were too difficult for my current knowledge base.

    ( ) 1 Strongly Disagree ( ) 2 Disagree ( ) 3 Neutral ( ) 4 Agree Strongly ( ) 5 Agree

18. I think that using technology to present scenarios is more motivational than using text-based cases.

    ( ) 1 Strongly Disagree ( ) 2 Disagree ( ) 3 Neutral ( ) 4 Agree Strongly ( ) 5 Agree

19. The level of analysis required in the scenarios was too difficult.

    ( ) 1 Strongly Disagree ( ) 2 Disagree ( ) 3 Neutral ( ) 4 Agree Strongly ( ) 5 Agree

20. Using technology to learn is distracting.

    ( ) 1 Strongly Disagree ( ) 2 Disagree ( ) 3 Neutral ( ) 4 Agree Strongly ( ) 5 Agree

21. What were two things that you enjoyed the most about the AT-ICE?
22. What are some improvements that you would suggest for the AT-ICE?
23. Describe how you could use the AT-ICE as a part of your learning about concussion care.

Authors

Colin D. King, PhD, CAT(C), is a Professor and Athletic Therapist in the School of Kinesiology at Acadia University in Nova Scotia, Canada. He also sits on the Board of Directors for the World Federation of Athletic Training and Therapy and acts as the Program Director of the CATA accredited athletic therapy program at Acadia. *Email:* colin.king@acadiau.ca

Loriann M. Hynes, PhD, CAT(C), is an Associate Professor and Athletic Therapist in the School of Kinesiology & Health Science at York University in Ontario, Canada. She is also the Program Director of the CATA accredited Athletic Therapy Certificate at York. *Email*: lhynes@yorku.ca

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Mathematics Student Teachers' Behavioural Intention Using ChatGPT

Intention comportementale des stagiaires en mathématiques d'utiliser ChatGPT

Tang Minh Dung, *Ho Chi Minh City University of Education, Vietnam*
Vo Khoi Nguyen, *Ho Chi Minh City University of Education, Vietnam*
Doan Cao Minh Tri, *Ho Chi Minh City University of Education, Vietnam*
Bui Hoang Dieu Ban, *Ho Chi Minh City University of Education, Vietnam*
Phu Luong Chi Quoc, *Ho Chi Minh City University of Education, Vietnam*

Abstract

The rapid rise of artificial intelligence (AI), exemplified by ChatGPT, has transformed education. However, few studies have examined the factors influencing its adoption in higher education, especially among Mathematics student teachers. This study investigates factors that influence the behavioural intentions of Mathematics student teachers regarding using ChatGPT. Guided by the Unified Theory of Acceptance and Use of Technology (UTAUT) model, data were collected through a questionnaire of 24 items across six factors on a 5-point Likert scale. Using multiple linear regression analysis with RStudio, the findings reveal that Intrinsic Motivation, Performance Expectancy, Social Influence, and Perceived Trust positively affect behavioural intentions to adopt ChatGPT. The study emphasizes implications for developers and educators to enhance AI integration in education, thereby supporting personalized and engaging learning experiences.

Keywords: artificial intelligence, behavioural intention, ChatGPT, Mathematics student teacher

Résumé

L'essor rapide de l'intelligence artificielle (IA), illustré par ChatGPT, a transformé l'éducation. Cependant, peu d'études ont examiné les facteurs influençant son adoption dans l'enseignement supérieur, en particulier parmi les stagiaires en mathématiques. Cette étude examine les facteurs qui influencent les intentions comportementales des stagiaires en mathématiques concernant l'utilisation de ChatGPT. Guidés par le modèle de la théorie unifiée de l'acceptation et de l'utilisation des technologies (UTAUT), les données ont été collectées au moyen d'un questionnaire de 24 éléments portant sur six facteurs sur une échelle de Likert à 5 points. À l'aide d'une analyse de régression linéaire multiple avec RStudio, les résultats révèlent que la motivation intrinsèque, les attentes en matière de performance, l'influence sociale et la confiance perçue affectent positivement les intentions comportementales d'adopter ChatGPT. L'étude met l'accent sur les implications pour les personnes développeuses et enseignantes d'améliorer l'intégration de l'IA dans l'éducation, soutenant ainsi des expériences d'apprentissage personnalisées et engageantes.

Mot-clés: ChatGPT, intelligence artificielle, intentions comportementales, stagiaires en mathématiques

Introduction

Artificial intelligence (AI) has emerged as a social phenomenon appearing in many fields. One prominent AI tool today is ChatGPT, developed by OpenAI. With the release of version 4.0, which is more complete compared to previous versions, and equipped with a vast source of information and data from the Internet, along with the ability to learn and converse in a way that mimics human interaction, ChatGPT has garnered significant attention for its advanced features, pushing the boundaries of what chatbots can achieve (Jo, 2023). Additionally, its accessibility from any device and OpenAI's free use policy via personal email registration have enhanced its popularity.

Regardless of accuracy and source information, ChatGPT is a versatile tool for students' educational purposes. It provides text replies, offers translations, and helps with writing tasks. It also facilitates calculations, assists in solving mathematical problems, and supports understanding of complex mathematical concepts for those studying Mathematics.

Since its public release in 2022, ChatGPT has generated significant interest across various sectors, notably research in understanding ChatGPT adoption. Research on behavioural intentions concerning ChatGPT and the factors impacting it continues to grow (Bernabei et al., 2023; Duong et al., 2023; Lai et al., 2023; Ma & Huo, 2023; Menon & Shilpa, 2023; Strzelecki, 2023).

Studies underscore the need for education to adapt and equip individuals with the skills and knowledge necessary to thrive via the integration of rapidly evolving technology into education (Firat & Köksal, 2019; Kale, 2018; Keengwe & Bhargava, 2013; Voogt et al., 2012). However, as Montenegro-Rueda et al. (2023) pointed out, scientific research on using ChatGPT in education is still scarce, likely due to its recent emergence. Nevertheless, the limited existing research highlights a growing interest and signals an emerging trend of broader adoption of ChatGPT. For example, Kabudi (2022), Lo (2023), and Sullivan et al. (2023) indicate that an increasing number of teachers and students are adopting ChatGPT, drawn to its potential to enhance learning experiences. Similarly, Talan and Kalinkara (2023) report its broad integration into higher education, emphasizing its appeal. Even so, as Montenegro-Rueda et al. (2023) stress, not enough studies have been conducted to address the specific use of ChatGPT in higher education. Given that educational technology, including ChatGPT, is an evolving field, its implementation in higher education remains relatively new and underexplored compared with other educational levels.

Albion et al. (2010) argue that teacher quality is crucial for student success, with Teo and Milutinovic (2015) emphasizing teachers' key role in effectively integrating technology into education. Szymkowiak et al. (2021) further highlight that students often emulate teachers who use modern technologies in their teaching. These findings underscore that the use of technology integration in teaching largely depends on teachers (Marshall & Cox, 2008) and technology integration should focus on achieving pedagogical goals rather than being driven by technology itself (Angeli & Valanides, 2009; Enochsson, 2009). Therefore, teachers must thoughtfully and purposefully adopt technology to shape its effective use in education. Marshall and Cox (2008) and Teo and Milutinovic (2015) emphasize that the training period is a critical time for teachers to develop proficiency in using technology for teaching. Early preparation ensures that future teachers can effectively integrate technological tools into their classrooms (Agyei & Voogt, 2011; Drent & Meelissen, 2008). Student teachers are pivotal to this process as they represent the next generation of educators who will shape how emerging technologies such as ChatGPT are adopted and utilized in education. Consequently, there is a need for comprehensive research into the factors influencing student teachers' behavioural intentions of using ChatGPT.

Mathematics requires a high degree of precision both in logical reasoning and in resultant outcomes. Notwithstanding its capacity to enhance mathematical education, ChatGPT often delivers inaccurate or irrelevant responses, particularly to complex problems or those necessitating a comprehensive understanding of mathematical principles (Lo, 2023; Wardat et al., 2023). Furthermore, it may generate solutions that surpass students' cognitive abilities or the expectations of educational programs (Egara & Mosimege, 2024). This dichotomy—between the significant potential of ChatGPT in Mathematics education and its propensity for errors in a domain that demands the highest level of precision—renders the behavioural intentions of Mathematics student teachers unique, potentially setting them apart from their peers in other disciplines.

Given this context, this research aims to identify the factors influencing Mathematics student teachers' behavioural intention toward ChatGPT. The article's primary objective is to address the question: What factors influence Mathematics student teachers' behavioural intention of using ChatGPT for educational purposes at university?

Addressing this research gap will help us better understand how student teachers actively embrace ChatGPT to enhance their learning experiences and academic success, starting with future Mathematics educators. This will provide foundational insights that could offer valuable guidance for the strategic implementation of AI tools in education. Ultimately, these insights could inform broader educational strategies and future research in curriculum development, teacher training, and AI tool refinement.

Theoretical Framework

To investigate the determinants influencing Behavioural Intention (BI) towards the utilization of ChatGPT thoroughly, we employed a modified iteration of the Unified Theory of Acceptance and Use of Technology (UTAUT) model posited by Venkatesh et al. (2003), which has garnered extensive validation within the realm of technology acceptance research. The sample consisted of Mathematics student teachers from a university of education. Given the constraints associated with accessing this demographic, we engaged a Mathematics educator and four student teachers to ascertain pivotal variables (factors) likely to exert the most significant influence on BI. Following this preliminary analysis, we retained three fundamental variables from the original UTAUT model—Performance Expectancy (PE), Social Influence (SI), and Effort Expectancy (EE)—due to their consistent affirmation in prior empirical studies. Furthermore, the Facilitating Conditions factor in the UTAUT model was excluded as it has been determined that Vietnamese student teachers typically possess adequate access to ChatGPT through the web platform (www.chatgpt.com). Additionally, OpenAI provides free versions of ChatGPT, enabling users to access and utilize it for basic purposes. To enhance the study's contextual applicability, we integrated two variables: Perceived Trust (PT), as informed by Rahim et al. (2022) – which addresses issues of integrity, ethics, and privacy in the context of AI-based chatbot usage – and Intrinsic Motivation (IM), sourced from Davis et al. (1992) – which captures the distinct enthusiasm and engaged involvement of younger users (ages 18–22) with emerging technologies (Table 1).

Table 1

Definitions of Factors

Factor	Definition (in the case of ChatGPT)	Reference
BI	The level of the strength of the user's intention to use a ChatGPT.	Ajzen (2020), Fishbein & Ajzen (1977)
EE	The level of ease associated with using ChatGPT.	Duong et al. (2023), Rahim et al. (2022), Venkatesh et al. (2003)
IM	Refers to the internal drive to engage in using ChatGPT for the inherent satisfaction it brings instead of external rewards or pressures. This includes the fun, enjoyment, pleasantness, and interest that interacting with ChatGPT brings.	Davis et al. (1992)
PE	The level to which the user perceives that using ChatGPT will help them to attain gains in study performance.	Nikolopoulou et al. (2021), Venkatesh et al. (2003)
PT	The level of user's perceptions about the expected reliability, integrity, and privacy of ChatGPT.	Menon & Shilpa (2023), Rahim et al. (2022)
SI	The level to which the user perceives that significant others believe he or she should use ChatGPT.	Venkatesh et al. (2003)

Note. BI is Behavioural Intention; EE is Effort Expectancy; IM is Intrinsic Motivation; PE is Performance Expectation; PT is Perceived Trust; SI is Social Influence.

The following hypotheses are suggested (Figure 1):

H1: Performance Expectancy is positively correlated with Behavioural Intention to use ChatGPT.

H2: Effort Expectancy is positively correlated with Behavioural Intention to use ChatGPT.

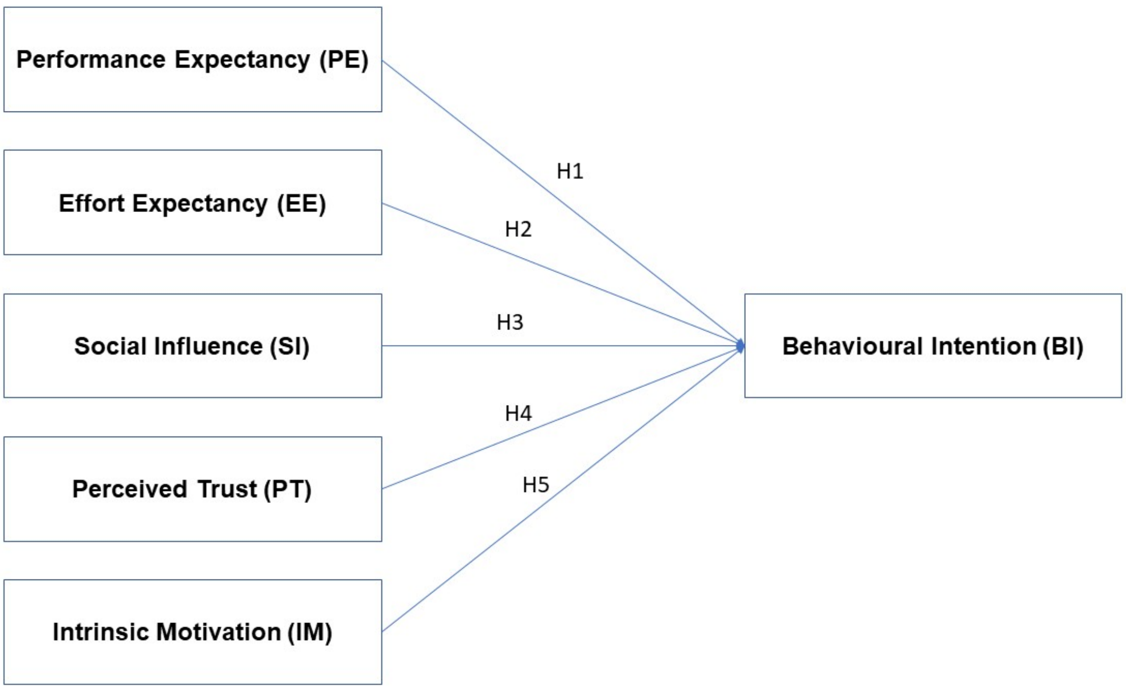
H3: Social Influence is positively correlated with Behavioural Intention to use ChatGPT.

H4: Perceived Trust is positively correlated with Behavioural Intention to use ChatGPT.

H5: Intrinsic Motivation is positively correlated with Behavioural Intention to use ChatGPT.

Figure 1

Hypotheses Suggested



Methods

Design

To test the hypotheses, a quantitative approach was used to explore the factors influencing BI according to the UTAUT model.

Participants and Data Collection

First year to fourth year student teachers in the Department of Mathematics at a university of education in Vietnam were surveyed. We visited classrooms and had student teachers scan a QR code to participate in the survey through Google Forms. Participants were informed that their participation was voluntary, and their responses would be confidential and used solely for academic purposes. The survey was carried out from January 21, 2024, to March 29, 2024.

Criteria by Hair et al. (2018) were used to estimate the total sample size needed for Exploratory Factor Analysis (EFA). Specifically, the minimum sample size is 50, but a size of 100 or more is preferred. Additionally, the number of valid responses (excluding those who had never heard of ChatGPT or student teachers in their fifth year or beyond) should be at least five times the number of survey questions. Since there were 24 survey questions, a minimum of 120 valid responses were needed. Additionally, Green (1991) suggests that if the purpose is to evaluate factors from each independent variable, such as *t*-tests or testing the regression coefficient, the minimum sample size for a regression analysis should be 104 + *m* (where *m* is the number of independent variables). Out of 281 responses received, 274 were deemed valid. Non-serious answers like selecting the same level for all items, were removed. Thus, this sample size was considered suitable for EFA.

Table 2 shows the general and demographic characteristics of the study sample after the data were cleaned. Notably, only 16.4% of student teachers answered *Never* to the question *Frequency of ChatGPT use*, indicating that ChatGPT usage had become relatively common. However, with only 15.3% of student teachers responding *Frequently*, it can be concluded that ChatGPT had not yet been widely adopted in their daily lives.

Table 2

Participant Demographics (N = 274)

	Variable	*N*	%
Gender	Male	163	59.5
	Female	111	40.5
Grade	First	88	32.1
	Second	76	27.7
	Third	65	23.7
	Fourth	45	16.4
Frequency of ChatGPT use	Frequently	42	15.3
	Sometimes	187	68.2
	Never	45	16.4

Instrument

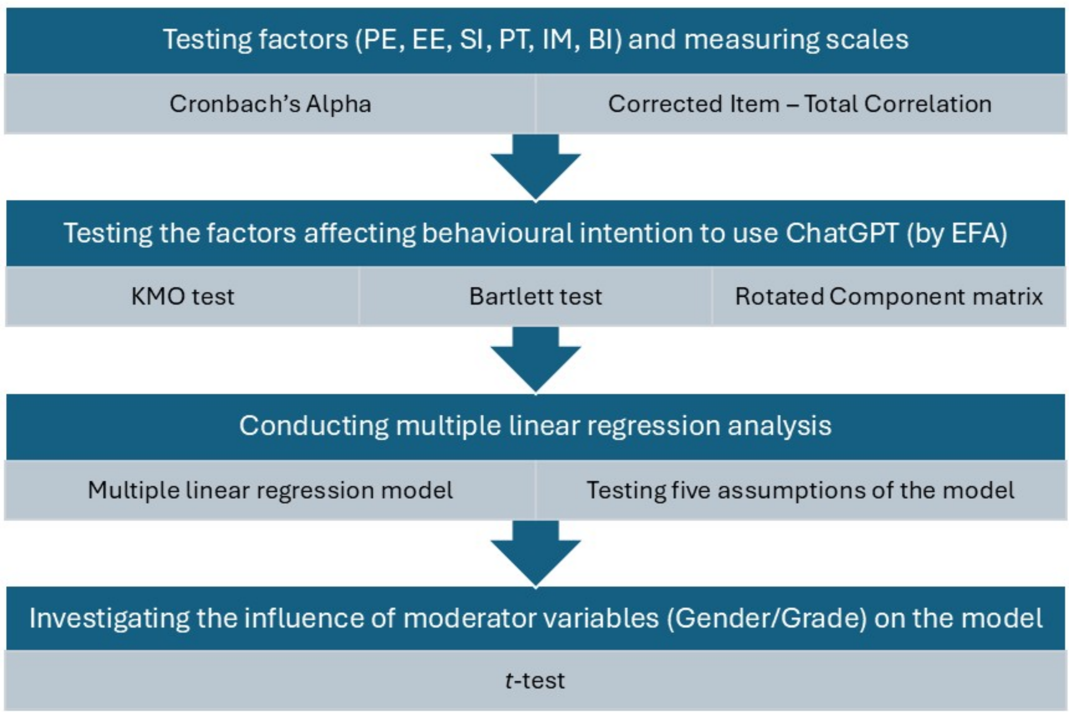
Participants were asked to provide demographic information and respond to a questionnaire consisting of 24 items structured into six factors (PE, EE, SI, PT, IM, and BI) with four items in each factor (Table 1). All items were adapted from existing studies and modified to fit the survey context among Mathematics student teachers and scored using a 5-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree).

Data Analysis

RStudio software was used to process the cleaned data, following these analytical steps: (1) testing factors and measuring scales, (2) testing the factors affecting behavioural intention to use ChatGPT, (3) conducting multiple linear regression analysis, and (4) investigating the influence of moderator variables on the model (Figure 2).

Figure 2

Steps of Data Analysis



Note. BI = Behavioural Intention, EE = Effort Expectancy, EFA = Exploratory Factor Analysis, IM = Intrinsic Motivation, KMO = Kaiser-Meyer-Olkin, PE = Performance Expectancy, PT = Perceived Trust, and SI = Social Influence.

Testing Factors and Measuring Scales

Cronbach's Alpha (or coefficient alpha) measures reliability or internal consistency. The term *Reliability* refers to how a survey (or questionnaire) measures what it is supposed to measure. This study used Cronbach's Alpha to verify the survey reliability based on the Likert scale with multiple questions. A high Cronbach's Alpha result of a factor indicates that the listed observed variables are closely related, accurately reflecting the characteristics of the parent factor. Conversely, a low result suggests that the observed variables might be measuring something else or not measuring anything at all. In the statistics results, the following indices were considered: Overall Alpha (raw_alpha) of the factors, Coefficient Alpha of each observed variable in the *raw_alpha* column in the *Reliability if an item is dropped* table, and Corrected Item – Total Correlation coefficient in the *r.drop* column of the *Item statistics* table.

According to Henseler et al. (2009) and Hair et al. (2018), a suitable scale should have an Overall Alpha greater than 0.7. Further, Hoang and Chu Nguyen (2008) suggest that the Cronbach's Alpha coefficient values are as follows: if Coefficient Alpha is between 0.8 and 1.0, the scale is very good; if Coefficient Alpha is between 0.7 and 0.8, the scale is good; if Coefficient Alpha is greater than 0.6, the scale is acceptable.

For the *Reliability if an item is dropped* table, each row refers to each observed variable and the Coefficient Alpha if the item is dropped. This value will be evaluated with the Corrected Item – Total Correlation coefficient in the *Item statistics* table. A good scale will have a Corrected Item – Total Correlation coefficient greater than 0.3 (Cristobal et al., 2007). If the Coefficient Alpha after dropping an item is greater than the Overall Alpha, and the Corrected Item – Total Correlation coefficient of that variable is less than 0.3, the observed variable will be removed to increase the scale's reliability. If the Coefficient Alpha after dropping an item is slightly higher than the following Overall Alpha (the difference is less than 0.1) but the Corrected Item – Total Correlation coefficient of that variable is greater than 0.3, we consider keeping it.

Testing the Factors Affecting Behavioural Intention to Use ChatGPT

In this study many items generated by the questionnaire can be interrelated, complicating the interpretation and analysis of data. Exploratory factor analysis was used to group variables that were correlated with each other into more general underlying factors, thereby providing a clearer view of the data by reducing the original list of variables to fewer easily interpretable common factors.

Before conducting EFA, the Kaiser-Meyer-Olkin (KMO) test and the Bartlett test were used to confirm that the dataset were suitable for this type of analysis. According to Kaiser (1974), a KMO value greater than 0.5 and a *p*-value less than 0.05 indicate that the correlation among observed variables is sufficient for EFA. For the Bartlett test, if the *p*-value is less than 0.05, it suggests that the observed variables within the factor are correlated.

Parallel analysis was used to determine the number of factors to extract from the data for EFA. Next, we assessed the scale's values through EFA, where two essential values were considered: convergent validity and discriminant validity. According to Hair et al. (2018), in the rotation matrix table, if the factor loading of an observed variable within a factor is at least 0.5, the observed variable is good quality. According to Pituch and Stevens (2015), a factor is considered reliable if it comprises more than three measuring variables. For convergent validity, observed variables of the same nature converge towards the same factor; when displayed in the Rotated Component matrix, these variables will be in the same column. For discriminant validity, observed variables converge towards this factor and must be distinct from observed variables converging on other factors; when displayed in the Rotated Component matrix, each group of variables will separate out into distinct columns.

After removing observed variables with factor loading of less than 0.5, we rearranged our factors and conducted a second round of EFA analysis for these new variables.

Multiple Linear Regression Analysis to Examine the Impact of the Factors in the Model

The factors were entered into the regression model. We used multiple linear regression analysis to examine the hypotheses about the impact of the new factors on BI in the model, thereby testing five proposed hypotheses with statistical significance at the level of 5%.

After the analysis we tested five of the assumptions of the multiple linear regression model to ensure that our model was statistically meaningful.

Assumption 1: Normal distribution of the model's residuals.

+ The residuals are normally distributed when the *p*-value of the Anderson-Darling test is less than 0.05, or the Normal Q-Q Plot of residuals has all points concentrated around the line $y = x$.

+ The residuals have a mean of zero if the *p*-value of the *t*-test is greater than 0.05.

+ The residuals have constant variance: We can check this with the Goldfeld-Quandt test if the *p*-value is greater than 0.05 or using the Scatter Plot of Standardized Residuals and Standardized Fitted Values if the standardized residuals are randomly distributed around the line $y = 0$.

Assumption 2: Linear relationship between the dependent and independent variables. This assumption can be tested using the partial residual plot method. If the purple line is closer to the blue line, then the relationship between the dependent and independent variables is linear.

Assumption 3: No autocorrelation of the residual series. This assumption can be tested using the Durbin-Watson test. If the value *d* of this test is between 1.5 and 2.5, there is no autocorrelation.

Assumption 4: No significant outliers or highly influential points.

+ A point is an outlier if, in the Q-Q Plot, it does not lie too far from the line $y = x$.

+ A point may be an influential point if its Cook's distance value is greater than 0.5.

Assumption 5: No multicollinearity. Multicollinearity occurs when the Variance Inflation Factor (VIF) is greater than 5 (Frost, 2019). Additionally, if the absolute value of the Pearson correlation coefficient is greater than 0.8, multicollinearity is likely to exist (Young, 2017).

Next, we evaluated the importance of each independent variable to the dependent variable based on the coefficient of determination Multiple R^2 by Lindeman et al.'s (1980) method.

Investigating the Influence of Moderator Variables on the Models

The moderator variables *Gender* and *Grade* were considered to emphasize the importance of demographics when studying participants' BI in using ChatGPT. Specifically, we examined the impact of the moderator variables Gender and Grade on the linear regression models for the hypotheses. The metric used to test this impact was the *p*-value from the *t*-test, with a statistical significance of 5%.

For the moderator variable Gender, when assessing the impact of each variable X_i (EE, IM, PE, PT, SI) on the variable BI, two variables – the moderator variable Male and the interaction variable $X_i\,Male$ – were added to the linear regression model. We concluded that there is an influence of the Gender variable on the original linear regression model if the value of the interaction variable $X_i\,Male$ is less than 0.05, even when the Male variable individually has a *p*-value greater than 0.05. According to James et al. (2021), "The hierarchical principle states that if we include an interaction in a model, we should also include the main effects, even if the p-values associated with their coefficients are insignificant." (p. 89). For the moderator variable Grade, we used a similar statistics analysis process.

Results

Testing Factors and Measuring Scales

To check survey reliability, based on the Likert scale with multiple questions, the Cronbach's Alpha reliability test was used to ascertain whether the observed variables could represent the parent factor's characteristics. This tool helped to determine which observed variables were appropriate and which were not suitable for inclusion in the scale. The test outcomes are shown in Table 3.

Table 3

Reliability Estimates

Construct	Internal reliability Cronbach's Alpha	Item	Cronbach's Alpha, if an item is dropped	Corrected item – total correlation
BI	0.88	BI1	0.83	0.80
		BI2	0.84	0.79
		BI3	0.87	0.70
		BI4	0.87	0.71
EE	0.87	EE1	0.81	0.75
		EE2	0.81	0.76
		EE3	0.80	0.79
		EE4	0.89	0.57
IM	0.90	IM1	0.87	0.79
		IM2	0.88	0.77
		IM3	0.88	0.77
		IM4	0.87	0.79

Construct	Internal reliability Cronbach's Alpha	Item	Cronbach's Alpha, if an item is dropped	Corrected item – total correlation
PE	0.89	PE1	0.85	0.77
		PE2	0.85	0.77
		PE3	0.86	0.75
		PE4	0.87	0.73
PT	0.82	PT1	0.77	0.65
		PT2	0.77	0.67
		PT3	0.75	0.70
		PT4	0.81	0.57
SI	0.86	SI1	0.81	0.74
		SI2	0.81	0.74
		SI3	0.82	0.72
		SI4	0.85	0.63

Note. BI is Behavioural Intention; EE is Effort Expectancy; IM is Intrinsic Motivation; PE is Performance Expectation; PT is Perceived Trust; SI is Social Influence.

Referencing Table 3, we noted that the Internal Reliability Cronbach's Alpha of the parent factors ranged from 0.82 to 0.9, which satisfied the reliability threshold (greater than 0.7). Each row in the Cronbach's Alpha if an item is dropped column referred to the Overall Alpha if the corresponding observed variable is dropped. The findings revealed that all observed variables contributed meaningfully, except for EE4. Regarding the Corrected Item – Total Correlation coefficient column, all values exceed 0.3, signifying a robust correlation between each observed variable and the remaining variables within the scale. Based on these insights, we deduced that the factor scale possessed adequate reliability and exhibited strong consistency. Moreover, we considered the exclusion of the observed variable EE4 to enhance the scale's reliability. In the EFA test phase, relying on the Rotated Component matrix, we excluded the observed variable EE4.

Testing the Factors Affecting Behavioural Intention to Use ChatGPT

Exploratory factor analysis was utilized to examine the factors influencing the intention to use ChatGPT among Mathematics student teachers. According to the initial hypothesis, there were six factors (24 observed variables). Hair et al. (2018) and Nguyen (2014) stated that separate EFA analyses were required for the independent and the dependent variables.

Exploratory Factor Analysis For the Independent Variables

For the EFA suitability test, a KMO value of 0.92 indicated that the dataset were appropriate for exploratory factor analysis (i.e., > 0.5). The result of Barlett's test with a *p*-value less than 0.05 showed that the correlation among the variables was sufficiently significant to conduct EFA.

Parallel analysis indicated that five factors needed to be extracted for the independent variables. The results from the Rotated Component matrix revealed that the variable EE4, with a factor loading below 0.5, was excluded from the model. The remaining variables, each with a factor loading greater than 0.5, were organized into five factors.

A second EFA was conducted, satisfying the criteria of the KMO test (KMO value = 0.92), Barlett's test (*p*-value < 0.05), and parallel analysis (five factors extracted from the data). The results from the Rotated Component matrix indicated that 19 observed variables were divided into five factors, all of which had factor loading of at least 0.5 (Table 4). These five factors explained 66% of the variance in the data of the 19 observed variables involved in the EFA.

Table 4

Rotated Component Matrix (second round)

Construct	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
PE1	0.74				
PE2	0.80				
PE3	0.69				
PE4	0.66				
PT1		0.66			
PT2		0.65			
PT3		0.79			
PT4		0.50			
EE1			0.83		
EE2			0.83		
EE3			0.70		
SI1				0.77	
SI2				0.85	
SI3				0.57	

Construct	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
SI4				0.52	
IM1					0.67
IM2					0.55
IM3					0.61
IM4					0.65

Note. BI is Behavioural Intention; EE is Effort Expectancy; IM is Intrinsic Motivation; PE is Performance Expectation; PT is Perceived Trust; SI is Social Influence.

Exploratory Factor Analysis For the Dependent Variable

The dependent variable was conducted using a process similar to that of the independent variable. For the EFA suitability test, a KMO value of 0.83 indicated that the dataset were suitable for exploratory factor analysis. The result of Bartlett's test with a p-value less than 0.05 indicated that the correlation among the variables was sufficiently significant to conduct EFA.

Parallel analysis showed that one factor needed to be extracted for the dependent variable. The factor loadings for BI1, BI2, BI3, and BI4 were 0.88, 0.87, 0.75, and 0.75, respectively. These factors explained 66% of the variance in the data from the four observed variables involved in the EFA.

Multiple Regression Analysis

After conducting the EFA, the observed variables were reorganized and subsequently included in the multiple linear regression model (Table 5).

Table 5

Revised Factors and Variables

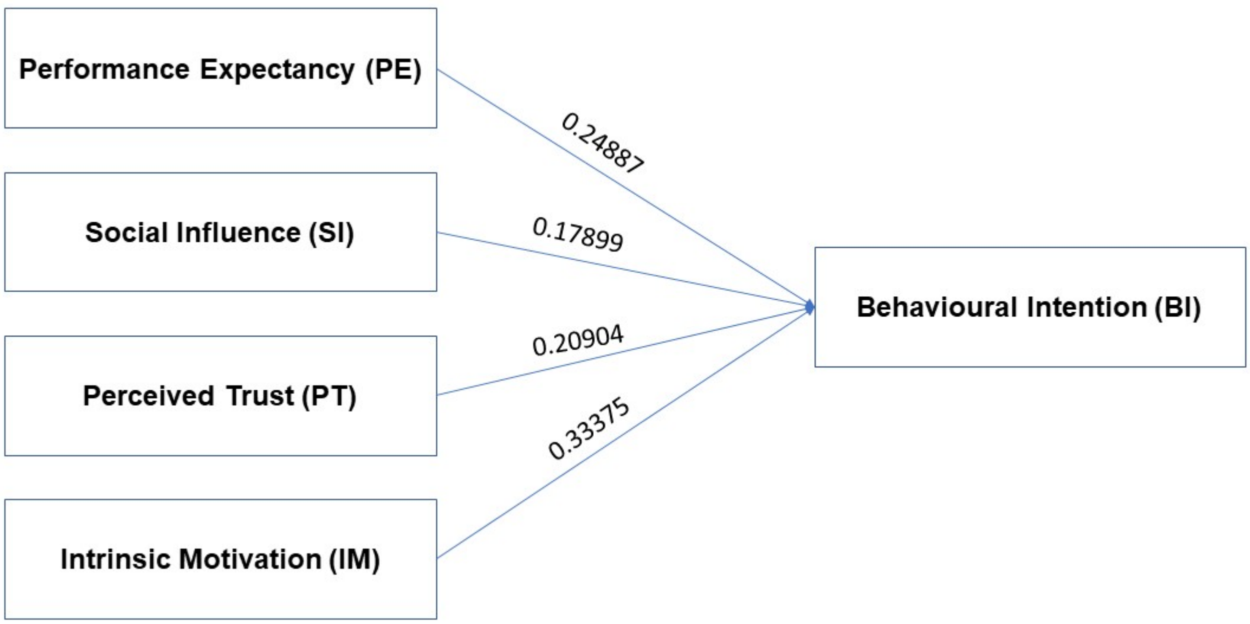
Factors	Observed Variables	Variable Type
X_1 (PE)	PE1, PE2, PE3, PE4	Independent
X_2 (EE)	EE1, EE2, EE3	Independent
X_3 (SI)	SI1, SI2, SI3, SI4	Independent
X_4 (PT)	PT1, PT2, PT3, PT4	Independent
X_5 (IM)	IM1, IM2, IM3, IM4	Independent
Y (BI)	BI1, BI2, BI3, BI4	Dependent

Note. BI is Behavioural Intention; EE is Effort Expectancy; IM is Intrinsic Motivation; PE is Performance Expectation; PT is Perceived Trust; SI is Social Influence.

According to Table 5, we had the analysis model: $Y = f(X_1, X_2, X_3, X_4, X_5)$. By performing multiple regression analysis, we observed that the impact of the variable X_2 (EE) on the dependent variable Y (BI) was not statistically significant, as the p-value of the t-test was 0.879, which is greater than 0.05. The remaining variables all positively impacted the dependent variable Y (BI). Therefore, the variable X_2 (EE) was removed from the model.

Figure 3

The Resulting Linear Regression Model



After removing the variable EE, the resulting linear regression model is:

$$Y = 0.12299 + 0.24887X_1 + 0.17899X_3 + 0.20904X_4 + 0.33375X_5 + \varepsilon \qquad (*)$$

where ε represented the residuals of the linear regression model (Figure 3).

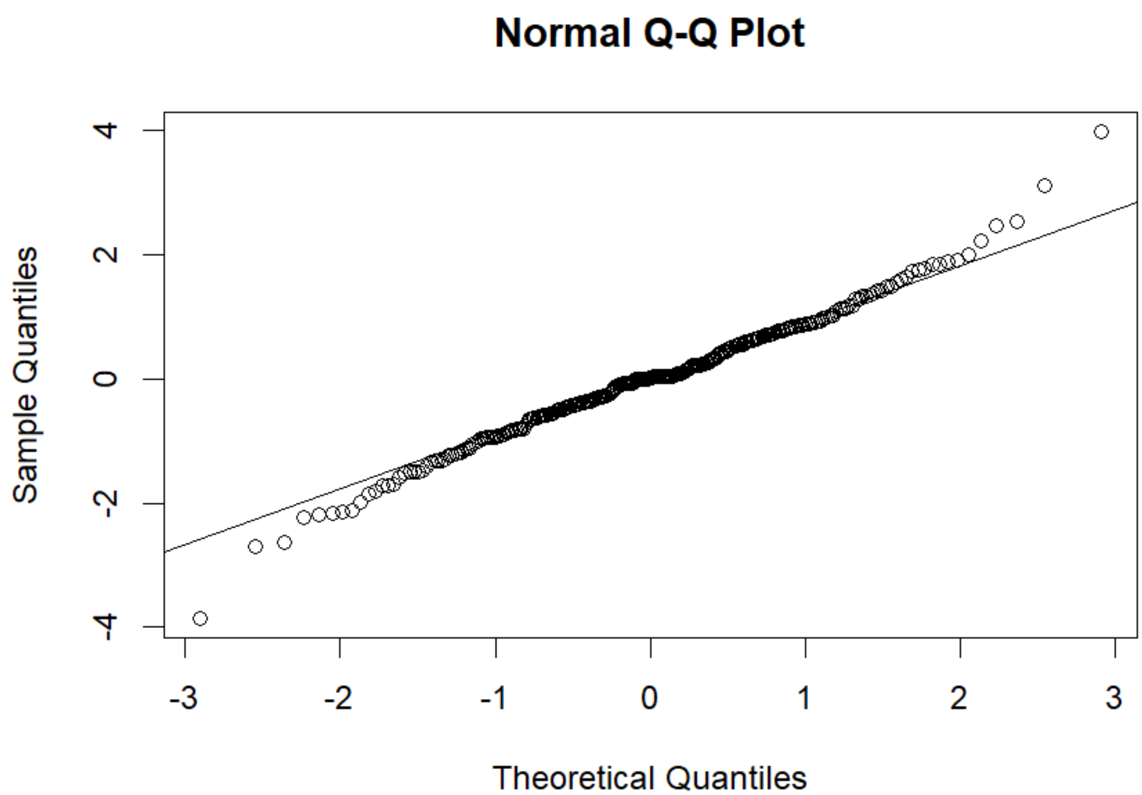
We evaluated the fit of the multiple linear regression model through the Adjusted R^2, which reflects the extent to which the independent variables in the regression model explain the dependent variable. The Adjusted R^2 is 66.99, indicating that the independent variables IM, PE, PT, and SI explain 66.99% of the variance in the dependent variable BI, and factors outside the research model explain the remaining 33.01% of the BI variance. The F-test is 139.5 with a rejection probability of less than 0.05, which was sufficient to conclude that the multiple linear regression model is appropriate for the dataset under study.

Next, we proceeded to test the assumptions of the multiple regression model.

Assumption 1: Normal distribution of the model's residuals. The Anderson-Darling test yielded a p-value = 0.03535 < 0.05, combined with the Normal Q-Q Plot (Figure 4), confirming that the model's residuals were normally distributed.

Figure 4

Normal Q-Q Plot



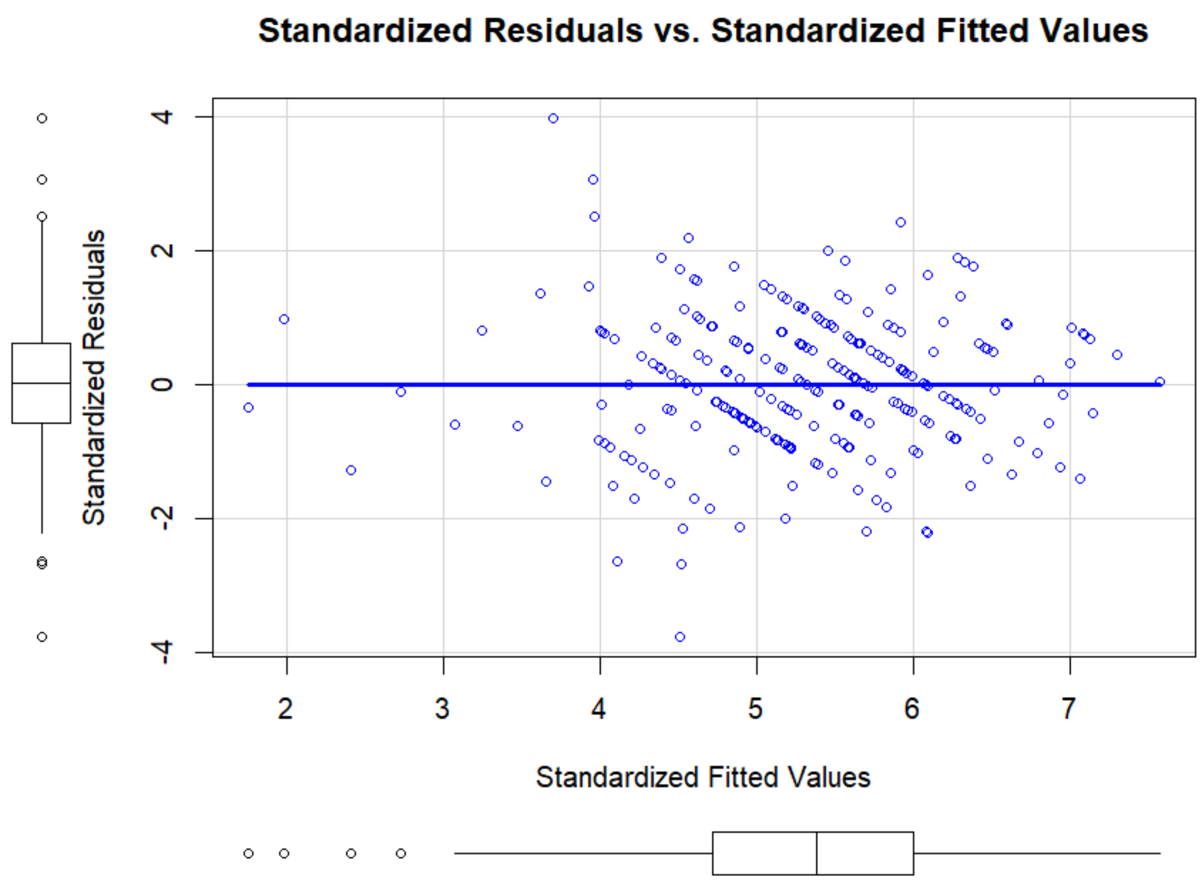
Note. Figure generated from the data processing software.

The *t*-test resulted in a *p*-value = 0.9998 > 0.05, indicating that the residuals had a zero mean.

Based on the Scatter Plot of Standardized Residuals and Standardized Fitted Values (Figure 5) and a *p*-value from the Goldfeld-Quandt test greater than 0.05, we concluded that the residuals had constant variance.

Figure 5

Standardized Residuals and Standardized Fitted Values

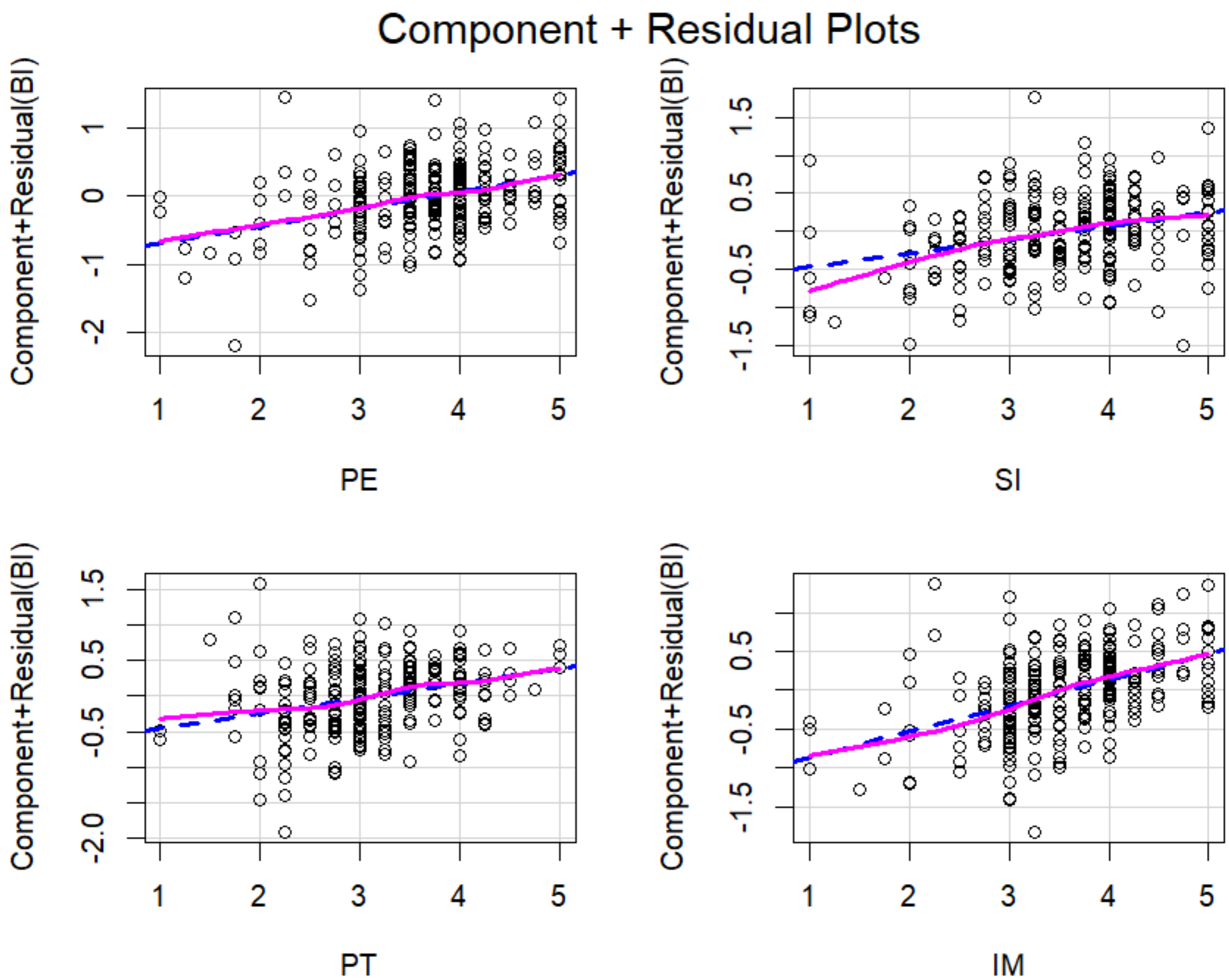


Note. Figure generated from the data processing software.

Assumption 2: Linear relationship between the dependent and independent variables. Figure 6 demonstrates a linear relationship between the dependent and independent variables.

Figure 6

Partial Residual Plots



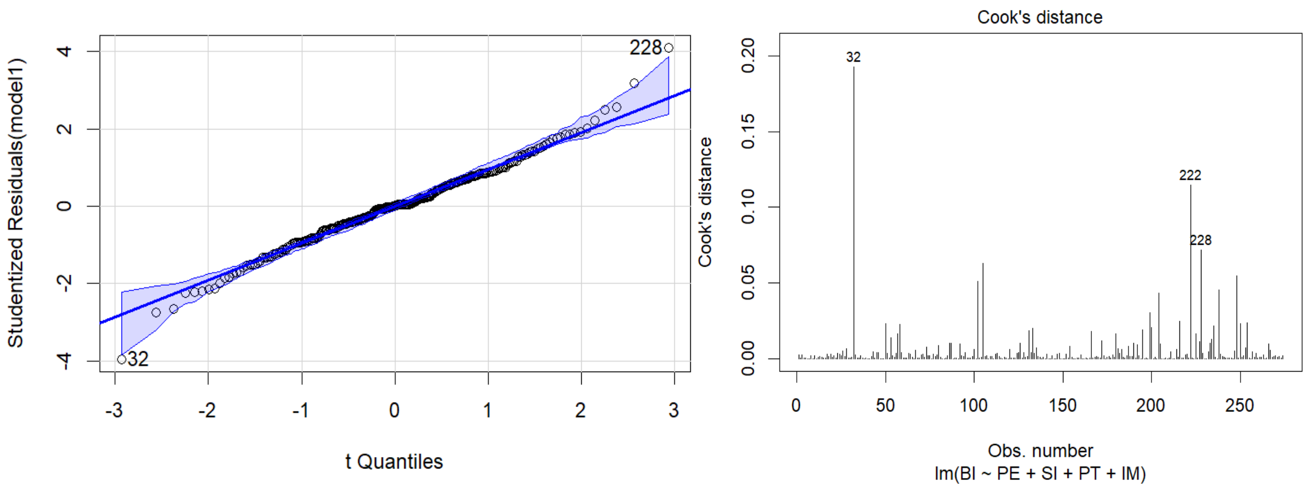
Note. Figure generated from the data processing software.

Assumption 3: No autocorrelation of the residual series. The Durbin-Watson test produces $d = 2.1071$ in the interval 1.5 and 2.5. Hence, we concluded that there was no autocorrelation of the residual series.

Assumption 4: No significant outliers or highly influential points. Figure 7 demonstrates that the model had nearly no significant outliers or highly influential points.

Figure 7

Q-Q Plot and Cook's Distance (x2) Plot



Note. Figure generated from the data processing software.

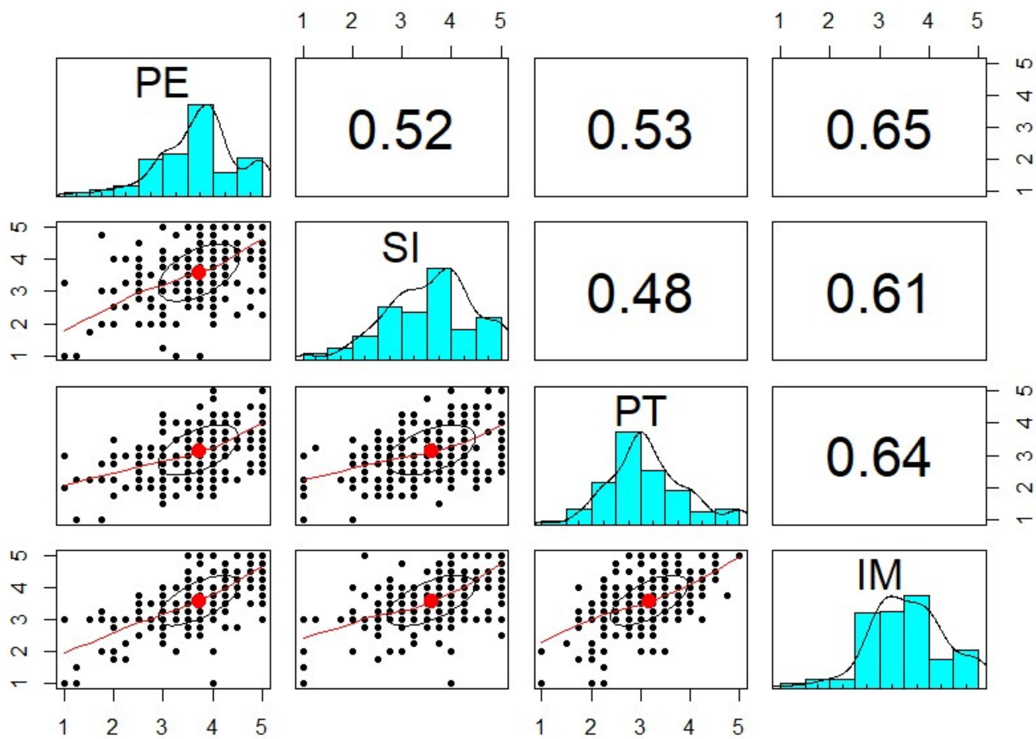
Assumption 5: No multicollinearity. The results showed that the independent variables had VIFs less than 2.5, and the absolute values of the Pearson correlation coefficients were less than 0.7 (Figure 8), indicating that no multicollinearity occurs.

The test results indicated that our model satisfied all five assumptions. Therefore, we concluded that the independent variables IM, PE, PT, and SI positively impact the dependent variable BI. The regression equation (*) was statistically significant.

Next, we assessed the importance of each predictor variable to the dependent variable using the "lmg" method (Lindeman et al., 1980). The findings showed that the R^2 of the model is 67.47%, with the variables SI, PT, PE, and IM having R^2 values of 13.93%, 14.63%, 17.18%, and 21.73%, respectively. Consequently, IM had the most significant influence on the dependent variable BI, whereas SI had the most minor influence.

Figure 8

Pearson's Correlation Coefficients



Note. Figure generated from the data processing software.

The Influence of Moderator Variables on the Models

We tested the impact of the moderator variables *Gender* and *Grade* on the linear regression models of hypotheses H1, H3, H4, and H5 based on the *p*-value of the *t*-test for the coefficients of the moderator variables and the interaction variables added. The results showed that these *p*-values were all greater than the 5% significance level. This indicates that the differences are insufficient to conclude that the moderator variables *Gender* and *Grade* influence the models.

Discussions

Factors Influencing the Behavioural Intention

This study deepens understanding of Mathematics student teachers' perceptions of ChatGPT in educational contexts, addressing a significant research gap. Utilizing the UTAUT scale, findings identified key factors influencing their BI toward ChatGPT, which is essential for AI integration discussions in education. Results showed that IM, PE, PT, and SI positively impacted BI, with IM being the most significant. However, SI had a low impact on BI. This research underscored the varied influences of UTAUT constructs on the acceptance and use of ChatGPT among student teachers.

Intrinsic Motivation was observed to be the most substantial positive influence on the BI of Mathematics student teachers towards using ChatGPT. This finding aligns with recent studies emphasizing the central role of IM in adopting technological aids in educational contexts, which pointed out a positive correlation between IM and BI (Hsu & Lin, 2021). In the context of ChatGPT, Lai et al. (2023) found that IM was a critical factor for Hong Kong undergraduates' use of ChatGPT, primarily driven by the pleasure and satisfaction derived from its use in addressing academic questions. Therefore, our findings indicated that if student teachers find ChatGPT interesting to interact with, they will have a greater intention to use it. Moreover, our findings supported those of Li and Yanagisawa (2021), who identified IM as a significant motivator in virtual assistant interactions.

In our research, PE was identified as a crucial predictor of BI to use ChatGPT among Mathematics student teachers, ranking second in importance. Our data indicated that student teachers with higher levels of PE were more inclined to integrate ChatGPT into their learning processes. This observation aligns with previous research in the domain of ChatGPT within educational settings, including studies by Alshammari and Alshammari (2024), Duong et al. (2023), Foroughi et al. (2023), and Strzelecki (2023), and extends to chatbot research, as seen in Rahim et al. (2022) and Tian et al. (2024). This may be due to the nature of math, where students need to find precise solutions to advanced math problems, explain complex math concepts, or develop activities appropriate to teaching in the context of Mathematics.

This study discovered that PT had a positive but moderate influence on the BI of Mathematics student teachers towards using ChatGPT. This aligns with Rahim et al. (2022), who found a direct relationship between PT and BI among postgraduate students within the context of ChatGPT, and with Cheng and Jiang (2020) and De Cosmo et al. (2021) in chatbot research. This indicated that if student teachers' trust issues are not a concern, they will likely prefer using ChatGPT. However, Menon and Shilpa (2023) indicated that although most respondents admitted to being aware that their interactions and information with ChatGPT are not confidential, they still found it safe and secure.

In addition, our study unveiled that SI had a low impact on the BI of Mathematics student teachers to use ChatGPT, aligning with findings in similar ChatGPT research by Strzelecki (2023) and in chatbot studies by Rahim et al. (2022) and Tian et al. (2024). Alshammari and Alshammari (2024) and Foroughi et al. (2023) even found no impact of SI on BI within the context of ChatGPT. This demonstrates SI's indirect influence on students' behavioural intentions regarding using ChatGPT for the educational purposes of university student teachers. However, this contrasts with studies by Singh et al. (2020) on mobile wallet services and Terblanche and Kidd (2022) on chatbots, where users were concerned with the opinions of their family, friends, and colleagues regarding using a chatbot.

Contrary to our initial hypothesis, EE did not significantly impact Mathematics student teachers' BI to use ChatGPT, aligning with findings from Alshammari and Alshammari (2024) and Strzelecki (2023) on ChatGPT, and Rahim et al. (2022) and Tian et al. (2024) on chatbots. This reveals that student teachers do not perceive difficulties with using ChatGPT, suggesting minimal effort is required to utilize this technology in higher education, hence its negligible influence on BI. This may be due to the recent development of information technology applications in teaching, especially in Mathematics teaching, which has made student teachers accustomed to accessing new technologies.

Implications

This study provides valuable insights into how Mathematics student teachers perceive and intend to use ChatGPT, offering practical guidance for developers, educational institutions, and educators to optimize its integration into educational settings.

Given that Intrinsic Motivation (IM) significantly influences Behavioural Intention (BI), it is essential to organize workshops that illustrate the capabilities of ChatGPT in fostering creativity within the educational field. These workshops could exemplify the generation of lesson plans, engaging activities, and real-world applications of Mathematics. Additionally, the pedagogical insights and recommendations offered by ChatGPT present innovative resources and persuasive solutions to the diverse challenges and inquiries faced by student teachers.

In light of Performance Expectancy (PE), it is crucial for different stakeholders to enhance ChatGPT's effectiveness in the educational sphere. Developers should focus on refining the accuracy and relevance of responses (Getenet, 2024; Pham et al., 2024), particularly in challenging areas like advanced mathematics and abstract concepts, ensuring alignment with curriculum standards. Institutions need to offer training that highlight how ChatGPT can bolster teaching outcomes, such as developing differentiated instruction plans and supporting diverse learners through tailored problem-solving strategies. Educators should consider integrating ChatGPT into their teaching methods, using it not only to supplement traditional approaches but also to provide alternative explanations and facilitate complex problem-solving.

To enhance Social Influence (SI) within educational institutions, fostering collaboration among student teachers is essential. By encouraging future educators to work together, they can share insights and experiences on using ChatGPT effectively. This collaborative approach will help cultivate a culture where technology integration is recognized as valuable and aligns seamlessly with established professional teaching practices. By modeling the appropriate use of ChatGPT, student teachers can pave the way for its acceptance and effective classroom implementation.

To foster Perceived Trust (PT) in ChatGPT, developers must prioritize transparency by addressing effectively users' concerns regarding reliability, integrity, and privacy. This involves implementing clear disclaimers, robust privacy protections, and easily accessible mechanisms for reporting inaccuracies. Institutions can further bolster confidence in ChatGPT by educating users about its strengths and limitations, framing it as a supportive tool rather than a complete replacement for traditional methods. Additionally, educators play a crucial role by modeling responsible usage; they should verify ChatGPT's outputs, promote critical evaluation among students, and discuss constructively any potential errors in the classroom setting, thereby nurturing a balanced approach to technology in learning environments.

Limitations and Future Research

This study was conducted in Vietnam, a developing country, which may limit the generalizability of our findings to other regions with different technological and cultural contexts. The participant pool was confined to Mathematics students from a teacher training institution. Future research could be broadened to include all university students and faculty or extended to other institutions. Moreover, given the rapid advancements in AI, some aspects of our research need to be updated quickly. Therefore, future studies should explore ChatGPT's use in more diverse and novel contexts.

This study was limited to specific variables influencing Behavioural Intention (BI), as outlined in the Theoretical Framework section. Although the selected factors provided valuable insights, broader external variables such as educational policies, access, or institutional support also play a critical role in shaping learning outcomes. These factors may influence significantly the adoption of ChatGPT among student teachers. Future research should examine these external influences to develop a more comprehensive understanding of the multifaceted elements impacting BI in educational contexts, particularly in regions where access to technology and institutional frameworks vary significantly.

Additionally, our focus on utilizing ChatGPT for general educational purposes at the university level limited our capacity to provide nuanced insights into its integration, specifically within Mathematics education. Future inquiries should explore how ChatGPT can be adapted to fulfill the distinctive requirements of Mathematics education, including resolving complex problems, enhancing conceptual understanding, and creating engaging instructional activities. Such research could offer guidelines for integrating ChatGPT into preservice teacher training programs, ultimately equipping future educators with the competencies necessary to effectively incorporate AI technologies into their instructional practices.

Conclusion

Our study applied the Unified Theory of Acceptance and Use of Technology (UTAUT) model to explore factors that influence the intention of Mathematics student teachers to use ChatGPT. We found that Performance Expectancy (PE), Perceived Trust (PT), Intrinsic Motivation (IM), and Social Influence (SI) positively affected students' intentions to use ChatGPT, whereas Effort Expectancy (EE) did not. These findings demonstrate ChatGPT's potential as an effective teaching and learning support tool. A focus on raising perception of the usefulness and performance of ChatGPT can promote its adoption in educational settings, especially in the context of current digital transformation. The research results provide important information for the development of teacher training programs, helping them to become familiar with and effectively use AI technologies such as ChatGPT in the future. At the same time, the research also contributes to the development and improvement of AI tools, especially in the educational field, by identifying important factors that influence user acceptance. These insights suggest future research on the cross-cultural applicability and expanded demographic inclusion, underlining its implications for curriculum development, teacher training, and AI tool refinement.

References

Agyei, D. D., & Voogt, J. (2011). ICT use in the teaching of mathematics: Implications for professional development of pre-service teachers in Ghana. *Education and Information Technologies*, *16*, 423–439. https://doi.org/10.1007/s10639-010-9141-9

Ajzen, I. (2020). The theory of planned behavior: Frequently asked questions. *Human Behavior and Emerging Technologies*, *2*(*4*), 314–324. https://doi.org/10.1002/hbe2.195

Albion, P., Jamieson-Proctor, R., & Finger, G. (2010). Auditing the TPACK confidence of Australian pre-service teachers: The TPACK confidence survey (TCS). In D. Gibson & B. Dodge (Eds.), *Society for Information Technology & Teacher Education International Conference* (pp. 3772–3779). Association for the Advancement of Computing in Education (AACE). https://www.learntechlib.org/primary/p/33969/

Alshammari, S. H., & Alshammari, M. H. (2024). Factors affecting the adoption and use of ChatGPT in higher education. *International Journal of Information and Communication Technology Education*, *20*(1), 1–16. https://doi.org/10.4018/IJICTE.339557

Angeli, C., & Valanides, N. (2009). Epistemological and methodological issues for the conceptualization, development, and assessment of ICT–TPCK: Advances in technological pedagogical content knowledge (TPCK). *Computers & Education*, *52*(1), 154–168. https://doi.org/10.1016/j.compedu.2008.07.006

Bernabei, M., Colabianchi, S., Falegnami, A., & Costantino, F. (2023). Students' use of large language models in engineering education: A case study on technology acceptance, perceptions, efficacy, and detection chances. *Computers & Education: Artificial Intelligence*, *5*, 100172. https://doi.org/10.1016/j.caeai.2023.100172

Cheng, Y., & Jiang, H. (2020). How do AI-driven chatbots impact user experience? Examining gratifications, perceived privacy risk, satisfaction, loyalty, and continued use. *Journal of Broadcasting & Electronic Media*, *64*(4), 592–614. https://doi.org/10.1080/08838151.2020.1834296

Cristobal, E., Flavián, C., & Guinalíu, M. (2007). Perceived e-service quality (PeSQ): Measurement validation and effects on consumer satisfaction and web site loyalty. *Managing Service Quality: An International Journal*, *17*(3), 317–340. https://doi.org/10.1108/09604520710744326

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1992). Extrinsic and intrinsic motivation to use computers in the workplace. *Journal of Applied Social Psychology*, *22*(14), 1111–1132. https://doi.org/10.1111/j.1559-1816.1992.tb00945.x

De Cosmo, L. M., Piper, L., & Di Vittorio, A. (2021). The role of attitude toward chatbots and privacy concern on the relationship between attitude toward mobile advertising and behavioral intent to use chatbots. *Italian Journal of Marketing*, *2021*(1–2), 83–102. https://doi.org/10.1007/s43039-021-00020-1

Drent, M., & Meelissen, M. (2008). Which factors obstruct or stimulate teacher educators to use ICT innovatively? *Computers & Education*, *51*(1), 187–199. https://doi.org/10.1016/j.compedu.2007.05.001

Duong, C. D., Vu, T. N., & Ngo, T. V. N. (2023). Applying a modified technology acceptance model to explain higher education students' usage of ChatGPT: A serial multiple mediation model with knowledge sharing as a moderator. *International Journal of Management Education*, *21*(3), 100883. https://doi.org/10.1016/j.ijme.2023.100883

Egara, F. O., & Mosimege, M. (2024). Exploring the integration of artificial intelligence-based ChatGPT into Mathematics instruction: Perceptions, challenges, and implications for educators. *Education Sciences*, *14*(7), 742. https://doi.org/10.3390/educsci14070742

Enochsson, A.-B. (2009). ICT in initial teacher training. Organisation for Economic Co-operation and Development. https://citeseerx.ist.psu.edu/document?repid=rep1&type=pdf&doi=5dcec359fa38aa677c4beabf85b7257284ee6b18

Firat, E. A., & Köksal, M. S. (2019). Effects of instruction supported by web 2.0 tools on prospective teachers' biotechnology literacy. *Computers & Education*, *135*, 61–74. https://doi.org/10.1016/j.compedu.2019.02.018

Fishbein, M., & Ajzen, I. (1977). Belief, attitude, intention, and behavior: An introduction to theory and research. *Contemporary Sociology*, *6*, 244. https://api.semanticscholar.org/CorpusID:144301400

Foroughi, B., Senali, M. G., Iranmanesh, M., Khanfar, A., Ghobakhloo, M., Annamalai, N., & Naghmeh-Abbaspour, B. (2023). Determinants of intention to use ChatGPT for educational purposes: Findings from PLS-SEM and fsQCA. *International Journal of Human–Computer Interaction*, *40*, 4501–4520. https://doi.org/10.1080/10447318.2023.2226495

Frost, J. (2019). *Regression analysis: An intuitive guide for using and interpreting linear models*. Statistics by Jim Publishing.

Getenet, S. (2024). Pre-service teachers and ChatGPT in multistrategy problem-solving: Implications for mathematics teaching in primary schools. *International Electronic Journal of Mathematics Education*, *19*(1), em0766. https://doi.org/10.29333/iejme/14141

Green, S. B. (1991). How many subjects does it take to do a regression analysis. *Multivariate Behavioral Research*, *26*(3), 499–510. https://doi.org/10.1207/s15327906mbr2603_7

Hair, J. F., Black, B., Babin, B., & Anderson, R. E. (2018). *Multivariate data analysis* (8th ed.). Cengage.

Henseler, J., Ringle, C. M., & Sinkovics, R. R. (2009). The use of partial least squares path modeling in international marketing. In R. R. Sinkovics & P. N. Ghauri (Eds.), *New challenges to international marketing* (Vol. 20, pp. 277–319). Emerald Group Publishing Limited. https://doi.org/10.1108/S1474-7979(2009)0000020014

Hoang, T., & Chu Nguyen, M. N. (2008). *Phan tich du lieu nghien cuu voi SPSS 2008 (tap 1)* [Research data analysis with SPSS 2008 (Volume 1)]. Hong Duc Publisher.

Hsu, H. T., & Lin, C. C. (2021). Extending the technology acceptance model of college learners' mobile-assisted language learning by incorporating psychological constructs. *British Journal of Educational Technology*, *53*(2), 286–306. https://doi.org/10.1111/bjet.13165

James, G., Witten, D., Hastie, T., & Tibshirani, R. (2021). *An introduction to statistical learning: with applications in R* (2nd ed.). Springer.

Jo, H. (2023). Understanding AI tool engagement: A study of ChatGPT usage and word-of-mouth among university students and office workers. *Telematics and Informatics*, *85*, 102067. https://doi.org/10.1016/j.tele.2023.102067

Kabudi, T. M. (2022, May). Artificial intelligence for quality education: Successes and challenges for AI in meeting SDG4. In Y. Zheng, P. Abbott, & J. A. Robles-Flores (Eds.), *International conference on social implications of computers in developing countries* (pp. 347–362). Springer. https://doi.org/10.1007/978-3-031-19429-0_21

Kaiser, H. F. (1974). An index of factorial simplicity. *Psychometrika*, *39*(1), 31–36. https://doi.org/10.1007/BF02291575

Kale, U. (2018). Technology valued? Observation and review activities to enhance future teachers' utility value toward technology integration. *Computers & Education*, *117*, 160–174. https://doi.org/10.1016/j.compedu.2017.10.007

Keengwe, J., & Bhargava, M. (2013). Mobile learning and integration of mobile technologies in education. *Education and Information Technologies*, *19*, 737–746. https://doi.org/10.1007/s10639-013-9250-3

Lai, C. Y., Cheung, K. Y., & Chan, C. S. (2023). Exploring the role of intrinsic motivation in ChatGPT adoption to support active learning: An extension of the technology acceptance model. *Computers & Education: Artificial Intelligence*, *5*, 100178. https://doi.org/10.1016/j.caeai.2023.100178

Li, C., & Yanagisawa, H. (2021). Intrinsic motivation in virtual assistant interaction for fostering spontaneous interactions. *Plos One*, *16*(4), e0250326. https://doi.org/10.1371/journal.pone.0250326

Lindeman, R. H., Merenda, P. F., & Gold, R. Z. (1980). *Introduction to bivariate and multivariate analysis*. Scott, Foresman and Company. https://doi.org/10.2307/2287559

Lo, C. K. (2023). What is the impact of ChatGPT on education? A rapid review of the literature. *Education Sciences*, *13*(4), 410. https://doi.org/10.3390/educsci13040410

Ma, X., & Huo, Y. (2023). Are users willing to embrace ChatGPT? Exploring the factors on the acceptance of chatbots from the perspective of AIDUA framework. *Technology in Society*, *75*, 102362. https://doi.org/10.1016/j.techsoc.2023.102362

Marshall, G., & Cox, M. J. (2008). Research methods: Their design, applicability and reliability. In J. Voogt & G. Knezed (Eds.), *International handbook of information technology in primary and secondary education* (pp. 983–1002). Springer. https://doi.org/10.1007/978-0-387-73315-9_62

Menon, D., & Shilpa, K. (2023). "Chatting with ChatGPT": Analyzing the factors influencing users' intention to Use the Open AI's ChatGPT using the UTAUT model. *Heliyon*, *9*(11), e20962. https://doi.org/10.1016/j.heliyon.2023.e20962

Montenegro-Rueda, M., Fernández-Cerero, J., Fernández-Batanero, J. M., & López-Meneses, E. (2023). Impact of the implementation of ChatGPT in education: A systematic review. *Computers*, *12*(8), 153. https://doi.org/10.3390/computers12080153

Nikolopoulou, K., Gialamas, V., & Lavidas, K. (2021). Habit, hedonic motivation, performance expectancy and technological pedagogical knowledge affect teachers' intention to use mobile internet. *Computers and Education Open*, *2*, 100041. https://doi.org/10.1016/j.caeo.2021.100041

Nguyen, D. T. (2014). *Giao trinh phuong phap nghien cuu khoa hoc trong kinh doanh* [Textbook on Scientific Research Methods in Business]. Finance Publishing.

Pham, V. L. P., Vu, D. A., Hoang, N. M., Do, X. L., & Luu, A. T. (2024). ChatGPT as a math questioner? Evaluating ChatGPT on generating pre-university math questions. In J. Hong, J. W. Park, & A. Przybylek (Eds.), *Proceedings of the 39th ACM/SIGAPP Symposium on Applied Computing* (pp. 65–73). Association for Computing Machinery. https://doi.org/10.1145/3605098.363603

Pituch, K. A., & Stevens, J. P. (2015). *Applied multivariate statistics for the social sciences* (6th ed.). Routledge.

Rahim, N. I. M., Iahad, N. A., Yusof, A. F., & Al-Sharafi, M. A. (2022). AI-based chatbots adoption model for higher-education institutions: A hybrid PLS-SEM-neural network modelling approach. *Sustainability*, *14*(19), 12726. https://doi.org/10.3390/su141912726

Singh, N., Sinha, N., & Liébana-Cabanillas, F. J. (2020). Determining factors in the adoption and recommendation of mobile wallet services in India: Analysis of the effect of innovativeness, stress to use and social influence. *International Journal of Information Management*, *50*, 191–205. https://doi.org/10.1016/j.ijinfomgt.2019.05.022

Strzelecki, A. (2023). Students' acceptance of ChatGPT in higher education: An extended unified theory of acceptance and use of technology. *Innovative Higher Education*, *49*, 223–245. https://doi.org/10.1007/s10755-023-09686-1

Sullivan, M., Kelly, A., & McLaughlan, P. (2023). ChatGPT in higher education: Considerations for academic integrity and student learning. *Journal of Applied Learning & Teaching*, *6*(1), 1–10. https://doi.org/10.37074/jalt.2023.6.1.17

Szymkowiak, A., Melović, B., Dabić, M., Jeganathan, K., & Kundi, G. S. (2021). Information technology and Gen Z: The role of teachers, the internet, and technology in the education of young people. *Technology in Society*, *65*, 101565. https://doi.org/10.1016/j.techsoc.2021.101565

Talan, T., & Kalınkara, Y. (2023). The role of artificial intelligence in higher education: ChatGPT assessment for anatomy course. *Uluslararası Yönetim Bilişim Sistemleri ve Bilgisayar Bilimleri Dergisi* [International Journal of Management Information Systems and Computer Science], *7*(1), 33–40. https://doi.org/10.33461/uybisbbd.1244777

Teo, T., & Milutinovic, V. (2015). Modelling the intention to use technology for teaching mathematics among pre-service teachers in Serbia. *Australasian Journal of Educational Technology*, *31*(4), 363–380. https://doi.org/10.14742/ajet.1668

Terblanche, N., & Kidd, M. (2022). Adoption factors and moderating effects of age and gender that influence the intention to use a non-directive reflective coaching chatbot. *Sage Open*, *12*(2). https://doi.org/10.1177/21582440221096136

Tian, W., Ge, J., Zhao, Y., & Zheng, X. (2024). AI Chatbots in Chinese higher education: adoption, perception, and influence among graduate students—an integrated analysis utilizing UTAUT and ECM models. *Frontiers in Psychology*, *15*, 1–16. https://doi.org/10.3389/fpsyg.2024.1268549

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, *27*(3), 425–478. https://doi.org/10.2307/30036540

Voogt, J., Fisser, P., Pareja Roblin, N., Tondeur, J., & van Braak, J. (2012). Technological pedagogical content knowledge–a review of the literature. *Journal of Computer Assisted Learning*, *29*(2), 109–121. https://doi.org/10.1111/j.1365-2729.2012.00487.x

Wardat, Y., Tashtoush, M. A., AlAli, R., & Jarrah, A. M. (2023). ChatGPT: A revolutionary tool for teaching and learning mathematics. *Eurasia Journal of Mathematics, Science and Technology Education*, *19*(7), em2286. https://doi.org/10.29333/ejmste/13272

Young, D. S. (2017). *Handbook of regression methods.* Chapman and Hall/CRC. https://doi.org/10.1201/9781315154701

Appendix

Glossary of Key Statistics Terms

Bartlett Test: A statistical test to check whether the variables in the dataset are related enough to perform EFA. A *p*-value less than 0.05 means the variables are sufficiently correlated.

Coefficient of Determination (R^2): A value that explains how much of the variation in the dependent variable can be explained by the independent variables. Higher values indicate a better fit for the model.

Cronbach's Alpha: A measure of how consistent the items in a survey or questionnaire are. Higher values (above 0.7) indicate that the survey items are reliable and measure the same concept.

Durbin-Watson Test: A test to check if residuals are independent or autocorrelated (they should not follow a pattern). A value between 1.5 and 2.5 indicates no autocorrelation.

Exploratory Factor Analysis (EFA): A statistical method to group related survey items into broader factors. This helps to simplify data and identify underlying relationships between variables.

Factor Loading: A number that shows how strongly an item is associated with a factor. Values above 0.5 are considered good.

Goldfeld-Quandt Test: A test used to check if the residuals have constant variance, which is an assumption for a valid regression model.

Interaction Variable: A term used in regression analysis to capture the combined effect of two variables (e.g., trust and gender) on the dependent variable.

Kaiser-Meyer-Olkin (KMO) Test: A test to determine if the data suits EFA. A value above 0.5 indicates that the data are adequate for this type of analysis.

Moderator Variable: A variable influencing the relationship between independent and dependent variables. For example, gender might affect how trust influences behavioural intention.

Multiple Linear Regression Analysis: A statistical method used to examine how several independent variables (e.g., motivations, trust) affect a dependent variable (e.g., behavioural intention).

Normal Q-Q Plot: A graphical tool to check if residuals follow a normal distribution (a key assumption for regression analysis).

***p*-value:** A number that shows the probability of a result occurring by chance. A value below 0.05 is usually considered statistically significant.

Residuals: The differences between the observed values and those predicted by the regression model. They help assess the accuracy of the model.

Variance Inflation Factor (VIF): A measure to check if independent variables are highly correlated with each other (multicollinearity). Values above 5 indicate potential issues.

Authors

Tang Minh Dung, PhD, earned his doctorate in Mathematics - Informatics from Université Grenoble Alpes in France. He is a lecturer in the Department of Mathematics and Informatics at Ho Chi Minh City University of Education in Vietnam. His research focuses on teacher education and technology-enhanced mathematics education. *Email*: dungtm@hcmue.edu.vn *ORCID*: https://orcid.org/0000-0001-5401-1395

Vo Khoi Nguyen is a senior mathematics education student at the Department of Mathematics and Informatics, Ho Chi Minh City University of Education in Vietnam. His research focuses on harmonic analysis and teacher education. *Email*: 4701101107@student.hcmue.edu.vn
ORCID: https://orcid.org/0009-0009-3738-6967

Doan Cao Minh Tri is a senior mathematics education student at the Department of Mathematics and Informatics, Ho Chi Minh City University of Education in Vietnam. His research focuses on representation theory, number theory, and mathematics teaching methodology.
Email: minhtridoancao06@gmail.com *ORCID*: https://orcid.org/0009-0001-7783-1393

Phu Luong Chi Quoc is a senior mathematics education student at the Department of Mathematics and Informatics, Ho Chi Minh University of Education in Vietnam. His research focuses on technology-enhanced mathematics education. *Email*: chiquocphuluong26012002@gmail.com
ORCID: https://orcid.org/0009-0009-4151-954X

Bui Hoang Dieu Ban is a senior mathematics education student at the Department of Mathematics and Informatics, Ho Chi Minh University of Education in Vietnam. Her research focuses on technology-enhanced mathematics education and mathematics teaching methodology.
Email: buihoangdieuban12012003@gmail.com *ORCID*: https://orcid.org/0009-0008-1696-1195