GCCCE 2022

第26屆
全球華人計算機教育應用大會
邁向數位學習的新常態
大會論文集 (英文論文)

Conference Proceedings (English Paper)

of the 26th Global Chinese Conference on Computers in Education (GCCCE 2022)

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第 26 屆全球華人計算機教育應用大會

The 26th Global Chinese Conference on Computers in Education

GCCCE 2022 大會論文集（英文論文）

GCCCE 2022 Main Conference Proceedings

(English Paper)

Editors

Chiu-Pin Lin, Tsing Hua University, Taiwan

Yi-Hsuan Wang, Tamkang university, Taiwan

Bo Jiang, East China Normal University, Mainland China

Ju-Ling Shih, Central University, Taiwan

Siu Cheung Kong, The Education University of Hong Kong, Hong Kong

Xiaoqing Gu, East China Normal University, Mainland China

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Main Conference English Paper Track

1. Message from the Organizer

Global Chinese Conference on Computers in Education (GCCCE) is an annual international academic conference organized by the Global Chinese Society for Computers in Education (GCSCE). The 24th GCCCE was held at Northwest Normal University, Lanzhou in September 2020. The 25th GCCCE was held by The Education University of Hong Kong, Beijing Normal University, Taiwan Normal University and National Institute of Education, Nanyang Technological University in blended mode on 11 – 15 September 2021. The conference has been developed as a premier academic event for researchers, practitioners and policy makers in the Chinese communities for the worldwide dissemination and sharing of ideas for research in the field of Computers in Education.

The 26th Global Chinese Conference on Computers in Education (GCCCE 2022) will be organized online by Taiwan Tsing Hua University, The Education University of Hong Kong and East China Normal University on 28 May – 1 June 2022. The conference program will comprise keynotes, paper presentations, workshops, forums, Doctoral Student Forum and Teacher Forum.

It is worth noting that, this is the third year of conference since the English Paper Track (EPT) has been found, inviting both ethnic Chinese and non-ethnic Chinese leading international scholars to form a Program Committee in attempt to attract papers from non-Chinese authors around the world. The EPT comes with an individual English-only sharing session, welcoming all conference participants to attend and interact with international scholars. All papers accepted by EPT will be independently edited and published as the GCCCE2022 English Paper Track Proceedings. In addition, like last year, two English keynote speeches will be delivered by two leading scholars.

Unfortunately, the COVID-19 pandemic continues to rage around the world amid the year-long preparation of GCCCE. Both the International Program Committee and the Local Organizing Committee have been monitoring the situation and therefore decided to turn GCCCE 2022 into an online conference. The meetings can be held successfully.

Apart from the inaugurated EPT, nine theme-based sub-conferences are featured in this GCCCE as usual, namely,

C1: Learning Sciences & Computer-Supported Collaborative Learning
C2: Mobile, Ubiquitous & Contextual Learning
C3: Joyful Learning, Educational Games & Digital Toys
C4: Technology in Higher Education & Adult Learning, and Teachers' Professional Development
C5: Technology-Enhanced Language and Humanities Learning
C6: Artificial Intelligence in Education & Smart Learning Environments
C7: Learning Analytics & Assessments
C8: STEM & Maker Education
C9: Educational Technology: Innovations, Policies & Practice

Within EPT and each sub-conference, an Executive Chair, Co-Chairs and Program Committee (PC) Members were appointed to shoulder the review and programming process. Each sub-conference was also set up with additional evaluation. GCCCE 2022 calls for papers from scholars around the world (not limited to ethnic Chinese), this year, the conference received a total of 242 submissions by 520 authors from mainland China, Hong Kong, Taiwan, Singapore, USA, the United Kingdom, Kazakhstan, and some other regions. Table 1 shows the statistics of regions of origin of the authors

Table 1. Statistics of regions of origin of GCCCE 2022 authors in the nine sub-conferences and EPT

Region	Mainland China	Taiwan	HK	USA	Japan	Total
No. of author	352	133	19	16	1	530

Each submission was assigned to at least 3 PC members for the first round of review. The results were then meta-reviewed by the chair and co-chairs of the corresponding sub-conference or EPT before a final decision was made. Through the rigorous review process, 193 papers were accepted (see Table 2). Among them, 10 papers were nominated for Best Chinese Research Paper Award (limited to long papers accepted by the sub-conferences), 3 were nominated for Best English Research Paper Award (limited to long papers accepted by the EPT), 7 were nominated for Best Student Paper Award (limited to long papers accepted by the sub-conferences and the EPT), 6 were nominated for Best Technical Design Paper Award (limited to long or short papers accepted by the sub-conferences and the EPT), and 3 were nominated for Best K-12 Teachers' Paper Award (limited to long or short papers accepted by K-12 Teachers' Forum).

Table 2. Statistics of paper acceptance of each sub-conference and the EPT in GCCCE 2022

Sub-conference	Full paper	Short paper	Poster	Elimination	Acceptance Rate	Subtotal
C1: Learning Sciences & Computer-Supported Collaborative Learning	4	8	2	3	82%	17
C2: Mobile, Ubiquitous & Contextual Learning	3	7	3	2	87%	15
C3: Joyful Learning, Educational Games & Digital Toys	5	6	6	6	74%	23
C4: Technology in Higher Education & Adult Learning, and Teachers' Professional Development	4	8	4	5	76%	21
C5: Technology-Enhanced Language and Humanities Learning	3	8	5	2	89%	18
C6: Artificial Intelligence in Education & Smart Learning Environments	8	10	5	9	72%	32
C7: Learning Analytics & Assessments	8	12	7	6	82%	33
C8: STEM & Maker Education	5	10	5	5	80%	25
C9: Educational Technology: Innovations, Policies & Practice	8	14	3	7	78%	32
English Paper Track	4	15	3	4	85%	26
Total	**52**	**98**	**43**	**49**	**80%**	**242**

This year, four academic experts and scholars are invited to be the keynote speakers. These keynotes are,

Keynote 1：Learning Analytics through the Lens of Designing for Children's Rights
Speakers：Daniel Spikol, Associate Professor, Center for Digital Education and Department of Computer Science, University of Copenhagen, Denmark

Keynote 2：從華人看世界 – PBL 主題跨域課程培養學生終身學習素養之實證研究
Speakers：楊雅婷 特聘教授，成功大學創新數位內容研究中心主任

Keynote 3：技术支持的高校课堂教学改革探索及效果研究
Speakers：李艷 教授，浙江大學教育學院副院長、課程與學習科學系系主任、智慧教育研究中心主任

Keynote 4：Incorporating Artificial Intelligence in K12 Schools
Speakers：Lin Lin Professor，Department of Learning Technologies, College of Information University of North Texas, Denton, Texas, USA

The four keynotes, the nine sub-conferences, the EPT and two topical discussion panels form the main conference of GCCCE 2022. Other than that, like previous years, there will be three pre-conference events, including K-12 Teachers' Forum, workshops and Doctoral Student Forum. In particular, the Teachers' Forum accepted 40 teachers' papers from mainland China, Taiwan and Hong Kong, 3 of which were nominated for Best K-12 Teachers' Paper Award.

A total of 8 workshops on various research topics were featured this year, which accepted 68 workshop papers in total, namely,

Workshop 1: 迎接「元宇宙」的世代,如何融入新科技於教學工作坊

Workshop 2: 創新互動回饋科技提升學習動機

Workshop 3: 電腦支援個人化與合作學習

Workshop 4: 第四屆「親身體驗，好就用」: 遊戲式/遊戲化與教育玩具工作坊

Workshop 5: 數位人文跨域應用

Workshop 6: 學習科學與遊戲化學習

Workshop 7: ICT 辅助教育

Workshop 8: 學習投入與學習行為建模

Besides, Doctoral Student Forum will be established in the conference and 6 doctoral candidates will participate. A total of 5 experts and scholars will be invited to make comments and review.

We would like to express our deepest gratitude to all the chairs, co-chairs, committee members and volunteers of the sub-conferences, EPT, workshops, Teachers' Forum, Doctoral Student Forum, and the Local Organizing Committee. We thank them for their contributions and assistance to the conference, particularly their swift adaptability in responding to the emergent challenges posed by the ever-evolving COVID-19 pandemic.

We are running GCCCE2022 at unprecedented times. Yet we sincerely hope that our conference will bring inspiration and a magnificent experience to all the online or physically attending participants. Together, we shall build a stronger, resilient and more internationalized GCCCE community, and continue to relay the GCCCE torch to successive hosts and new generations of scholars in the coming years.

JuLing Shih, Central University, Taiwan

Conference Chair

ChiuPin Lin, Tsing Hua University, Taiwan

International Program Coordination Chair

Bo Jiang, East China Normal University, Mainland China

YiHsuan Wang, Tamkang University, Taiwan

International Program Coordination Co-Chair

SiuCheung Kong, The Education University of Hong Kong

Local Organizing Committee Co-Chair, Hong Kong

Xiaoqing Gu, East China Normal University, Mainland China

Local Organizing Committee Co-Chair, Shanghai

2. Conference Organisation

Organiser:

Global Chinese Society for Computers in Education (GCSCE)

Hosts:

National Tsing Hua University, Taiwan

East China Normal University, China

The Education University of Hong Kong, Hong Kong

Conference Chair:

Ju-Ling Shih, Central University ,Taiwan

International Program Coordination Chair:

Chiu Pin Lin, Tsing Hua University, Taiwan

International Program Coordination Co-Chair:

Yi Hsuan Wang, Tamkang University, Taiwan

Bo Jiang, East China Normal University

Local Organizing Committee Co-Chair

Chiu Pin Lin, Tsing Hua University, Taiwan

Siu Cheung Kong,The Education University of Hong Kong

Xiaoqing Gu, East China Normal University

English Paper Track Programme Committee:

Executive Chair:

Chengjiu Yin, Kobe University

Co-Chairs:

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Pei-Yi Lin, National Tsing Hua University

Jane Yin-Kim Yau, University of Mannheim

Juan Zhou, Tokyo Institute of Technology

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Huiyong LI, Kyoto University

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Yun Wen, Nanyang Technological University

Tak-Lam Wong, Douglas College

Jing Wu, Nanyang Technological University

Longkai Wu, Nanyang Technological University

Euphony Yang, National Central University

Ruining Yang, Hunan University

Boxin Zheng, the University of Macau

3. Keynotes

Keynote Speech 1

2022 年 5 月 30 日(星期一) 10:00 - 11:00 **30 May 2022 (Monday)**

Speech Title: Learning Analytics through the Lens of Designing for Children's Rights

Daniel Spikol Associate Professor
Center for Digital Education and Department of Computer Science,
University of Copenhagen, Denmark

Speech Abstract:

Learning analytics faces many challenges for adoption that range from privacy and ethics to validation beyond large online courses and the perceived lack of benefits for learners and students. However, one can argue that a design deficit contributes to the low uptake of learning analytics coupled with the complex nature of education. I will present the Designing for Children's Rights (D4CR) Design Principles that can help alleviate some of these challenges. The D4CR design principles have been collectively developed over the last several years by designers, researchers, and practitioners to help guide the design of products and services for children. The design principles are derived from the UN's Convention on the Rights of the Child and address the legally binding international agreement for children's rights. Unfortunately, when we investigate the field of learning analytics, we see little concern for these rights and that the children and learners are not always the focus of the work. My talk will introduce the D4CR design principles in the context of different learning analytics projects, focusing on the multiple traces that learners provide across the digital and physical spaces– multimodal learning analytics.

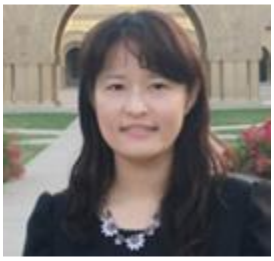
Speaker Bio

Daniel Sipkol is Associate Professor of Computational Thinking at the Center for Digital Education, Departments of Computer Science and Science Education. His research investigates how people collaborate with multimodal learning analytics (inspired by social signal processing ambient computing). He develops technologies that support learning, play, and reflection. His current work uses physical computing to inspire learners for computational tinkering and thinking.

Keynote Speech 2

2022 年 5 月 30 日(星期一) 13:20 - 14:20 **30 May 2022 (Monday)**

Speech Title: 從華人看世界 –PBL 主題跨域課程培養學生終身學習素養之實證研究



Ya-Ting Carolyn Yang Distinguished Professor
Institute of Education, National Cheng-Kung University

Speech Abstract:

聯合國教科文組織(UNESCO)在 2020 年底出版「Embracing a culture of lifelong learning-擁抱終身學習文化」,該報告勾勒出兩大終極目標:(1)使終身學習成為教育政策之「主導原則」:所有教育目的都是為培養學生終身學習素養。(2)為人民營造出可提供終身學習機會之「有利環境」:包括學校、家庭與社會。此外,為邁向 2050 年終身學習之願景,聯合國教科文組織認為必須營造學習型社會/社群,以培養學習者高層次思考與學習素養。因應此教育潮流,在臺灣教育部推動中小學數字學習深耕計畫,每年帶領 30-33 間中小學種子學校,以 PBL 主題跨域課程為主,科技為輔,將基礎學科能力進行橫向整合,融會貫通,解決真實生活問題,落實學用合一。在實務推動的同時,也進行實證研究,採主客觀和品質並重之研究方法探討學生學習素養的改變和教師教學行為模式與學生學習行為模式的轉變。(1)首先,根據種子學校之個別實施成果進行後設分析(meta-analysis),有效控制各校的內在效度後,再分析種子學校(以 110 年為例,30 間種子學校 1832 位學生)之整合結果。研究結果顯示「PBL 主題跨域課程」可有效提升學生學習素養,包括:學習興趣、自我效能、問題解決態度、學業成績與實作能力。(2)另外,本計畫團隊於教學現場實際觀測課室中「教」與「學」的轉變,運用即時課室行為觀測系統,收集每分鐘教師的教學行為模式和學生的學習行為模式與其批判思考行為。研究結果顯示:教師教學行為從期初「以教師為中心(課堂比例 51%)」的模式,到期末轉換為「以學生中心(課堂安排比例 82%)」的模式。(3)在學生學習行為模式,「PBL 主題跨域課程」促進學生高層次的個人建構和互動建構,進而提出問題解決方案與創新作為。最後,在學生批判思考行為,「PBL 主題跨域課程」提供學生真實情境問題以進行有意義的學習,引導學生在學習歷程中進入更深層、高階的邏輯思考,以掌握問題重點並養成嚴謹的判斷能力。綜上所述,「PBL 主題跨域課程」除了活用傳統教學所著重的知`識、理解與應用,更提升學生的學習態度和強化科技應用能力、跨域整合實作能力和高層次思考能力,可有效培育具備終身學習素養的世界公民。

Speaker Bio

Ph.D., Educational Technology, Department of Curriculum and Instruction, Purdue University. Her research interests include E-Learning, Technology-Integrated Implementation into Instruction, Critical Thinking Skills and Disposition, Instructional Design and Research of Critical Thinking, Instructional Design and Research of Creative Thinking, Instructional Design and Research of Problem Solving, Digital Language Learning.

Keynote Speech 3

2022年5月31日(星期二) 09:30 - 10:30 **31 May 2022 (Tuesday)**

Speech Title: 技术支持的高校课堂教学改革探索及效果研究

Yan Li professor
Vice Dean of College of Education; Director of Department of Curriculum and Learning Sciences; Director of Research Center for AI in Education, Zhejiang University, China.

Speech Abstract:

高校课堂是国家创新人才培养最主要的场所之一，然而，传统高校课堂存在以教师为中心，以讲授模式、直接教学模式和概念教学模式为主，学生高阶思维和能力训练不足，师生交互有限，教学评价无法全面、精准等顽疾。国内外诸多研究表明，信息技术的运用有助于解决传统高校课堂的困境,《地平线报告》十余年的内容也显示信息技术与教育教学深度融合创新是当今全球高校课堂教学改革的重要趋势。本报告在文献综述的基础上重点介绍三个技术支持的高校课堂教学改革实践案例：（1）基于在线课程资源的翻转课堂实践；（2）基于可视化工具的小组探究式学习实践；（3）基于可视化工具的在线论证式教学实践。通过混合研究方法收集三个实践案例中教学效果评价的质性和量化数据，数据分析结果显示，三个实践探索均达到了预期的教改目标和令学生满意的教学效果，经过创新的教学实践和学习体验，学生在专业知识、技能、情感态度等方面有明显的改善，基于三个实践案例，报告最后提出了技术支持的高校课堂教学改革的一些启示和建议。

Speaker Bio

李艳，教授，博士生导师，博士毕业于美国得克萨斯 A&M 大学农业教育专业，浙江大学教育学院副院长，课程与学习科学系系主任。主要从事远程教育、数字化学习等领域研究。近十多年来主持的课题包括国家自然科学基金面上项目、国家科技创新 2030-"新一代人工智能"重大项目"人工智能综合影响社会实验研究"子课题、国家社会科学基金重大项目"人工智能促进未来教育发展"子课题、国家社会科学基金青年项目、全国教育科学规划课题、浙江省哲学社会科学规划课题等。在 Computers & Education、British Journal of Educational Technology、Educational Technology Research & Development、Computer Assisted Language Learning、International Journal of STEM Education、Thinking Skills and Creativity、Asia Pacific Journal of Education、Frontier in Psychology、《电化教育研究》、《开放教育研究》、《中国电化教育》、《远程教育杂志》、《现代远程教育研究》、《现代教育技术》、《现代远距离教育》、《华东师范大学学报（教科版）》等）上国内外期刊上发表论文 60 余篇，担任国内外多本期刊的编委和外审。2013 年，入选浙江省"之江青年社科学者"。2014 年，入选浙江省 151 人才工程"第二层次"培养人员，2018 年，荣获"浙江大学优质教学一等奖"及"全国第六届教育硕士优秀教师"称号。

Keynote Speech 4

2022年6月1日(星期三) 09:30 - 10:30 **1 June 2022 (Wednesday)**

Speech Title: Incorporating Artificial Intelligence in K12 Schools

Lin Lin Professor
Development Editor-in-Chief
Educational Technology Research and Development (ETR&D)
Professor and Director of Texas Center for Educational Technology Education (TCET)
Department of Learning Technologies, College of Information
University of North Texas, Denton, Texas, USA

Speech Abstract:
Artificial intelligence (AI) in education is an emerging field in educational technologies. It is unclear to educators how to take advantage of AI for teaching and learning while considering the ethics, embedded biases, and privacy issues around AI. In this presentation, we will discuss current AI integrations (e.g., machine learning, naturally language processing, and robotics) in educational practices and the impact of AI in education and society. We will also discuss the ethical concerns around AI, so that we, as educators and educational technology researchers, can work with AI technologies to truly create new opportunities to help students learn and prepare students for future workforce.

Speaker Bio
Dr. Lin's research looks into intersections of mind, brain, technology and learning. Specifically, she has published in areas including creativity, virtual reality, media multitasking, multimedia design, CSCL, critical thinking, computational thinking, and learning in virtual spaces. Lin currently serves as the Director for the Texas Center for Educational Technology (TCET, https://tcet.unt.edu/), and as the Development Editor-in-Chief of the journal Educational Technology Research and Development (ETR&D, http://www.springer.com/11423). She also plays several other leadership roles in affiliated professional associations. Lin is passionate about helping people develop and maintain curious minds and life-long learning with cognitive exercises and new technologies.

Lin, C. P., Wang, Y. H., Jiang, B., Shih, J. L., Kong, S. C., & Gu, X. (Eds.) (2022). *Conference Proceedings (English Paper) of the 26th Global Chinese Conference on Computers in Education (GCCCE 2022).*
Taiwan: National Tsing Hua University.

Human-Machine Collaborative Data Wisdom: A Mechanism to Gain Insights from Big Data

Hongchao Peng [1*], Shuting Yang [2], Jiabin Zhao [2,] Yuqing Jiang [3]

[1] School of Open and Learning Education, East China Normal University

[2] Department of Education Information Technology, East China Normal University

[3] School of educational information technology, South China Normal University

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Abstract: *At present, data as an asset has been highly valued by the education community. Although strong artificial intelligence (AI) couldn't be weighted as wisdom, it can be complementary to human beings to realize human-machine collaborative data wisdom. The study mainly introduces the origin and development of data wisdom as well as the core concepts and three development stages (i.e. data wisdom mechanism) of data wisdom in smart education. All these can depict an HMCDW blueprint for scholars and educators, and also provide them with a new way to implement personalized learning.*

Keywords: data wisdom, human-machine collaboration, personalized learning, smart education

1. Introduction

The rapid development of smart devices makes the digital universe comparable to the physical universe. According to an analysis report released by International Data Corporation (IDC,2014), the amount of data will be expected to reach 44ZB by 2020. Given such a large amount of digital assets, the education community is increasingly focusing on the mining and application of its potential value. The value density of big data is very low. Therefore, how to extract high value from the big data has become an urgent problem to be solved. In the "weak rule" fields such as smart education, data wisdom should be a new cognitive paradigm which is based on human-machine collaboration. Currently, there is some consensus over the four levels of the data wisdom model (i.e., data, information, knowledge, and wisdom), but how data can better evolve into wisdom through information and knowledge still remains elusive.

2. Related Work

2.1. The Origin and Development of Data Wisdom

Data Wisdom is also commonly referred to as DIKW (data-information-knowledge-wisdom) pyramid, DIKW hierarchy, knowledge hierarchy, information hierarchy, wisdom hierarchy or knowledge pyramid, etc. (Rowley, 2007) It is a model that represents the structural or functional relationship among data, information, knowledge, and wisdom. (Zins, 2007) Czechoslovak educator Zeleny is commonly believed to be the proponent of "data wisdom". (Eva, 2007) In 1987, he mapped the four elements of the data wisdom hierarchy into the formation of knowledge: know-nothing, know-what, know-how, and know-why. (Zeleny, 1987) Cleveland (1982) paid more attention to the importance of facts and proposed a structure of "facts & ideas-information-knowledge-wisdom". In fact, although Zeleny (1987) focused on the four elements of data, information, knowledge, and wisdom and their mapping, it was also mentioned that there should be one additional layer beyond wisdom: enlightenment - enriching the still value-free wisdom by the dimension of 'truth'. However, as a new layer, it seems that enlightenment hasn't been recognized by scholars. Ackoff is one of them. He is still concerned about the original four-element structure of DIKW. Moreover, he added a new layer called "understanding" between knowledge and wisdom to form a DIKUW structure. (Ackoff, 1989) Bellinger, Castro, and Mills (2004) believed that "understanding" should not be a separate layer, but a band of DIKW. It is a cognitive process based on connectedness. (Bellinger, Castro & Mills, 2004) This variety mainly results from the following two reasons: 1) Different perspectives from different disciplines. 2) Different purposes of the application bring different focuses.

2.2 Core Concepts of Data Wisdom in Smart Education

Although the understandings towards the elements/levels of data wisdom are not the same, they basically contain four elements/levels: data, information, knowledge, and wisdom. Based on such a consensus, the DIKW structure is adopted. Specifically, as shown in Figure 1. Data is a set of discrete, objective symbols, numbers, signs, signals about the attributes of objects and events. (Zins, 2007) It has no meaning/value because of lack of context and interpretation. (Bellinger, Castro & Mills, 2004) While information is data that has been given meaning through relational connections. Knowledge is patterned or pattern-associated information. (Bellinger, Castro & Mills, 2004) Data, information, and knowledge focus on the past. They deal with existing things or events. (Ackoff, 1989) Wisdom is the best decision-making behavior under a framework of principles. Wisdom focuses on the future, and even creates the future. Evolving from data to wisdom is a process of the relational organization of data, the pattern recognition and interpretation of information, and the principle derivation of knowledge. It is also a process of value refinement. At the human side, there are four levels of understanding: know by practicing, know by sensing, know by constructing, and know by criticizing; At machine side, they are also four levels of understanding: know by perceiving, know by describing, know by mining, and know by learning. The human-machine collaboration between the understanding of each level at both sides forms the cognitive state of know-nothing of the data, know-what of the information, the know-how of the knowledge, and the know-actions of wisdom. Each level has its corresponding value in smart education: data in the state of know-nothing can be used for communicating and storing the learning traces and resources; Information of know-what can be used for visual representation of data meaning; knowledge of know-how can be used for insight-making; wisdom of know-actions can be used for decision making of learning services.

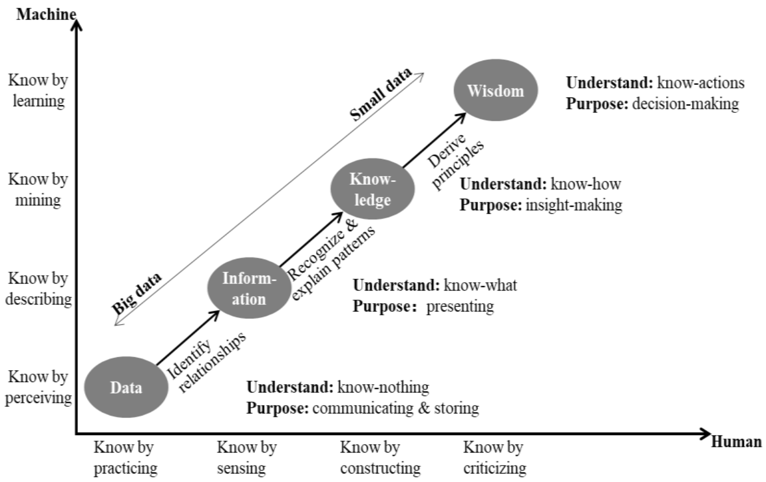

Figure 1. Human-machine collaborative map of data wisdom in smart education.

3. The Three Stages of Data Wisdom Mechanism

The process of human-machine collaboration includes three stages: the relational organization of data, the pattern recognition and interpretation of information, and the principle derivation of knowledge.

3.1 Relational Organization of Data

In smart education, the data comes from relevant educators' practices and the machine's records. The process of organizing data is composed of four steps: purpose adding, relationship establishing, data shaping, and meaning representing. The former two are mainly processed by humans and the last two are mainly processed machines. The purpose of adding step aims to add monitoring purposes of smart education in a specific learning context, and then build the interpretation dimension based on these purposes. Valuable data sets or resources could be marked, further be categorized and filtered in the phase of in the relationship establishing step, and eventually converted into highly effective data. The data shaping step aims to solve the problem of redundant, duplicated, inconsistent, missing-value, and/or invalid data, and then form a structured data view. In the meaning representing step, structured data is mainly represented by descriptive analysis and visualization. Afterward, the data can evolve into meaningful information, and this information is easily perceived by teachers and students (know by sensing) to form a preliminary understanding of the data meaning.

3.2 The Pattern Recognition and Interpretation of Information

For the accurate decision-making of smart education, the implicit pattern behind the facts is more valuable. Identifying and interpreting the patterns from the information has four steps: feature extracting, information patterning, meaning understanding, and pattern interpreting. The former two are dealt with by machines, but the latter two are by humans. The feature extracting step mainly reduces the dimension by mapping or transformation to acquire a set of fewer features that can be more represent the essence of events or things. The meaning understanding step aims to explain the physical and structural features in the data diagram. The information patterning step mainly uses data mining technology to mine law or trend. The pattern obtained by information patterning needs to be further explained in order to solve the problems of redundancy or inability of data to meet the learning and teaching requirements or the problem of internalizing pattern into human knowledge.

3.3 The Principle Derivation of Knowledge

The information and knowledge are all the understanding of what has happened or is happening. But this understanding is not enough to be applied to new situations or problems. Therefore, knowledge still needs to be further evolved into wisdom to meet the needs of accurate decision-making. The process of principle derivation of knowledge has four steps: expert exploring, value judging, machine learning, and decision making. The expert exploring is the expert inquiry method inspired by the data pattern, which can be divided into three sub-steps: associating, reasoning and attributing. Associating is used to explore relevant clue intelligence, reasoning is used to derive unknown the relationship of explored clues, and attributing is used to further explore the causality of these clues. Wisdom is value-driven, experts also need to make valuable judgments on the understanding of the learning imprint. This step is value judging. Through the value judging step, experts can form a thorough understanding about the problem of how to determine the effective time, conditions, objects, and patterns of learning services. In addition to insights, the value judging step will also form a series of learning service criteria. The service criteria obtained from the value judging step and the service decision-making rules generated by the decision-making step can be used as a training set for machine learning. Through learning, the machine's own algorithms will be optimized. In this way, the personalized learning service plan developed by the machine will be more suitable and appropriate. When people get insights about learning services (the results of value judgments) and machines get that are optimized algorithms (the results of machine learning), they can generate learning services individually or collaboratively. This is an insight-based action the generated "smart actions" can be referred to as "smart behaviors".

4. Human-Machine Collaborative Data Decision-Making

According to the concept of human-machine collaboration, data decision-making can be done by data-driven decision-making of the machine and data-informed decision-making of human.

4.1 Strategies of Data-Informed Decision-Making

The rules and development trends of student learning obtained from educational data mining are mostly presented by visual digital dashboards. On this basis, the educators judge whether it is necessary to adjust the teaching strategies and how to adjust the strategies by answering “whether the student’s learning has problems or what are the causes”. This process is accomplished through data-informed decision-making: 1)Connecting similar or related things or events through associating; 2) sorting out related things and various clues contained in things or events through logical reasoning; 3) exploring the causalities behind each clue through attributing; 4) making appropriate decisions about the adjustment of teaching strategies based on the causalities.

4.2 Strategies of Data-Driven Decision-Making

The machine learning technology of artificial intelligence is increasingly mature. At present, there are three main types of machine learning technologies that have huge potential in education: deep learning, reinforcement learning, and transfer learning. Deep learning can acquire teachers' knowledge and experience through continuous training by using the teachers' effective decision data as a training set. On this basis, machines can try to make new decisions by themselves through reinforcement learning. Regardless of whether the decisions were learned from teachers or made by the machines themselves, they can be applied to another new situation through transfer learning, which can achieve good decision-making on similar learning problems. By these tree machine learning technologies, data-driven decision-making has the function of “reproduction of decision-making to the same problem, automatically make new decision-making to the same problem, and automatically make decision-makings to similar problems”.

4.3 Optimization of Data-Inspired and Data-Driven Decision-Making

Decisions made based on data, especially education big data, by machines, are based on correlations rather than causalities. So, it cannot be fully affirmed that a decision is effective, even if the decision brings good results in this time. To solve this problem, educators need to cognize the decisions made by the machine to get deep insights about it: what the learning problems are, what decisions are made, and what results from the decisions bring. And then, the judgment of whether these decisions made are effective, whether the educators need to further adjust teaching strategies, and whether there is a better decision. etc.. This process can also bring inspiration to educators to optimize their decision-making. Personalized learning or adaptive learning supported by technology is to achieve the purpose of adaptive adjust teaching strategies by the cyclic process of machines’ continuous learning to acquire the teacher's teaching wisdom while teachers’ cognition to evaluate the machine’s decision and be inspired for their own decision-making.

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Examining the Relationship between English Language Learners' New Media Literacy and Their Self-efficacy

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Abstract: *New media literacy in English learning has received increasing attention, but limited studies focus on the correlation between English new media literacy (ENML) and English language self-efficacy (ELSF). This quantitative study explores the relationship between English as a foreign language (EFL) learners' ENML and English language self-efficacy with two questionnaires. A total of 327 EFL learners from a comprehensive university in mainland China participated in this study. The results further confirmed the association between the two constructs. Results showed that both critical consuming and critical presuming have an active impact and prediction on the four aspects of English learners' self-efficacy. This study also provided implications for the research on ENML and English teaching.*
Keywords: English new media literacy, English language self-efficacy, EFL learner

1. Introduction

New media technologies enable people to enjoy and criticize media resources. Therefore, these activities that rely on new media literacy are indispensable in the 21st century. It is believed that media is highly effective and can provide a better environment for language learning (Nuri et al., 2021). An increasing amount of research explores the integration of new media literacy and English learning (e.g. Rachels & Rockinson-Szapkiw, 2018), but few studies on ENML of EFL learners in recent years. This study aims to further explore the relationship between ENML of EFL learners and their language self-efficacy, and the predictive role of new media literacy on EFL learners' self-efficacy.

2. Literature Review

2.1. New Media Literacy

The framework of new media literacy proposed by Chen and his colleagues (2011) consists of two continua referred to consuming and prosuming. Four types of new media literacy can be recognized, including (a) functional consuming, (b) functional presuming, (c) critical consuming, (d) critical prosuming. Functional consuming literacy focus on consumers' ability to be accessible to create new media and fully understand the meaning being conveyed; functional prosuming literacy refers to the competence of participating in the creation of media content. In the meantime, critical consuming literacy involves consumers' capacity to deeply identify the new media contents on the basis of its social, political, and cultural context; critical prosuming literacy refers to individuals' ability to comprehend and product the context of the media content when participating in the new media activities.

2.2. English Language Self-efficacy

Self-efficacy refers to a person's perceived and cognitive capabilities and the belief about their ability to do successfully with the skills they possess (Bandura, 1997). There is an increasing attention to the research of EFL learners' English language self-efficacy in recent years (Su et al., 2017). For instance, Wang and his colleagues (2014) regarded

English self-efficacy as 'one's belief about how well he/she can successfully accomplish a task in English based on his/her previous experience.

2.3. New Media in EFL Learning

With the great popularity of media, some researchers focused on the integration of media and language learning (eg. Nuri et al; Yang, 2013). A large number of studies found that media impacts language learning (Nuri et al., 2021; Rachels & Rockinson-Szapkiw, 2018), but there still exists controversy on the relationship between English language self-efficacy. For instance, several researchers claimed that media has a positive effect on English language learning (Laire, Casteleyn, & Mottart, 2012). By contrast, other researchers (e.g. Wu & Hsu, 2011) have found that the public environment of social media might decrease learners' motivation and bring anxiety to some learners.

3. Method

3.1. Research Context and Participants

This study was conducted in the context of a comprehensive university in mainland China. It involved a random sample of 327 sophomores (around 20.2 years old) engaged in an EFL language course. The proportion of male students (230 males) is higher than female students in this research since most of the participants were majoring in computer science and telecommunications. Besides, all the participants had received formal English education for more than twelve years.

3.2. Instruments

Based on the theoretical framework and instrument of EFL learners' new media literacy (Luan et al., 2020) and English learners' self-efficacy (Su et al., 2017), the study employed two questionnaires to assess EFL English new media literacy and English language self-efficacy. A five-point Likert scale was used in both questionnaires from 1 'Strongly Disagreed' to 5 'Strongly Agreed'. All questionnaires were translated into Chinese based on China's specific social and cultural background. It took about 15 minutes to complete both questionnaires. Seven undergraduate students were invited to try to fill in the questionnaires, and adjust the inappropriate contents of the questions reflected by them to further ensure the readability and simplicity of the two questionnaires.

3.3. Data Collection and Analysis

A total of 327 valid questionnaires were collected. SPSS 22.0 statistical analysis software was employed for data processing and analysis. It takes three stages to analyze the data. First, the exploratory factor analysis (EFA) was employed to discuss the factor structure of questionnaires about English new media literacy and English language self-efficacy. The reliability was confirmed by collecting its coefficient to ensure the consistency of the instruments. Second, the correlation analysis was conducted to explore the relationship between the factors and items of the two questionnaires. Third, stepwise regression analyses were employed. Taking EFL learners' English new media literacy as the predictive variables and learners' English language self-efficacy as the outcome variables, this study explores whether college students' English new media literacy is the positive predictor of their language self-efficacy.

4. Results

4.1. Factor Analysis of the ENML Questionnaire

We applied an exploratory factor analysis by using the principal component analysis with varimax rotation to clarify the structure and validity of the ENML instrument. We adopted Stevens' (1996) suggestion and retained the loadings with a correlation coefficient higher than 0.40 and all other coefficients less than 0.40 in the finalized ENML. 37 items were retained and were divided into four subscales. Students showed strongest consistency on functional consuming (Mean =3.66, SD = 0.67) among the four subscales, followed by functional prosuming (Mean = 3.52, SD = 0.73), critical consuming (Mean = 3.39, SD = 0.77), and critical prosuming (Mean = 3.33, SD = 0.69). The reliability coefficient (Cronbach's alpha) for each scale in this survey ranged from 0.67 to 0.85, with an overall reliability of 0.93. The results confirmed the reliability of the questionnaire for assessing EFL learners' English new media literacy.

4.2. Factor Analysis of the ELSF Questionnaire

A process similar to exploratory factor analysis was employed to verify its structure. We displayed four factors with 25 items in the finalized ELSE, explaining 69.23% of the total variance. Specifically, the students scored highest on writing (Mean = 3.79, SD = 0.69), followed by speaking (Mean = 3.65, SD = 0.76), reading (Mean = 3.52, SD = 0.72), and listening (Mean = 3.22, SD = 0.75). The reliability coefficients ranged from 0.65 to 0.84, with an overall alpha of 0.89, suggesting the sufficiency of the internal consistency and adequate reliability of the four scales for measuring students' English language self-efficacy.

4.3. Correlations between the Factors of ENML and ELSE

We conducted Pearson correlation analysis by collecting participants' responses to the two questionnaires to investigate whether there is a correlation between the EFL learners' ENML and ELSF during the learning process. The statistics show the active link between the factors of the two constructs ($r = 0.38$-0.63, $p < 0.001$).

4.4. Stepwise Regression Analysis of Predicting Students' ELSE Based on ENML

Stepwise regression analysis was applied to further investigate the predictive role of students' ENML on ELSE. This analysis employed EFL learners' ENML scales as the predictor and ELSE factors as the outcome variables. First, the analysis showed that the 'functional consuming' serves as the strongest role in predicting all the factors of learners' self-efficacy. Besides, functional consuming also played the significant role in predicting the listening ($\beta = 0.22$, $t = 3.63$, $p < 0.001$), speaking ($\beta = 0.25$, $t = 4.75$, $p < 0.001$), reading ($\beta = 0.24$, $t = 3.46$, $p < 0.01$) and writing ($\beta = 0.32$, $t = 4.91$, $p < 0.001$) scales. Moreover, the results implied that functional prosuming in ENML positively predicted all the factors of learners' self-efficacy, namely listening ($\beta = 0.35$, $t = 5.41$, $p < 0.001$), speaking ($\beta = 0.32$, $t = 5.96$, $p < 0.001$), reading ($\beta = 0.33$, $t = 4.75$, $p < 0.001$) and writing ($\beta = 0.28$, $t = 4.30$, $p < 0.001$). It was also found that critical consuming positively predicted learners' self-efficacy in both listening ($\beta = 0.16$, $t = 2.57$, $p < 0.05$) and reading ($\beta = 0.16$, $t = 2.07$, $p < 0.05$).

5. Discussion

This study investigated the correlation between EFL learners' English new media literacy and their English language self-efficacy. A close connection between EFL learners' ENML and their ELSE was confirmed by the analysis. This result is consistent with previous findings of the positive connection between new media literacy and self-efficacy (e.g. Rachels & Rockinson-Szapkiw, 2018).

The regression analysis further indicates the predictive role of EFL learners' ENML for their ELSE. Functional consuming and functional prosuming significantly predicate all factors of students' English efficacy, including listening, speaking, reading, and writing. It is in accordance with the previous findings that audio-visual aids might be useful to improve EFL learners' listening and reading comprehension (Lee, 2016). Similar evidence can be found that social media platforms are effective for EFL learners to engage in language learning (Abdulaziz, 2020), and Web 2.0 tools might enhance EFL students' confidence in language learning (Sun & Yang, 2015).

The study also confirmed that critical consuming is a major predictor for English language self-efficacy in listening and reading. Critical consumers have the ability to analyze the economic, political and cultural context of social media content (Luan et al., 2020). It implies that EFL learners have more confidence in listening and reading activities when they have the ability to interpret and analyze new media artifacts.

6. Conclusion

A high correlation between English new media literacy and English language self-efficacy was confirmed based on the current research. It reveals the positive prediction of ENML on learners' language self-efficacy. Functional consuming and functional presuming is an important predictor of ELSF in listening, speaking, reading, and writing. Some pedagogical implications are also provided in this study. First, it is necessary for EFL instructors to pay attention to the multi-level cultivation of students' ENML and effective teaching strategy to improve the predictive role of ENML on ELSF. Second, it also reminds English language administrators of the necessity of putting new media literacy education into the syllabus and curriculum to promote the quality of English teaching. Besides, due to the limited questionnaires, more qualitative studies based on samples from different regions and universities, as well as interviews, could ensure the validity of research results and further reveal the complex interactions between the two constructs.

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Are We Ready for Online Learning? Developing an Instrument for Assessing EFL Learners' Online Learning Engagement

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Abstract: *Student engagement is considered as perhaps one of the robust predictors of their academic achievement in second language acquisition. However, the rising prevalence of online courses brings significant challenges for language educators to engage language learners. Although previous research focused on the conceptualization of student engagement, the literature lacks a subject-specific measuring instrument to implement engagement in online settings. To fill this gap, this study focuses on developing and validating an online language learning scale (OLLE) for university students. A random sample of 372 students was involved. The 19-item OLLE scale comprised four components: behavioral engagement, cognitive engagement, emotional engagement, and social engagement. The results indicated that EFL learners had the highest level of behavioral engagement and the lowest level of emotional engagement in the process of online language learning. Related pedagogical implications are also discussed.*

Keywords: online language learning, student engagement, scale development, EFL learner, higher education

1. Introduction

The outbreak of COVID-19 pandemic witnessed a growing number of learning activities shifted from traditional education to online learning. In turn, the use of portable devices and an online environment may bring changes in an EFL learner's feelings and interaction with a course, hence, in his or her engagement with that course (Oraif & Elyas, 2021). Previous studies have supported the notion of understanding student engagement within a specific learning context or subject (Luan et al., 2020). However, few studies have as yet extended the context to consider the situation of online language learning during the COVID-19 lockdown. Therefore, the present study aimed to explore EFL learners' online learning engagement during the pandemic.

2. Literature Review

Student engagement is considered to be responsive to variations in the learning environment and is characterized by a student's energized, directed, and sustained action associated with a learning activity (Miller et al., 2020). Previous conceptualization of student engagement concerned behavioral, emotional, and cognitive dimensions. However, a fourth dimension – social engagement has been proposed and received extensive empirical support (Fredricks et al., 2016). As language acquisition is practically a social act requiring learners' interaction (Alsowat, 2016), the current research adopted these four constructs to delineate online learning engagement. Behavioral engagement refers to students' participation and their specific learning behavior in autonomous learning. Emotional engagement concerns students' experience towards the learning process and outcome. Cognitive engagement includes students' use of learning and self-regulated strategies. Social engagement involves the quality of interpersonal relationships with teachers and peers in learning activities.

The dramatic differences between conventional classroom-based and online learning environment call for the development of subject-specific measures of engagement. The current research focused on examining English language learners' engagement in an online learning environment, by seeking to adapt and validate the math and science engagement scale of Fredricks et al. (2016) with the participation of Chinese EFL learners.

3. Methodology

3.1. Research Context

The present study was conducted in an English course at a comprehensive university in China. A random sample of 372 freshmen were involved in this study. All the participants responded to the questionnaire anonymously. It took them roughly 10 minutes to complete the questionnaires.

3.2. Instruments

The questionnaire was based on the instrument developed by Fredricks et al. (2016). The original survey was reported to have high overall internal consistency reliability (Wang et al., 2016). First, the four factors in the original questionnaire for assessing Math and Science Engagement (Fredricks et al., 2016), namely, "Cognitive engagement," "Behavioral engagement," "Emotional engagement," and "Social engagement" were reserved in the OLE scale, while some questionnaire items were changed slightly by replacing "learning math and science" with "learning English online." For instance, we changed the item ' I build on others' ideas while studying.' to ' I build on others' ideas while studying English online. All the questionnaire items were presented in participants' native language, Chinese, on a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree).

3.3. Research Procedure

First, the quantitative data obtained from 372 participants were randomly divided into equal halves with 186 students respectively. Second, an EFA was performed to test the construct validity of the OLLE questionnaire among the first set of participants (186 students, including 141 male and 45 female students). Then, CFA was conducted to provide the constructive validity of the scale among the second set of participants (141 male and 45 female students).

4. Results

4.1. Exploratory Factor Analyses

Table 1 shows the results of the exploratory factor analysis for the OLLE instrument. A total of 19 items were retained and grouped into four factors. The four factors were "cognitive engagement" (α = 0.91, Mean = 3.24, SD = 0.96), "behavioral engagement' (α = 0.89, Mean = 3.50, SD = 0.86), "emotional engagement" (α = 0.91, Mean = 2.92, SD = 0.97), and "social engagement" (α= 0.92, Mean = 3.33, SD = 0.93). The factor loadings for all the items were all greater than 0.70, ranging from 0.71 to 0.88. The total variance explained for the scale was 70.15%. The Cronbach's alpha value for each factor ranged from 0.89 to 0.92, indicating satisfactory internal reliability and validity for conducting further confirmatory factor analysis.

Table 1. The EFA analysis of the OLLE scale (N = 227).

	Factor 1 Cognitive	Factor 2 Behavioral	Factor 3 Emotional	Factor 4 Social
Cognitive Engagement (CE) (M=3.24, SD=0.96, α=0.91)				
Cognitive 1	0.75			
Cognitive 2	0.74			

Cognitive 3	0.78			
Cognitive 4	0.78			
Cognitive 5	0.76			
Cognitive 6	0.72			
Behavioral Engagement (BE) (M=3.50, SD=0.86, α=0.89)				
Behavioral 1		0.82		
Behavioral 2		0.83		
Behavioral 3		0.81		
Behavioral 4		0.73		
Behavioral 5		0.71		
Emotional Engagement (EE) (M=2.92, SD=0.97, α=0.91)				
Emotional 1			0.86	
Emotional 2			0.87	
Emotional 3			0.83	
Emotional 4			0.79	
Social Engagement (SE) (M=3.33, SD=0.93, α=0.92)				
Social 1				0.85
Social 2				0.88
Social 3				0.87
Social 4				0.80

Overall alpha: 0.93; total variance explained: 70.15%

4.2. Confirmatory Factor Analysis

Confirmatory factors analysis was conducted to verify the construct of the OLLE scale. As shown in Table 2, all Average Variance Extracted values (AVE) of components of online learning engagement had exceeded the cut-off value of 0.50, the Composite Reliability values (CR) ranged from 0.90 to 0.93, all alpha values were above 0.90 and the overall Cronbach's value was 0.95. Therefore, the reliability of the questionnaire was established. Moreover, χ^2 /df =2.214, RMSEA=0.070, IFI=0.92, CFI=0.93, NFI=0.92, GFI=0.91. Hence, statistics all indicated that OLLE scale demonstrates good reliability and structural validity.

Table 2. The CFA analysis of the OLLE scale (N = 227)

Factor and item	Factor loading	t-value	CR	AVE	Alpha value	Mean	S.D.
Cognitive Engagement	–	–	0.92	0.62	0.91	3.11	1.02
Cognitive 1	0.81	–				3.04	1.35
Cognitive 2	0.82	14.05*				3.03	1.28
Cognitive 3	0.84	15.58*				3.32	1.17
Cognitive 4	0.83	14.25*				3.05	1.26
Cognitive 5	0.83	14.13*				3.17	1.28
Cognitive 6	0.75	11.29*				3.09	1.17
Behavioral Engagement	–	–	0.90	0.71	0.92	3.43	0.87
Behavioral 1	0.83	–				3.46	1.07
Behavioral 2	0.83	13.88*				3.43	1.08
Behavioral 3	0.84	14.06*				3.43	1.07

Behavioral 4	0.78	12.03*				3.50	1.12
Behavioral 5	0.76	10.26*				3.34	1.13
Emotional Engagement	–	–	0.91	0.72	0.93	2.83	1.03
Emotional 1	0.85	–				2.82	1.13
Emotional 2	0.88	4.68*				2.91	1.22
Emotional 3	0.89	15.33*				2.83	1.24
Emotional 4	0.83	13.21*				2.84	1.14
Social Engagement	–	–	0.93	0.65	0.92	3.26	0.96
Social 1	0.75	–				3.43	1.08
Social 2	0.87	11.82*				3.13	1.24
Social 3	0.86	11.97*				3.30	1.16
Social 4	0.88	12.27*				3.09	1.17

Total alpha: 0.95

Note: CFA: Confirmatory factor analysis; CR: Composite reliability; AVE; Average Variance Extracted; SD: Standard deviation.

5. Discussion and Conclusion

This paper focuses on the development and validation analyses for the scale of students' online language learning engagement conducted in an EFL online learning context. The research supported the findings of Fredricks et al.'s (2016) study concerning learners' online language learning engagement. The results also suggested that EFL learners had the highest scores in behavioral engagement, and the lowest scores in emotional engagement. The reasons partly resulted from distracting from learning tasks, and superficial interactions in the online learning environment (Li, 2021).

This study also has several limitations and implications. First, future research should combine multiple data collection methods, except quantitative measures. Second, the resources of participants should be enlarged to explore whether some dimensions of engagement are more important than others (Fredricks et al., 2016).

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An Instrument Design to Measure Teacher Perceptions, Implementation, and Challenges with Social Emotional Learning (SEL)

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Abstract: *Research from numerous studies around the world consistently shows that integrating social and emotional learning (SEL) development into the structures and practices of schools is a path to creating safe, supportive environments that foster positive cognitive, emotional, and behavioral skills. The researchers designed an instrument to investigate teachers' perceptions of SEL needs in their schools; their knowledge, skills, training, and experiences fostering students' SEL in their classrooms; and barriers to implementing practice. A pilot study was conducted to assess the feasibility of the survey questionnaire, participant recruitment, and data collection and analysis processes. This paper describes the pilot testing procedure which is used to ensure methodological rigor and content and face validity of the instrument before commencing the main research project surveying K-12 teachers in the state of Florida.*

Keywords: online instrument design, pilot study, social emotional learning, teacher preparation

1. Introduction

Substantial empirical data document that students can develop the social and emotional skills and attitudes they need to effectively navigate their multicultural world and contribute actively and meaningfully to their schools, families, careers, and communities. As an integrated approach to learning, SEL can promote social and emotional competence and foster cognitive, emotional, and behavioral skills while also preventing or reducing problem behaviors (Durlak et al., 2011). This includes the long-term development of academic achievement, problem-solving skills, ethical decision-making, health-promoting behaviors, pro-social attitudes about self, others, and work, and positive contributions to community and society (Taylor et al., 2017).

While research data include positive impacts on student academic and behavior outcomes with the implementation of SEL interventions, certain school-wide conditions are crucial to provide support to the practices for the development and implementation (Martinez, 2016). In order to accomplish this, teachers require proper training, support, and resources in order to implement SEL practices and interventions with fidelity. Despite the recognized importance of teachers' beliefs about SEL and their preparation to teach these programs, few studies have examined teachers' experiences with adopting SEL programs and implementing them in classrooms (Durlak et al., 2011). The purpose of this pilot study was to produce a valid and effective instrument to measure teacher perceptions of the importance of SEL in school settings, their knowledge, implementation, and training to use SEL with students, and any potential barriers to implementation. The research questions guiding our literature review and construction of the survey instrument were: (1) What are K-12 teachers' perceptions of SEL? (2) To what extent are K-12 teachers implementing SEL? (3) In what areas do these teachers feel they should have received more training in teacher preparation programs?

The survey was constructed by a team including two K-12 education experts each with over twenty years of experience working with students from traditionally marginalized populations; a content expert completing her dissertation on SEL and school counseling; and a professor of research design, assessment, and evaluation. The items included in the instrument are all aligned to research, prior surveys on SEL, and new developments in the field such as the relationship between SEL and reducing impact of childhood trauma.

2. Literature Review and Theoretical Framework

In recent years, social emotional learning (SEL) has moved to the forefront of research and legislative measures to reduce common behavioral problems in schools that interfere with student learning and positive social outcomes (Collaborative for Academic, Social, and Emotional Learning [CASEL], 2020). Students are more likely to benefit from SEL when staff receive training, and the program or strategy is implemented well and embedded in everyday teaching and learning (Jones & Bouffard, 2012). However, classroom teachers typically receive little training on how to promote these skills or deal with peer conflict or social and emotional development (Schonert-Reichl et al., 2015). As a result, teachers report limited confidence in their ability to respond to student behavioral needs and, in turn, to support students' social and emotional development. Ultimately, training should be embedded in educators' pre-service and in-service experiences, and administrative and supervisory support should be integrated in ongoing ways (Katz et al., 2020).

This study used the SEL conceptual framework developed by CASEL (2020), a model that is gaining an increasing amount of empirical support while becoming highly influential in SEL policy in all 50 U.S. states and internationally (Dusenbury et al, 2019). In this framework, SEL is comprised of five core competencies: self-awareness, self-management, social awareness, relationship skills, and decision making. This framework uses a systemic approach that emphasizes the importance of coordinating practices across key settings of classrooms, schools, families, and communities to enhance all students' social, emotional, and academic learning. Applying an equity lens, Jagers et al. (2019) extended this model and recommended a "transformative SEL" to better articulate the potential of SEL to mitigate the educational, social, and economic inequities derived from racialized cultural oppression in the United States and globally.

3. Research Methods

Survey research designs quantitative research procedures in which investigators administer a survey to a sample to describe attitudes, opinions, behaviors, or characteristics of the population (Colton & Colvert, 2007). To reduce measurement error, it is important to use an instrument with clear, unambiguous questions and response options. For our study, the research design included attention to item writing, questionnaire delivery methods, response data collection and analysis, and improvement of survey items and the questionnaire. This pilot study was implemented with 34 participants and feedback was received on clarity, impartiality, formatting, and length of time to complete the instrument. Fink (2013) recommended that all surveys be pilot tested before launching a research project to ensure methodological rigor and content and face validity. For online administration, we used Qualtrics, a web-based survey platform. The survey questionnaire structure is displayed in Table 1. The researchers used multiple statistical approaches to analyze the data obtained in the pilot testing such as descriptive analysis, cross-tab analysis, and factor analysis.

4. Preliminary Results of Pilot Study

The questionnaire was distributed online to 56 individuals between November 22 and December 2, 2021 and 34 fully completed surveys were submitted for a response rate of 60.7%. Members of this research team sent an email invitation with the survey link to K-12 educators in their respective school districts. Participants recruited were asked to time themselves and provide constructive feedback on the structure and content of the instrument. Based on our analysis of participant feedback and data collected, we added more options to a few items in the demographic section, we changed the format of two ranking scale items to Likert scale or multi-select, and we revised the wording on both open-ended questions to reduce bias. Cronbach's Alpha was used on the Likert scale items and calculated at .82 for items related to school need for SEL and .87 for those regarding benefits of SEL, thus satisfying reliability of the instrument in terms of internal consistency. The average time to completion was 11 minutes, with a minimum time of four minutes and a maximum of 25 minutes.

Table 1. The structure of the questionnaire design

		Goals	Number of items	Format	Sample item
Section 1	Demographics	Background and contextual information	10	Multiple choice	Which grade level are you currently teaching?
Section 2	Perceptions (RQ 1)	School Need	2	4 pt. Likert-scale	SEL should be included in state education standards.
		Benefits	6	4 pt. Likert-scale	SEL programs create opportunities for teachers to recognize and serve young people exposed to trauma.
		Responsibility	2	Ranking scale	Teaching SEL skills should be the primary responsibility of which staff members?
Section 3	Implementation (RQ 3)	Preparation	5	Multiple choice	Have you received training on how to teach SEL skills?
	(RQ 2)	Level of Implementation	2	Multiple choice	How often do you intentionally incorporate SEL?
		Interest in Training	1	Multiple choice	How interested are you in receiving further training on teaching SEL to students?
		Potential Barriers	1	Ranking scale	Which issues are a barrier to implementing SEL?
Section 4		Elicit additional information	1	Open-ended	What are your suggestions to enhance SEL knowledge and skills for future teachers?

We were satisfied with the completion time, a figure which has been shown in previous studies of web-based surveys to correlate to a higher completion rate (Liu & Wronski, 2018). The qualitative data collected through open-ended questions was useful, with 16 of 34 participants (47%) providing feedback related to their own training for SEL, any obstacles they have faced, and recommendations for professional development. Twenty-two study participants (64.7%) agreed or strongly agreed that students' lack of interest in learning is a problem in their school, a finding we found concerning yet perhaps related to our current pandemic situation with social and emotional, financial, and health repercussions for many students and families. Overall, the pattern of survey responses for this pilot study was consistent and the improvements to our instrument will ensure reliability and validity of data collected during our future large scale implementation.

5. Limitations

Our study limitations include the self-selected and reported nature of surveys, in which respondents can be influenced by social desirability to overreport responses that make them look good (Colton & Covert, 2007). To fully verify teachers' reported practices with SEL, researchers would need to follow up with classroom observations and/or interviews. We used a convenience sample for this pilot study and all participants were located in three school districts in one geographic region of Southwest Florida, which could limit generalizability to teachers in other regions and states.

6. Significant Contributions

The significance of SEL continues to grow in the context of policy debates concerning school improvement and individual student achievement. While incorporating a SEL perspective is necessary to provide students with an equitable, high-quality education, it is particularly critical to closing the opportunity gap and addressing the needs of traditionally under-served populations of students of color and low-income students (Hamedani & Darling-Hammond, 2015). Our questionnaire can be used in multiple sites and contexts as a tool for assessment of readiness and barriers to SEL program implementation, providing formative feedback for school leaders, curriculum developers, and teacher educators. As noted by van Teijlingen and Hundley (2001), well-designed and well-conducted pilot studies can inform others about the best research process and occasionally about likely outcomes, therefore investigators should be encouraged to report their pilot studies in detail to establish stronger validity and reliability of the research study.

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Who are the Leaders? A Discussion on Distributed Leadership to Promote Interdisciplinary STEM Education in Primary Schools

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Abstract: *Although interdisciplinary STEM education is receiving increasing emphasis in many curriculum documents and policy reports, there appears inadequate practices or research to guide schools to distribute the leadership and responsibilities to promote quality curriculum and learning outcomes. This paper provides a critical literature review and discussion on deploying distributed leadership to design, implement and promote interdisciplinary STEM education in ICT-enhanced environments of primary schools. Possibilities of distributed leadership for effective STEM practices are proposed. It is recommended that school principals should build up strategic partnerships with higher education institutions, school sectors, communities, and industries. Head teachers of relevant disciplines are encouraged to closely work with each other, take an active part in planning an integrated curriculum, and seek frontline teachers' advice on designing in-class or out-of-classroom STEM activities. ICT Head shall keep the teachers abreast of the latest technologies and tools that can facilitate ICT-enriched learning and teaching environment and provide timely support for the frontline teachers. Finally, it is essential for frontlines teachers of various disciplines to collect first-hand data and provide feedback to the whole team after implementing the interdisciplinary STEM activities with their students. Further, the challenges and the direction of future studies are summarized.*

Keywords: distributed leadership, ICT-enhanced, interdisciplinary, primary schools, STEM Education

1. Introduction

With the funding and resource supports from the Hong Kong government, primary schools have been promoting STEM Education in full swing since 2016 (EDB, 2016; So et al., 2018). However, all the investment was in doubt when the Trends in International Mathematics and Science Study (TIMSS) released the internationally comparable test results and ranking in December 2020 (ACER, 2020). In TIMSS 2019, among all the 64 participating countries and regions, Hong Kong remained 2nd place in primary mathematics and 5th in secondary mathematics, however surprisingly dropped from 5th to 15th in primary science and from 6th to 17th in secondary science respectively (SCMP, 2020). The inconsistency of students' performance in STEM disciplines was one of the issues of STEM education in Hong Kong. Although a few studies have been done trying to address the problem, limited studies have been conducted for seeking ways in the perspectives of ICT leadership in interdisciplinary STEM education. This review study attempts to propose the solutions based on a critical review together with discussions on the distributed leadership that may boost the interdisciplinary STEM education in an ICT-enhanced environment in primary schools. The current study is steered by the research question: How distributed leadership can promote interdisciplinary STEM education in an ICT-enhanced environment in primary schools?

2. Literature Review

2.1 Distributed Leadership and Shared Leadership

In general, distributed leadership and shared leadership are two terms to be used interchangeably (Storey, 2004). Some scholars defined distributed leadership "as a shared process of enhancing the individual and collective capacity of people to accomplish their work effectively" (Yukl, 2002, p. 432). In enacting interdisciplinary STEM education, it is essential to make good use of the collective capacity and individual expertise of teachers from various disciplines to accomplish learning and teaching effectively. Educational researchers have investigated the distributed leadership in ICT implementation at schools of different regions (Chen, 2013; Yee, 2000; Yuen et al.; 2003). Chen (2013) found that transformational and instructional leadership were distributed among various leaders including Principals, Heads of ICT and Heads of Subject. Yuen and his colleagues (2003) concluded three models of ICT leadership change. A previous study outlined a framework with eight categories of characteristics of ICT leadership (Yee, 2000). Some commissioned research found that the successful school leaders understood the limitation of a sole leader and showed the willingness to empower other colleagues to lead (Harris & Chapman, 2002). Harris (2003) highlighted that distributed leadership cannot swipe away the structural, cultural and micro-political barriers at schools. Storey (2004) warned that distributed leadership may result in conflicts among school leaders who were competing with each other, and may also lead to issues of boundaries of management and responsibilities. In the process of promoting STEM education supported by an ICT-rich environment, the leaders and teachers will encounter more challenges as STEM education is a transformational change in the school sector.

2.2 Interdisciplinary STEM Education

Despite the increasingly common use of the term "STEM education", there is still uncertainty as to what constitutes STEM education and what it means in terms of curriculum and student learning outcomes. STEM education can be considered a single or multi-disciplinary field, and in the case of the latter, no clear consensus exists on the nature of the content and pedagogic interplay among the STEM fields (Holmlund et al., 2018). From the perspectives of interdisciplinary education, STEM education is defined as an interdisciplinary approach to learning where rigorous subject knowledge and concepts are coupled with real-world problems as students apply science, technology, engineering, and mathematics in the contexts where they can connect school, community, work, and global enterprise so as to develop STEM literacy, and therefore gain the ability and skills to compete in the new economy (Southwest Regional STEM Network, 2009). Researchers argued that to equip students with problem-solving skills using a multi-disciplinary approach, STEM learning should be an integrating notion that connects the four disciplines effectively (Breiner et al., 2012; Sanders, 2012). However, an effective model to integrate STEM is not yet in place and therefore most teachers do not use an interdisciplinary approach to teaching STEM in K-12 classrooms (Roehrig et al., 2012).

Some scholars recently attempted to develop a framework for developing STEM literacy that summarized the main concepts and themes of STEM education to be STEM capabilities, skills, and dispositions; STEM curriculum and pedagogy; and STEM discipline knowledge (Falloon et al., 2020). Moreover, fundamental mathematical concepts are widely used in science, engineering, and technology (Honey et al., 2014, p.14). In the last two decades, studies have been conducted to investigate the integration of mathematics and science among STEM. Researchers tend to agree that STEM education relies on the subject disciplines of science and mathematics in the primary school setting as these two subjects are the main components of the curriculum or extra-curriculum (Kurup et al., 2019; Beswick & Fraser, 2019; So et al., 2018). Maass and his colleagues (2019) probed the role of mathematics in the learning process of STEM and they also pointed out STEM education is in nature has its interdisciplinary connection. Beswick and Fraser (2019) articulated that the integrated approaches to teaching STEM depend on teachers' expertise in one or more than one of the disciplines. Hobbs and her colleagues (2018) summarised a STEM teaching model at school based on their mixed methods research.

3. Discussion

3.1 Distributed Leadership in Interdisciplinary STEM Education: Barriers

Although research evidence indicated the advantages of distributed leadership in promoting interdisciplinary STEM education, there are still barriers along with the widespread adoption and adaptation in schools. In Hong Kong's primary curriculum, STEM-related learning lies in the key learning areas (KLAs), namely Mathematics Education, Science Education, and Technology Education, and STEM education has been currently initiated and implemented either through the academic discipline of General Studies that introduces fundamental knowledge of science and technology or in the form of co-curricular activities organised by teachers or education vendors. In Hong Kong, teachers' workload and duties are allocated based on the disciplines they teach. Unless they are assigned to teach multi-disciplines of STEM, they may not have time and expertise to design good pedagogies and curricula. Therefore, distributed leaders are desired to overcome the barriers as concluded and pointed out by Geng and his colleagues (2019). These barriers and challenges include time, resources, teachers' beliefs, and the redesign of curricula. Further, to help students make STEM connections across disciplines, teachers of various disciplines are highly recommended to take up leading roles in designing interdisciplinary STEM activities. School principals and headteachers are expected to foster these interdisciplinary connections, for example, to design appropriate curriculum frameworks, offer resources and support.

3.2 Teacher Professional Development on Interdisciplinary STEM Education and Leadership

As the government is committed to enhancing the training of teachers (HKSAR, 2015), subsidized professional development programmes have been offered to teachers. Schools have been sending teachers to participate in the short-term STEM-related professional development programmes aiming to catch up with the rapid pace of STEM education and identify an effective and pragmatic way to design and organise STEM activities based on individual school's strengths and student's need. However, survey results of some recent studies indicated that schools encountered a series of obstacles when they promoted STEM education, from lack of scheduled STEM lessons to difficulties in conducting interdisciplinary STEM teaching, from insufficient STEM teaching examples to the ambiguity of STEM teaching guidelines (HK Youth I.D.E.A.S., 2018). Geng et al., (2019) studied Hong Kong teachers' self-efficacy and concerns about STEM education, and found that only 5.53% of the teacher respondents perceived themselves well prepared for implementing STEM education, and the respondents also expressed their concerns on implementing STEM education in their schools.

Around the globe, more and more postgraduate degrees and professional development programmes have been launched to groom quality STEM teachers. Researchers argued that teacher leaders should be groomed to have the ability to use appropriate resources to enhance student learning and which kinds shall be discarded (Merrill & Daugherty, 2010). Beattie (2002) pointed out that teacher leadership, which is a sub-set of distributed leadership, is an alternative model of school leadership. Krovetz and Arriaza (2006, p.25) stated that this form of distributed leadership model is riding on the prerequisite that the majority of school teachers already possess leadership skills and take up leadership roles at their schools aiming to effectively educate their students and that by coherently utilizing these resources, schools will be more effective in educating students.

4. Conclusion: Challenges and Future Study

To effectively promote and enact STEM education in K-12, stakeholders should make changes and transform the curriculum. Neither one singular leader nor a group of individual leaders with different subject expertise can make a difference easily. Although STEM integration is receiving increasing emphasis in many curriculum documents and policy reports, there appears inadequate practices and research to guide the schools to distribute the leadership and responsibilities. We believe that distributed and shared leadership at school may provide opportunities for this endeavour. School principals shall be the one who spares no effort to build up strategic partnerships with higher education institutions, school sectors, community, and industries. Head teachers of relevant disciplines shall closely work with each other and take an active part in planning an integrated curriculum and seeking frontline teachers' advice on designing in-class or out-of-classroom learning and teaching STEM activities. Heads of ICT shall keep the teachers abreast of the latest development of technologies and tools that can enhance and facilitate learning and teaching and provide an ICT-enriched environment and timely support for the frontline teachers. Last but not least, it is essential for the frontlines teachers of various disciplines to collect first-hand data and provide feedback to the whole team after implementing the interdisciplinary STEM activities with their students. They also play a key role in evaluating the learning outcome of every single subject and related generic skills. In order to have a better understanding of schools' implementation of interdisciplinary STEM education, future studies can be conducted to recruit schools at various levels of promoting STEM education and to probe schools' perceptions and needs in implementing interdisciplinary STEM education. Besides, more communities of practices (CoPs) can be formed to facilitate the exchange and experience on interdisciplinary STEM education, and offer a platform for the school leaders at various levels to mingle and learn from each other.

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Taiwan: National Tsing Hua University.

An Immersive Hakka Learning System Using Human Centered Artificial Intelligence

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Abstract: *In this research, we develop a human-computer interaction system for Hakka, one of the low-resource Chinese dialects, to help preschool children learn the native language of their families. The system adapts the deep learning algorithm toolkit to classify the common keywords included in the normal speech acts in Hakka. The goal is to propose a new approach to language immersion by creating an interactive system for keeping the habit of actively using Hakka in kindergarten.*

Keywords: human-computer interaction, low-resource, deep learning algorithm, language immersion, kindergarten

1. Introduction

Because the teaching and learning languages in compulsory education in Taiwan are mainly Mandarin Chinese, many families start to use Mandarin Chinese to communicate with their children, even if the common language of the elders in the family is not Mandarin Chinese. Facing the phenomenon that the elders in the family are multilingual and the younger generations are monolingual, Hakka Affairs Council has provided substantial assistance in the implementation of Hakka language teaching plans since 2016, allowing some kindergartens to start immersive teaching. Given that immersion language learning is the best way to learn a new language, there are not many teachers capable of teaching the minor varieties of Hakka (e.g. Hoi-liug), because most kindergarten teachers were not born and raised in the local area.

There are 23.57 million residents living in Taiwan, of which 2.37 million have Hakka as their first language. Hakka consists of several accents, of which the Hoi-liug accent accounts for 35.8%. In other words, there are about 848,460 people who can speak the Hoi-liug dialect, accounting for 3.6% of Taiwan's population. According to this distribution, most kindergarten teachers are not good at speaking the Hoi-liug dialect. There are few children's songs and teaching materials in Hoi-liug readily available. In this study, we develop a human-computer interaction system for Hoi-liug, one of the low-resource Chinese dialects, to help preschool children learn the native language of their elders in their family.

2. Related works

Many innovative applications and good results on learning through the interaction of humans and machines have been reported in the recent conference proceedings (e.g. "4th International Conference on Human Interaction and Emerging Technologies: Future Applications, IHIET – AI 2021 C3 - Advances in Intelligent Systems and Computing," 2021; "22nd International Conference on Human-Computer Interaction, HCII 2020 C3 - Communications in Computer and Information Science," 2020)。

Among the successful cases, human-computer interaction is used to promote language learning for adults (e.g. Lala, Nakamura, & Kawahara, 2019; Liu, Yuizono, Lu, & Wang, 2019), but also many interactive design systems are used to teach children English (e.g. Cóndor-Herrera, Jadán-Guerrero, Acosta Rodas, & Ramos-Galarza, 2021; Penichet, Lozano, Garcia-Garcia, & Beletsov, 2021). It is undeniable that in the field of natural language processing, English has a lot of basic resources and open source programs, while Chinese has relatively less. Especially when developing a system for the Chinese dialects other than Mandarin, many details need to be dealt with. However, these technical problems are not insurmountable.

When children learn a new language, special attention needs to be paid on the active habit of starting to speak to others on their own initiatives. At the same time, many language researches also emphasize the feedback obtained after the speech act initiated by the student (e.g. Emmorey, Bosworth, & Kraljic, 2009; Paudyal, Banerjee, & Gupta, 2020). However, in the kindergarten classroom, teachers are always busy dealing with the most urgent emergencies, and there is no time to respond one by one to the speech behaviors initiated by each individual child. In this study, therefore, an AI system is designed to take over the teacher's responses to the children's active use of the new language.

3. Methods

The Immersive Hakka learning HAI System includes three modules: the design thinking process, human centered parameters, and the AI. The system design concept came out with the design thinking process: Emphasize, Define, Ideate, Prototype and Test（Tim Brown & Jocelyn Wyatt, 2010）. The Empathy step mostly focuses on analysis the situation how students in kindergarten learn a new language. Through in-depth interviews with several teachers, the teaching experiences has been considered while the system design stage, furthermore the kindergartens which are going to apply this system have been visited for several times, observing, engaging and empathizing with teachers and students to understand their experiences and learning motivations. This indicates an important observation which is transforming the students into a Hakka learning situation, which is defined as the problem. The Immersive Hakka learning HAI System goal is to trigger the students move into Hakka situated learning. While visiting the kindergartens, the environment issues are adapted to system hardware and network.

While the Ideate stage, designers, software engineers, project managers, education experts and language academics, those were bring together to figure out the mostly simple system design the functions. The system prototype has been design as simple as it could be, due to the audience feedback and the design should understand the audiences are kids between 2 years old to 5 years old.

Before starting to organize the Artificial intelligence model, the context analysis is first considered, especially the prototype has been defined to be as simple as it could be. There is no such a Hakka nature language processing tool, thus our system considers the teaching experience and materials, the data featuring convergences on those keywords which fit student's' daily school life.

Finally, it comes to the UX/UI Output layer, which is the interface directly facing the audiences, kids between 2 years to 5 years old. The output layout for this practical research has been designed in four types, it is fine-tuned from complex design to simple and friendly design. Four types of output layer are: (1) humanoid robot with completed customized Hakka Nature Language Processing, (2) Commercial wheeled robot with open NLP toolkit, (3) Paper craft cardboard with machine learning development, (4) Resized paper craft cardboard with open machine learning toolkit.

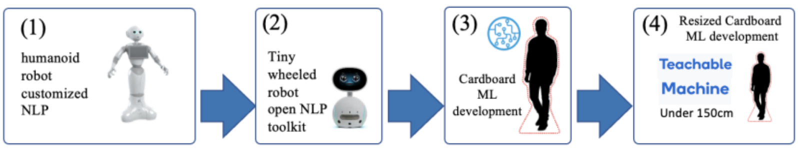

Figure 1. Four types of output layer (Interfaces) design for Immersive Hakka learning HAI System Model

The humanoid robot with customized NLP development will be the completed learning assistance in the future, however since Hakka is one of the low-resource Chinese dialects, the type 1 and type 2 designs are robotic based with an

NLP development, both takes time and high cost. Furthermore, the user survey indicates although robotic is fantastic and fun for kids between 2 years to 5 years old, it is not much with the follow-through. The non-electronic product with affinity and familiarity design is strongly suggested. This is also considered at the Information Feedback step.

Information feedback are those audio responses to the students, it is suggested to be related with the person familiar to the students. Thus, this paper adapts the type 4 design, the UX/UI output layer applies the downsize Principal cardboard cut-out , adding a mobile speaker with AI language process hardware, to response the situational audios. Combining the education experts opinion, the testing includes the time parameter, which is important to keep the students anytime school life in a Hakka learning vibe. The AI language process applied in this paper, we simply import the Google Teachable Machine, the training data are situational Hakka teaching materials (mostly are short vocabularies) recorded from 90 students and Sampled in different rates. Every speech is designed for one situational response, this helps in getting an easy and quick computation time and cost.

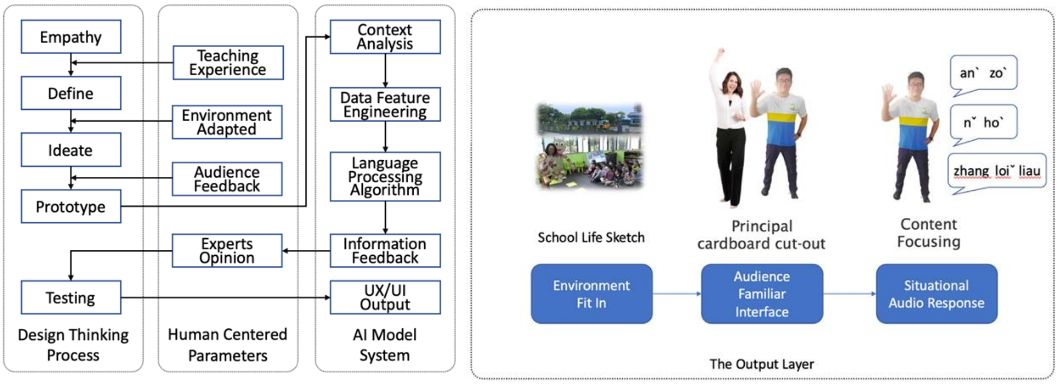

Figure 2 Immersive Hakka learning HAI System Model and the output layer design

Immersive Hakka learning HAI System is applied in three kindergartens, with 3 Principal cardboard cut-out and those parts of students and teachers' voices are also applied as training data in the Teachable Machine module.

Even this paper simply uses the Google teachable machine as Hakka language processing unit, there exits several practical issues. First, the unstableness of children speaking is one important issue, the adults' voices sound familiar when one speaks the same word, especially while they are using voice recognition techniques. During the training data collection, the unstableness of children speaking becomes the extreme data, which means kids in school usually spoken with emotion such as shy or exciting. It directly affects the results of experiments.

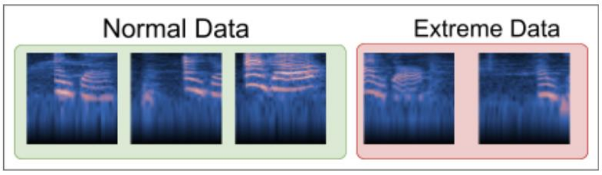

Figure 3 The difference between Normal Data and Extreme Data from 「an' zo'」

Data filtering was needed for the training dataset. We manually compared the dataset visual feature abstracted by fft(Fast Fourier transform), and removed the extreme data from the training dataset. About 20% of data were removed from the dataset. Syllables is an other issue. The google teachable machine does well in single syllable word recognition. Syllables of Hakka is complex, the accuracy is obviously lower in the results. A recognition tree is designed to improve the accuracy. Split the voice with syllables and train an independent model for each syllable. Simplifying each recognition algorithm and then combining the syllable recognition result improves the accuracy and could recognize complicated words.

4. Results:

At the beginning, when we set up the AI system in the shape of the principal of the kindergarten on the campus, the children were full of interest in this system that could respond to them in the voice of their principal. We interviewed the teachers in the kindergarten, and they all had optimistic expectations regarding the subsequent behavior prediction of children using this system. As one month passed, the children did not lose their freshness to this system still. What is more, whenever the children walked by its side, they got used to taking the initiative to speak to it in Hakka. Even the children who were relatively shy, because they saw their peers actively greet the system every day, gradually let go of their vigilance, and gradually began to speak Hakka loudly to the system. According to the evaluations of the teachers, such atmosphere affected the children in the whole kindergarten, regardless of whether the class was participating in the Hakka language teaching plan or not.

5. Conclusion

In this research, we confirmed the feasibility of using AI to promote the learning of low-resource language in young children. The kindergarten teachers who participated in the development have expressed a strong interest in such a system, and expectations to further strengthen the algorithm of this system, in the hope to take up more work to assist teachers in language courses. This paper also suggests while applying AI to promote the learning of low-resource language in young children, both high-accuracy AI algorithm and human centered design thinking are equally important. The output interface should focus on affinity and familiarity

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An Instrument Design to Measure Institutional Support of Transfer Students

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Abstract: *Only 10% of institutional services in higher education are transfer specific (Bobbitt et al., 2021). The researchers designed an instrument, modified from the Laanan Transfer Student Questionnaire (L-TSQ), to investigate the relationship between institutional support and student success for transfer program participants at a mid-sized university in Southwest Florida. The findings may help institutions to improve institutional support offerings for students in transition by understanding what types of institutional support have positively influenced transfer student success. Prior to undertaking a larger quantitative study on the relationship of institutional support and transfer student success, a pilot study was conducted to assess the feasibility of the survey questionnaire and data collection processes. The purpose of this study was to describe the pilot testing process, explore feasibility issues, and improve the instrument and methodology before initiating the main research project with a sample of transfer program participants at one university.*

Keywords: pilot study, instrument design, student transfer, transfer program, transfer student questionnaire

1. Introduction

The traditional college student who enrolls immediately following graduation from high school no longer represents most of today's students; thus, the focus needs to shift to attracting and retaining transfer students (Florida College Access Network [FCAN], 2018). Upon transferring to a university, students are overwhelmingly introduced to larger classrooms, increased financial demands, and expectations to perform academically at the same level as peers who entered immediately following high school graduation. As a result, transfer students can undergo overwhelming academic and social adjustments when transitioning to the university. To make the transfer student pathway viable, to increase access to underrepresented populations, and to provide necessary support to complete a degree, it is essential to think beyond simply linking two institutions to support transfers throughout the adjustment period. To understand the complexities of supporting AA graduates in transition, it is important that an appropriate instrument is developed to examine the relationship between institutional support and transfer student success. The purpose of this pilot study was to produce a suitable instrument to measure the relationship of institutional support and transfer student success for participants of a transfer program in a university in Southwest Florida. The study also aimed to understand the influence of state/community college factors and university factors in relation to student success as defined by student grade point average (GPA).

2. Brief Literature Review

Alternative transfer pathways are more formally taking shape to combat the rising admission standards and tuition costs, but they are not producing graduates at the same pace as traditional pathways (Burke, 2019; Solodev, 2021). Transferring and adjusting to a university is complex and requires psychological, academic, and environmental adjustments (Laanan et al., 2010). Laanan was the first to introduce the social and psychological perspective of the transfer adjustment and introduced the L-TSQ. The L-TSQ is a comprehensive instrument designed to gather demographic, social, and academic experiences of transfer students at 2- and 4- year higher education institutions to understand the complexity of the students' adjustment to the receiving institution (Laanan, 1996, 1998, 2001, 2004).Transfer students tend to represent a diverse student population (i.e., first-generation status, race, age, gender, experience, etc.), so background data paralleled with institutional support can inform transition services (Laanan, 2004). As a result, development of an instrument to examine the relationship of institutional support and transfer student success will complement existing research and provide new understanding founded on student experiences, outcomes, and institutional data. Laanan (2004, 2007) has previously conducted extensive analysis to ensure the L-TSQ instrument can yield valid and reliable results. All questions included in the modified survey were deemed reliable with a coefficient value of .7 or higher (Laanan, 2004). Laanan's (2004, 2007) studies on community college transfers enable future researchers to develop similar research designs and applications. The present pilot study intends to further confirm the instrument's consistency in collecting data from transfer students to examine the relationship of institutional support and student success.

3. Research Methods

The research design included item design, questionnaire delivery data, collection and data analysis, and advanced improvement of survey items and the questionnaire. The instrument was designed in Qualtrics, a popular Web-based survey company, chosen for the economy of design and rapid turnaround time. To ensure the instructions were understandable and communicated efficiently, a pilot study was conducted for three weeks to obtain feedback on clarity, errors, and impartiality of questions. The research instrument is a modified version of the L-TSQ developed to measure various academic and social components of support within the context of the state college or the university. It is important to note that previously validated surveys require the collection of additional reliability and validity in this specific study’s context (Rickards, et al., 2012). The L-TSQ was modified to limit the number of questions with the intent of increasing the response rate. The modified survey is composed of three main sections that collected specific data on institutional support received throughout the transfer adjustment in relation to student success as defined by GPA. The structure of the questionnaire design for each section is shown in Table 1.

Table 1. The structure of the questionnaire design

		Goals	Number of questions	Types of questions	Question samples
Section 1	Background	Basic demographic and academic information (age, gender, entry term, academic program)	9	Multiple choice, text answer, and sliding scale	What is your academic major at FGCU?
Section 2	Institutional Factors	State/community college factors	12	Likert-scale	I consulted with academic counselors regarding transfer.
		University Factors	12	Likert-scale	Upon transferring, I felt alienated at this 4-year university.
Section 3	Institutional Experiences	Influential experiences	4	Open-ended	Please share any experiences you feel positively influenced your adjustment to the university.

4. Preliminary Results

The pattern of survey responses for this pilot study provided useful feedback to improve the instrument for future research. As a result of the pilot study, a handful of questions were reworded to increase clarity and align interpretation with researchers' intent. Through the initial responses and feedback received, improvements were made to several of the instrument's items to increase clarity and remove unintentional bias; thereby increasing the likelihood that respondents will interpret the items in the manner intended (Rickards, et al., 2012). For example, in the institutional experiences section, questions inquiring about experiences were amended to explicitly ask for examples to generate more fruitful responses. Additionally, questions were added to the institutional experiences section to capture respondent contact information for a follow-up interview to capture insightful qualitative data.

5. Limitations

There are several limitations to the study. The respondents may fail to provide honest answers pertaining to GPA that would skew the understanding of student success and invalidate data. Another limitation is the limited scope of the survey data as it only measures a single point in time to examine a single transfer program unless additional surveys are conducted (Creswell & Clark, 2017).

6. Significant Contributions

This instrument design was developed as the initial phase to conduct a future study. For the future project, the researchers will employ a mixed methods approach to collect data through survey questionnaire to measure the relationship between institutional support and transfer student success for participants of a transfer program in Southwest Florida. In addition to the survey questionnaire, in-person interviews will be conducted from the sample providing additional opportunity for instrument improvement. The research project can also provide a platform for researching other transfer programs. Future studies should focus on specific institutional support services or transfer program benefits to determine the individual support provided in relation to success indicators.

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Investigating Online Learning Competencies of Learners in the Continuing Education Context

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Abstract: *With the rapid development of the Internet, online learning has emerged as an important route to continuing education and lifelong learning, which is of great significance for building a "Learning Society." The purpose of this study was to develop and validate a measuring instrument for continuing education learners' online learning competencies, to find the relationship among different factors in online learning competencies of continuing education learners, and to analyze the differences among different groups. A total sample of 5,392 learners of continuing education from the Open University of China (OUC) participated in this study. Through a confirmatory factor analysis, the Online Learning Competencies Scale (OLCS) for continuing education learners was validated in four dimensions: Online Learning Motivation (OLM), Online Learning Technologies (OLT), Self-Control (SC), and Self-Directed Learning (SDL). The survey results found that continuing education learners at OUC had good OLM, OLT, SC, and SDL, which were all above the medium level, but SC was significantly lower than other factors. The results indicated that OLM had a positive effect on OLT, SC, and SDL; OLT had a positive effect on SC; SC had a positive effect on SDL; but OLT had a negative effect on SDL.*

Keywords: continuing education, online learning motivation, online learning technologies, self-control, self-directed learning

1. Introduction

With the development of the Internet, lifelong learning has become much easier (Li, 2017; Selwyn, Williams, & Gorard, 2001; Zhang & Li, 2015). It has expanded the scope of continuing education learners, who have become more heterogeneous and diverse (Lai, Tao, & Chen, 2019; Rutkauskiene, Volungeviciene, & Rutkauskas, 2005), encompassing students from a variety of cultural and educational backgrounds (Kuo & Belland, 2016). Against this background, the research on continuing education learners' online learning has become important.

Although online learning provides a convenient channel for people to receive further continuing education, previous researchers found that many learners had problems in online learning such as lack of motivation (Ripiye, 2016), weak self-control, and low learning execution (Sui & Sui, 2018), which seriously affected the quality of their online learning. For continuing education learners, online learning is a kind of self-directed learning, the success of which depends on their personal characteristics (Zheng, Chen, & Chen, 2016). Therefore, it is important to investigate learners' online learning characteristics in continuing education contexts to promote their online self-directed learning.

The Open University of China (OUC) is an important organization for continuing education in China. In order to determine Chinese continuing education learners' online learning competencies, and to explore the main factors influencing learners' online self-directed learning, the Online Learning Competencies Scale (OLCS) was developed in this study. The study also aimed to improve the instructional design and learning services of online courses at OUC.

2. Literature review

Online learning competencies have been the focus of distance learning research in recent years. Dabbagh (2007) proposed that distance learners should have competencies such as being skilled in the use of online learning technologies, having strong self-control, and having self-directed learning skills through the deployment of time management and cognitive learning strategies. Lawson, Askell-Williams, and Murray-Harvey (2005) proposed that adult learners should have the lifelong abilities of objectiveness and self-awareness, knowledge of how to learn, personal characteristics, and should be development oriented. From the comprehensive perspective of distance learning competencies and continuing education, Self-Directed Learning (SDL), Online Learning Motivation (OLM), Online Learning Technologies (OLT) and Self-Control (SC) were investigated as the main factors of online learning competencies of adult continuing learners.

2.1 Self-Directed Learning

Self-Directed Learning (SDL) means the skill of "learning how to learn," and is an important characteristic of online learners (Dabbagh, 2007). It is a consciously controlled psychological process for the purpose of gaining knowledge and understanding, or strengthening a skill (Long, 2010). Online learners have to possess self-discipline, self-monitoring, self-initiative, and self-management, which are characteristics of self-directed learning (Cheurprakobkit, Hale, & Olson, 2002). Self-directed learning is an important skill for life-long learning (Sze-Yeng & Hussain, 2010). SDL in online environments has recently gained attention (Butcher & Ferguson, 2021). For distant continuing learners, SDL is an essential learning approach.

2.2 OLM and SDL

"Motivation" is a psychological feature that instigates and sustains goal-directed activities, and has a significant impact on students' behavior (Schunk, Pintrich, & Meece, 2008). It has been proved that motivation has a reciprocal relationship with learning performance (Morris, Finnegan, & Wu, 2005). Learning motivation, as a factor to promote students' learning, and to improve their learning competencies and learning effects (Kao, Wu, & Tsai, 2011), has been studied by researchers in different situations. For online learners in higher education, lack of online learning motivation is an important factor leading to high dropout rates in online courses (Rabin, Henderikx, Kalman, & Kalz, 2020).

In previous studies, researchers found that learning motivation had a significant impact on SDL (Rabin, Henderikx, Kalman, & Kalz, 2020). Zhu, Bonk, and Doo (2020) found that motivation had a direct impact on self-monitoring in online self-directed learning, while Law and Nguyen-Ngoc (2008) found that motivation had an impact on self-directed learning with social software. For distance continuing education learners, it can be inferred that OLM will affect learners' online SDL. Therefore, the hypothesis was as follows:

H1: Continuing education learners' OLM has an impact on SDL.

2.3 OLT and SDL

Learners' OLT refers to the skills of information retrieval and analysis using the Internet (Sumuer, 2018). For distance continuing education learners, OLT is necessary for learning online (Dabbagh, 2007). Kim, Jang, and Innwoo (2019) found that OLT had positive effects on learners' self-directed learning in primary school, and that students' level of self-directed learning had a correlation with the frequency of using OLT in the Romanian educational context. For distant continuing education learners, it can be inferred that OLT will affect their online SDL. Therefore, the hypothesis was as follows:

H2: Continuing education learners' OLT has an impact on SDL.

2.4 SC and SDL

Learners' SC means the ability to make and implement plans in the face of difficulties and challenges, including thinking about long-term goals, resisting temptation, delaying satisfaction, and controlling emotional impulses (Zhu, Au, & Yates, 2016). Previous studies found the substantial individual differences in people's SC, especially when it is indexed as the ability to go beyond temptation and avoid impulsive behavior to achieve a goal (Mangu-Ward & Swain, 2011). SC strategies were identified for college students to focus on learning in an online environment (Tsai, 2009). To avoid distraction due to interference, SC focusing on learning and effective use of time have been found to be very important for students' online learning (Zhu et al., 2016). Previous studies found that SC would significantly affect SDL (Ma et al., 2021; Nuri & Jeong-ryeol, 2020). For distance continuing education learners, SC is necessary for learning online (Dabbagh, 2007). Previous studies suggested that SC affects self-directed learning ability (Kim, Park, Yoo, & Kim, 2020; Uus, Seitlinger, & Ley, 2020). For distance continuing education learners, it can be inferred that SC will affect their online SDL. Therefore, the hypothesis was as follows:

H3: Continuing education learners' SC has an impact on SDL.

2.5 OLM, OLT, and SC

There may also be intercorrelations among OLM, OLT, and SC. Some studies have suggested that learners' online learning motivation had effects on their OLT self-efficacy (Aharony & Gazit, 2020; Ross, Perkins, & Bodey, 2016). Meanwhile, learning motivation has a positive impact on learners' SC (DiMenichi & Tricomi, 2015), and some studies have suggested that achievement motivation plays a moderating role in the process of the influence of interpolated pre-questions on SC (Yang, Zhang, Pi, & Xie, 2021). For distance continuing education learners, the hypotheses were as follows:

H4: Continuing education learners' OLM has a positive effect on OLT.

H5: Continuing education learners' OLM has a positive effect on SC.

H6: Continuing education learners' OLT has a positive effect on SC.

3. Method

3.1 Participants

The questionnaire was published on the learning website of the Open University of China. It went online from September 25, 2019, and ended on November 15, 2019, and finally obtained a total of 5,392 valid responses from the distance continuing education learners. Table 1 shows the demographic information of participants in this survey.

Table 1. Participants' Demographic Information

Demographic Profile	Types	Percent (%)
District	urban area	65.54%
	rural area	34.46%
Educational background	junior high school or below	0.96%
	technical secondary school	19.27%
	senior high school	14.58%
	junior college	48.96%
	bachelor	15.73%
	Master's and doctorate	0.15%
	other	0.35%
Occupation	service and entertainment	11.39%
	administration	14.30%
	scientific research and education	17.04%
	agriculture	7.25%
	business	14.30%
	production and processing	6.94%
	public management	9.40%

manufacturing industry	6.58%

3.2 Survey Instrument

The survey instrument was the OLCS (the Online Learning Competencies Survey), consisting of four factors, Online OLM (OLM), Online Learning Technologies (OLT), Self-Control (SC), and Self-Directed Learning (SDL). It adopted a 5-point scale ranging from 1 to 5, with 5 for "strongly agree," 4 for "agree," 3 for "neutral," 2 for "disagree," and 1 for "strongly disagree." All items were positive descriptions.

OLM means the psychological feature that instigates and sustains goal-directed online learnings (Schunk, Pintrich, & Meece, 2008), of which sample item was as "I like learning online to satisfy my interest"(Kao, Wu, & Tsai, 2011b). OLT refers to the skills of information retrieval and analysis using the Internet, of which sample item was as "I can well retrieve the information I need online" (Sumuer, 2018). SC means the ability to make and implement plans in the face of difficulties and challenges (Zhu, Au, & Yates, 2016), of which sample item was as "I can concentrate when I study online"(Martinez-Lopez, Yot, Tuovila, & Perera-Rodriguez, 2017). SDL means the skill of "learning how to learn," and is an important characteristic of online learners (Dabbagh, 2007), of which sample item was as "I set a goal for myself when I study online"(Hung, 2016).

4. Model testing results

The Cronbach's alpha value of the OLCS was .931 in the reliability test with SPSS 20.0, and the values of OLM, OLT, SDL, SC were .70, .89, .89, and .85 respectively, which are all over the standard of .7 (see Table 2), indicating good internal consistency (Fornell & Larcker, 1981).

Confirmatory factor analysis (CFA) was then conducted using AMOS 23.0. The factor loadings ranged from 0.64 to 0.89. The correlations between the five factors were between 0.61 and 0.81. The model fit indices of the structure of the OLCS by confirmatory factor analysis (CFA) indicates the fitting degree of the actual model structure and the hypothesis model. The Root Mean Square Error of Approximation (RMSEA) was 0.059, the Normed Fit Index (NFI) was 0.974, the Incremental Fit Index (IFI) was 0.975, the Tucker-Lewis Index (TLI) was 0.967, and the Comparative Fit Index (CFI) was 0.975. All values were above 0.90, which shows that the scale had good structural validity (Hair et al., 2014).

According to the above data analysis, the questionnaire of this study had good reliability and validity, ensuring that the survey results were reliable and stable.

5. Descriptive statistics

Table 2 provides the Means and Standard Deviations of each factor of online learning competencies of the continuing education learners. As shown in Table 2, the means of all the factors ranged from 3.891 to 4.083, indicating the online learning competencies of online learning of the continuing education learners reached above-medium (3.000) levels. In order to investigate the differences among the five factors, we conducted a paired sample t test for every two factors. The results showed that the mean of self-control was significantly lower than that of other factors, including OLM (t = 26.254, p < 0.01), OLT (t = 18.900, p < 0.01), and SDL (t = 21.067, p < 0.01), indicating that the SC of distance continuing education learners needs to be promoted.

Table 2. Means and Standard Deviations of online learning competencies factors

Factor	OLM	OLT	SC	SDL
Mean	4.083	4.005	3.891	4.011
SD	0.584	0.586	0.632	0.607

To test for educational background difference in online learning competencies of continuing education learners, the Analysis of Variance (ANOVA) was used. The results indicated a significant difference among different educational background learners However, there was no significant difference in the ANOVA test of OLM ($F = 1.399$, $p = 0.221$), SC ($F = 1.748$, $p = 0.120$), and SDL ($F = 1.885$, $p = 0.093$). For OLT, there was a significant difference ($F = 2.696$, $p = 0.019 < 0.05$) among the junior high school (below) group and other groups ($p < 0.05$). In general, the online learning competencies of junior high school (below) students were significantly lower than those of other groups, and those of master's and doctoral students were higher than those of other groups, while there was no significant difference among other groups.

To test for occupation differences in the online learning competencies of the continuing education learners, ANOVA was used. It indicated significant difference among different occupations, revealing that occupations made a significant difference in SDL ($F = 3.970$, $p < 0.01$), SC ($F = 4.907$, $p < 0.01$), and OLT ($F = 4.417$, $p < 0.01$), but no significant difference in OLM ($F = 1.699$, $p = 0.117$). Learners engaged in public management performed best in all factors among all the learners, followed by learners engaged in scientific research and education. Learners engaged in business performed above average in OLM, OLT, and SDL, but SC was below average. Learners engaged in administration performed below average in OLM, but above average in other factors. Learners engaged in the manufacturing industry, service and entertainment, agriculture, production, and processing performed below average in all the factors of online learning competencies.

6. Structural equation model analysis

The model fit indices of the structural equation model (SEM) were good. The value of RMSEA was 0.065 (< 0.10), NFI = 0.971, IFI = 0.972, TLI = 0.963, and CFI = 0.972, which were all above 0.90, showing that the hypothesis model of the scale had good structural validity, indicating a good fit of the structural equation model (Hair et al., 2014).

The verification of the research model was as shown in Table 3. All the paths were positively significant except for the path coefficient of OLT to SDL which was negatively significant. H1, H3, H4, H5, and H6 were supported, but H2 was not supported.

Table 3. Path coefficients of the model

Hypothesis	Path	Standardized estimate	*p*	results
H1	OLM→SDL	0.47	***	supported
H2	OLT→SDL	-0.12	**	Not supported
H3	SC→SDL	0.61	***	supported
H4	OLM→OLT	0.90	***	supported
H5	OLM→SC	0.13	***	supported
H6	OLT→SC	0.74	***	supported

Note: ***$p < 0.001$, **$p < 0.01$.

7. Discussion

The results of this study show that continuing education learners in the Open University of China have strong OLM, OLT, SC, and SDL, beyond the neutral level (3 points). This is in line with expectations, because the wide popularity of the Internet now allows adults to obtain online learning opportunities anytime, anywhere. Adults who attend continuing education are not forced to study like K-12 students. Learners in continuing education often have strong learning needs based on personal growth, career promotion, and interest development (Kao et al., 2011). This makes them higher than the medium level in online learning competences. However, their performance in SC is significantly lower than that in other dimensions, indicating that continuing education learners face some difficulties in resisting temptation, controlling their emotional impulses, and so on (Zhu, Au, & Yates, 2016) in the complex online world.

The results show that OLM could significantly and positively predict OLT, SDL, and SC. This is consistent with expectations (Zou, Zhang, Xie, & Wang, 2021). Driven by higher online OLM, students who participate in continuing education can become more proficient in mastering network technology, pay more attention to learning in the network environment, and carry out better self-directed learning.

The results shows that OLT can significantly and positively affect SC. When learners had higher network skills, they could often deal with the complex network world more skillfully and stay more focused in the network environment. If we want to improve learners' concentration, we can try to train learners to master network skills, so that they can better deal with the complex situation in the network environment.

The results shows that OLT would negatively affect SDL, which is inconsistent with the hypothesis. The OLT skills of continuing education learners measured in this study mainly included retrieval of information, analysis of information, and reflection on information, while SDL mainly measured the goal setting, scheduling, and learning method selection of continuing education learners. This may be because learners with higher OLT skills would spend more time analyzing and reflecting on information, so they will critically reflect on and evaluate their self-directed learning. The specific reasons need to be further explored.

The results show that SC will positively affect SDL, which is consistent with the hypothesis. When learners have higher SC, they can devote themselves to online learning, free from the interference of redundant and complex information in the online world, and achieve better self-directed learning.

8. Conclusion

This study developed a scale with good reliability and validity to measure the online learning competences, including online learning motivation, online learning technologies, self-control, and self-directed learning. The survey results found that continuing education learners in OUC had good OLM, OLT, SC, and SDL, which were all above the medium level (3 points). However, learners faced some difficulties in resisting temptation, controlling their emotional impulses, and so on (Zhu, Au, & Yates, 2016) in the complex online world. Different groups of continuing education learners have differences in online learning literacy. Therefore, in the implementation of continuing education, we need to pay attention to the differences of different groups, so that learners of different levels can gain benefits from online learning.

For continuing education learners, online learning is an important learning method. Continuing education learners with strong OLM can not only have higher online learning technology skills and online learning focus, but can also achieve better self-directed learning. In the field of continuing education, we can improve learners' focus and further improve their ability of self-directed learning by improving their OLM and training their online learning technology skills.

Despite the interesting results, this study also has some deficiencies. In our follow-up research, we will conduct in-depth interviews with typical continuing education learners to understand their real thoughts, so as to supplement the research conclusions of this study.

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The complete intermediary effect of network course service quality on personalized learning

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Abstract: *This study analyzes the personalized learning and self-directed learning. And it holds that personalized learning develops on the basis of self-directed learning ability, which involves students' choice and application of various learning strategies. This study revised the MSLQ to measure students' personalized learning level in the network learning environment. In this study, interviews and questionnaires were used, and the research results were obtained through pre-research and formal research. The conclusion is that the service quality of online courses affects the personalized learning level by influencing the online learning experience. Network service can also affect the level of personalized learning by influencing learning motivation. In addition, the learning experience in the network learning environment can also influence the personalized learning level by influencing the learning motivation. However, the online course service does not directly affect the personalized learning level. Therefore, in order to improve students' learning effect in the network environment, it is necessary to optimize the network curricula service.*
Keywords：network curricula service, network learning experience, learning motivation, personalized learning

1. Introduction

The *2016 National Educational Technology Plan* of the United States-*Learning for the Future: Remodeling the Role of Technology in Education* emphasizes the implementation of personalized learning based on big data analysis(Technology, Plan, Duncan, & Cator,2010). The Consortium for School Networking released the *Driving K-12 Innovation (Hurdles)* in 2019 and *Driving K-12 Innovation 2020 Hurdles and accelerators*(CoSN,2020), which also analyzed that promoting students' character is one of the five major trends of future education development. Online learning has become the mainstream of students' learning form, but some previous studies have not analyzed the influence of the online learning on students' personalized learning. This study aims to explore the influencing factors of personalized learning of students in higher education in the ubiquitous network learning environment.

2. Literature review

From 2011 to 2018, the number of published papers continued to increase, which may be related to the reports published by the United States, such as *Promoting Teaching and Learning through Educational Data Mining and Learning Analysis*, *Learning for the Future: Reshaping the Role of Technology in Education*, *Horizon Report*, etc. CiteSpace is used to co-quote the core documents in WOS, and it is found that the three most cited authors are Dabbagh, Akbulut and Brusilovsky. Through keyword cluster analysis, it is found that the first three research trends are personal learning environment, educational games and intelligent tutor system, which are the most studied topics in the field of personalized learning. By co-occurrence analysis of keywords, it is found that the top eight co-occurrence keywords in personalized learning research are personalized learning, performance, adaptive learning, motivation, personalization, personality, learning style and personal learning environment. These keywords reflect the trend of personalized learning research. However, the measurement of personalized learning has not been studied.

2.1 Personalized learning

CCSSO puts forward six key elements of personalized learning: free time and open space, task-driven real learning opportunities, student-centered learning path, personalized learning process, information technology support and new teacher definition(CCSSO,2014). Song et al. believe that personalized learning means learning from receiving the same educational input and opportunities to learning from acquiring unique learning experience and learning resources according to individual needs(Song, Wong, & Looi,2012). Don Mcleod, founder of the Center for Educational Leadership Research of the American College Education Management Committee, put forward four key transformations to promote the personalization of learning process(Peterson,2018), including student ability, classroom leadership, learning activities and learning environment. This study holds that personalized learning is supported by rich learning tools, learners choose learning resources they are interested in, use various learning strategies to promote learning, and get personalized and free development in the process.

Nowadays, most of the researches on personalized learning evaluation at home and abroad are based on the learning system newly created by researchers, and then asking students to fill out questionnaires to measure students' personalized learning level. For example, Souto et al. studied and modeled learners' cognitive ability under the network learning environment (Souto & Verdin,2006). Chen and Hsu(Chen & Hsu,2008) designed a personalized intelligent learning system in order to effectively support students' English learning. They also conducted a questionnaire survey on students after the experiment. Jeong et al. designed the PLCPS personalized learning system, and conducted a questionnaire survey on the students studying in this system(Jeong, Choi, & Song,2012). Nedungadi and Raman integrate e-learning and mobile learning(Nedungadi & Raman,2012), and measure the effectiveness of this personalized learning method by measuring students' support perception and emotional experience of mobile devices and other environments in this experience. Liaw and Huang proved that perceived satisfaction, perceived usefulness and interactive learning environment are the predictive factors of self-regulation in the network learning environment by involving students in the designed learning environment and combining with a questionnaire survey(Liaw & Huang,2013). The studies mentioned above were based on the learning system designed by researchers themselves, but there are not popular personalized learning systems around the world. Therefore, we changed the research perspective. Instead of combining personalized learning with the use of specific learning tools, we paid attention to what learning behaviors occurred and what learning strategies learners used.

Personalized learning and self-directed learning pay attention to different aspects though their connotations overlapping to a great extent. Personalized learning emphasizes arranging learning methods according to one's own personality preference and paying attention to the learners' personality development. Self-directed learning emphasizes that learners actively regulate and monitor cognitive processes and behaviors (Hong, ChenLi, Qinhua, & Shanshi,2014). Therefore, the evaluation elements of self-directed learning ability are used for reference in the evaluation of personalized learning methods.

At present, the internationally widely accepted evaluation instruments for self-directed learning, such as Motivated Strategies for Learning Questionnaire (MSLQ) developed by Pintrich and his team (Pintrich, Smith, Gracla, & McKeachie,1991), related scales used by OECD in PISA (OECD,2009,2012) and Zimmerman's self-directed learning interviewing structure(Zimmerman,1989,2000). MSLQ was used after comparing the feasibility. MSLQ was revised to make it suitable for the implementation of this study. And finally use it in four dimensions: cognitive strategy(CS), metacognitive strategy (MCS), resource management strategy(RMS) and learning motivation(LM).

2.2 Network curricula service & network learning experience

Network curricula service refers to providing various tools for students to help them learn better on the network learning platform. Network curricula service can help students to take exams, communicate with others, and access the learning resources, assignments, diversified teaching methods, discussions, feedback, stable environment(Lypson, Ross, & Goldrath,2016;Zhou, Zhao, Jiang, & Wang,2017).

The network experience is an important component with using emerging technologies to enlarge the learning effect. Some researchers found that system quality, course design, learner-learner interaction, learner-instructor interaction, learner-content interaction, and self-discipline have positive effect on students' learning outcomes. And the learner-content interaction is the strongest determinant(Su & Guo). But Jiying found that satisfaction was not related to any of the learning environment factors(Han, Geng, & Wang,2021). Fabriz found that greater fulfillment of psychological needs and higher technology acceptance coincided with outcomes that are more favorable(Han, Geng, & Wang,2021). In addition, Mahmoud found that distraction and reduced focus led to students' dissatisfaction during online learning(Maqableh & Alia,2021). Some hypotheses are as follows:

H1: The network curricula service quality of online courses will affect the level of personalized learning;

H2: Network learning experience will affect the level of personalized learning;

H3: Network learning experience will affect the level of learning motivation;

H4: The network curricula service quality of online courses will affect the level of learning experience;

H5: The network curricula service quality of online courses will affect the level of learning motivation;

2.3 Learning motivation

The study by Kuan-Chung supported SDT's main theorizing that intrinsic motivation, extrinsic motivation, and a motivation are distinctive constructs(Chen & Jang,2010). Liang-Yi found that the quality of online learning resources would enhance students' motivation(Li & Tsai,2017). Hamdan et al. found that the potential of implementing personalized learning principles in online courses to support students' psychological need satisfaction and intrinsic motivation(Alamri, Lowell, Watson, & Watson,2020). The hypothesis is as follows:

H6: Learning motivation will affect the level of personalized learning.

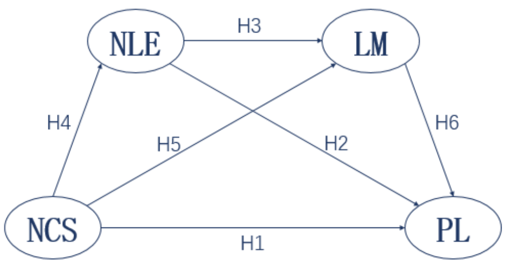

Figure 1. Major constructs and hypotheses

3. Methodology

3.1 Pilot study

The research methods in this study including interviews and questionnaires. In the pre-research, a preliminary questionnaire was compiled according to the results of literature research. Then, two rounds of group interviews were carried out to optimize the dimensions. After that, we distributed pretest questionnaires, and a total of 1062 valid questionnaires were collected. We conducted exploratory factor analysis and confirmatory factor analysis, and deleted some questions with poor validity, and optimized the validity of the questionnaire.

3.2 Formal research

In the formal research, formal questionnaire had become the main research tool. The formal survey instrument is Network Personalized Learning Assessment Questionnaire (NPLAQ). The reliability and validity of it were obtained by calculation in SPSS. Also, the structural model was obtained in AMOS.

3.3 Participants

A total of 625 questionnaires were collected. All the participants are undergraduate students, postgraduate students and doctors. Among the participants, 40.0% are male, and 60.0% are female. Among these students, 23.4% are from Peking University, 40.6% are from Beijing Normal University, and 36.0% are from other universities, involving 108 schools at home and abroad.

4. Results

SPSS 21.0 was used for reliability analysis, and AMOS was used for confirmatory factor analysis. The Cronbach's α of the questionnaire was 0.962, and the reliability coefficient of each dimension was greater than 0.8, which indicated that the questionnaire was highly reliable.

Table 4. reliability test

Factor	NCS	NLE	LM	PL	ALL
Cronbach’s α	0.877	0.891	0.817	0.935	0.962
number of terms	4	5	3	11	23

The factor loadings were all higer than 0.7, and the average extracted variance (AVE) of all the constructs were higher than 0.5, and the composite reliability values (CR) were higher than 0.7. The average extracted variance values (AVE) of all factors were lower than the composite reliability values (CR) respectively, which indicating good internal consistency.

Table 5. The composite reliability values (CR) and average extracted variance (AVE)

Factor	NCS	NLE	LM	CS	MCS	RMS	PL
AVE	0.643	0.619	0.6	0.637	0.639	0.544	0.896
CR	0.878	0.89	0.817	0.875	0.876	0.781	0.963

The model fitting indices can be obtained by confirmatory factor analysis (CFA), and the degree of fitting shows the gap between the actual model and the hypothetical model. The ratio of $\chi2$ to its degree of freedom ($\chi2$/df), the root mean square error of approximation (RMSEA), comparative fit index (CFI), Adjusted goodness-of-fit index (AGFI), Goodness-of-fit index (GFI), Normalized fit index (NFI), Comparative fit index(CFI) and the Tucker-Lewis Fit index (TLI). The actual indices of the model all meet the required values, as shown in Table 4, which shows that the model fits well.

Table 6. Model fit indices

Model fit indices	$\chi2$/df	RMR	GFI	AGFI	NFI	TLI	CFI	PNFI	RMSEA
Recommended value	1-3	<0.05	>0.9	>0.9	>0.9	>0.9	>0.9	>0.5	<0.05
Obtained value	2.19	0.039	0.937	0.921	0.952	0.97	0.973	0.835	0.044

5. Descriptive statistics

It can be seen from Table 6 for the average and standard deviation, minimum and maximum values of each dimension. The average score of online course service is 21.8, the average score of online learning experience is 27.60, the average score of learning motivation is 17.44 and the average score of personalized learning level is 60.78.

Table 7. Descriptive statistics of each dimension

Factors	Mean	SD	Min-value	Max-value
NCS	21.98	4.248	4	28
NLE	27.60	5.067	5	35
LM	17.44	2.628	3	21
PL	60.78	10.352	11	77

6. The structural model

There are three ways for NCS to influence the level of personalized learning on the Internet: (a) NCS-> LM-> PL; (b)NCS—>NLE—>PL; (c)NCS—>NLE—>LM—>PL. These standard regression weights are very significant and all the path coefficients are positive, which means that all the influences are positive. The higher the quality of network service, the better the learning experience in the network environment, the higher the students' learning motivation, and the higher their personalized learning level. However, the online course service does not directly affect the online personalized learning ability. Compared with personalized learning ability, network service plays a completely intermediary role.

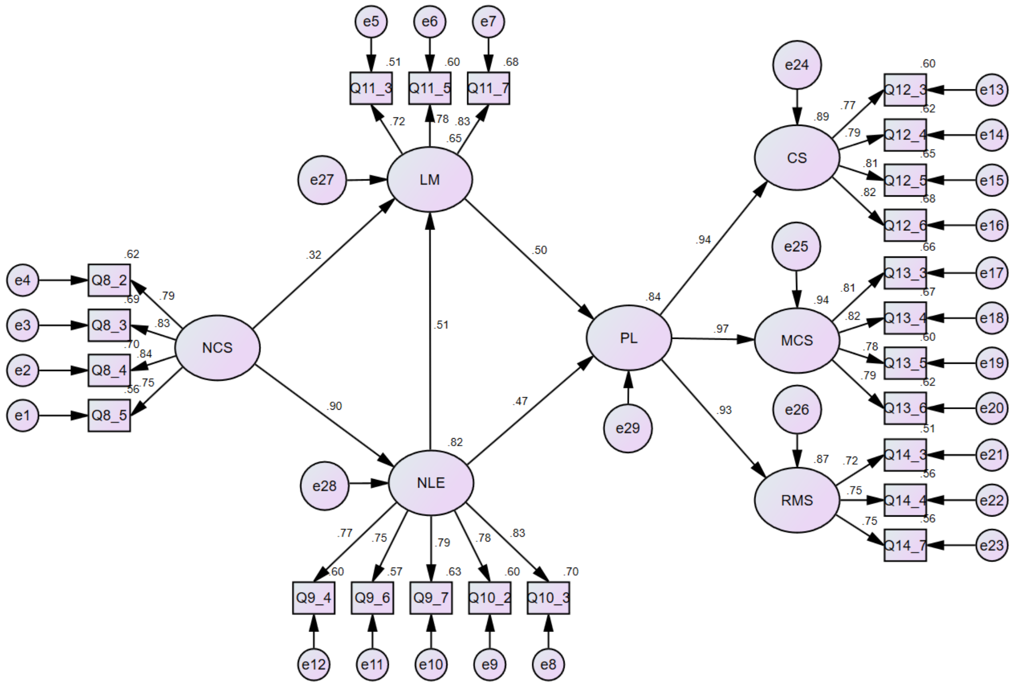

Figure 2. Network self-directed learning ability structural equation model

6.1 Gender differences in online personalized learning level

Independent sample t-test shows that there is a significant difference between male and female PL ($p=0.03<0.05$), and then independent sample t-test shows that there is a significant difference between male and female CS($p=0.031<0.05$) and MCS($p=0.049<0.05$), but there is no significant difference in RMS dimension. Compared with female, male scored higher on CS and MCS in their personalized learning level. The above shows that male are better than female in the application of cognitive strategies and metacognitive strategies. But there is no significant difference between male and female in the practical application of resource management strategies.

6.2 Learning ability and personalized learning level

Single-factor variance analysis of learners' learning ability level and personalized learning level shows that there are significant differences in personalized learning level among students with different learning ability ($F=6.214$, $p=0.000<0.01$). There is no significant difference in students' personalized learning level among Grade B, Grade C and Grade D. But there are significant differences among other groups. The personalized learning level of students in Grade A is significantly higher than that of other groups, and that of students in Group E is significantly lower than that of other groups. While there is no significant difference among the middle three groups. From very negative to very positive group, the average scores of each group were 63.69, 60.13, 60.01, 59.15 and 48.33 respectively.

6.3 Learning form and personalized learning level

Regular study such as school education, training, etc.; irregular learning, for example, learners assign learning tasks independently, and self-directedly look for learning resources to study. Informal learning, such as playing badminton, is getting better and better. Both regular learning and irregular learning belong to formal learning, aiming at obtaining certificates, while informal learning does not aim at obtaining certificates.

One-way ANOVA analysis of different learning forms and personalized learning levels shows that $F=28.928$, $p=0.000<0.01$, as shown in Table 15. Post Hoc test shows that there are significant differences in students' personalized learning level between regular learning and irregular learning, and between regular learning and informal learning. The PL score for students who like regular learning is 63.12, which is significantly higher than that of the other two groups. The PL score of students who like irregular learning is 56.79 and that of students who like informal learning is 57.24. Students' PL in regular learning is higher than that in informal learning.

6.4 Research on different educational background

According to the educational background, the samples are classified into undergraduate stage, master stage and doctoral stage. The analysis of variance shows that there is no significant difference in LM ($F=0.433$, $p=0.649>0.05$) of students in different learning stages ($F=3.558$, $p<0.01$), but the NCS ($F=2.657$, $p<0.01$) and NLE ($F=7.800$, $p<0.01$) of students in different learning stages.

This shows that no matter what stage of students, they all have the same degree of learning motivation, which has not changed because of the change of learning background. Further Post Hoc analysis shows that there are significant differences in NCS, NLE and PL dimensions between undergraduate and postgraduate students. Undergraduate students' cognition of network course service, learning experience of network environment and scores of personalized learning level are higher than those of postgraduate students and doctors.

7. Discussion

The results show that NCS has a significant positive predictive effect on NLE and LM. This is consistent with expectations, because a good experience is inseparable from the powerful and comprehensive services provided. Learners are active rather than passive. The more functions, the more personalized needs of more students can be met, thus improving NLE. High-quality NCS will enhance learners' interest in using online learning support tools, thus enhancing their learning motivation. Additionally, NCS cannot influence PL directly, which indicates that the effect of NCS having been transformed mainly to NLE by learners.

The results show that high LM can promote learners to use a variety of learning strategies, and deepen the degree of use, thus improving the PL. Some studies have also found that the application of learning strategies can improve students' LM, at the same time the influence of LM in this study shows a more fundamental nature.

NLE can directly and positively predict students' PL. The better the experience of NLE, the more willing students are to deploy their own learning strategies through various online learning tools. At the same time, NLE also positively predicts PL by positively predicting LM. A good learning experience will help learners generate positive emotions. Driven by positive emotions, learners' LM will improve, which is consistent with some previous research results.

8. Conclusion

The quality of network course service affects students' learning experience in the network environment, and the quality of network course also affects students' learning motivation. Both learning experience and learning motivation in the network environment affect students' personalized learning level. In addition, the learning experience in the network environment also affects students' learning motivation, and then affects their personalized learning level. Therefore, it is necessary to create a powerful, convenient, easy-to-use and beautiful network learning environment for students. Only in such learning environment can students have a good learning experience and be willing to continue learning. Although it can't be said that this can improve learning motivation, it will maintain learning motivation to a certain extent.

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The Effectiveness of a Teacher Development Course on Artificial Intelligence Teaching Empowerment

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Abstract: *To prepare the next generation to live in a world filled with countless artificial intelligence (AI) applications, it is necessary to cultivate students' AI literacy in K-12 education. Key to the implementation of AI education in K-12 is teachers' capability. We propose a seven-step model to structure a lesson for learning to teach AI based on the four content-related dimensions of the technological pedagogical content knowledge (TPACK) framework. A 6-hour teacher development course that incorporated the seven-step model was implemented with 79 in-service primary school teachers who were required to teach AI after the course. We evaluated the effectiveness of the course using a newly designed instrument of AI teaching empowerment. Exploratory factor analysis yielded three factors: (1) AI meaningfulness, (2) AI application, and (3) AI teaching self-efficacy. All three factors were akin to the three constructs identified in the empowerment literature. The t-test results suggested significant improvement in AI teaching self-efficacy after the course, but no significant changes were found in AI meaningfulness and AI application. These findings indicate that the 6-hour course was effective in enhancing teachers' self-efficacy in using AI technology and in teaching AI. However, the course could be enhanced to improve their understanding of AI meaningfulness and AI application. We will re-evaluate the teachers' perceptions after they practise teaching AI in their classrooms and will further develop the teacher development course.*

Keywords: artificial intelligence, empowerment, K-12 education, teacher development, TPACK

1. Introduction

Artificial intelligence (AI) is developing rapidly around the globe, leading to new lifestyles and new job opportunities. AI is expected to contribute a global economic impact of nearly US$15.7 trillion by 2030 (PricewaterhouseCoopers, 2017) and to have unprecedented industrial and societal impacts. The rapid growth of the computation power of AI and its expansion across various fields necessitate a workforce with strong knowledge and capability to work with AI. When today's primary students complete their formal education, they will enter a workforce increasingly powered by AI. To prepare these students for an AI world, AI education in primary schools is critical, and teacher development on AI plays an important role in this education. Students may choose to study AI in their undergraduate or postgraduate studies with a well-established curriculum; however, primary education should begin to foster AI literacy (Kim et al., 2021).

The following questions are therefore essential: What should be taught in teacher development? What kind of support should be given to teachers? How should a development course for teachers be planned? We present the design of a 6-hour teacher development course on AI literacy intended to raise teachers' awareness of AI and provide them with basic knowledge on AI teaching. The teachers were introduced to the '5 Big Ideas of AI': (1) perception, (2) representation and reasoning, (3) learning, (4) natural interaction, and (5) societal impact (Touretzky et al., 2019), with two AI applications for illustration. In the course, the teachers also acquired a basic understanding of machine learning through hands-on experience training an AI model and using it in an AI application. The effectiveness of the course was evaluated based on a newly created AI teaching empowerment survey instrument developed in this study.

2. Background

2.1. AI Empowerment

In a review of how AI technology is introduced in the field of education, Ouyang and Jiao (2021) identified three paradigms according to the learners' role: (1) AI-directed, with learners as recipients, (2) AI-supported, with learners as collaborators, and (3) AI-empowered, with learners as leaders. The third paradigm emphasises AI as an empowering tool to give learners agency over their learning (Ouyang & Jiao, 2021). It echoes the idea of the computer as an empowering tool for young learners put forward decades ago by Papert (1972), who argued that access to computers gives children unprecedented power to invent and carry out exciting projects. For learners to be empowered, they need to see the meaning of the learning task (i.e., meaningfulness), feel that they are competent to complete the task (i.e., self-efficacy), and perceive that they can make an impact, such as solving everyday problems, with what they have learnt (i.e., impact) (Frymier et al., 1996). Regarding the cultivation of students' computational thinking (CT) through programming activities, Kong et al. (2018) argued that allowing students to create should be considered a component of student empowerment; hence, their instrument of programming empowerment includes the sub-constructs of meaningfulness, self-efficacy, impact, and creativity (Kong et al., 2018). AI technology also empowers teachers, as it can free them from routine work and enable them to develop creative teaching approaches (Xu, 2020). As teacher development is key to educational innovation (Fullan, 2007), we believe that to actualise the potential of AI technology to empower students, their teachers must be empowered first, and the crucial aspect of teachers' empowerment in AI education is their capability to teach AI to their students.

2.2. AI Teaching: Learning to Teach AI Through a Seven-Step Model Based on TPACK

To introduce AI in K-12 education, several important challenges must be addressed, including the lack of curriculum guidelines and teachers' insufficient knowledge and immature pedagogical understanding of teaching AI (Kong et al., 2021; Wang & Cheng, 2021). As K-12 teachers seldom have AI background knowledge, they must be properly supported to teach AI. AI involves the use of technology, such as tools for recognising and classifying images and programming environments for developing the algorithms of AI applications. The framework of technological pedagogical content knowledge (TPACK) (Mishra & Koehler, 2006) has been proposed for understanding teacher competency in teaching AI (e.g., Yao, 2021). In the context of cultivating students' CT, which can be defined as the 'thought processes involved in formulating problems and their solutions so that the solutions are represented in a form that can be effectively carried out by an information-processing agent' (Wing, 2011, p. 20), Kong et al. (2020) highlighted the importance of four content-related TPACK dimensions in teachers' capacity building: CK, TCK, PCK, and TPACK. CK refers to content knowledge, including the concepts and practices covered. TCK refers to the use of tools in a programming environment to develop programming artefacts, such as a program or an app. PCK refers to the knowledge of designing pedagogical activities for CT development without using the tools in a programming environment. TPACK refers to the integration of technology, pedagogy, and content in context for developing students' CT. Building on these four TPACK dimensions, Kong and Lai (2021) proposed a seven-step model to design a lesson for learning to teach CT.

The first step involves the introduction of tools in a curriculum unit for the development of an artefact (TCK). The second step involves the description of the specific concepts and practices in this unit (CK). The third step involves the introduction of pedagogies, such as unplugged activities and project-based learning, suitable for this unit (PCK). The fourth step involves the completion of the artefacts in the programming environment incrementally through testing and debugging. The fifth step involves revisiting the newly introduced tools for consolidation and brainstorming future applications (TCK). The sixth step involves the consolidation of the concepts and practices learnt (CK). The seventh step involves the teachers' reflections on the pedagogies applied in this unit and how to further improve the teaching process to optimise students' learning (PCK). In addition, Kong and Lai (2021) proposed 'to play, to think, to code, to reflect' as an approach to teaching CT in primary education. This approach allows students to use the app first to understand the objective of learning the unit. Then, they need to think about the components involved and the coding process to finish developing the app. Finally, the students must consolidate the knowledge that they have learnt by reflecting and brainstorming on the possible use of the tools in other contexts. The teachers identified the seven-step model and the 'to play, to think, to code, to reflect' approach as useful in building their capacity to teach CT (Kong & Lai, 2021).

As the development of AI application is closely connected with CT, with common basic concepts, such as algorithm thinking involves the design of the application (Burgsteiner et al., 2016), and as AI and CT education share common ideas, such as students' agency in learning and the importance of abstraction (Gadanidis, 2017), the seven-step model and teaching approaches of CT can be extended to AI education to design a teacher development course to empower teachers to teach AI.

2.3. Conceptualising AI Teaching Empowerment: AI Empowered and AI Teaching Empowered

As discussed, empowerment in an educational context involves the sub-constructs of meaningfulness, impact, creativity, and self-efficacy. In the context of AI education, meaningfulness refers to the recognised importance and usefulness of AI. Impact refers to the application of AI to solve daily problems and make daily life easier. Creativity refers to the application of AI to express ideas and create interesting artefacts. Impact and creativity in this context are both related to the application of AI. Self-efficacy refers to confidence in using AI technology. Teachers in AI education should feel confident not only to use AI technology but also to teach AI to their students. Hence, teachers' self-efficacy in AI education should include both components. In this study, we conceptualise AI teaching empowerment as consisting of the sub-constructs of AI meaningfulness, AI application, which covers the application of AI to solve daily problems (impact) and express ideas in creative ways (creativity), and AI teaching self-efficacy, which covers self-efficacy in the use of AI technology and confidence in teaching AI to empower students to live in the AI era.

2.4. Research Questions

We examine the effectiveness of a teacher development course in enhancing teachers' AI teaching empowerment. The following research questions are explored: (1) What are the factors related to AI teaching empowerment as perceived by the teachers? Are they similar to the factors identified in the literature? (2) Do the teachers perceive an improvement in the factors related to AI teaching empowerment after attending the teacher development course?

3. Method

3.1. Participants

We recruited 79 in-service primary school teachers as participants in a teacher development course for learning to teach AI in primary schools. After completing the course, they were required by the study to use the material that they learnt in the course to teach AI in their classrooms. Of the 79 teachers, 30 (38.0%) were women and 49 (62.0%) were men. We asked the teachers to indicate the major subjects that they taught in their schools, and they were allowed to indicate more than one subject. The most frequently mentioned subject was computer studies (72), followed by mathematics (48), general studies (40), English (13), and Chinese (9).

3.2. The 6-Hour Teacher Development Course

The in-service teachers joined a 6-hour development course on teaching AI literacy in primary schools. The course consisted of two lessons, each of which took 3 hours. The first lesson was about teaching an AI unit on using voice recognition to instruct the computer to do arithmetic. The second lesson was about teaching an AI unit on facial recognition to play peekaboo. Table 1 shows the plan for the second lesson.

Table 1. A lesson plan for teaching an AI unit on facial recognition for playing peekaboo and developing the PICaboo App in the MIT App Inventor programming environment

Duration	Content	Activity
5 mins	Step 1: TCK on introducing image classification in the MIT App Inventor environment	Lecture
5 mins	Step 2: CK on introducing the five big ideas of AI and the related CT concepts, practices, and perspectives involved in this unit	Lecture
15 mins	Step 3: PCK on encouraging teachers to play with the PICaboo App, covering and showing faces in front of the camera to see how the app responds	To Play
20 mins	Step 3: PCK on guiding teachers to think about why the baby on the app showed different facial expressions, how the app worked and recognised the user's actions, and why the percentage showing Me/NotMe confidences of the app kept changing to plan the development of the app	To Think – Discussion with peers
30 mins	Step 4: TPACK on asking teachers to use the personal image classifier website by taking various pictures showing and covering the face to train an AI model to understand how machines learn from data, and then discussing how to train an AI model with good data quality	Train the AI model and discuss its quality
30 mins	Step 4: TPACK on guiding teachers to complete the coding activities by examining the user interface of the app using a programming template and then understanding the programming feature of 'Dictionary' in the programming environment, using Me/NotMe confidences as variables to store the returned result from the trained AI model, calculating the two variables and turning them into percentages, and finally using if-then-else conditional to show the baby's expression based on the AI's result	To Code
15 mins	Step 5: Guiding teachers to reflect on the possible use of the image classification feature to foster their digital creativity by asking them what the benefits are of using personal image classifiers in the MIT App Inventor environment and what other apps they want to create using it	To Reflect
15 mins	Step 6: Guiding teachers to reflect on the five big ideas of AI and discuss the social impact of AI	To Reflect
5 mins	Step 6: Guiding teachers to reflect on the CT concepts, practices, and perspectives introduced in this unit	To Reflect
10 mins	Step 7: Guiding teachers to reflect and sharing on the PCK deployed in this unit and to discuss how to teach students about AI ethics, such as privacy issue, and how they will use the worksheet provided in this course in the lessons	To Reflect

In the second lesson, the teachers were taught about the concepts of personal image classifiers (PIC) and image classification. The details are shown in Table 1. Through the data model training, the teachers used the application 'PICaboo' as an introduction to the concepts of classification in machine learning. They also learnt to apply the data model. They built the app's human–computer interface with the support of an MIT App Inventor programming template. These teachers then used their CT knowledge to develop the app. Finally, they completed the reflection activities. In the first lesson, which had the same structure, the teachers learnt the 'SpeechRecognizer' and 'TextToSpeech' tools in the MIT App Inventor programming environment using an AI application of 'Voice Calculator', which uses voice recognition to instruct the app to do arithmetic. After learning basic AI knowledge using the five big ideas in this unit, the teachers were guided to gain coding experience in developing this application. They then went through the steps of consolidation and reflection, as in the second lesson.

3.3. Instrument and Procedure

The teachers were required to complete a survey on AI teaching empowerment before and after the 6-hour course. The instrument items were adapted from the student empowerment instrument developed in Kong et al. (2018). The original instrument covers the sub-constructs of meaningfulness, impact, creativity, and self-efficacy. We adapted the items so that this instrument could be used to evaluate teachers in the context of teaching AI in primary schools. We combined items related to perceptions of impact and creativity to form the AI application construct. We then added three items related to teachers' self-efficacy in teaching AI, which was not covered in the previous empowerment instrument, and formulated the new construct of AI teaching self-efficacy with the original self-efficacy items. An expert in K-12 AI education and an expert in educational assessment were asked to review and modify the items to ensure content validity. As shown in Table 2, the AI teaching empowerment instrument has a total of 15 items: 3 on AI meaningfulness, 6 on AI application, and 6 on AI teaching self-efficacy, with 3 items on self-efficacy in using AI technology and 3 items on teaching AI. Each item was scored on a 5-point Likert scale (1 = strongly disagree; 5 = strongly agree). The instrument was administered online, and the teachers had 5 minutes to complete it. Reliability analyses suggested satisfactory results for both the pre-test ($\alpha = .91$) and post-test ($\alpha = .95$).

4. Results and Discussion

4.1. Factor Analysis

To explore the factor structure of the instrument, we conducted a factor analysis on the pre-test data of the 15 items using SPSS, with maximum likelihood and promax as the extraction and rotation methods, respectively, which yielded three factors that were similar to the factors of AI meaningfulness, AI application, and AI teaching self-efficacy, as shown in Table 2. The Kaiser–Meyer–Olkin value was 0.83 > 0.8, and the chi-square value for Bartlett's test of sphericity was 1,130.43 (df = 105, $p < .001$), indicating that the three factors had good explanatory power. The total variance accounted for by these three factors was 76.75%.

The factor analysis result suggested the similarity between the teachers' perceptions of AI teaching empowerment and the findings of prior studies. In a previous study with primary students, the sub-constructs of impact and creativity formed separate factors (Kong et al., 2018), whereas in this study, they were both related to the application of AI, which can be used to solve everyday problems and create interesting artefacts. An additional finding in this study was that from the teachers' perspective, self-efficacy in using AI technology and in teaching AI belonged to the same factor, suggesting that teachers with higher confidence in using AI technology would also have higher confidence in teaching AI.

4.2. T-test

According to the factor analysis results, we calculated the pre-test and post-test means of the three factors and conducted t-tests to examine whether there were significant improvements after the completion of the course. The t-test results of the three factors, together with those of individual items, were as shown in Table 2. The results showed a significant increase in AI teaching self-efficacy, suggesting that the course was effective in enhancing teachers' self-efficacy in AI teaching. No significant changes were found in AI meaningfulness and AI application, although a significant improvement was found for the item 'I like to express my ideas through AI' under AI application, as shown in Table 2.

Table 2. Means, standard deviations, and t-test results for AI teaching empowerment before and after the course

		Factor loading	Pre-test		Post-test		t-value
			M	SD	M	SD	
AI meaningfulness			4.02	0.58	4.15	0.57	-1.39
1.	Knowing AI is important to me.	0.96	3.99	0.65	4.13	0.63	-1.37
2.	Knowing AI is useful to me.	0.85	4.05	0.62	4.20	0.59	-1.59
3.	Knowing AI allows me to create AI applications (e.g., apps) that are useful to the world.	0.40	4.03	0.60	4.1	0.66	-0.88
AI application			4.19	0.54	4.24	0.57	-0.50
4.	I want to apply my AI knowledge and skills to solve problems in daily life.	0.91	4.29	0.62	4.22	0.73	0.70
5.	I want to apply my AI knowledge and skills to make people's lives better.	0.93	4.25	0.59	4.23	0.78	0.23
6.	I want to apply my AI knowledge and skills to make daily life easier.	0.96	4.32	0.57	4.27	0.73	0.49
7.	I want to apply my AI knowledge and skills to develop more innovative pedagogy to teach AI.	0.80	4.18	0.64	4.27	0.59	-0.91
8.	I want to apply my AI knowledge and skills to create interesting things.	0.85	4.27	0.61	4.29	0.64	-0.25
9.	I like to express my ideas through AI.	0.43	3.85	0.77	4.15	0.62	-2.73**
AI teaching self-efficacy			3.58	0.72	4.00	0.58	-3.99***
10.	I have the knowledge and skills to use AI.	0.61	3.54	1.05	4.10	0.61	-4.08***
11.	I have confidence in my ability to use AI.	0.59	3.43	0.94	3.99	0.74	-4.13***
12.	I am good at using AI.	0.44	3.23	0.96	3.75	0.82	-3.65***
13.	I have confidence to motivate my students to learn AI.	1.01	3.78	0.75	4.05	0.70	-2.32*
14.	I have confidence to guide my students to use AI knowledge to create interesting things.	1.05	3.77	0.73	4.01	0.67	-2.15*
15.	Knowing how to teach AI allows me to be impactful to my students.	0.82	3.73	0.78	4.08	0.59	-3.06**

*p ≤ .05; **p ≤ .01; ***p ≤ .001

The results suggested that after the teacher development course, the teachers believed that they had the knowledge and skills to use AI technology, and they felt more confident in their ability to motivate their students to learn AI and to guide them in creating interesting things using AI. However, their perception of the meaningfulness of AI for themselves (e.g., 'Knowing AI is important to me') and intention to use AI in their everyday lives (e.g., 'I want to apply my AI knowledge and skills to solve problems in daily life') were not as greatly enhanced by the 6-hour course. A longer time for capacity building may be needed to bring about these changes, or the teachers may need to practise AI teaching before these changes take place. Another possible reason for the result is that the teachers had already rated themselves high on AI application (M = 4.19) and AI meaningfulness (M = 4.02) in the pre-test, leaving relatively little room for enhancement. As reported earlier, the majority of the teachers mentioned computer studies as their major teaching area, it was understandable that they had already indicated interest in applying AI and understood its importance at the beginning.

5. Conclusion, Limitations, and Further Studies

In this study, we developed an instrument of AI teaching empowerment, with the factor analysis yielding three factors, namely (1) AI meaningfulness, (2) AI application, and (3) AI teaching self-efficacy, which were similar to the factors identified in the empowerment literature (Kong et al., 2018). Based on a seven-step model built upon the TPACK framework for structuring a lesson on learning to teach AI (Kong & Lai, 2021), we designed a teacher development course to build teachers' capabilities. The t-test result suggested a significant improvement in the teachers' AI teaching self-efficacy, indicating the positive impacts of the course, as it could provide the knowledge and skills for the teachers to use AI technology, increase their confidence to motivate students to learn AI, and guide them to create artefacts using AI. In the pre-test, the teachers rated themselves high on AI meaningfulness and AI application, suggesting that they had already perceived AI as a meaningful and important element in society and had a high intention to apply AI in daily and creative use even before participating in the teacher development course. These findings suggest that the teachers understood AI's important role in the world and its tremendous application potential in the coming years.

The positive effects of the course shown in this study suggest the course's potential to enhance teachers' AI knowledge and promote their AI literacy. The course can be targeted not only to teachers in the field of information and communication technology but also to teachers from other subject areas to promote AI literacy to all teachers and students. To validate the success of the design and implementation of the teacher development course, the course should be offered to more teachers. With the participation of teachers from more subject areas, we can further investigate how the course affects teachers who teach subjects other than information and communication technology or computer studies.

As the sample size requirement for an exploratory factor analysis is 5 to 10 participants per item (Bryant & Yarnold, 1995), the sample size of this study only met the minimum requirement. A larger sample is needed in future studies to examine the factor structure and evaluate the course's effectiveness. A larger sample would also enable a more detailed analysis of the relationship with teachers' gender and their major teaching areas. The research design can also be improved by including a control group. Another limitation of this study was that the course only lasted for 6 hours, which was convenient for the teachers to complete in 1 day but might not be long enough to effect changes in teachers' perceptions of AI meaningfulness and AI application. A longer duration might also be needed for a broader and deeper understanding of AI literacy. As the teachers will teach AI in their classrooms after the course, we will examine whether there are significant changes after they obtain teaching experience.

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Automated Diagnosis of Novice Programmers' Misconceptions Based on Machine Learning

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Abstract: *This study proposed a mechanism for building a dynamic model to advise novice programmers of their misconceptions; it was mainly through monitoring the programming process and diagnosing their codes directly on the learning platform. It aims to provide a personal supervisor for suggestions of misconceptions and improve the previous lack of objective diagnosis. The development of the model was started by reviewing the misconceptions found in the prior researches and then designing the corresponding programming test to elicit these related misconceptions. After collecting 1213 students' codes, these codes were preprocessed by extracting features and encoding these codes to feature vectors. The clustering analysis was conducted to confirm that these feature vectors can indeed classify misconceptions from students' codes. As a result of data mining, this study summarized 9 categories of misconceptions; then, these feature vectors and their multi-labels were used to build a diagnosis model using supervised machine learning skills. In the experiment, there were 27 questions with 5 languages (Python, C++, C, Java, and Javascript) in the programming test, the clustering analysis adopted spectral clustering, the feature vector of one student's codes was 183 dimensions, the machine learning was implemented by multilayer perceptron, and the result demonstrated that the proposed mechanism performed 97.9% accuracy of the diagnosis model. The periodic development will dynamically change the categories of misconceptions and diagnosis models in response to students' codes until stable.*

Keywords: Misconception, Programming, Automatic diagnosis, Machine Learning, Novice programmer

1. Introduction

The programming misconceptions often cause novice programmers to experience difficulties while learning to program, causing them to have poor ability to learn advanced-level programming knowledge in the future. Consequently, this will lead to poor quality of written programs. Many related studies were conducted through manual analysis to provide ways to explore programming misconceptions. However, most of these research methods have a small sample size and were aimed at a single programming language, so they have been pointed out that they are not objective enough and have low applicability. If the students' misconceptions can immediately be grasped, the corresponding solution could be given to the students as soon as possible.

Therefore, this study aims to provide novice programmers with a personal programming supervisor for suggestions of possible misconceptions while practicing programming exercises on the learning and improve the previous lack of objective diagnosis. In order to implement the personal programming supervisor on the platform, this study developed an automatic diagnosis mechanism that can be widely used and accurately predict students' programming misconceptions. It was mainly through monitoring the programming process and diagnosing their codes directly on the learning platform. The knowledge about programming misconceptions of the supervisor should be constructed and refined periodically until the set of misconceptions is approaching stable. At first, this study predefined programming misconceptions by reviewing prior researches, then used clustering analysis to confirm the basic categories of misconception, discovered supplementary misconceptions and used machine learning technology to predict the misconceptions students may hold.

The study focused on process control (if-else, for-loop, while-loop) and designed the corresponding programming test to elicit these related misconceptions not limited to a single programming language. While more than one thousand programming test data were collected, these codes were preprocessed by extracting features and encoding these codes to feature vectors. As a result of clustering analysis, this study summarized 9 categories of misconceptions; then, these feature vectors and their multi-labels were used to build a diagnosis model using supervised machine learning skills MLP (multilayer perceptron). Furthermore, the result demonstrated that the proposed mechanism performed 97.9% accuracy of the misconception diagnosis model, giving the students relevant teaching assistance.

2. Literature review

2.1. misconceptions and misconceptions in programming

The issue of misconception in learning has always existed and cannot be ignored; if the student's misconception is not discovered in time and the corresponding correction is given, it may be due to a misconception in the future. If the mental model built up misconception instead of correct knowledge, problems would arise when new knowledge is absorbed, which will hinder learning (Zehetmeier, 2015).

Various researches had different definitions of misconception, and there was still controversy about the precise definition of misconception in the research field (Clement, 1993). There were two approaches; one used the concepts established by the learner to define misconceptions, that the misconception was an incorrect belief in the learner's mind, and the learner was convinced of it. The other defined the misconception from the learner's knowledge construction process. The misconception was a wrong concept caused by the conflict when the old knowledge met the new knowledge (Clement, 1993). In modern research, it was proposed that the misconception was a wrong composite concept, i.e., students will try to combine the old knowledge with the new knowledge in their minds instead of directly letting the new knowledge completely change the old knowledge. Although such behavior was helpful for learning sometimes, it also possibly caused learning disabilities (Durkin & Rittle-Johnson, 2015).

The reason for programming misconception included natural language influence (Pea, 1986), differences in teacher teaching, unfamiliarity with computer operations (Gal-Ezer & Zur, 2004). For example, Bonar and Soloway (1985) observed students' comprehension of programs by observing the program sentences written by students. They found that students understood the code by reading verbatim like natural language. However, formal programming languages cannot use natural language reading to understand, so students were prone to difficulties when learning programs. In 1986, the researcher used the term "hidden mind" to describe the misconception commonly held by novice programmers. The researcher proposed three types of misconception common to novice programmers: parallelism, intentionality, egocentrism (Pea, 1986). Although some novice programmers knew that the computer executed the code from the top down, they also considered that it could execute multi-line code in parallel. This type of misconception is called parallelism. The novice programmer used the natural language to interpret the code and the operation of computers, thinking that the code was the same as the natural language, which allowed an out-of-order process. While programming, the necessary details were easily ignored by novice programmers since they think that the computer can fully understand their meaning. The conditions or format of the program, such as the incorrect definition of variables, and the failure to write down every execution situation in detail, were called egoistic misconceptions (Pea, 1986; Kwon, 2017).

From various related literature, it can be found that most of the reason for the programming misconception is due to students' incomprehension of the actual operation of the computer or the belief that the operation of the computer is the same as human thinking. These wrong ideas will cause students to design incorrect logic during programming. This study adopted natural language, learning experience, analogy reasoning, and simultaneous execution for misconception diagnosis. If educators can understand which programming concepts the students are upset with, they can accurately give corresponding learning help to prevent these errors (Albrecht, E., & Grabowski, J., 2020).

2.2. diagnosis of misconceptions in programming

From past researches, it could be found that the diagnostic method of misconceptions can be roughly divided into two types: online tests and paper-and-pencil tests. The online programming platform for diagnostic test question type design was based on the experimenter's misconception type requirements for test planning. There were also programming practice platforms to collect learners' programming data (Kurvinen, Hellgren, Kaila, Laakso, & Salakoski, 2016) or a series of problems designed for data collection (Altadmri & Brown, 2015). There were two online tests for misconception diagnosis, which tests were conducted through a series of programming questions. The difference was that one was the development platform to collect programming data, and the other was to collect the original files of the learner's stored program. Both were to manually inspect the code submitted by the learner and use the experimenter's knowledge of the misconception to diagnose the misconception. Whether it was an online test or a paper test, the diagnostic methods implemented by the two had nothing to do with which test item design method was used. The common point of the research methods was that the experimenter collected and used the test data to diagnose misconceptions manually.

It could be seen that most researches on the diagnosis of misconception still required a manual diagnosis. The diagnosis used in this study is based on misconception data exploration, which is different from the previous diagnosis methods. It no longer uses the manual diagnosis mechanism implemented by most research institutes but uses data mining and machine learning to diagnose misconceptions.

The misconception has been a topic of constant discussion in computer science for the past 30 years. The use of neural networks to predict misconceptions in education was beneficial and effective. However, there are few references about using neural networks to predict the programming misconceptions held by students (Albrecht, E., & Grabowski, J., 2020). Therefore, this study proposed an automatic diagnosis mechanism for novice programmers' misconceptions. If the automated diagnosis mechanism can accurately predict the concept of programming misconceptions that students may have, it will be a good aid for educators in programming language teaching. Educators can more accurately understand students' problems in learning programming languages.

3. Method

3.1. Research design

This study aims to provide novice programmers with a personal programming supervisor to advise possible misconceptions while practicing programming exercises on the learning platform. Therefore, this study has to design and implement an automatic diagnosis mechanism to collect data, generate feature vectors, discover and identify categories of misconceptions by clustering analysis periodically, as shown in Figure 1. It would use timely categories of misconceptions discovered to build a diagnosis model by a multilayer perceptron dynamically. This study implemented these research instruments and procedures as in the following sections.

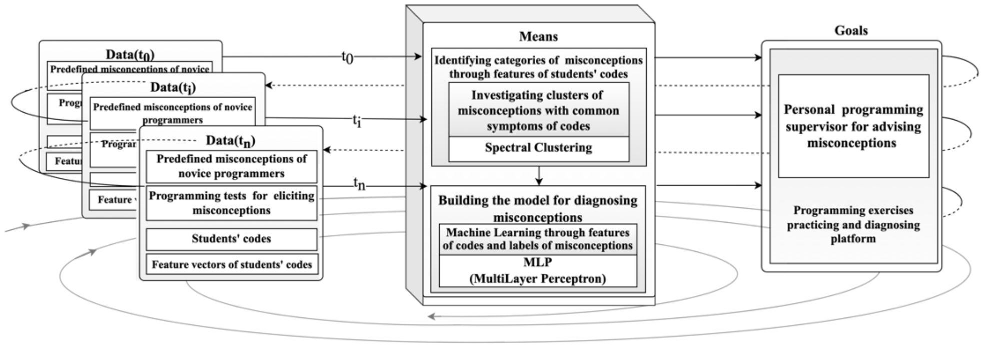

Figure 1. conceptual research framework.

3.2. Participations

Participants in this study were all novice programmers who studied programming language for six months to one year, from 8 universities (366 male and 161 female students) and 7 high schools (270 male and 419 female students) in Taiwan's northern, southern, and eastern regions. They have studied the conditional branch and loop and were familiar with different languages. Therefore, this study developed programming tests using 5 languages, such that what language is familiar to participants would not affect the result of this study.

3.3. Instruments

Most related researches on programming misconceptions focused on "variable" or specific topics. In fact, learners also usually encountered problems or difficulties while learning conditional branch and loop (Kaczmarczyk, Petrick, East, & Herman, 2010), causing misconceptions (Green, 1977). This study mainly focused on the flow control (if-else, for-loop, and while-loop) to investigate misconceptions of novice programmers.

3.3.1. Categories of misconceptions

The development of the diagnosis model was started from reviewing the misconceptions found in the prior researches and summarized, organized, and listed in Table 1.

Table 1 Categories of misconceptions in programming

Categories	Descriptions
M1.1.1 Natural language Topics: while/ if	Affected by natural language, it is believed that "if" and "while" have the same semantic meaning (Soloway & Ehrlich, 1985).
M2.1.1 Learning experience Topics: loop	Students learn programming from the teacher's program example, so they believe that the loop grammar has a fixed way of writing (Sadler & Sonnert, 2016).
M2.1.2 Learning experience Topics: loop	When students write loops, they will imitate the loop examples they have learned before and consider that the variables used in the body of the loop-block should be the same as the control variables in the loop condition judgment (Sekiya & Yamaguchi, 2013).
M2.2.1 Learning experience Topics: if & loop	Confuse "if" and loop, think "if" is an if-loop, "if" can be used as a loop (Zehetmeier, Böttcher, Brüggemann-Klein, & Thurner, 2015).
M3.1.1 Analogy reasoning Topics: loop	It is believed that when the loop is running, the computer will first determine whether the execution result meets the loop condition. The computer will list the execution result if it meets the loop condition. Otherwise, it will jump out and not output the execution result. Therefore, the student's answer is usually one time less than the execution result (Pea & Kurland, 1984).
M3.1.2 Analogy reasoning Topics: loop	According to life experience, it is believed that when two variables in the loop are to be exchanged, they can be exchanged directly, without the need to use temporary variables (Kurvinen, Hellgren, Kaila, Laakso, & Salakoski, 2016).
M3.2.1 Analogy reasoning Topics: if-else	It is believed that conditional judgment must be added after "else" to cover conditions other than "if" judgment.
M4.1.1 Simultaneous execution Topics: loop	Think that all the statements in the loop execute at the same time
M4.2.1 Simultaneous execution Topics: loop	Think that all "if" conditional branches are executed at the same time

3.3.2. Platform for learning to program and diagnosing misconceptions

The online Python programming learning platform developed in this study allows learners to select courses and item banks and write programs in question groups. While the learners submit answers, the misconceptions diagnosis will be performed. The web pages for teachers include setting the topic and the main description of the question, the input and output test cases, and checking related misconceptions in the checkboxes.

3.3.3. Programming tests for eliciting misconceptions

This study's programming test for misconception diagnosis was developed based on the misconception proposed in previous researches. There are 27 questions and a total test time of 45 minutes. Each question only diagnoses one kind of misconception and tries to clarify the learner's real thoughts and programming concepts through these questions. Before the test, an interview will be conducted with the teacher or the learner himself to determine the learner's programming ability and learning status.

This programming test is conducted in five programming languages, including Python, C++, C language, Java, and JavaScript. Corresponding test questions can be given according to the programming language that students are familiar with. In order to collect the complete student response information, if the student fails to complete it within the set time, the test time can be flexibly increased until the student completes the entire test.

3.4. Automatic diagnosis mechanism for novice programmers' misconceptions

This study proposed a mechanism for building a dynamic model to advise novice programmers of their misconceptions; it works mainly through monitoring students' programming processes and diagnosing their programs. The automatic diagnosis mechanism includes students' test data collection, programs' feature extraction and encoding, categories of misconceptions mining by clustering analysis, and diagnosis model construction by machine learning skills.

3.4.1. Data collection and features extraction

The features extraction for each question is according to the topic, the main concept, the correct statements, and the type of misconception that the question belongs to.

After collecting student test data, the critical parts of students' actual answers are captured and converted into text feature codes. After encoding the answers to each question, all the codes are joined to get a feature vector. The text codes need to be replaced with one-hot encodings to perform the calculations required for the feature vector used in the neural network. The one-hot encoding length of each question will be determined according to the number of students' program behavior characteristics, and Hamming distance is used to calculate the difference between the two questions. The coding process is shown in Figure 2.

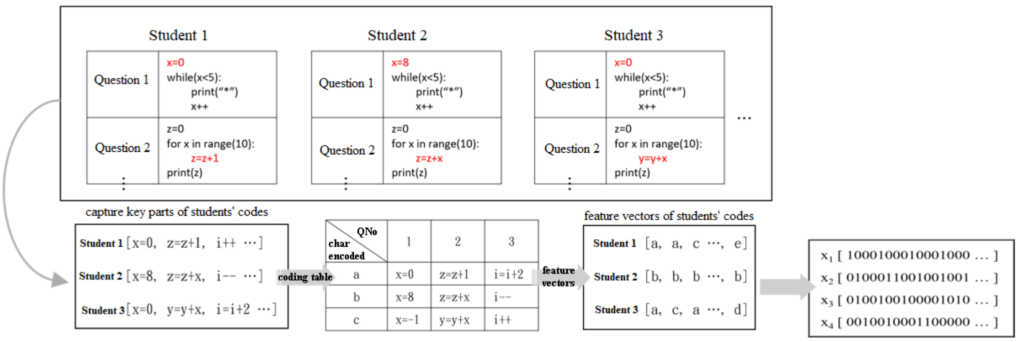

Figure 2. Program feature extraction and encoding - text code to binary code.

3.4.2. Conducting spectral clustering

The spectral clustering analysis was conducted to confirm that these feature vectors can indeed classify misconceptions from students' codes. Spectral clustering is an algorithm based on graph theory, each node represents a data entity, and the link refers to the similarity between two nodes. The similarity between individuals is observed through their distance. If there is a more significant similarity between data nodes, they are connected by links, and nodes with similar features will be clustered into the same connected subset.

3.4.3. Building multilayer perceptron architecture

As a result of data mining by spectral clustering, this study will summarize categories of misconceptions. After that, these features vectors and their one-hot encoding with multi-label vectors are then used to build a diagnosis model using supervised machine learning skills. While labeling the misconceptions according to students' program features, it also uses manual judgment to determine the programming misconceptions that each student may have from the students' actual answers and the interview responses. When the student answers a question incorrectly, it is inferred that the student may hold the misconception to which the question belongs, then the misconception is labeled as "1"; if it is determined that there is no such misconception, it is labeled as "0". This classification problem is a multiclass and multi-label problem. After labeling all possible misconceptions held by the students, the data will be used as the ground truth output vector y.

In this study, machine learning was implemented by a multilayer perceptron that most related education researches used, and the 2-layer perceptron architecture was shown in Figure 3.

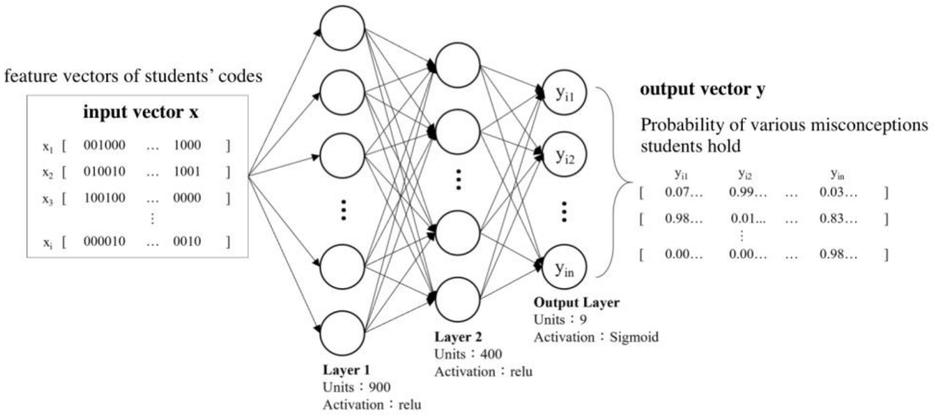

Figure 3. The architecture of the 2-layer perceptron in this study

4. Results and discussions

4.1. Clustering analysis

The clusters of misconceptions through clustering analysis are shown in Figure 4. Through the statistics of the main misconceptions in each cluster, common misconceptions occurred by these students were presented. In parentheses under the misconception code were the percentage of this misconception owned by the students of this cluster, and each cluster was named with the misconceptions occupying a high percentage. Then, the correlation between the misconceptions was obtained by the students' frequency of occurrence of these main misconceptions in each cluster. Among them, M3.1.1 was more related to other misconceptions. In Figure 4, it was found that different misconceptions may be related to each other. When students have a specific misconception, it is highly probable that another misconception will occur, which means there are correlations between misconceptions. For example, cluster 3 has both M3.1.1 and M3.2.1 misconceptions; students in this cluster thought that the execution of the loop is like a general program execution from top to bottom, which ignored the particular loop execution logic. In this circumstance, it is very likely that students also think conditional statements must be added after "else" to cover conditions other than those covered in the "if" statement.

After the clustering analysis, it was confirmed that the categories of misconceptions could emerge through feature vectors of students' codes, representing the characteristics of students' programming behaviors.

4.2. MLP prediction

This study implemented the automatic diagnosis mechanism for misconceptions that train the multilayer perceptron to learn diagnosing misconceptions of students by the feature vectors of the code written by students as the input of the neural network. This study used 727 training data and 486 testing data with an accuracy rate of 97.9% (Learning rate is 0.0085, 100000 epochs, and batch size is 400). The result of the prediction model listed the probability of each misconception in the output vector and what the misconceptions the student may hold would be retrieved from the output vector with a probability greater than 0.5.

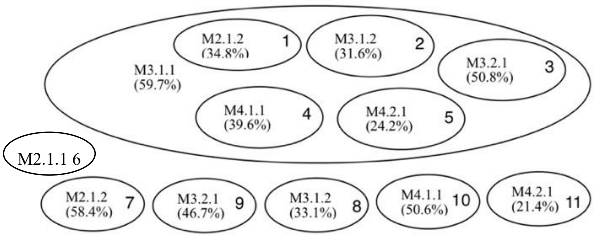

Figure 4. The clusters of programming misconceptions by data mining

From the prediction results, most results were the same as the results of manual judgments. However, there were also the prediction results of some data that were slightly different from the initial manual judgment results. The results of the two cases are explained below.

case 1. **Type I error:** Student No. 383 (Model predicted misconceptions: M3.2.1, Manual labeled: ~~M2.1.2~~, M3.2.1)

Because the manual misconception labeling of students' program behavior was to determine the status of each question individually, it lacked overall consideration, so it was not accurate enough. However, through machine learning, the machine can learn about a large number of students' occurrence of various misconceptions, which can be more comprehensively considered. This is a significant advantage of machine learning. Therefore, this study considered that when the student's symptoms do not entirely conform to the existing misconceptions, it can refine a sub-misconception under the certain one to supplement it or add a new one. This mechanism can improve the accuracy of the machine learning model by refinement of misconceptions discovered from students' programs.

case 2. **Type II error:** Student No. 124 (Model predicted misconceptions: M2.1.1, M2.1.2, ~~M3.1.1~~, M3.1.2, M4.1.1, M4.2.1, Manual labeled: M2.1.1, M2.1.2, M3.1.2, M4.1.1, M4.2.1)

The current prediction accuracy of the model was 97.9%. Errors like this were unavoidable. Furthermore, because of the wide variety of programming misconceptions, the situation of students holding programming misconceptions is more complicated. The prediction results of student No. 124 extended the issues as the previously described viewpoints. Suppose the number and diversity of training samples are increased, and the number of samples held by various misconceptions can be approached to a uniform distribution. The accurate rate can also be effectively improved.

4.3. Supplementary categories of programming misconceptions discovered

Some learners' programming misconceptions were not mentioned in the literature, and most of them needed to be interviewed to understand the actual concepts of the learners. This study was based on interviews and data mining to discover the supplementary misconceptions in flow control programming. The categories based on cognitive perspectives included "M'1 Narrative habits of natural language about the topic: if statement", "M'2 Programming learning experience about the topic: for/while loop", and "M'3 Result of analogical reasoning about the topic: for/while loop".

5. Conclusions

Apart from the manual diagnosis in previous research, this study integrated data mining and neural network to predict programming misconceptions. Although manual analysis of programming misconceptions could precisely diagnose a student's misconception through experts, it could not diagnose quickly when the amount of data is significant. Furthermore, the automated diagnosis process could read a large amount of data and accurately identify each student's misconceptions in a short amount of time. To make the automated diagnosis process more accurate, it must precisely define the corresponding label of each sample in the data preprocessing stage. In this study, if the existing definitions of misconception were not enough to describe the student's misconceptions, a sub-misconception or a new category of misconceptions would be supplemented to fully identify the student's misconceptions. Therefore, the knowledge about students' misconceptions of personal programming supervisors will be up-to-date. The results of this study can effectively help novice programmers perceive their misconceptions during self-learning.

In the literature, it was suggested that the misconceptions would affect each other. Therefore, the future work will explore which misconceptions often co-occur by association rule analysis. Such findings will help teachers understand the reasons for programming misconceptions and the influence between various misconceptions and promoting teaching.

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Effects of a Self-regulation Scheme Embedded in a Mobile App on Undergraduate Students' English Vocabulary Learning Performance and Cognitive Engagement

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Abstract: *This article reports on a quasi-experimental study examining the effects of a self-regulation scheme embedded in a mobile app on undergraduate students' English vocabulary learning performance and cognitive engagement. A total of 45 university students were involved in this study. They were randomly assigned to the experimental and control groups. Each group utilised the mobile app for two weeks, with and without the self-regulation scheme, respectively. Data collection involved pre-and post-vocabulary tests and cognitive engagement questionnaire. The findings revealed that students in the experimental group performed significantly better in English vocabulary learning than those in the control group. Furthermore, there was a statistically significant difference in cognitive engagement between students in the experimental and control group.*

Keywords: self-regulation scheme, English vocabulary learning performance, cognitive engagement, mobile-assisted vocabulary learning

1. Introduction

Recent studies have reported that an online learning environment could provide factors that facilitate students' ability to self-regulate their learning (Fathi et al., 2018) and vocabulary learning (Hong et al., 2015). Pintrich (2000) defined SRL as "an active, constructive process whereby learners set goals for their learning and then attempt to monitor, regulate, and control their cognition, motivation, and behaviours" (p. 453). An increasing number of studies have been conducted on self-regulated vocabulary learning (SRVL) mediated by technology (e.g., Chen & Lee, 2018; Chen et al., 2019). Despite the fact that many studies have been conducted, few have examined how mobile technologies can be used to support students' holistic SRL process (e.g., goal-setting, monitoring, reflection) during the vocabulary learning process in English. Thus, a more systematic tool is needed to facilitate the whole SRVL process. However, little is known about whether a mobile-assisted self-regulation scheme, premised on the self-regulation theory (Zimmerman, 2002), could influence students' English vocabulary learning.

Furthermore, it has recently been reported that mobile-assisted technology could enhance students' engagement (Song & Yang, 2019; Fithriani, 2021), but little attention has been paid to the study of exploring cognitive engagement (Greene, 2015) in English vocabulary learning in particular. To be specific, according to Greene (2015), cognitive engagement can be divided into two parts based on the level of processing strategies used, and the level of efforts exerted. Deep cognitive engagements involve higher-order or meaningful processing (e.g., connecting new materials, generating more complex knowledge), and shallow cognitive engagements are more mechanical in nature (e.g., rereading class notes) (Green, 2015; Shi et al., 2021).

In the light of the above background, this study aimed to investigate the effects of a self-regulation scheme embedded in a mobile app on undergraduate students' English vocabulary learning performance and cognitive engagement. The following research questions were addressed:

(1) To what extent did students' English vocabulary learning performance differ across the experimental and control groups?

(2) To what extent did students' cognitive engagement differ across the experimental and control groups?

2. Research Design

2.1. The App Used in This Study

The mobile app was developed by the second author and her research team. It allowed students to create vocabulary learning logs by taking pictures with contextualised information tagged with GPS, recording and inputting words or sentences (Song & Yang, 2019; Song & Ma, 2020). Premised on self-regulatory processes proposed by Zimmerman (2002), the proposed self-regulation scheme embedded in the mobile app this study allowed students to set vocabulary learning goals (e.g., specify the number of words to be learned and the amount of time spent on learning), monitor the learning process (e.g., view learning status via the dashboard and categorise the mastery levels of vocabulary) and reflect on their learning performance (e.g., do quizzes and complete self-evaluation forms).

2.2. Participants

In this study, convenience sampling was used as the sampling technique. The study lasted for two weeks. The sample size for the study consisted of 45 junior university students from Mainland China. They were first invited to complete the consent forms. In the following step, the researcher randomly allocated each participant to either the experimental or control groups while maintaining gender balance. The students in the experimental group (male=11, female=9) used the mobile app with the self-regulation scheme to learn English vocabulary, while the students in the control group (female=13, male=12) used the mobile app without the self-regulation scheme.

2.3. Data Collection and Analysis

In this study, data sources included pre-and post-vocabulary tests and questionnaires. The pre-test was used to assess students' prior English vocabulary levels. The items were selected from Nation's (2012) Vocabulary Size Test. The post-tests were made by researchers and were used to measure students' vocabulary knowledge. The questionnaire was adapted from Miller et al.'s study (1996) with 11 items. The questionnaire was used to assess students' cognitive engagement regarding deep and shallow English vocabulary strategies use. The Cronbach's alpha of deep and shallow cognitive engagement were 0.70 and 0.73 as validated in Shi, Tong, and Long's study (2021). The responses were given on a five-point Likert scale, ranging from 1 for "strongly disagree" to 5 for "strongly agree". Quantitative data analysis was used to address the two research questions. For the first research question, a Mann-Whitney U test was first used to analyse the pre-vocabulary test results of students in the experimental group and the control group. Then, an independent samples t-test was used to analyse the post-vocabulary test results of students in the experimental group and the control group. For the second research question, Hotelling's T^2 was adopted to determine the effect of the self-regulation scheme embedded in the mobile app on students' deep and shallow English vocabulary strategies use in the experimental and control groups.

3. Results

3.1. Students' Vocabulary Learning Performance

Pre-test was not normally distributed, as assessed by Shapiro-Wilk's test ($p < .05$). Therefore, a non-parametric test called the Mann–Whitney U test was adopted (Leow & Morgan-Short, 2004). A Mann-Whitney U test indicated that there was no significant difference in students' English levels of experimental group (Mdn = 35.00) and control group (Mdn = 32.00), U = 145, z = -.527, p = .598, using an exact sampling distribution for U (Dineen & Blakesley, 1973). The results indicated no significant difference in students' prior English levels of the experimental group (Mean rank = 24.15) and control group (Mean rank = 22.08).

An independent samples t-test was used to analyse any significant differences between the experimental and control groups students in terms of their post- English vocabulary tests. Levene's test (F=.004, p >.05) did not achieve a level of significance, so equal variances were assumed. Table 1 shows a significant difference was observed between students in the experimental group (M=35.90, SD=5.41) and control group (M=32.20, SD=5.87), M= 3.70, 95% CI = [-7.13, -.27], t(43)=-2.18, p= .035 <.05.

In conclusion, it is reported that the students who used the mobile app with the self-regulation scheme showed better English vocabulary learning performance than that of the students who used the mobile app without the self-regulation scheme.

Table 1. Results of independent samples t-test for the participants' post-vocabulary tests.

Group	N	M	SD	t	*p*
Control group	25	32.20	5.87	-2.18	0.035*
Experimental group	20	35.90	5.41		

Note. *p <.05*

3.2. Students' Cognitive Engagement

Hotelling's T^2 was run to determine the effect of the self-regulation scheme embedded in the app on students' deep English vocabulary strategies use and shallow English vocabulary strategies use. Preliminary assumption checking revealed that data was normally distributed, as assessed by Shapiro-Wilk test (p > .05); there were no univariate or multivariate outliers, as assessed by boxplot and Mahalanobis distance (p > .001). There were linear relationships, as assessed by scatterplot; no multicollinearity (|r| < .9); and there was homogeneity of variance-covariance matrices, as assessed by Box's M test (p = .964).

The results showed that there was a statistically significant difference in cognitive engagement between the students in the experimental and control group, F (2, 42) = 6.27, p =.004 < .05; Wilks' Λ = .77; partial η^2 = .23. Students in the experimental and control group scored higher in shallow English vocabulary strategies use (M = 27.48, SD = 3.81 and M = 23.38, SD = 3.81, respectively) than their deep English vocabulary strategies use (M = 27.05, SD = 4.77 and M = 23.36, SD = 4.75, respectively). There was a statistically significant difference in deep English vocabulary strategies use (p < .05) and shallow English vocabulary strategies use (p < .05) for students in the experimental and control group.

4. Discussions and Limitations

The results of the study showed that university students who used the mobile app with the self-regulation scheme had significantly better English vocabulary learning performance. The results were in line with the study of Chen et al. (2019) that technology-supported learning with SRL mechanism support significantly improves English vocabulary learning performance. In addition, students in the experimental group had higher cognitive engagement regarding both deep and shallow strategies use than students in the control group. Nevertheless, students' shallow strategies use was higher than deep strategies use. This suggests that further research needs to be conducted in this regard.

In conclusion, this study revealed that the self-regulation scheme had the potential to enhance English vocabulary learning performance and cognitive engagement among university students. We recommend that future research explore empirical studies in implementing holistic self-regulated learning supported by the mobile application to help students improve their ability to use deep English vocabulary learning strategies to enhance cognitive engagement.

The limitations of the study lie in mainly two aspects. First, due to the short length of the study and the small number of participants involved, the findings of the study cannot be generalised. Secondly, this study was primarily based on quantitative data analysis. Future studies will include qualitative data, such as reflective journals and interviews.

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Researching and Assessing Language Learner's Online Self-Regulated Learning: A Review of Selected Journal Publications from 2017-2021

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Abstract: *With the increasing attention to online self-regulated learning in second language acquisition, there has been a concomitant rise of interest in assessing self-regulated and examining how it is related to learning performance in online learning environments. In order to provide new insights in this promising field, this study reviews representative empirical studies on language learners' online self-regulated learning published from 2017 to 2021 in top-tier journals specializing in online language learning. The review was conducted from perspectives including context and participants, technology tools, target language and target language skills. In particular, detailed analysis was conducted on how self-regulated learning is assessed, what self-regulated constructs are measured, and what assessment tools have been employed to measure and analyze these self-regulated constructs. This paper also puts forward some suggestions for researchers to conduct relevant research in the future.*

Keywords: self-regulated learning, online learning, target language skills, technology tools, measurement methods

1. Introduction

Students' self-regulated learning strategies in online learning settings (especially since the COVID-19 pandemic) have drawn increasing attention in the field of second language education. Self-regulated learning refers to the metacognitive control of cognitive, behavioral, motivational and emotional conditions by individual learners through a repeated process of planning, monitoring, evaluation and change (Schunk & Greene, 2017). Students' self-regulated learning strategies have been considered as critical factors influencing their performance and achievement in online learning settings. As self-regulation is a context-specific construct, students' self-regulation in online learning environments may be different from those in conventional learning environment (Su, Zheng, Liang, & Tsai, 2018). As research on language learners' self-regulated learning in online language learning environments continues to expand during recent years, a systematic review of these empirical studies is needed. Despite that some review studies have been conducted on self-regulated learning, few review papers have focused specifically on online second language learning settings. Therefore, this study aims to review studies on language learners' online self-regulated learning published from 2017 to 2021 in top-tier journals specializing in online language learning. The research questions proposed by this study are as follows:

(1) What research context and participants, technology tools, target language and target language skills have been investigated in the selected articles?

(2) What self-regulated learning constructs are measured and what measurement methods have been adopted to assess online self-regulated learning?

2. Methodology

Following Li's (2018) method for reviewing computer assisted language learning research, the literature search of this study focuses on four top-tier journals that specialize in technology-enhanced language learning, namely, *Computer Assisted Language Learning*, *ReCALL*, *System,* and *Language Learning and Technology.* We searched the websites of these four journals with the key word "self-regulated learning" and "self-regulation", with the publication dates set from

2017 to 2021. This initial literature search resulted in 25 articles. After the collection of the articles, the first author reviewed titles, abstracts, and method sections together, and the articles that meet the following criteria from were selected: a) addressed online learning settings; b) empirical studies; c) journal articles. Finally, 17 studies were retained for the review and analysis in this study. Using a holistic approach, the author takes an overview of the 17 articles by displaying the key information from the aspects of context and participants, technology tools, target language and target language skills.

3. Results

Table 1 below shows these selected articles from context and participants, technology tools and target language. It was found that the majority of past research investigated self-regulated learning strategies using online second language learning tools among university students. A few studies explored elementary and high school students. In addition, most of the target languages are English. Few studies have targeted other languages like Spanish, German and French. Figure 1 presents the target language skills of studies on online self-regulated learning in the second language acquisition. Studies on self-regulated learning in online writing have gained the most attention in recent years. However, there is a lack of studies on self-regulated learning in online reading, speaking, and listening in recent years.

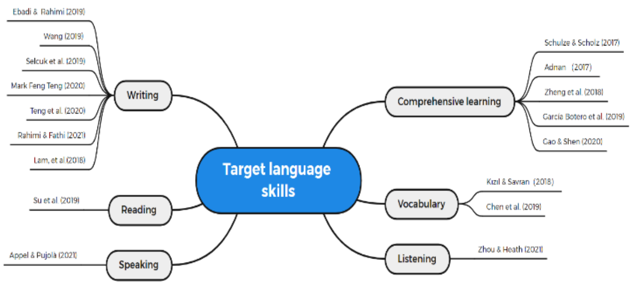

Figure 1. Target language skills.

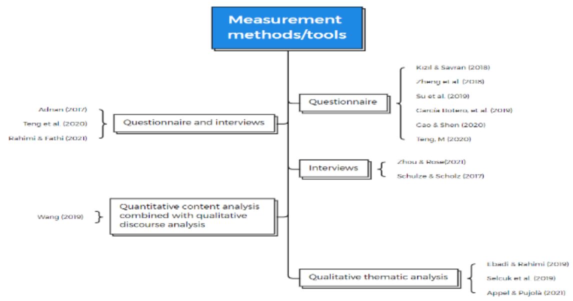

Figure 2. Methods for measuring self-regulated learning.

Table 1. Overview of research articles.

Author	Context and participants	Technology tools	Target language
Schulze & Scholz (2017)	6920 online students	Online website	German
Adnan (2017)	70 senior ELT students	Adobe Connect Virtual Classroom System	English
Lam et al. (2017)	72 Grade 10 students	Edmodo.	English
Kızıl & Savra（2018）	77 EFL learners	Information and Communication Technologies	English
Su et al. (2019)	285 university students in China	Wiki	English
Zheng et al. (2018)	293 Chinese university students	Online learning management systems	English
Chen et al. (2019)	46 Grade 5 students	EVLAPP-SRLM	English
Garc ía Botero et al. (2019)	Modern languages students in Colombia	Mobile assisted language learning (MALL)	French
Ebadi & Rahimi (2019)	Senior students selected from Razi University	Google Docs	English
Wang (2019)	ESL university students in China	Shimo	English
Selcuk et al. (2019)	16 from a high school in Izmir	Web-based collaborative writing	English
Teng, M (2020)	120 EFL students at a university in China	Google+	English
Gao & Shen. (2020)	75 Chinese EFL learners	M-Learning	English
Rahimi & Fathi (2021)	389 Chinese undergraduates	Pigaiwang	English
Teng et al. (2020)	67 EFL learners at university	Wiki	English
Zhou & Rose (2021)	412 students in mainland China	The Oxford Online Placement Test	English
Appel & Pujolà(2021)	1098 online learners (data in 2019)	MOOC	Spanish

Different studies on self-regulated learning may have different measurement dimensions. This study summarizes measurement dimensions of the selected research articles (See Table 2). As can be seen in Figure 2, the most popular measurement of online self-regulation in previous studies is questionnaires survey (e.g., Gao & Shen, 2020; García Botero, Botero Restrepo, Zhu, & Questier, 2019; Kızıl & Savran, 2018; Su, Li, Liang, & Tsai, 2019; Teng, 2020; Zheng, Liang, Li, & Tsai, 2018). Some researchers also use the method of qualitative thematic analysis to assess and analyze self-regulated learning (e.g., Appel & Pujolà, 2021; Ebadi & Rahimi, 2019; Selcuk, Jones, & Vonkova, 2019). In addition, there are several studies which evaluate self-regulated learning by semi-structured interviews (e.g., Schulze & Scholz, 2017; Zhou & Rose, 2021). Furthermore, there are some studies using mixed methods to triangulate data, which can make the assessment of online self-regulation more reliable. For example, some studies (Adnan, 2017; Rahimi & Fathi, 2021; Teng, Yuan, & Sun, 2020) employ both questionnaire and interviews to evaluate students' online self-regulated learning. Wang (2019) combines the quantitative content analysis with qualitative discourse analysis to assess students' online self-regulated learning.

Table 2. Assessing for measurement dimensions.

Author	Measurement dimensions
Schulze & Scholz (2017)	No specific dimensions
Adnan (2017)	No specific dimensions
Kızıl & Savra（2018）	Commitment regulation, metacognitive regulation, affective regulation, social regulation and resource regulation through ICT
Su et al. (2019)	Goal setting; environment structuring; task strategies; time management; help seeking; self-evaluation
Zheng et al. (2018)	
Garcí a Botero et al (2019)	Forethought; performance and self-reflection
Ebadi & Rahimi (2019)	No specific dimensions
Wang (2019)	Students' writing goals for writing
Selcuk et al. (2019)	Providing praise and motivational phrases
Teng, M (2020)	Planning, executing, monitoring, evaluation, orientation and elaboration activities
Gao & Shen (2020)	Metacognitive, commitment, and environmental control strategies
Teng et al. (2020)	Interest enhancement; performance self-talk; mastery self-talk; emotional control; environment structuring
Zhou & Rose (2021)	Forethought phase; performance phase; and self-reflection phase
Rahimi & Fathi (2021)	Planning, organizing, and managing students' EFL writing goals and processes
Appel & Pujolà(2021)	No specific dimensions

4. Discussion and Conclusion

Many scholars see Internet and information technology as important scaffolding tools to promote self-regulated learning goals and improve learners' performance. This study reviews the target articles published from 2017 to 2021 in top-tier language education journals and summarizes tools used for the measurement of self-regulated learning and its underlying multi-dimensional constructs. Two findings can be generated from this review study. First, researchers investigating online self-regulated learning strategies mainly focused on writing skills and there is a lack of studies on language learner's online self-regulation in listening, reading, speaking and vocabulary learning. In addition, this study analyzes the measurements methods and measurement dimensions of the selective studies. It was found that questionnaire survey was the most frequently used tools for assessing online self-regulated learning. According to above findings, there are some suggestions for the future research as follows. First, future researchers are suggested to explore self-regulated learning in online reading, speaking, listening, and vocabulary learning. Second, future studies in the area of second language acquisition can also integrate multimodal methods to accurately measure self-regulated learning and use reliable measurements to explore self-regulated learning.

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The Impact of Switching Intention of online learning in COVID-19 Epidemic's Era: From Chinese Teachers' Perspectives

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Abstract: *The study is based on the push-pull mooring model. We explored the impact of online learning on teachers' switching intention during the COVID-19 pandemic. We found that the push effect (service quality, security risk), pull effect (task-technology fit, challenge motivation, teaching self-efficacy) and habit had a significantly influence the switching intentions of teachers from physical course to online learning platforms. The finding of this study will bring more insights into e-learning of Chinese colleges and universities in the future after the epidemic.*
Keywords: Online Learning, COVID-19 pandemic, Push-Pull Mooring, China, e-learning

1. Introduction

The pandemic has made a drastic impact on educational institutions around the world. To avoid greater spread of the virus, educational institutions stopped off-line teaching and encouraged teachers and students to switch to online teaching, so as to achieve the purpose of suspending school without suspending teaching Chen, Chen, Ling & Lin, 2020) In order to control the risk and the possibility of the spreading of the virus, the Chinese Ministry of Education has urgently issued relevant education policies, requiring all schools to take their response measures, and expecting all school teachers to achieve educate purposes by teaching online (Lin et al., 2021).

Previous studies related to the transfer behavior from off-line to online education mainly used Push-Pull-Mooring Model, and these studies all discussed students' switching intention from off-line to online learning (Lin et al., 2021; Xu et al., 2021). However, there were no study about teachers' switching intention from off-line to online teaching. PPM is special and applicable to study the switching intention mainly in that it does not have a fixed variable in its concept. However, no fixed variables do not mean arbitrary use, but requires clear use of Push, Pull and Mooring oriented views to explain the possible impact of migration behavior in different situations (Yan, Zhang & Yu, 2019). During the COVID-19 pandemic, it may be more suitable to use PPM for research since there are concerns about the virus, because the switching behavior occurring during the pandemic is a necessary change resulting from an uncertain, risky environment. Therefore, this study will construct the theoretical foundation from the past literature and try to take the quality of service and safety risks as the Pull factors, take Task-Technology-fit, challenge motivation and student learning utility as the Pulling factors, and take habits as the Mooring factor. This study tries to use statistics to verify the possible impact that habits could have on the switching intention. This study takes university teachers in China as the main study subject to explore the possible motivation of teachers' intention to switch from off-line to online teaching.

2. Literature Review and Hypotheses

2.1. Push–Pull–Mooring

Push effects originally referred to negative influences that force an individual to leave their place of residence and seek out a more livable or acceptable home elsewhere (Lee, 1966). The term was later expanded to include influences driving users to leave existing services (Lin et al., 2021). Cheng et al. (2019) and Lin et al. (2021) identified safety risk as a push effect; their results indicate that users may change services because they are concerned about an uncontrollable safety risk in the original service. Lin et al. (2021) defined safety risk as a risk users deem to be uncontrollable or unacceptable; when a risk reaches the level of uncontrollable or unacceptable, users feel forced to seek other services. Chen and Keng (2019) defined quality of services as follows: when users perceive the quality of the original service to be insufficiently satisfactory, they feel forced to seek out alternative services. Previous PPM studies have verified quality of services as a type of push effect (Lin et al., 2021). Therefore, in accordance with previous studies, the present study identified quality of services and safety risk as push effects and developed the following hypothesis:

H1: When the service quality decreases and the safety risk increases, instructors' intentions to change from on-site lectures to online instruction increases.

Pull effects refer to the attractions that lead individuals to wish to leave the original place of residence and seek out other places to live (Lee, 1966). Lin et al. (2021) used the concept to discuss online learning, explaining that, when students perceive learning through online platforms to be more satisfactory than on-site instruction, the students are induced to switch from on-site learning to online learning platforms. In addition, according to the task-technology fit theory, the users' needs being satisfied affects whether users can successfully complete tasks and will continue their intention to use the technology (Goodhue & Thompson, 1995). Challenge motivation is another pull effect. Intrinsic motivations may be realization of goals or wishes (Amabile, 1997). For teachers, teaching self-efficacy is another pull effect; it can be defined as the instructor's ability to realize students' expectations of active participation and effective learning despite predicaments or problems (Tschannen-Moran & Hoy, 2001). Through reference to previous studies, this study employed task-technology fit, challenge motivation, and teaching self-efficacy as pull effects and developed the following hypothesis.

H2: When task-technology fit, challenge motivation, and teaching self-efficacy increase, instructors' intentions to switch from on-site lectures to online teaching may increase.

A habit is a norm accumulated through experience, which results in a slack mind (Wang et al., 2019). Habits are not easily changed; however, dissatisfaction with the current situation can cause individuals with habits to attempt changes (Polites & Karahanna, 2012). When a determined individual changes an old habit, the individual is highly likely to develop a new habit (Chen & Keng, 2019). Therefore, with reference to previous studies, this study employed habits as the main mooring effect and developed the following hypotheses:

H3: Stronger habits lead to instructors having lower levels of intention to switch from on-site lectures to online teaching.

H3a: Stronger habits lead to a weaker relationship between the push f effect and the intention to switch.

H3b: Stronger habits lead to a weaker relationship between the pull effect and the intention to switch.

3. Data collection

In this study, the valid respondents were defined as university teachers who were required to conduct both physical and online teaching during the COVID-19 pandemic. The questionnaires were distributed on the WJX platform mainly due to the convenience of collection, time saving, higher efficiency, and isolation during the pandemic. The questionnaire was released in mainland China to university teachers under the influence of COVID-19. A total of 297 questionnaires were collected from mid-March to early May 2020, and 283 valid questionnaires were accepted with the remaining being deleted due to incomplete responses. According to the basic information, the proportion of male respondents was 53.85%, while the proportion of female respondents was 46.15% in terms of gender; the proportion of senior teachers was 60.99%;

the proportion of those who had never used online learning before the pandemic was 64.29%, which shows that teachers in Chinese universities and colleges generally had not worked with online learning platforms before the pandemic.

4. Research Results

SmartPLS 3.2.8 software was used in this study for the validation of assumptions in the model. In order to ensure that the questionnaire measures were free of bias, common method variance was conducted in the study, mainly by reducing common method variance through the paged form of questionnaire completion. Secondly, the presence of common method variance was tested by Harman's single factor. Based on the results of this study, there were no significant common method variances, and the results were consistent with the criteria suggested in the past (Shiau & Luo, 2012). he factor loadings in this study were based on the recommendation of Hair et al. (2006), and the resultant values of factor loadings for all constructs and for each of them are greater than 0.7. The Cronbach's α values for all constructs are greater than the value of 0.7 recommended by Hair et al. (2019). The component confidence for all constructs is greater than the value of 0.7 recommended by Hair et al. (2017). In all mean variances, the factor loadings are greater than the value of 0.5 proposed by Fornell and Larcker (1981). In terms of discriminant validity, this study met the past recommended indicators in terms of the test criteria of discriminant validity proposed by Fornell and Larcker and the Heterotrait-monotrait (HTMT) criteria of discriminant validity (Fornell & Larcker, 1981; Henseler et al., 2014), showing acceptable results for all constructs in this study.According to the second-order results for push and pull, the weight values ranged from 0.355 to 0.877 and the results were significant ($p<0.05$). In terms of the analysis result of the structural model, push (H1, Beta=-0.173) had a negative significant effect on willingness to switch; pull (H2, Beta=0.643) had a positive significant effect on willingness to switch; and H3 had a negative significant effect for habit on willingness to switch. In terms of the regulating effects, habit had positive and negative effects on push (H3a) and willingness to switch and pull (H3b) on willingness to switch, respectively. The overall explanatory power of the model is 0.621 for willingness to switch, which shows that this study has good predictive performance.

5. Conclusion and Implication

The results of H1 indicated that push effects are negative effects prompting teachers to switch from physical to online teaching.With the environmental uncertainty caused by COVID-19, teachers may refuse to continue physical teaching in a classroom environment because of the push effects represented by security risks and service quality. This finding is consistent with research results on the push effects in PPM(Chen & Keng, 2019; Lin et al., 2021).Regarding future teaching-related emergency management, special attention should be paid to the stability and quality of online teaching platforms. The results of H2 demonstrated that pull effects are a positive factor prompting teachers to switch from physical to online teaching. In online teaching services, teachers' intention to switch from physical classroom to online teaching is enhanced by the following pull effects: task–technology fit, motivation to overcome challenges, and self-efficacy in teaching. During the pandemic, teachers face considerable challenges because of their lack of unified online teaching experience. The results of H3 revealed that teachers' past habits had negative effects on their intention to switch; these results on intention to switch are consistent with those of prior studies on PPM (Cheng et al., 2019; Lin et al 2021). Despite the numerous advantages of physical teaching, online platforms have specific strengths during the pandemic. If these platforms enhance these strengths and promote the benefits of online platform usage, teachers will be encouraged to develop new habits concerning online teaching. This study has some limitations. First, snowball and convenience sampling were employed. Because the sampling was conducted during a period of high COVID infection, the samples were primarily concentrated in major coastal provinces in China; thus, not all regions of China were represented. Second, this study principally involved the collection and analysis of survey data during the pandemic period. However, to further elucidate the effects and benefits of switching to a new behavior, qualitative analysis should be employed.

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Using the ISTE Standards to Examine the Roles of Teacher and Students in Technology-Enhanced Learning Environments

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Abstract: *The use of technology in teaching and learning has transformed how we redesign a learning environment for future learning. One common myth would occur if a teacher is not aware of the purpose of technology integration. This study proposed an approach to utilize the ISTE standards on both teachers' and students' roles as instrumental rubrics to review three pre-service teachers' lesson plans about its technology integration in teacher use and students' use. Results revealed the importance of considering pedagogical process over technology product itself. This study prompted to demonstrate using the ISTE standards can help improve teacher preparation's training in technology integration with purposeful evaluation.*

Keywords: ISTE standards, technology integration, pre-service teachers, learning environments

1. Introduction

The changing role of technology and its influences on teaching and learning has transformed how teachers perceive their roles and students' role in the classroom. Today's teachers are still being asked to rethink the fundamental connection between pedagogy and technology. A growing constellation of perspectives from fields spanning cognitive science to computer science call for teachers to rethink teaching, learning, and technology in order to prepare learners for the contemporary world. For example, while some research has focused on teachers' digital literacy (Knobel & Kalman, 2018) and the impact of teachers' beliefs on educational technology use (Ertmer, 2005), other research projects have centered on the role of technology integration in active learning, performance tasks, and learning environments (Laine & Nygren, 2016). Currently, the internet is breaking down barriers between knowledge and learners and creating new opportunities for distance education and open resources (Fishman & Dede, 2016). These new opportunities are accessible for learners to learn, search, contribute, collaborate, share, and even review or assess their peers. In other words, teachers are no longer the only knowledge resource or assessment standard in classrooms. The teacher's role is evolving into a facilitator that designs and supports differentiated learning to meet individual learners' needs. To avoid students becoming simply consumers of technology, the teacher's role is to prioritize pedagogy above the usage of technology (Roblyer & Hughes, 2018).

Currently, the International Society for Technology in Education (ISTE) has updated its standards for students (2016), and identified learners who actively use technology as being as knowledge constructors (e.g., use digital tools to produce creative artifacts), innovative designers (e.g., use various digital tools to design and solve problems by creating new solutions), computational thinkers (e.g., use algorithmic thinking to create new solutions), and creative communicators (e.g., use various digital media to express themselves creatively) (https://www.iste.org/standards/for-students). ISTE provides a short summary of the evolution of its student standards on its website from 1998 to 2016. These changes reflect the expectations for skills and dispositions adults need in the world today, changing expectations for learners are mirrored in the updated standards for teachers. In 2017, ISTE further outlined revised standards for educators that encouraged them to include empowerment within the use of technology in the classroom (https://www.iste.org/standards/for-educators). These standards named seven roles that educators can use in their teaching practices (e.g., collaborator, facilitator, designer). The revised ISTE standards demonstrated a shift from "using technology for facilitating certain skills" to "using technology through active roles for continued growth."

The updates to standards and models of technology integration also reflect and drive the multiple and changing role(s) of the K-12 teacher. Therefore, preparing teachers for the information age and examining how to design and use technology in practice are emerging challenges for K-12 teacher preparation. There is also a critical need to specifically examine the role of technology in teaching practices which can constrain or expand students' learning. Thus, this study aimed to apply the ISTE standards as instrumental rubrics to uncover how teachers and students' roles can be shifted when integrating technology into instructional designs. The driving question was: How does the ISTE standards reflect the changing roles among teachers and students in technology integration?

2. Methods

2.1. Context

Three pre-service teachers who enrolled in a teacher preparation course about educational technology in the U.S. were pilot focal cases in this study in order to review their lesson plan designs. These three pre-service teachers were purposefully sampled based on the same profession in early childhood training. There were no intervention during the course and the lesson plans were collected after the end of the course.

2.2. Data and Analysis

Lesson plans were the main data resources of three pre-service teachers. With the role of technology among teachers and students represented the unit of analysis in this case study, three phases of data analysis were conducted. First, each lesson plan were decoded with lesson activities and identified the role of technology in each lesson activity. Next, the role of technology were further categorized and labeled its context as teacher use or students use. Finally, ISTE standards for students (2016) and educators (2018) were applied as an instrumental rubrics (see Table 1) to analyze the what teachers' and students' roles can be leveraged in technology-enhanced lessons.

Table 1. Roles for Students (2016) and Educators (2018)

ISTE Standard for Students (2016)	ISTE Standard for Educators (2018)
1. Empowered Learner	1. Learner
2. Digital Citizen	2. Leader
3. Knowledge Constructor	3. Citizen
4. Innovative Designer	4. Collaborator
5. Computational Thinker	5. Designer
6. Creative Communicator	6. Facilitator
7. Global Collaborator	7. Analyst

3. Results

Among these three cases (PT#1, PT#2, and PT#3), PT#2's lesson presented a consist role in using technology for certain purpose. For example, she chose the Smartboard mostly for students as knowledge constructors to discuss the present content, whereas the teacher is positioned as the facilitator during the entire lesson to invite students interact with the display content for group discussion.

On the other hand, in PT#1 and PT#3's lesson plan chose different approach to integrate technology and brought varied roles shifting between teachers and students. In PT#1's lesson, the researcher found that students exercised their roles as knowledge constructors, creative communicators, and global collaborators; and the teacher had roles as a collaborator, designer, and facilitator. For example, in the first part of the lesson when students view a video on YouTube together, the teacher plays the role of a facilitator to "facilitate a class discussion about different foods and culture." Students become knowledge constructors that build knowledge about the world and themselves by reflecting on their own favorite food and telling the class a story about this food. In the next part of the lesson when students work collaboratively on drawing, taking pictures, annotating, and video editing, PT#1 takes on a dual-role as a designer and a collaborator to expand students' authentic learning experiences. Students work as communicators and collaborators while working on their digital creations.

In PT#3's lesson, the researcher found that students function as empowered learners, knowledge constructors, and creative communicators. The teacher's role is as a designer. For instance, students in this lesson construct and evaluate their knowledge together by creating charts on mind-mapping platforms and by drawing life cycles on the Smartboard. They have opportunities to create original work and use technology as a medium for communicating and sharing their understanding. At the same time, the teacher designs authentic learning activities by integrating digital tools that enrich/deepen students' learning experiences.

Table 4. Focal cases analysis

	PT#1	PT#2	PT#3
Technology-enhanced environments	YouTube, Smartboard, Photo-editing Apps	Smartboard	Mind-mapping platforms, Smartboard
Teacher use	- collaborator - designer - facilitator	- facilitator	- designer
Student use	- knowledge constructors - creative communicators - global collaborators	- knowledge constructor	- empowered learners - knowledge constructors - creative communicators

4. Discussion and Conclusion

Using the ISTE standards to analyze the role of technology and its influences on teachers and students' roles , this study found how pre-service teachers expanding teacher's role into a collaborator or a designer along with learners becoming creative communicators. Interestingly, another pre-service teacher chose to use technology for instructional uses only for the limited purposes of displaying information on a SMARTboard but still offering multiple constructive non-technology-based activities for students. To continue deepening technology integration practice research, future research need further examination on transferring the ISTE standards into more accessible rubrics into teacher education when incorporating technology into future classrooms.

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