PERSONALIZED ADAPTIVE TEACHER EDUCATION TO INCREASE SELF-EFFICACY: TOWARD A FRAMEWORK FOR TEACHER EDUCATION

Atikah Shemshack

Dissertation Prepared for the Degree of

DOCTOR OF PHILOSOPHY

UNIVERSITY OF NORTH TEXAS

May 2022

APPROVED:

Kinshuk, Committee Chair and Dean of the College of Information
Jonathan Spector, Committee Member
Gerald Knezek, Committee Member
Yunjo An, Chair of the Department of Learning Technologies
Victor Prybutok, Dean of the Toulouse Graduate School

Shemshack, Atikah. *Personalized Adaptive Teacher Education to Increase Self-Efficacy: Toward a Framework for Teacher Education*. Doctor of Philosophy (Learning Technologies), May 2022, 191 pp., 13 tables, 8 figures, chapter references.

This study investigated personalized adaptive learning, teacher education, and self-efficacy to determine if personalized adaptive teacher education can increase self-efficacy. It is suggested that teachers with higher self-efficacy tend to stay in the teaching profession longer. Chapters 2 and 3 are literature reviews on personalizing adaptive learning to determine what common components are used in personalized adaptive learning systems to get a clear understanding of what previous literature suggests building this study on it. Chapter 4 investigates the data collected from 385 teachers to understand better what teachers report on factors that increase their self-efficacy. As a result, it was found that teachers' self-efficacy increases with more training, support, and resources. In chapter 5, a framework was developed based on previous findings, with components of personalized adaptive learning to provide support/help at the right time for teachers to increase their self-efficacy. An empirical study was conducted to validate this framework, where the framework was used as a guide to personalize and adapt summer teacher preservice training and survey teachers on their self-efficacy before and after the training to see its impact on teachers' self-efficacy. However, since summer preservice training was virtual, the framework could not be implemented fully, as we were not able to observe teachers' behaviors and monitor their learning to provide them help and support, as needed and being in the post-COVID-19 year as educators dealing with about two-year learning loss systemwide, seems decreased teachers' self-efficacy. The findings of this study can guide preservice teacher education institutions and decision-makers of teacher education to assess inservice teachers' needs and self-efficacy to help and support them with a more personalized adaptive education to improve their self-efficacy.

ACKNOWLEDGEMENTS

All our dreams can come true if we have the courage to pursue them.
Walt Disney

This has been a dream coming true for me since I was a child; I am a first-generation college graduate from a minority background and have always wanted to learn and learn more. This dissertation would not have been possible without the support of my family and friends, who supported me through my doctorate journey with all the coursework, early mornings, weekends spent at my desk, and sacrificed family time. Throughout the construction and writing of the dissertation, I have received a great deal of support and assistance. I would first like to start my acknowledgment by expressing my appreciation and gratitude to my husband, Fawzy, who has stood by my side to support me to make my dream come true. This Ph.D. journey has not been a solitary individual endeavor but accompanied by many mentors, friends, and family members. My kids Ferat and Yusuf, thank you for giving up on our family time so that I could work on my Doctorate. My Ph.D. major professor, Dr. Kinshuk, provided essential guidance, support, and encouragement throughout my intellectual journey. He pushed me harder and harder every day to try my best and believe in myself. Thank you for being there for me and guiding me through this journey. Indeed, I would also like to thank my committee members, Dr. Knezek and Dr. Spector, for their full support with the construction and writing of this dissertation. I sincerely appreciate my committee members for their valuable guidance and time throughout my studies. You provided me with the tools that I needed to choose the right direction and successfully complete my dissertation. I would also thank Taylor Davis for his collaboration and friendship. Those professors and friends who support me during this journey, your support and help are greatly appreciated. Also, a huge thank you to teachers who participated in my studies to ensure I have data to make a possible impact for future generations.

TABLE OF CONTENTS

LIST OF TABLES

Page

LIST OF FIGURES

CHAPTER 1

INTRODUCTION

Personalized adaptive learning has been a major topic of research for a long time (Xie et al., 2019); however, very limited research has explicitly looked at personalized adaptive preservice teacher education to provide better support by providing preservice teachers with resources to prepare them according to their diverse needs and skills to improve inservice teachers' self-efficacy. Teachers' professional proficiency comprises professional cognitive knowledge and affective professional belief components, which are generally assumed to be related and impact instructional practice (Colson et al., 2018; Depaepe & König, 2018; Jenset et al., 2018; Schleicher, 2016). To provide meaningful learning opportunities to students, meaningful learning opportunities need to be offered to preservice teachers to prepare them for teaching better (Natividad Beltrán del Río, 2021; Nel, 2017; Siko & Hess 2014; Thoma et al., 2017). However, studies on preservice teacher education that simultaneously relate cognitive and affective components to instructional practice are limited (Depaepe & König, 2018).

Preservice teacher education is a complex process that requires teachers' cognitive and emotional involvement. This process requires the willingness to examine where each teacher stands and provides personalized adaptive tools for improvement or change (Depaepe & König, 2018) according to their diverse goals and needs. While many studies have analyzed preservice teacher education and current practices, very little research has focused on personalized adaptive preservice teacher education to improve inservice teachers' self-efficacy. Focusing on how personalized adaptive preservice teacher education might contribute to improving inservice teachers' self-efficacy, and as a result, improving the learning experience for students and inservice teachers need to be explored further.

To fill this gap, the researcher has used current literature on personalized adaptive learning, the components used for personalized adaptive learning, and preservice teacher education, and has analyzed factors that contribute to increasing inservice teachers' self-efficacy to develop a framework for personalized adaptive preservice teacher education to improve inservice teachers' self-efficacy. The framework was validated through expert feedback and an empirical study on inservice teachers. Growing evidence has suggested that efforts to tie teacher preparation more closely to practice can significantly impact inservice teachers' impact on student learning (Colson et al., 2018; Depaepe & König, 2018; Jenset et al., 2018; Schleicher, 2016). Preservice teacher education is crucial in producing quality inservice teachers (Levine, 2006; Mergler & Spooner-Lane, 2012; Wright & Wilson, 2005). Surveys of graduates, teachers, principals, and education systems nationally and internationally report that initial teacher education preparation does not adequately prepare graduates for actual teaching (Commonwealth of Australia, 2007; Naylor et al., 2015; Roofe & Miller, 2013).

Moreover, learning to teach is dynamic because there are influences from students, curriculum, policy, leadership, school environments, and teachers' personal beliefs about teaching and learning (Hattie, 2012; Naylor et al., 2015; Opfer et al., 2011). There is evidence that some features of teacher preparation can make a difference concerning inservice teachers' sense of efficacy (Darling-Hammond et al., 2002; Ronfeldt et al., 2014) and with teachers' retention in the profession (Ingersoll et al., 2014; Ronfeldt et al., 2014). Furthermore, Christensen and Knezek (2017) suggested that understanding teacher confidence and competence in learning is essential in designing appropriate teacher education. Thus, this framework will be used for personalized adaptive preservice teacher education that will increase inservice teachers' self-efficacy and, as a result, improve the learning experience for all.

To serve the purpose of this study and address the gaps suggested earlier, the following research questions are addressed:

1. How can preservice teacher education be personalized according to teachers' diverse needs and skills to improve self-efficacy during inservice teaching?

The following sub-questions follow the first primary research question to understand better a well-defined, comprehensive, personalized adaptive learning model.

a. How is personalized adaptive learning defined?

b. What components need to be included in well-defined personalized adaptive learning?

This question narrowed the focus of the study on components and their impact on learning. The researcher highlighted components in each system to look for patterns and similarities while paying attention to differences and their impact on learning outcomes.

The following sub-question helped compare different personalized adaptive learning models, so any relationship between used systems/models and components could be identified:

c. What systems and models are available to personalize and adapt preservice teacher education to improve their self-efficacy once they become inservice teachers?

Sub-questions provided a more focused approach to the study. Moreover, the researcher focused on analyzing and synthesizing different personalized learning approaches that consider various learning components, so an evolving cooperative agreement on a dynamic, personalized adaptive learning model can be created for preservice teachers to improve inservice teachers' self-efficacy that impact their teaching practices and beliefs.

The second research question focuses on identifying factors that contribute to improving inservice teachers' self-efficacy. As noted by Jenset et al. (2018), growing evidence has suggested that efforts to tie teacher preparation more closely to practice can significantly impact student learning:

2. What are identifying factors that contribute to the inservice teachers' self-efficacy?

Following the lead of Christensen and Knezek (2017) that understanding teacher confidence and competence in learning is essential in designing appropriate education, the research is focusing more in-depth with the following questions:

3. How can the PAL framework be used to personalize and adapt professional development programs to address teachers' diverse needs and skills to improve their self-efficacy?

Also, to analyze the effectiveness and impact of PAL framework following sub-questions were asked:

   a. Was personalized adaptive teacher education framework effective to improve teachers' self-efficacy?
   b. What impacts teachers' self-efficacy?
   c. Why did teachers' self-efficacy decrease after school started?

These sub-questions narrowed the focus of the study on PAL framework's impact on teachers' self-efficacy.

To provide a personalized adaptive learning environment to learners, the field research related to preservice teacher education and providing preservice teachers with a personalized adaptive education to improve their self-efficacy could benefit from studying the data and efforts to improve preservice teacher education. Tools and systems are available to assess and collect data on preservice teachers' knowledge, skills, and affective states, and provide them with appropriately planned education according to their individual needs and goals. Current personalized adaptive learning research mainly focuses on students, and there is limited attention to personalizing preservice teachers' education.

This research is a manuscript-style dissertation based on five published/in-progress papers. The first paper, "Systematic Literature Review on Personalized learning Terms," published in *Smart Learning Environments*, is a systematic review of personalized adaptive learning literature. This is a study I co-authored with Dr. J. Michael Spector. I reviewed the literature, decided on research methodology, and put together a draft that Dr. Spector reviewed to provide suggestions and feedback to finalize and polish before sending it to the journal.

The first paper's findings identified overemphasis on personalized adaptive learning but nothing practical for preservice teacher education. This systematic review of personalized adaptive learning literature was conducted using Okoli's guidelines to conduct a systematic literature review for Information Systems Research (Okoli, 2015). This review study found and analyzed 56 relevant studies based on the research protocol. The findings support that personalized adaptive learning has become a fundamental learning paradigm in the research community of educational technologies.

Furthermore, the findings suggested that the personalized adaptive learning models have gained more attention from governments and policymakers than educators and researchers (Shemshack & Spector, 2020). Even though the findings are not directly tied to preservice teacher education, this study leads that personalized adaptive learning can be an approach for preservice teacher education due to the increased use of personalized adaptive learning approaches and their promising impact on learning (Pane et al., 2015). Also, because of this literature review, a need for analyzing components that have been used for personalized adaptive learning was identified.

The second paper, titled "A Comprehensive Analysis of Personalized Learning Components, published by *Computers in Education,*" examines common elements that have been used for personalized adaptive learning. These components needed to be analyzed to determine what will be suitable for personalized adaptive preservice teacher education. This theoretical study is a work I coauthored with Dr. Kinshuk and Dr. J. Michael Spector. My contribution is centered on the comprehensive, though not exhaustive, literature review regarding common elements that have been used for personalized adaptive learning. I wrote the paper draft, and Dr. Kinshuk reviewed it several times and suggested revisions. Dr. Spector reviewed the paper and proposed modifications before submitting it to the journal. Both Drs. Kinshuk and Spector reviewed and approved the article one last time before submitting it to the journal.

As a result of the focus of this study, what components need to be included in a comprehensive, personalized learning approach, it was concluded that one of the components that most educators and researchers agreed upon is allowing learners to learn at their own pace, which is a strength and advantage that personalized adaptive learning provides. The findings of this study revealed that the range of components being used to personalize learning is widening as technology develops. As we learn more about human learning and what technology can provide us with a personalized adaptive learning experience, such as gathering data of learners' emotions using bio-trackers, which might bring up some privacy concerns, we are also redefining our understanding of personalized adaptive learning.

The third paper is titled "Factors Contributing to Teacher Self-efficacy for Distance Learning," under review by the *Journal of Digital Learning in Teacher Education*. In this study, the Distance Learning Support (DLS) (Shemshack & Davis, 2020) instrument was used to assess inservice teachers' needs to identify how administrator support, inservice teacher training, and access to materials can help teachers increase their self-efficacy for distance learning. This empirical study is a work I coauthored with Taylor Davis, Dr. Gerald Knezek, and Dr. Kinshuk. My contribution is centered on the introduction, literature review, methods, design of the study, discussion, conclusion, and general structure of the paper. I wrote the paper draft, and Taylor

Davis monitored data collection and analyzed data. Once I put together the final draft, Drs. Knezek and Kinshuk reviewed it several times and suggested revisions. Dr. Kinshuk reviewed the paper and proposed modifications before submitting it to the journal. Both Drs. Knezek and Kinshuk reviewed and approved the article one last time before submitting it to the journal.

This research stemmed from Bandura's (1982) suggestion that self-efficacy determines how much effort people will expend and how long they will persevere in the face of obstacles or aversive experiences. The study results revealed that the more training teachers receive, the more confident they feel teaching online. Furthermore, this study provides a reliable and valid instrument for school administrators to support their teachers in successfully integrating technology by providing them with need-based training and support. Having tools and intentional support to help inservice teachers improve their distance teaching practices and build confidence in distance learning becomes an essential component of efficient teaching. This study collected information regarding the support teachers received from their administrators during COVID-19 distance learning and how it impacted inservice teachers' self-efficacy regarding distance teaching. This paper's findings shed light on the underlining questions, what factors help improve inservice teachers' confidence with distance learning, how administrator support can be improved, and which inservice teacher demographics have the highest confidence regarding online learning. The findings of this study can guide preservice teacher education institutions and decision-makers of teacher education to assess inservice teachers' needs and self-efficacy online learning to help and support them with a more personalized adaptive education to improve their self-efficacy.

The fourth paper, titled "Developing a Framework for Personalized Adaptive Preservice Teacher Education to Improve inservice Teachers' Self-efficacy," focuses on a conceptual framework developed based on the literature review and in-depth analysis of personalized adaptive learning components preservice teacher education and self-efficacy. Further, it will allow us to develop a tool to provide personalized adaptive preservice teacher education according to inservice teachers' diverse needs to improve their self-efficacy. This theoretical study is a work I coauthored with Dr. Kinshuk. My contribution is centered on the introduction, literature review, methods, design of the study, conclusion, discussion, developing framework, and general structure of the paper. Once I put together the final draft, Dr. Kinshuk reviewed it several times and suggested revisions and proposed modifications before submitting it to the journal. Dr. Kinshuk reviewed and approved the article one last time before submitting it to the journal.

This study provides an overview of current personalized adaptive learning practices and systems used to personalize and adapt learning and analyses current literature on self-efficacy. Furthermore, it analyzed what factors help increase inservice teachers' self-efficacy. The findings resulted in the proposal of a conceptual framework that is expected to guide personalized adaptive preservice teacher education to increase inservice teachers' self-efficacy. The proposed framework for personalized adaptive preservice teacher education is expected to be used as a tool for teacher education to improve teachers' self-efficacy and ultimately improve inservice teachers' and students' learning experience.

Also, this study proposed a framework that can be used in different settings with different scenarios. A step-by-step example for preservice teacher education is provided in this study to reflect its usage in learning environments. In this study, the proposed framework is focused on increasing inservice teachers' self-efficacy by providing personalized adaptive learning support, which is expected to improve self-efficacy and increase perseverance and efforts to learn new skills and acquire new knowledge. This study can be used as a reference for future research and preservice teacher education.

This fourth study's findings suggest that dynamic data collection requires dynamic adaptation, intervention, and correctness feedback to close any learning gaps or avoid losing interest in learning progress. We need to focus on preservice teacher education, as growing data has shown that efforts to improve preservice teacher education can significantly impact student learning.

The fifth paper is an empirical study that focused on validating the framework proposed in paper four by using the framework to analyze the pre and post-self-efficacy of two inservice teacher groups before personalized adaptive training. inservice teachers are selected as participants for this study since this framework is suggested to be used in different teacher education settings. Also, inservice teachers are primarily graduating from preservice education and can provide more comprehensive feedback on the framework's validity. This empirical study combined a few primary teacher self-efficacy instruments to modify them to fit current teacher groups best to get the most relevant one. This empirical study is research that I worked on with Dr. Kinshuk and Dr. Knezek. My contribution is centered on the introduction, literature review, methods, design of the study, data collection, data analysis, conclusion, discussion, and general structure of the paper. I got guidance and help from Dr. Knezek on instrument development and data analysis. Once I put together the final draft, Dr. Kinshuk reviewed it several times and suggested revisions and proposed modifications. Dr. Kinshuk reviewed and approved the article one last time before adding it to the dissertation.

Table 1.1

Author's Contributions to Each Manuscript

Chapter Number	Paper Name	Journal	Publication Status	My Contribution
2	A Systematic Literature Review of Personalized Learning Terms	*Smart Learning Environments*	Published (2020)	Contributed to design of the study, the literature review, decided on research methodology, and put together a draft to be reviewed by co-author.
3	Comprehensive Analysis of Personalized Learning Components	*Journal of Computers in Education.*	Published (2021)	Contributed to design of the study, literature review, and wrote whole paper draft to be reviewed by co-authors.
4	Factors Contributing to Teacher Self-Efficacy in Distance Learning	*Tech Trends*	Under review	Contributed to the introduction, literature review, methods, design of the study, discussion, conclusion, and general structure of the paper.
5	Developing a Framework for Personalized Adaptive Teacher Education to Improve Teachers' Self-Efficacy	*Jtate*	Preparing for resubmission	Contributed to the introduction, literature review, methods, design of the study, conclusion, discussion, developing framework, and general structure of the paper.
6	Empirical Study to Validate Framework	Not Yet Submitted	Preparing for submission	Contributed to the introduction, literature review, methods, design of the study, data collection, data analysis, conclusion, discussion, and general structure of the paper.

The collection of these five papers in the form of this dissertation aims to point out the need for personalized adaptive preservice teacher education and address how it might improve teachers' efficacy and provide a framework that can be used for personalized adaptive preservice teacher education and validate the framework through expert feedback and empirical study. This framework is based on previous studies and has many possible practical uses in educational settings. Primarily it can be used for preservice teacher education, formal inservice teacher education, and many more educational settings. Furthermore, this framework can be used for any educational activities that allow instructors to empower learners to be life-long learners.

This research is expected to be the foundation for future studies on personalized adaptive preservice teacher education. National Research Council (2000) pointed out that teachers are key to enhancing learning in schools. Therefore, we need to prepare our preservice teachers properly and support them with personalized adaptive education that focuses on their diverse needs. If we want to improve the learning experience of students, first, we need to make sure our teachers are provided with the opportunity to receive preservice teacher education and training according to their needs, so they are appropriately prepared to help and support their students with learning.

Current studies point out that teachers are the main determinants of instructional practice and student learning outcomes (Colson et al., 2018; Darling-Hammond, 2000; Depaepe & König, 2018; Jenset et al., 2018; Schleicher, 2016). Therefore, teachers need to be adequately prepared by providing them with personalized adaptive preservice teacher education to improve their self-efficacy beliefs regarding their teaching skills. Teachers' beliefs shape their teaching practices by filtering interpretations, framing situations or problems, and guiding actions (Heinonen et al., 2019). Considering Bandura's (1994) suggestion, self-efficacy beliefs determine how people feel, think, motivate themselves, and perform; it is paramount that preservice teachers have a strong sense of self-efficacy to help them maintain their interest in the profession of teaching and use those skills to help all students they teach (Gedzune, 2015, as cited in Colson et al., 2018).

Teaching is a stressful and high workload profession that will benefit from having good stress managing skills. Bandura (1997) pointed out that preservice teachers with repeated success feelings more successfully manage teaching stress. Preservice teachers need to feel connected and have a sense of self-efficacy for the responsibilities they face when teaching (Ryel et al., 2001, as cited in Colson et al., 2018). This research will also be the first to focus on personalized adaptive preservice teacher education.

Chapter References

Bandura, A. (1982). Self-efficacy mechanism in human agency. *American Psychologist*, *37*(2), 122–147. https://doi.org/10.1037/0003-066X.37.2.122

Bandura, A. (1994). Self-efficacy. In V. S. Ramachaudran (Ed.), Encyclopedia of human behavior (Vol. 4, pp. 71-81). New York: Academic Press. (Reprinted in H. Friedman [Ed.], Encyclopedia of mental health. San Diego: Academic Press, 1998).

Bandura, A. (1997). *Self-efficacy: the exercise of control.* New York: W. H. Freeman and Company.

Christensen, R., & Knezek, G. (2017). Validating the Technology Proficiency Self-Assessment Questionnaire for 21st Century Learning (TPSA C-21). *Journal of Digital Learning in Teacher Education*, *33*(1), 20–31. https://doi.org/10.1080/21532974.2016.1242391

Colson, T., Sparks, K., Berridge, G., Frimming, R., & Willis, C. (2018). Preservice Teachers and Self-Efficacy: A Study in Contrast. *Discourse and Communication for Sustainable Education*, *8*(2), 66–76. https://doi.org/10.1515/dcse-2017-0016

Commonwealth of Australia. (2007). Top of the class; A report on the inquiry into teacher education. Canberra, Australia: House of Representatives.

Darling-Hammond, L. (2000). Teacher quality and student achievement: A review of state policy analysis. *Education Policy Analysis Archives, 8*(1) -3 7. http://epaa.asu.edu/epaa/v8n 1 .html

Darling-Hammond, L., Chung, R., and Frelow, F. (2002). Variation in teacher preparation: How well do different pathways prepare teachers to teach? *Journal of Teacher Education, 53*(4), 286–302.

Depaepe, F., & König, J. (2018). General pedagogical knowledge, self-efficacy, and instructional practice: Disentangling their relationship in preservice teacher education. *Teaching and Teacher Education*, *69*, 177–190. https://doi.org/10.1016/j.tate.2017.10.003

Hattie, J. (2012). *Visible learning for teachers: Maximizing impact on learning*. London, UK: Routledge.

Heinonen, K., Jaaskela, P., Hakkinen, P., Isomaki, H., & Hamalainen, R. (2019). University Teachers as Developers of Technology-Enhanced Teaching: Do Beliefs Matter? *Journal of Research on Technology in Education*, *51*(2), 135–151.

Ingersoll, R. M. (2001). Teacher turnover and teacher shortages: An organizational analysis. *American Educational Research Journal, 38*(3), 499-534.

Ingersoll, R., Merrill, L., & May, H. (2014). *What Are the Effects of Teacher Education and Preparation on Beginning Teacher Attrition? Research Report* (#RR-82). Philadelphia: Consortium for Policy Research in Education, University of Pennsylvania.

Jenset, I. S., Klette, K., & Hammerness, K. (2018). Grounding Teacher Education in Practice Around the World: An Examination of Teacher Education Coursework in Teacher Education Programs in Finland, Norway, and the United States. *Journal of Teacher Education*, *69*(2), 184–197. https://doi.org/10.1177/0022487117728248

Levine, A. (2006). *Educating School Teachers.* Retrieved 16 August 2008 from http: www.edschools.org/pdf/Educating_Teachers_Report.pdf.

Mergler, A. G., & Spooner-Lane, R. (2012). What pre-service teachers need to know to be effective at values-based education. *Australian Journal of Teacher Education*, *37*(8), 66–81. https://doi.org/10.14221/ajte.2012v37n8.5

National Research Council. (2000). *How People Learn: Brain, Mind, Experience, and School: Expanded Edition.* Washington, DC: The National Academies Press. https://doi.org/10.17226/9853.

Natividad Beltrán del Río, G. (2021). A useful framework for teacher professional development for online and blended learning to use as guidance in times of crisis. Education Tech Research Dev 69, 7–9. https://doi.org/10.1007/s11423-021-09953-y

Naylor, D. A., Campbell-Evans, G., & Maloney, C. (2015). Learning to Teach: What Do Preservice Teachers Report. *Australian Journal of Teacher Education, 40*(11). http://dx.doi.org/10.14221/ajte.2015v40n11.7

Nel, L. (2017). Students as collaborators in creating meaningful learning experiences in technology-enhanced classrooms: An engaged scholarship approach. British Journal of Educational Technology, 48, 1131–1142. https://doi.org/10.1111/bjet.12549.

Okoli, C. (2015). A guide to conducting a standalone systematic literature review. *Communications of the Association for Information Systems*, *37*(1), 879–910. https://doi.org/10.17705/1cais.03743.

Opfer, V., Pedder, D., & Lavicza, Z. (2011). The role of teachers' orientation to learning in professional development and change: A national study of teachers in England. *Teaching and Teacher Education, 27,* 443-453. http://dx.doi.org/10.1016/j.tate.2010.09.014

Pane, J. F., Steiner, E. D., Baird, M. D., & Hamilton, L. S. (2015). Continued Progress: Promising Evidence on Personalized Learning. *Rand Corporation*, ERIC, https://eric.ed.gov/?id=ED571009

Ronfeldt, M., Schwarz, N., and Jacob, B. (2014). Does preservice preparation matter? Examining an old question in new ways. *Teachers College Record, 116*(10).

Roofe, C., & Miller, P. (2013). ""Miss I am not being fully prepared"": Student Teacher'sTeacher's concerns about their preparation at the training institution in Jamaica. *Australian Journal of Teacher Education, 38*(5), 1-13. https://doi.org/10.14221/ajte.2013v39n5.5

Schleicher, A. (2016). Teaching excellence through professional learning and policy reform. Paris, France: OECD.

Shemshack, A., & Davis, T. (2020). Validating the Distance Learning Support Survey. In E. Langran (Ed.), *Proceedings of SITE Interactive 2020 Online Conference* (pp. 282-293).

Siko, J. P., & Hess, A. N. (2014). Win-win professional development: Providing meaningful professional development while meeting the needs of all stakeholders. TechTrends, 58, 99–108. https://doi.org/10.1007/s11528-014-0809-7.

Thoma, J., Johnson, D., Johnson, K., & Stromer, E. (2017). Planning for technology integration in a professional learning community. The Reading Teacher, 71(2), 167–175. https://doi.org/10.1002/trtr.1604.

Wright, V. H., & Wilson, E. K. (2005). From preservice to inservice teaching: A study of technology integration. *Journal of Computing in teacher Education*, *22*(2), 49-55.

Xie, H., Chu, H. C., Hwang, G. J., & Wang, C. C. (2019). Trends and development in technology-enhanced adaptive/personalized learning: A systematic review of journal publications from 2007 to 2017. *Computers and Education*, *140*(June), 103599. https://doi.org/10.1016/j.compedu.2019.103599

CHAPTER 2

A SYSTEMATIC LITERATURE REVIEW OF PERSONALIZED LEARNING TERMS*

Abstract

Learning is a natural human activity shaped by personal experiences, cognitive awareness, personal bias, opinions, cultural background, and environment. Learning has been defined as a stable and persistent change in what a person knows and can do. Learning is formed through an individual's interactions, including the conveyance of knowledge and skills from others and experiences. So, learning is a personalized experience that allows one to expand their knowledge, perspective, skills, and understanding. Therefore, personalized learning models can help to meet individual needs and goals. Furthermore, to personalize the learning experience, technology integration can play a crucial role. This paper provides a review of the recent research literature on personalized learning as technology is changing how learning can be effectively personalized. The emphasis is on the terms used to characterize learning as those can suggest a framework for personalized and will eventually be used in meta-analyses of research on personalized learning, which is beyond the scope of this paper.

Keywords*: personalized learning, adaptive learning, learning, intelligent tutoring systems, learning analytics, personalized adaptive learning, systematic review.*

Introduction

Personalized learning has been a topic of research for a long time. However, around 2008, personalized learning started to draw more attention and take on a transformed meaning thanks to technology integration to enhance personalized learning became a hot topic for

---

* This chapter is reproduced in its entirety from Shemshack, A., & Spector, J.M. (2020), A systematic literature review of personalized learning terms. *Smart Learning Environments, 7*(33). https://doi.org/10.1186/s40561-020-00140-9. Originally published under Creative Commons CC BY 4.0 license. Authors retain copyright.

researchers, as seen in Table 2.1. However, I believe the variety of terms that have been used for personalized learning seems to be an obstacle to the progress of personalized learning theories and research. Although there is an abundance of resources/studies on personalized learning, not having a readily agreed-upon term of personalized learning might hinder research progress on personalized learning. In response to this need, this paper is focused on analyzing the terms that have been used for personalized learning. A distinct personalized learning approach can help educational researchers build up research on previous data instead of starting new research from scratch each time. This paper will present a research-based framework for personalized learning and discuss future research directions, issues, and challenges through an in-depth analysis of the definitions and terms used for personalized learning.

Personalized learning has existed for hundreds of years in the form of apprenticeship and mentoring. As educational technologies began to mature in the last half of the previous century, personalized learning took the form of intelligent tutoring systems. In this century, big data and learning analytics are poised to transform personalized once again. Learning has been characterized as a stable and persistent change in what a person knows and can do. Personalized learning is a complex activity approach that is the product of self-organization or learning and customized instruction that considers individual needs and goals. Personalized learning can be an efficient approach that can increase motivation, engagement, and understanding (Pontual et al., 2018), maximizing learner satisfaction, learning efficiency, and learning effectiveness (Gómez et al., 2014). However, while such personalized learning is now possible, it remains one of the biggest challenges in modern educational systems. In this paper, a review of progress in personalized learning using current technologies is provided. The emphasis is on personalized learning characteristics that need to be taken into consideration to have a well-developed concept of personalized learning.

We started with the definition of personalized learning suggested by Spector (2014, 2018) and others that are discussed below, which requires a digital learning environment to be classified as a personalized learning environment to be adaptive to individual knowledge, experience, and interests and to be effective and efficient in supporting and promoting desired learning outcomes. These characteristics are those which are typically discussed in the research community, although I found it challenging to find a sufficient number of published cases that reported effect sizes and details of the sample to conduct a formal meta-analysis. Lacking those cases suggests that personalized learning in the digital era is still in its infancy. As a result, I conducted a more informal, albeit systematic review of published research on personalized learning.

Furthermore, along with many educational technologists, we believe an efficient, personalized learning approach can increase learners' motivation and engagement in learning activities to improve learning results. While that outcome now seems achievable, it remains a mostly unrealized opportunity, according to this research review. Truong (2016) stated that providing the same content to students with different qualifications and personal traits and having different interests and needs is not considered adequate anymore when learning can now be personalized. Miliband (2006, as cited in Lee et al., 2018) promoted personalized learning to be the solution to tailoring the learning according to individuals' needs and prior experience to allow everyone to reach their maximum potential through customized instruction (Lin et al., 2013; Hsieh &Chen, 2016). The customized instruction includes what is taught, how it is taught, and the pace at which it is taught. This allows learning to meet individual needs, interests, and circumstances, which can be quite diverse (Liu & Yu, 2011; Brusilovsky & Peylo, 2003). Furthermore, FitzGerald et al. (2018) pointed out that the personalization of learning is now a recurring trend across government agencies, popular media, conferences, research papers, and technological innovations.

Personalized learning is in demand (Huang et al., 2012) due to new technologies involving big data and learning analytics. It should be tailored to and continuously modified to an individual learner's conditions, abilities, preferences, background knowledge, interests, and goals and adaptable to the learner's evolving skills and knowledge (Sharples, 2000). Today's personalized learning theories are inspired by educational philosophy from the previous century's progressive era, emphasis on experiential, learner-centered learning, social learning, an extension of the curriculum, and fitting for a changing world. McCombs and Whisler (1997; as cited in Lee et al., 2018) claimed that a learner-centered environment develops as it considers learners' unique characteristics using the best knowledge of teaching and learning which are available. Furthermore, Lockspeiser and Kaul (2016) claimed that individualized learning is a tool to facilitate learner-centered education. FitzGerald et al. (2018) pointed out that personalization is a crucial topic of current interest in technology-oriented learning design and discussion for government policymakers, but less so in educational research. This might be a good explanation of the disunity of personalized learning approaches.

On the other hand, Niknam and Thulasiraman (2020) argued that educational society has been interested in having a personalized learning system that adjusts the pedagogy, curriculum, and learning environment for learners to meet their learning needs and preferences. A personalized learning system can adapt itself when providing learning support to different learners to defeat the weakness of one-size-fits-all approaches in technology-enabled learning systems. The goal is to have a learning system that can dynamically adapt based on a learner's characteristics and provide personalized learning. Human one-on-one tutors can do this, and now digital systems can do so as well. Schmid and Petko (2019) pointed out that a look at international research literature shows that personalized learning is a multilayered construct with numerous definitions and various implementation forms. This supports my claim that one of the most critical problems with personalized learning is, there is no readily agreed-upon meaning of the phrase 'personalized learning.' Schmid and Petko (2019) supported this claim by stating that a clearly defined concept of personalized learning is still lacking; instead, it serves as an umbrella term for educational strategies that try to do justice to the individual's abilities, knowledge, and learning needs of each student. Spector (2013) claimed that there would be more robust information to support personalized learning as technology develops. So many different terms have been used in the replacement of 'personalized learning.' Researchers could not locate a systematic literature review on personalized learning terms that review the terms that have been used for personalized learning, and it is essential to address this need. Therefore, this review was done to close that gap and respond to the need for a unified, personalized learning term. As a result, personalized learning definitions and the terms that have been used interchangeably, such as adaptive learning, individualized instruction, and customized learning, are analyzed in this paper. These terms were chosen because they have been most used in the education field (Reisman, 2014). In the next several sections, each term will be defined, and their relationship with personalized learning will be discussed. The analysis of these terms guided the systematic review of the research literature that follows.

Adaptive Learning

Most educators recognize the advantages of adaptive learning, but evidence-based research stays limited, as adaptive learning is still evolving (Liu et al., 2017). Adaptive learning is one of the terms that has been used interchangeably with personalized learning. The adaptive learning system is built on principles that have been around for a very long time dating back to the era of apprenticeship training and human tutoring. However, many other labels such as individualized instruction, self-paced instruction, and personalized instruction were used interchangeably while trying to produce the most suitable sequence of learning units for each learner (Garcia et al., 2015; Reisman, 2014). While early forms of adaptive learning (e.g., apprenticeship training and human tutoring) only dealt with one or a very small number of learners, the current interest is using adaptive learning for large numbers of learners, which is why there is such interest in big data and learning analytics.

For instance, adaptive learning has been interchangeably used by Yang et al. (2013) in their study that focused on the development of adaptive learning by considering students' preferences (Dwivedi & Bharadwaj, 2013) and characteristics, including learning styles (Cakiroglu, 2014; Klašnja-Milićević et al., 2011) and cognitive styles (Lo et al., 2012) which concluded to be effective. Wang and Liao (2011) defined adaptive learning as a developed system to accommodate a variety of individual differences (Scheiter et al., 2019; Wang & Liao,2011) such as gender, learning motivation, cognitive type, and learning style to determine optimal adaptive learning experience that accommodates a variety of individual differences (Afini et al., 2019) to remove barriers of time and location. Griff and Matter (2013) discussed that adaptive learning is also referred to as computer-based learning, adaptive educational hypermedia, and intelligent tutoring. Furthermore, Hooshyar et al. (2015) used personalized and adaptive learning to explain the importance of the Intelligent Tutoring System (Aeiad & Meziane, 2019) for implementing one-to-one personalized and adaptive teaching. "Although the terms' personalized learning' and 'adaptive learning' are different, they are often used interchangeably in various studies" (Aroyo et al., 2006; Göbel et al., 2010; Gómez et al., 2014; Lin et al., 2013, as cited in Xie et al., 2019, p.2).

Based on this review, adaptive learning systems are defined as those that are computerized learning systems that adapt learning content, presentation styles, or learning paths based on individual students' profiles, learning status, or human factors (Chen, Liu, & Chang, 2006; Tseng et al., 2008; Yang et al., 2013).

Individualized Instruction

Individualized instruction is one of the terms that are often used to talk about individuals' specific needs and goals to be addressed during instruction. It is not agreed upon whether individualization is a component of personalized learning, or another term used in place of personalized learning. The review results show that instead of being a component, individualized instruction has been used as a replacement term for personalized learning and is a product of personalized learning. Bahceci and Gurol (2016) created a portal that offers individualized learning content based on the individual's cognitive knowledge level. Bahceci and Gurol (2016) stated that education should be done by recognizing the students' differences, such as students learning styles (Cakiroglu, 2014; Klašnja-Milićević et al., 2011) and characteristics. The researchers observed that Bahceci and Goral (2016) used individualized learning and personalized learning interchangeably without pointing out that they were doing so.

Also, most individualized learning studies have used individualized instruction to refer to IEP (individualized educational plans) for students with disabilities to accommodate their needs and goals. Even though individualized instruction is suggested as an approach that individualizes material to improve students' learning experience with learning disabilities, it can benefit all students (Barrio et al., 2017; Ko et al., 2011). Personalized learning considers students' interests, needs, readiness, and motivation and adapts to their progress by situating the learner at the center of the learning process. Individualized learning allows for individualization of learning based on the learner's unique needs (Lockspeiser & Kaul, 2016). While a learner-centered paradigm of education has influenced personalized learning, the current teacher-student ratios in school systems seem to be an obstacle to making learning experiences personalized for individual students without technology (Lee et al., 2018), except for the requirement for IEPs in many school districts.

Customized Learning

While Lee et al. (2018) suggested a learner-centered system that supports the diverse needs and development of individual learners' potentials. This system develops customized instructional methods and learning content for individual learners with unique characteristics and interests. Lee et al. (2018) suggested that learner-centered learning and personalized learning are blended and considered together. Lee et al. (2018) defined a personalized learning plan (PLP) that refers to a customized instructional plan (Somyurek, 2015) that considers individual differences and needs, characteristics, interests, and academic mastery. The PLP includes the notions of individualization, differentiation, and personalization that allows learning to be personally relevant, engaging, appropriate to the learners' capabilities, and respectful of individual differences, making learning useful and motivational.

The review of those three terms reveals a great deal of overlap, emphasizing the need to use technology to support such efforts. This study reviews definitions of personalized learning terms used in research papers from 2010 to 2020 by systematically reviewing the literature to compare the similarities and differences in definitions of each of these terms. The hope is to synthesize the terms used for personalized learning to analyze and go through the research in the field and conduct meta-analyses and syntheses of the research literature. Also, analyzing the definitions of the term ‘personalized learning,’ ‘adaptive learning,’ ‘individualized instruction,’ and ‘customized learning’ that have been used can help develop a unified definition for personalized learning that can lead to a framework. The framework can help with having a shared understanding of personalized learning rather than a collection of loosely defined systems. A unified description of personalized learning and analyzing the studies related to personalized learning can help consolidate findings and suggest new areas to explore.

My idea of personalized learning rests on the foundation that humans learn through experience and by constructing knowledge. Personalized learning is influenced by a learner’s prior experiences, backgrounds, interests, needs, goals, and motivation. Moreover, it is accomplished via meaningful interactions in individual learners’ lives. Furthermore, no conscious effort is needed to be actively learning while engaged in everyday life (Kinshuk, 2012), although reflection and mega-cognition can promote learning.

Adaptive instruction, blended instruction, differentiation, customized instruction, individualized learning, adaptive learning, proactive supports, real-world connections, and applications are hallmarks of good personalized learning. In general, personalized-learning models seek to adapt to the pace of learning and the instructional strategies, content, and activities used to fit each learner’s strengths, weaknesses, and interests. Personalized learning is about giving students some control over their learning (Tomberg et al., 2013; Benhamdi et al., 2017; Jung et al., 2019), differentiating instruction for each learner, and providing real-time individualized feedback to teachers and learners (Nedungadi & Raman, 2012), which is all effortlessly blended throughout the learning activity. Putting a framework together can help with a practical personalized learning model for all. The model can be developed and evolved as technology develops, and we learn more about human learning and machine learning.

Research Methodology

For this review, Okoli's guidelines for conducting a systematic literature review for Information Systems Research were adapted (Okoli, 2015). Okoli's work provides a detailed framework for writing a systematic literature review with its information technology roots. As this systematic literature review is rooted in information technology, it was deemed appropriate to use Okoli's work as the basis for this body of work.

Okoli presented eight significant steps that need to be followed to conduct a scientifically rigorous systematic literature review. These steps are listed below:

1. Identify the purpose: The researchers identified the purpose and intended goals of the study to ensure the review is clear to readers.

2. Draft protocol and train the team: Reviewers agreed on procedures to follow to ensure consistency in completing the review.

3. Apply practical inclusion screen: Reviewers were specific about what studies they considered for review and which ones they eliminated without further examination. The reviewers created four phases to review papers to produce the final papers to review.

4. Search for literature: Reviewers described the literature search details and justified how they ensured the search's comprehensiveness.

5. Extract data: After reviewers identified all the studies to be included in the review, they systematically extract the applicable information from each study by going through four review phases they explained in the search query.

6. Appraise quality: The reviewers explicitly listed the criteria used to decide which papers they will exclude for insufficient search query quality. Researchers reviewed all papers and decided on final papers after explicit four search phases. They finalized the papers to be reviewed, depending on the content of the papers' content and quality.

7. Synthesize studies: The researchers analyzed the data obtained from the studies using appropriate qualitative techniques.

8. Write the review: The process of a systematic literature review was explicitly described in adequate detail that other researchers could independently reproduce the review's results.

Research Questions

This literature review promotes research on personalized learning in informational education. To fulfill the answer to "What are the similarities and differences of different terms used for personalized learning approaches?" we need a research base and theoretical framework that provides answers to basic questions. Furthermore, the following questions are sub-questions to be considered during the study.

1. How is personalized learning defined?
2. How adaptive learning has been used, and how it relates to personalized learning?
3. How individualized instruction has been used, and how it relates to personalized learning?
4. How is customized learning connected to personalized learning?
5. What components need to be included in a well-defined personalized learning term?

Also, researchers are seeking a unified definition of personalized learning that will include all those different components. That is the focus of this literature review was conducted.

Sources of Literature

To answer the research question, the researchers have selected the following well known and reputable databases to base this literature review: Scopus, Science Direct, EBSCOhost, IEEE Xplore, JSTOR, and Web of Science to ensure all related journals of the field are included. The most relevant journals for the systematic review were chosen consistently from these databases. Also, Google Scholar h5-index for the category" Educational technology" was used as the starting point since this category is a specific category for personalized learning studies. Databases in which the literature review is based are listed in Table 2.1.

Table 2.1

Search Results for "Personalized Learning" for Selected Databases

Database Name	#	Main Journals Listed (#articles)
EBSCOhost	4372	Computers & Education (130) Journal of Educational Technology & Society (72) Educational Technology Research and Development (53) Interactive Learning Environments (48) Computers in Human Behavior (43) International Journal of Emerging Technologies in Learning (36) British Journal of Educational Technology (33) Journal of Computer Assisted Learning (33)
Scopus	1826	Computers and Education (18) Computers in Human Behavior (10) Educational Technology Research and Development (10) Education and Information Technologies (9) Interactive Learning Environments (8)
Science Direct	796	Computers and Education (121) Procedia-Social and Behavioral Science (80) Computers in Human Behavior (68) Procedia Computer Science (58)
Web of Science	451	International Journal of Emerging Technologies in Learning (30) Computers Education (18) Educational Technology Society (16) Computers in Human Behavior (10) Educational Technology Research and Development (10)

(table continues)

Database Name	#	Main Journals Listed (#articles)
IEEE Xplore	426	Conference Proceedings (398) IEEE Access (7) IEEE Transactions on Learning Technologies (4) IBM Journal of Research and Development (2) IEEE Transactions on Emerging Topics in Computing (2)
JSTOR	241	Educational Technology & Society (102) Educational Technology (32) Educational Technology Research and Development (29)

The top nine journals from the "Educational Technology" category from Google Scholar h5-index were selected to keep the range of the papers manageable while ensuring the review is broad enough to include enough studies that can satisfactorily answer the research question. Later, most of the journals about educational technology were indexed. SJR (Scimago Journal Rank) was used to validate the impact of the selected journals. Even though the impact factor is not perfectly aligned with Google Scholar's h5-index order, the selected journals listed the most impactful journals in the educational technology field. Also, even though the Journal of Learning Analytics was listed on Google Scholar and showed having a high impact on education technology, researchers have not located any qualified paper according to selection procedures; thus, this journal was eliminated from review.

This review solely retrieved peer-reviewed article papers from online journals because those online academic journals are reliable and authoritative. They allow the readers to verify the facts from their sources, which increases the reliability of enriched studies filled with data and facts. They enable the readers to perform comprehensive research and allow the reader to access more data without the limitations of space and time. A defined method was set in this research for selecting journals to keep the process methodologically reliable and scientifically consistent. The researchers review the primary databases for educational technology to ensure all related journals are included. This review is only focused on journals to keep the scope of the review manageable and provide reviewed data to create a resource for future studies. Journals on which to base this literature review are listed in Table 2.2.

Table 2.2

Google Scholar h5-Index and Journal Impact for Selected Journals

Journal Name	h5-Index & List Order	SJR Impact Factor
Computers & Education	1-94	2.323
British Journal of Educational Technology	2-56	1.419
The International Review of Research in Open and Distributed Learning	3-54	1.202
The Internet and Higher Education	4-50	3.307
Journal of Educational Technology & Society	5-49	1.085
*Journal of Learning Analytics	6-36	1.072
Journal of Computer Assisted Learning	7-34	1.382
Education and Information Technologies	8-34	0.598
Educational Technology Research and Development	9-34	0.98

Supplementary Procedures

Relevant papers were initially identified through traditional searches of online databases and journals. These papers were subsequently analyzed to determine their applicability to the study.

Search Query

An appropriate search query was formulated that would find relevant, personalized learning papers. The search query was as follows: (Publication Title :("journal name")) AND ("term") and the journals listed in the table were searched for each of the following terms: "personalized learning, "adaptive learning," individualized instruction," and "customized learning."

Inclusion/Exclusion Criteria

Four phases were determined to meet the paper's inclusion criteria in the final set to be reviewed. First phase was initial search, searching each term 'personalized learning,' 'adaptive learning,' 'individualized instruction,' 'customized learning,' filtered years to 2010-2020 to review personalized learning papers, which has been a hot topic for the research and policymakers. The language was filtered to *English only* to not wait on translation; the paper addressed *technology integration* and type of the paper *research articles* published in one of the peer-reviewed scientific journals listed to keep the scope manageable. The second search phase was eliminated by title, reviewing the abstract and keywords; researchers went through titles, abstracts, and keywords of each result of the initial search and looked at the term.

The next search phase, reading the abstract of each paper of the second search result-set, looking for a definition to see if it mentions the definition and/or terms that have been used for the term and the paper was available at one of the free online databases or the researchers' university library. The fourth step was to download all those papers to Mendeley (indexing database) and index them under sub-folders for each journal database. The entire paper was then read to determine if the paper was to be included in the literature review by looking for components and definitions of personalized learning and star the ones to be included in the review. Each paper that met the inclusion criteria was read in its entirety a second time to validate the paper's decision in the final data set.

An initial search on Google Scholar on 'personalized learning' shows that the number of published papers on personalized learning has progressively increased year by year; especially there is a jump in 2008 (see Figure 2.1). The date range of 2010 to the present day was chosen as this when personalized learning terms started to gain more attention to research due to technology usage increase in education. The first smartphone was released in June 2007, which might increase due to the flexibility and access it provides. Cheung and Hew (2009) claimed that handheld devices are increasingly being used in educational settings. Primarily, papers published after the 2000s are focused on more technology-enhanced personalized learning. Table 2.3 shows the results of the initial Google Scholar search on *"personalized learning"* published papers.

Figure 2.1

Number of Published Papers on "Personalized Learning"

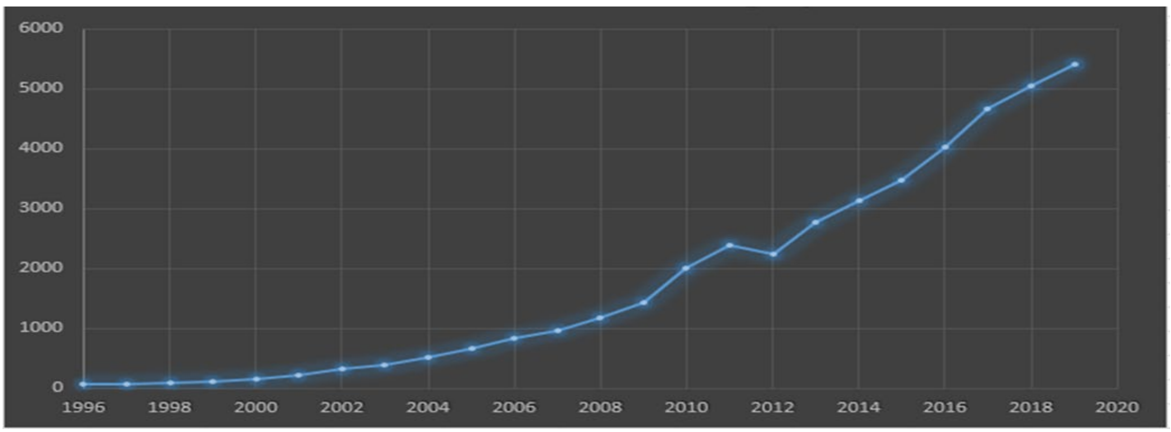


Table 2.3

Journal Articles Containing "Personalized Learning" during Each Research Phase (#)

Journal Name	Initial Search	Phase 1	Phase 2	Final Count
1. Computers & Education	121	32	10	9
2. British Journal of Educational Technology	82	6	3	1
3. The International Review of Research in Open and Distributed Learning	33	5	3	3
4. The Internet and Higher Education	11	1	1	0
5. Journal of Educational Technology & Society (ET&S)	102	18	6	6
6. *Journal of Learning Analytics	0	0	0	0
7. Journal of Computer Assisted Learning	35	7	3	3
8. Education and Information Technologies	91	25	8	8
9. Educational Technology Research and Development	59	13	5	3
TOTAL	534	107	38	33

Results

Nine journals were determined as the source of papers to be reviewed for this study. Each journal was searched for “personalized learning,” “adaptive learning,” “individualized instruction,” “customized learning,” and each result gone through the inclusion criteria and final phase; papers were saved in Mendeley under subfolders for each journal. Below are search results for each phase by journals.

The title, abstract, and when necessary, the full paper was reviewed to decide if the paper met the inclusion criteria. This process helped to finalize the papers that were used for this study, and the result set for “personalized learning” and the result set for each term to be reviewed is shown in Table 2.3. Some of the papers that did not fit the inclusion criteria are referenced in this paper as they provide valuable information about personalized learning. I reviewed 978 papers, and 4 phases of inclusion ended up with 56 relevant, high-quality papers. The 56 papers identified are marked in the references section with an asterisk. The systematic review methodology was used, and the literature search resulted in 56 relevant studies meeting the inclusion criteria. As shown in Table 2.4, 56 papers met the minimum quality criteria and were examined in detail; 33 of them use personalized learning, 17 adaptive learning, three individualized instruction, and three customized learning as the leading term in the paper.

Findings revealed that although so many terms are used in education settings, by policymakers and cooperate settings, in the research field, the terms used for personalized learning are unified, and mostly personalized learning and/or adaptive learning is being used. For example, Peng et al. (2019) are the ones who put the two most common terms used for personalized learning together and started to use “personalized adaptive learning,” which might be a good lead for future studies. Future research needs to focus on components included in the personalized adaptive learning term's definition, and components are included in it. Peng et al. (2019) s paper was put all together very well, and Peng et al. (2019) called it a personalized adaptive smart learning environment. Future studies can focus on what components are being used for each personalized learning approach and, at the same time, acknowledge it is a term that will evolve over time as I learn more about human learning and as technology development. Table 2.4 shows the results of the searches for each term by journals.

Table 2.4

Journal Articles Containing "Personalized Learning," "Adaptive Learning," "Individualized Instruction," and "Customized Learning" (#)

Journal Name	"Personalized Learning."	"Adaptive Learning."	"Individualized Instruction."	"Customized Learning."
1. Computers & Education	9	6	0	0
2. British Journal of Educational Technology	1	4	0	0
3. The International Review of Research in Open and Distributed Learning	3	1	0	3
4. The Internet and Higher Education	0	0	0	0
5. Journal of Educational Technology & Society (ET&S)	6	3	2	0
6. International Conference on Learning Analytics and Knowledge/Journal of Learning Analytics	0	0	0	0
7. Journal of Computer Assisted Learning	3	0	0	0
8. Education and Information Technologies	8	2	0	0
9. Educational Technology Research and Development	3	1	1	0
TOTAL: 56	33	17	3	3

Existing and Emerging Trends

Miliband (2006, as cited in Schmid & Petko, 2019) pointed out that the Organisation for

Economic Co-operation and Development OECD (2006) was among the first to use personalized learning term and described personalized learning in the report "Schooling for Tomorrow–Personalising Education" as a critical trend. According to this educational policy report, personalized learning is characterized by changes concerning five dimensions: assessment for learning by giving students individual feedback and setting suitable learning objectives, teaching, and learning strategies based on the individual needs, curriculum choices (Tomberg et al., 2013), student-centered approach to school organization, and strong partnerships beyond the school.

According to the United States National Education Technology Plan 2017, personalized learning is defined as "instruction in which the pace of learning and the instructional approach are optimized for each learner's needs. Learning objectives, instructional strategies, and instructional content (Shute & Rahimi, 2017) may differ depending on learner needs. Besides, learning activities are meaningful and relevant to learners, driven by their interests, and often self-initiated." (p. 9).

American Psychological Association Presidential Task Force on Psychology in Education (1993, as cited in Lee et al., 2018) explained that a personalized learning plan (PLP) refers to a customized instructional plan that considers individual differences or needs such as career goals, characteristics, interests, and academic mastery. This includes the notions of individualization, differentiation, and personalization. Preparing and implementing PLPs allows for adjusting the pace to individual learners, adjusting instructional methods to individual characteristics, and having different learning goals tailored to individual interests. Furthermore, Sungkur et al. (2016) suggested an eye-tracking system to determine the user's interest and behavior. The PLPs allow learning to be personally relevant, engaging, appropriate to the learners' capabilities, and respectful of individual differences, making learning useful and motivational.

Learning analytics seems to grow to ensure personalizing the content, which allows mechanisms to identify student characteristics and associate them with a learning pattern (Ramos de Melo et al., 2014). The ability to reactively organize personalized content may be a favorable factor in promoting the study support in virtual learning environments, respecting students' different individualities, preferences (Erumit & Cetin, 2020), and difficulty factors.

There is a research gap in an adaptive learning environment that focuses on emotions and personality, which play a significant role in parts of adaptive systems, such as feedback (Fatahi, 2019). Furthermore, Junokas et al. (2019) created a system based on multimodal educational environments that integrate gesture-recognition systems and found that it effectively improves the learning experience.

The personalization of learning has been achieved using various methods that have been made available by the rapid development of information communication technology (ICT) (Dawson et al., 2010). Furthermore, Ramos de Melo et al. (2014) stated that personalization is customizing the content that allows the present parts of the content needed by the student. That is one of the most common themes among most personalized learning approaches, which can be done using adaptive learning systems that can present personalized content for individual students (Hwang et al., 2013).

The higher-order thinking skills and communication had attracted little attention in terms of both learning outcomes and the process of adaptive/personalized learning due to the difficulty of measurement and the limited learning support types. Furthermore, virtual reality techniques might be a solution to this need. Developing learning approaches that build on students' current ability and support efficacy beliefs allows autonomy with a proper challenge to promote academic attainment (Foshee et al., 2016; Xie et al.,2019). Future studies can focus on higher order thinking skills cultivation by supporting these skills through personalized learning environments.

Discussion

The idea of personalized learning rests on the foundation that humans learn through experience and by constructing knowledge. It is heavily influenced by a learner's prior experiences and is accomplished via language and social interaction. Personalized learning is not the only way to think about teaching and learning. Moreover, learning will and should take many different forms. Proper instruction, blended instruction, differentiation, proactive supports, real-world connections, and applications are hallmarks of good, sound personalized learning. In general, personalized-learning models seek to adapt to the pace of learning and the instructional strategies, content, and activities used to fit each learner's strengths, weaknesses, and interests. Personalized learning is about giving students control over their learning, differentiating instruction for each child, and providing real-time feedback. Putting a framework together can help with practical personalized learning for all and can be developed as it faces challenges. The framework can help with having a structured common-sense personalized learning instead of a learning system interpreted differently. In conjunction with a well-designed curriculum, instructional practice plays a crucial role in how children learn.

Most of the current personalized learning models/ideas are built on technology integration. For example, while Chen et al. (2005) proposed a personalized system that provides learning paths (Nabizadeh et al., 2020) that can be adapted to various levels of difficulty of course materials (Zou & Xie, 2018) and various abilities of learners (p. 239). Klašnja-Milićević et al. (2011) stated that personalized learning occurs when e-learning systems make deliberate efforts to design educational experiences (Flores et al., 2012) that fit the needs, goals, talents, motivations, and interests of their learners (p. 885). The term of needs is not specified to clarify what needs of the learner need to be considered for robust personalized learning. Considering the needs of the learner is one of the most common components used in personalized learning. However, only a few studies clarify what needs are mentioned to be considered, such as emotional needs, social needs, learning needs, knowledge needs, etc. Even if we agree on a unified definition with each component commonly agreed on, we need to ensure that each component is well defined.

In the past decades, many methods and systems have been proposed to accommodate students' needs by proposing learning environments that consider personal factors. Learning styles (Klašnja-Milićević et al., 2011; Latham et al., 2013; Cakiroglu, 2014) have been among the broadly chosen components in previous studies as a reference for adapting learning. For example, George and Lal (2019) argued that personalized learning is meant to incorporate a learner's varied attributes, including learning style, knowledge level on a subject, preferences, and learner's prior knowledge while they discussed adaptive learning is adapting content according to learner's choice and pace. Chen et al. (2016) brought up the gender component to personalized learning. Furthermore, Atkinson (2006) found that there was a significant difference in learning achievement between male and female students and among students who used different learning styles (Klašnja-Milićević et al., 2011; Latham et al., 2013, Cakiroglu, 2014).

Findings revealed that individualized instruction mostly focuses on special education students, or students are limited compared to their peers. These students have IEPs (individualized educational plans) mandated by the state to be followed to ensure the schools are accommodating these students' needs. One goal could be to create IEPs for all learners.

Moreover, it seems in the education industry terms are quite varied, but when it comes to academia, it is mostly adaptive learning and personalized learning being used interchangeably Rastegarmoghadam and Ziarati (2017); however, most adaptive learning is being used when it is technology-enhanced learning. Adaptivity is typically referring to the content being adjusted according to prior knowledge (Huang & Shiu, 2012), while personalized learning is being used for more broad adjustments according to different needs, interests, and goals of individuals.

Another finding is that adaptive learning is the most used term that follows personalized learning. Individualized learning and customized learning, even though they are being used by cooperative, they are not commonly used in research. As shown in Table 2.5, I have found 56 papers met the minimum quality criteria and were examined in detail; 33 of them use personalized learning, 17 adaptive learning, three individualized instruction, and three customized learning.

However, it seems that also the lack of a commonly identified personalized learning approach is an obstacle. This might be due to the nature of technology involvement due to the rapid development increase in technology that makes personalized learning an evolving approach. That is fine if we all can agree that it should evolve as technology improves, and we learn more about humans and how human-machine interaction can improve the learning process.

Another obstacle is that the researchers and policymakers should show the same interest in personalized learning so the demand and research can align. Educators fear that machines will take over the teaching job if they allow technology to be used for teaching. Kinshuk et al. (2013) argued that the benefits of technology in education caught the interest of researchers, governments, and funding agencies. Computer systems were funded to help students in the learning process, consequently decreasing teachers' workload. As a result, educational technology research was able to study advanced issues such as intelligent tutoring, simulations, advanced learning management systems, automatic assessment systems, and adaptive systems. Some educators believe that since technology involves big budgets, policymakers' interest is not due to the interest of improving the learning experience (Troussas et al., 2020); their interest is due to the monetary benefit they gain from increased use of technology in education. Also, Kinshuk et al. (2013) pointed out that practitioners in education could not take advantage of all that research at an equally fast pace, and the implementation lagged severely behind. Researchers need to keep up with the demand for personalized learning. The alignment will help ensure the practices policymakers discuss are research-based efficient approaches that will increase learning/teaching efficiency.

The research progress in personalized learning shows that by technological improvement, personalized learning becomes more embedded with technology and taking advantage of the benefits technology can offer. Some of these advantages are gathering data of learners' emotions using bio-trackers, which might bring up some privacy concerns.

Limitations

This study encountered several shortcomings during the review and in its attempt to answer all the research questions. The enormous number of published papers might lead to missing relevant papers; numerous literature review studies face this problem. Furthermore, the effort to construct a search by identifying the keywords is crucial for the search process. The keyword determination method was conducted using a snowballing process to identify the reflections or keywords relevant to this study. Overlooking articles by omitting relevant information or keyword combinations is likewise possible due to the limited time frame.

Nevertheless, this study also faces the possible limitation caused by the selection criteria.

For example, this study focused on only journal articles and was limited to only documents written in English. Therefore, other pertinent articles that are not written in English and were not published in journals might not have included.

Summary

This study found and analyzed 56 relevant studies based on the research protocol. This study's findings support that adaptive/personalized learning has become a fundamental learning paradigm in the research community of educational technologies. Firstly, the findings are presented as they relate to the R.Q. (Research Question) s; then, the future direction and limitations are discussed. The SLR results show that using personality traits and their identification techniques has an enormously positive influence in adaptive learning environments. This study is related to several significant domains of psychology, education, and computer science. It likewise reveals the integration of personal traits in the adaptive learning environment, which involves many personality traits and identification techniques that can influence learning. Also, it found that there is an increase of interest in two areas that are oriented towards the incorporation and exploration of significant data capabilities in education: Educational Data Mining (EDM) and Learning Analytics (LA) and their respective communities (Papamitsiou and Economides, 2014) which seems to add another perspective to personalized learning and make it easier modify the learning according to individuals.

Personalized learning models gain more attention from governments and policymakers than educators and researchers. We need to focus on the obstacles of lack of interest to motivate the educators and researchers, the field experts, to voice their concerns and look for solutions to come up with a robust personalized learning model that will satisfy both instructor and learners' expectations. Personalized learning cannot be a solution to learning until it is defined as better and developed more thoroughly. Personalized learning for everyone looks different according to the needs and goals of the individual. Ennouamani et al. (2020) argued that learners are different in terms of their needs, knowledge, personality, behavior (Pliakos et al., 2019), preferences, learning style, culture, and the parameters of the mobile devices that they use. Furthermore, the researchers and educators' increasing involvement in proposing personalized learning approaches can increase trust towards the ICT supported personalized learning models.

In this review study, some critical research questions were answered, including the issues with different terms that have been used for personalized learning, components of personalized learning, and obstacles to the development of personalized learning. We need more research to be done about personalized learning. We also need the involvement of experts in the field, educators, pedagogues, researchers, software engineers, and programmers to create teams to work on the same goal to produce stable, unified, personalized learning systems/models.

Also, some research issues and potential future development directions are discussed. According to the discussions and results, it was found that adaptive/personalized learning systems seem to evolve as technology develops; however, a unified agreement on the components needs to be included in personalized learning models still needed. These components may evolve as we learn more about human-machine interaction and learn to take advantage of the technology to improve learning experiences. I suggest that researchers might use the consolidated terms of this review to guide future meta-analyses of the impact of personalized learning on student learning and performance.

To sum up, this study discusses the potential obstacles to personalized learning and practical solutions for these issues. Different components used for personalized learning models were discussed, and personalized learning evolves as technology develops, and we learn more about human-machine interaction.

Chapter References

Aeiad, E., & Meziane, F. (2019). An adaptable and personalized elearning system applied to computer. *Education and Information Technologies*, *78*, 674–681.

Afini Normadhi, N. B., Shuib, L., Md Nasir, H. N., Bimba, A., Idris, N., & Balakrishnan, V. (2019). Identification of personal traits in adaptive learning environment: Systematic literature review. *Computers and Education*, *130,* 168–190.

Atkinson, S. (2006). Factors influencing successful achievement in contrasting design and technology activities in higher education*. International Journal of Technology and Design Education, 16,* 193–213.

Bahçeci, F., & Gürol, M. (2016). The Effect of Individualized Instruction System on the Academic Achievement Scores of Students. *Education Research International*, *2016*, 1–9.

Barrio, B. L., Miller, D., Hsiao, Y. J., Dunn, M., Petersen, S., Hollingshead, A., & Banks, S. (2017). Designing Culturally Responsive and Relevant Individualized Educational Programs. *Intervention in School and Clinic*, *53*(2), 114–119.

Benhamdi, S., Babouri, A., & Chiky, R. (2017). Personalized recommender system for e-Learning environment. *Education and Information Technologies*, *22*(4), 1455–1477.

Brusilovsky, P., & Peylo, C. (2003). Adaptive and intelligent web-based educational systems. *International Journal of Artificial Intelligence in Education 13*, 156-169.

Çakıroğlu, Ü. (2014). Analyzing the Effect of Learning Styles and Study Habits of Distance Learners on Learning Performances: A Case of an Introductory Programming Course. *International Review of Research in Open and Distance Learning*, *15*(4), 161–185.

Chatti, M. A., Jarke, M., & Specht, M. (2010). The 3P learning model. *Educational Technology and Society*, *13*(4), 74–85.

Chatti, M. A., & Muslim, A. (2019). The PERLA framework: Blending personalization and learning analytics. *International Review of Research in Open and Distance Learning*, *20*(1), 244–261.

Chen, S. Y., Huang, P. R., Shih, Y. C., & Chang, L. P. (2016). Investigation of multiple human factors in personalized learning. *Interactive Learning Environments, 24*(1), 119–141.

Chen, C. M., Lee, H. M., & Chen, Y. H. (2005). Personalized e-learning system using item response theory. *Computers & Education, 44*(3), 237–255.

Chen, C. M., Liu, C. Y., & Chang, M. H. (2006). Personalized curriculum sequencing utilizing modified item response theory for web-based instruction. *Expert Systems with Applications*, 30(2), 378-396.

Cheung, W. S., & Hew, K. F. (2009). A review of research methodologies used in studies on mobile handheld devices in K-12 and higher education settings. *Australasian Journal of Educational Technology, 25*(2), 153-183.

Chou, C. Y., Lai, K. R., Chao, P. Y., Lan, C. H., & Chen, T. H. (2015). Negotiation based adaptive learning sequences: Combining adaptivity and adaptability. *Computers and Education*, *88*, 215–226.

Dawson, S., Heathcote, L., & Poole, G. (2010). Harnessing ICT potential: The adoption and analysis of ICT systems for enhancing the student learning experience. *International Journal of Educational Management, 24*(2), 116–128.

Dwivedi, P., & Bharadwaj, K. K. (2013). Effective trust-aware E-learning recommender system based on learning styles and knowledge levels. *Educational Technology and Society*, *16*(4), 201–216.

Dwivedi, P., Kant, V., & Bharadwaj, K. K. (2018). Learning path recommendation based on modified variable length genetic algorithm. *Education and Information Technologies*, *23*(2), 819–836.

Ennouamani, S., Mahani, Z., & Akharraz, L. (2020). A context-aware mobile learning system for adapting learning content and format of presentation: design, validation, and evaluation. *Education and Information Technologies*.

Erümit, A. K., & Çetin, İ. (2020). Design framework of adaptive intelligent tutoring systems. *Education and Information Technologies*.

Fatahi, S. (2019). An experimental study on an adaptive e-learning environment based on learner's personality and emotion. *Education and Information Technologies*, *24*(4), 2225–2241.

FitzGerald, E., Kucirkova, N., Jones, A., Cross, S., Ferguson, R., Herodotou, C., Hillaire, G., & Scanlon, E. (2018). Dimensions of personalisation in technology-enhanced learning: A framework and implications for design. *British Journal of Educational Technology*, *49*(1), 165–181.

Flores, R., Ari, F., Inan, F. A., & Arslan-Ari, I. (2012). The impact of adapting content for students with individual differences. *Educational Technology and Society*, *15*(3), 251–261.

Foshee, C. M., Elliott, S. N., & Atkinson, R. K. (2016). Technology-enhanced learning in college mathematics remediation. *British Journal of Educational Technology*, *47*(5), 893–905.

Garcia-Cabot, A., De-Marcos, L., & Garcia-Lopez, E. (2015). An empirical study on m-learning adaptation: Learning performance and learning contexts. *Computers and Education*, *82*, 450–459.

George, G., & Lal, A. M. (2019). Review of ontology-based recommender systems in e-learning. *Computers and Education*, *142* (July), 103642.

Gómez, S., Zervas, P., Sampson, D. G., & Fabregat, R. (2014). Context-aware adaptive and personalized mobile learning delivery supported by UoLmP. *Journal of King Saud University - Computer and Information Sciences*, *26*(1), 47–61.

Griff, E. R., & Matter, S. F. (2013). Evaluation of an adaptive online learning system. *British Journal of Educational Technology*, *44*(1), 170–176.

Hooshyar, D., Ahmad, R. B., Yousefi, M., Yusop, F. D., & Horng, S. J. (2015). A flowchart-based intelligent tutoring system for improving problem-solving skills of novice programmers. *Journal of Computer Assisted Learning*, *31*(4), 345–361.

Hooshyar, D., Ahmad, R. B., Yousefi, M., Fathi, M., Abdollahi, A., Horng, S. J., & Lim, H. (2016). A solution-based intelligent tutoring system integrated with an online game-based formative assessment: development and evaluation. *Educational Technology Research and Development*, *64*(4), 787–808.

Hsieh, C. W., & Chen, S. Y. (2016). A cognitive style perspective to handheld devices: Customization vs. personalization. *International Review of Research in Open and Distance Learning*, *17*(1), 1–22.

Huang, S. L., & Shiu, J. H. (2012). A user-centric adaptive learning system for e-learning 2.0. *Educational Technology and Society*, *15*(3), 214–225.

Hwang, G. J., Sung, H. Y., Hung, C. M., & Huang, I. (2013). A learning style perspective to investigate the necessity of developing adaptive learning systems. *Educational Technology and Society*, *16*(2), 188–197.

Hwang, G. J., Sung, H. Y., Hung, C. M., Huang, I., & Tsai, C. C. (2012). Development of a personalized educational computer game based on students' learning styles. *Educational Technology Research and Development*, *60*(4), 623–638.

Jung, E., Kim, D., Yoon, M., Park, S., & Oakley, B. (2019). The influence of instructional design on learner control, sense of achievement, and perceived effectiveness in a supersize MOOC course. *Computers and Education*, *128*(October 2018), 377–388.

Junokas, M. J., Lindgren, R., Kang, J., & Morphew, J. W. (2018). Enhancing multimodal learning through personalized gesture recognition. *Journal of Computer Assisted Learning*, *34*(4), 350–357.

Kinshuk. (2012). Guest editorial: Personalized learning. *Educational Technology Research and Development*, *60*(4), 561–562.

Kinshuk, Huang, H.-W., Sampson, D., & Chen, N.-S. (2013). Trends in Educational Technology through the Lens of the Highly Cited Articles Published in the Journal of Educational Technology and Society. *Educational Technology & Society, 16* (2), 3–20.

Klašnja-Milićević, A., Vesin, B., Ivanović, M., & Budimac, Z. (2011). E-Learning personalization based on hybrid recommendation strategy and learning style identification. *Computers and Education*, *56*(3), 885–899.

Ko, C. C., Chiang, C. H., Lin, Y. L., & Chen, M. C. (2011). An individualized e-Reading system developed based on multirepresentations approach. *Educational Technology and Society*, *14*(4), 88–98.

Latham, A., Crockett, K., & McLean, D. (2014). An adaptation algorithm for an intelligent natural language tutoring system. *Computers and Education*, *71*, 97–110.

Lee, D., Huh, Y., Lin, C. Y., & Reigeluth, C. M. (2018). Technology functions for personalized learning in learner-centered schools. In *Educational Technology Research and Development 6*(5).

Lin, C. F., Yeh, Y. C., Hung, Y. H., & Chang, R. I. (2013). Data mining for providing a personalized learning path in creativity: An application of decision trees. *Computers and Education*, *68*, 199–210.

Liu, M., McKelroy, E., Corliss, S. B., & Carrigan, J. (2017). Investigating the effect of an adaptive learning intervention on students' learning. *Educational Technology Research and Development*, *65*(6), 1605–1625.

Liu, M.-T., & Yu, P.-T. (2011). International Forum of Educational Technology & Society Aberrant Learning Achievement Detection Based on Person-fit Statistics in Personalized e-Learning Systems. *Journal of Educational Technology & Society*, *14*(1), 107–120.

Lo, J. J., Chan, Y. C., & Yeh, S. W. (2012). Designing an adaptive web-based learning system based on students' cognitive styles identified online. *Computers and Education*, *58*(1), 209–222.

Lockspeiser, T. M., & Kaul, P. (2016). Using Individualized Learning Plans to Facilitate Learner-Centered Teaching. *Journal of Pediatric and Adolescent Gynecology*, *29*(3), 214–217.

Nabizadeh, A. H., Gonçalves, D., Gama, S., Jorge, J., & Rafsanjani, H. N. (2020). Adaptive learning path recommender approach using auxiliary learning objects. *Computers and Education*, *147*(November 2019), 103777.

Nedungadi, P., & Raman, R. (2012). A new approach to personalization: Integrating e-learning and m-learning. *Educational Technology Research and Development*, *60*(4), 659–678.

Niknam, M., & Thulasiraman, P. (2020). LPR: A bio-inspired intelligent learning path recommendation system based on meaningful learning theory. *Education and Information Technologies*.

Okoli, C. (2015). A guide to conducting a standalone systematic literature review. *Communications of the Association for Information Systems*, *37*(1), 879–910.

Papamitsiou, Z., & Economides, A. A. (2014). Learning analytics and educational data mining in practice: A systemic literature review of empirical evidence. *Educational Technology and Society*, *17*(4), 49–64.

Peng, H., Ma, S. & Spector, J.M. (2019). Personalized adaptive learning: an emerging pedagogical approach enabled by a smart learning environment. *Smart Learning Environments.* 6(9).

Pliakos, K., Joo, S. H., Park, J. Y., Cornillie, F., Vens, C., & Van den Noortgate, W. (2019). Integrating machine learning into item response theory for addressing the cold start problem in adaptive learning systems. *Computers and Education*, *137*(April), 91–103.

Pontual Falcão, T., Mendes de Andrade e Peres, F., Sales de Morais, D. C., & da Silva Oliveira, G. (2018). Participatory methodologies to promote student engagement in the development of educational digital games. *Computers and Education*, *116*, 161–175.

Ramos De Melo, F., Flôres, E. L., Diniz De Carvalho, S., Gonçalves De Teixeira, R. A., Batista Loja, L. F., & De Sousa Gomide, R. (2014). Computational organization of didactic contents for personalized virtual learning environments. *Computers and Education*, *79*, 126–137.

Rastegarmoghadam, M., & Ziarati, K. (2017). Improved modeling of intelligent tutoring systems using ant colony optimization. *Education and Information Technologies*, *22*(3), 1067–1087.

Reisman, S. (2014). The future of online instruction, Part 2. *Computer*, *47*(6), 82–84.

Scheiter, K., Schubert, C., Schüler, A., Schmidt, H., Zimmermann, G., Wassermann, B., Krebs, M. C., & Eder, T. (2019). Adaptive multimedia: Using gaze-contingent instructional guidance to provide personalized processing support. *Computers and Education*, *139*, 31–47.

Schmid, R., & Petko, D. (2019). Does the use of educational technology in personalized learning environments correlate with self-reported digital skills and beliefs of secondary-school students? *Computers and Education*, *136*(March), 75–86.

Huang, Y. M., Liang, T. H., Su, Y. N., & Chen, N. S. (2012). Empowering personalized learning with an interactive e-book learning system for elementary school students. *Educational Technology Research and Development*, *60*(4), 703–722.

Sharples, M. (2000). The design of personal mobile technologies for lifelong learning. *Computers and Education*, *34*(3–4), 177–193.

Shute, V. J., & Rahimi, S. (2017). Review of computer-based assessment for learning in elementary and secondary education. *Journal of Computer Assisted Learning*, *33*(1), 1–19.

Somyürek, S. (2015). The new trends in adaptive educational hypermedia systems. *International Review of Research in Open and Distance Learning*, *16*(1), 221–241.

Spector, J. M. (2013). Emerging educational technologies and research directions. *Educational Technology and Society*, *16*(2), 21–30.

Spector, J. M. (2014). Conceptualizing the emerging field of smart learning environments. *Smart Learning Environments, 1*(2).

Spector, J. M. (2018). The potential of smart technologies for learning and instruction. *International Journal of Smart Technology & Learning, 1* (1), 21-32.

Sungkur, R. K., Antoaroo, M. A., & Beeharry, A. (2016). Eye tracking system for enhanced learning experiences. *Education and Information Technologies*, *21*(6), 1785–1806.

Truong, H. M. (2016). Integrating learning styles and adaptive e-learning system: Current developments, problems, and opportunities. *Computers in Human Behavior, 55*,1185–1193.

Tomberg, V., Laanpere, M., Ley, T., & Normak, P. (2013). Sustaining teacher control in a blog-based personal learning environment. *International Review of Research in Open and Distance Learning*, *14*(3), 109–133.

Troussas, C., Krouska, A., & Sgouropoulou, C. (2020). Collaboration and fuzzy-modeled personalization for mobile game-based learning in higher education. *Computers and Education*, *144* (September 2019), 103698.

Wang, Y. H., & Liao, H. C. (2011). Adaptive learning for ESL based on computation. *British Journal of Educational Technology*, *42*(1), 66–87.

Xie, H., Chu, H. C., Hwang, G. J., & Wang, C. C. (2019). Trends and development in technology-enhanced adaptive/personalized learning: A systematic review of journal publications from 2007 to 2017. *Computers and Education*, *140*(June), 103599.

Yang, T. C., Hwang, G. J., & Yang, S. J. H. (2013). Development of an adaptive learning system with multiple perspectives based on students' learning styles and cognitive styles. *Educational Technology and Society*, *16*(4), 185–200.

Zou, D., & Xie, H. (2018). Personalized word-learning based on technique feature analysis and learning analytics. *Educational Technology and Society*, *21*(2), 233–244.

CHAPTER 3

A COMPREHENSIVE ANALYSIS OF PERSONALIZED LEARNING COMPONENTS*

Abstract

Personalized learning aims to personalize the learning experience according to individuals' unique needs, goals, and skills, which can be achieved using current instructional technology that provides unique learning experiences in different learning environments. Technology is the main component that will enable and enrich personalized learning experience; however, even though the technology is available to personalize the learning experience, there is still a lack of unified agreement on what components need to be considered for a dynamic personalized learning approach that is to be able to provide a unique and effective learning experience to each learner. This study aims to analyze and synthesize different personalized learning approaches that consider different learning components to have an evolving agreement on personalized learning models and approaches to addressing this need. The findings of this research identified the following main components: learner profiles and attitudes, previous knowledge and beliefs, personalized learning paths, and flexible self-paced learning environments that are generated by learning analytics. These prominent characteristics imply that a personalized learning environment (PLE) would need to be dynamic to maintain a current record of learner interests and attitudes, past experiences, and performance and activities and interactions likely to match a particular learner and learning goal.

Keywords*: personalized learning, adaptive learning, intelligent tutoring systems (ITSs), technology-enhanced learning (TEL), smart learning environments (SLEs), learning analytics*

---

* This chapter is reproduced in its entirety from Shemshack, A., Kinshuk & Spector, J.M. (2021), A comprehensive analysis of personalized learning components, *Journal of Computers in Education*, 1-19. https://doi.org/10.1007/s40692-021-00188-7, with permission from Springer Nature.

Introduction

Peng et al. (2019) defined personalized adaptive learning as "a technology-empowered effective pedagogy which can adaptively adjust teaching strategies timely based on real-time monitored (enabled by smart technology) learners' differences and changes in individual characteristics, individual performance, and personal development." Learning involves activities shaped by personal experiences, awareness, personal bias and opinions, cultural background, and environment. This conception of learning implies a need to have a unique learning approach for individuals according to their unique situations. The typical learning situation is for a group of learners to be in the same learning environment and learning from the same source, regardless of their many differences and situations. The way one perceives and learns from resources and activities in a learning environment can vary significantly. However, a PLE's goal is to provide a unique and effective learning experience to each learner. This study analyzes and synthesizes different personalized learning approaches that consider different learning components. The goal is to develop general agreement on what is needed in an effective personalized learning environment in the form of a personalized learning model.

This study aims to review different personalized learning approaches and models used in research papers from 2010 to 2020 to compare the similarities and differences in components that have been used. Also, to analyze and synthesize the research done in the field, to use previous studies to analyze the problems and issues to allow further studies to build upon prior studies.

This paper presents a comprehensive review of personalized learning components based on published peer-reviewed research papers in the last ten years. The goal is to review different personalized learning approaches and models used in research papers published in primary databases and journals of learning technologies from 2010 to 2020 to compare the similarities and differences in components that have been used. The purpose is to thoroughly examine prior research and present an overview of findings to date.

Learning can be conceptualized as an experience or collection of experiences that expand knowledge, understanding, perspective, skills, thinking, interpretations, and perception. According to Spector (2012,2013), learning involves a stable and persisting change in what one knows and can do. Moreover, different learning models and approaches have evolved over the years. Learning models and approaches evolve along with technology and our knowledge of human learning. According to Xie et al. (2019), personalized learning has become a critical learning paradigm in the research community of educational technologies.

A promising learning method, personalized learning (PAL), is a new personalized learning approach that is computerized and makes decisions based on data gathered by a programmed system that accommodates learning to learners' real-time learning conditions and adjust the learning content and activities to meet learners' characteristics and needs through SLEs (Peng et al., 2019). While personalized learning is still in the early stages of development and evolution, there are important lessons to be learned from reviewing the existing research literature in this area.

This research literature analysis suggests that it is much too early, and there is too little evidence to conclude that one model is the best. Moreover, different learning approaches will be appropriate depending on different circumstances, including course content, learner experiences, learner maturity, learner intelligence, instructor goals, learner skills, and preferences. There are many more choices and opportunities than were available to previous generations of learners and teachers. At least in principle, it is now possible, if not yet widely implemented, for teachers to facilitate personalized learning approaches according to individual learners' unique needs.

Furthermore, Miliband (2006, as cited in Lee et al., 2018) discussed that the goal of personalized learning is to help and support everyone to reach their maximum potential by customizing instruction, including content, instruction delivery, and the pace at which it is learned, to meet unique needs, such as diverse learner characteristics and interests. The importance of personalized learning has been widely acknowledged by international organizations, governments, and education (Kinshuk et al., 2013). Also, there is growing evidence that the personalized, learner-centered paradigm can significantly enhance learning outcomes (Vandewaetere et al., 2012). In K-12 settings in the USA and other countries, it is already possible to create individual learning plans for students with disabilities that fit their capabilities with various learning goals and objectives. One way to characterize personalized learning in K-12 settings is to argue that every student should have an individualized learning plan.

For this review, Okoli's (2015) guidelines for conducting a systematic literature review for Information Systems Research were adapted to provide a detailed framework for writing a systematic literature review with its information technology roots. To analyze current literature, the researchers have selected the following well known and reliable databases to structure this literature review: Scopus, Science Direct, EBSCOhost, IEEE Xplore, JSTOR, and Web of Science to ensure all related journals of the field (Shemshack & Spector, 2020) are included in this study. The most relevant journals for this study were chosen consistently from these databases. Furthermore, the Google Scholar h5-index for the category "Educational technology" was used as the starting point since it is a specific category for personalized learning studies. Peer-reviewed article papers from online journals were retrieved for this study because those online academic journals are reliable and authoritative. The researchers reviewed the primary databases for educational technology to ensure all related journals are included. This review is only focused on journals to keep the scope of the review manageable and provide reviewed data to create a resource for future studies (Shemshack & Spector, 2020). Relevant papers were initially determined through searches of online databases and journals. These papers were subsequently examined to determine their applicability to the study. The papers explained what components they considered for personalized learning systems were selected for further analysis.

The researchers believe that a comprehensive, personalized learning experience can improve the learning experience for all. As a result, this primarily descriptive study analyzed components used in different personalized learning systems and models to provide a comprehensive analysis of personalized learning components that provide unique learning experiences to all. To serve this study's purpose and address the gap suggested earlier, the following research question was addressed:

1. What components need to be included in a comprehensive, personalized learning approach? We also considered the following sub-questions:

    a. What are the similarities and differences of used components of personalized learning approaches? This question narrowed the focus of the study on components and their impact on learning. The study focused on the differences and similarities of each component and how they impacted learning. This approach helped the researchers decide if the related component should be considered as a significant learning component. Researchers highlighted components in each system to look for patterns and similarities while paying attention to differences and their impact on learning outcomes.

    b. Furthermore, the following sub-question helped compare different personalized learning models, so any relationship between used systems/models and components could be identified. What systems and models are available to personalize adaptive learning experience for all?

Sub questions provided a more focused approach to the study. Moreover, researchers focused on analyzing and synthesizing different personalized learning approaches that consider various learning components, so an evolving cooperative agreement on a dynamic, personalized learning model can be created.

Researchers reviewed papers from primary databases and journals on learning technologies published between 2010 and 2020 years to analyze components of different systems and models of personalized learning. The articles were chosen to be reviewed, depending on the content of the papers' content and quality. Researchers thoroughly analyzed those components to provide a comprehensive analysis of personalized learning components that provide unique learning experiences to all. The researchers identified the study's purpose and intended goals to ensure the analysis is clear to readers.

Researchers presented previous work on personalized learning in the literature review section. The review results are explained in detail on different components used in different personalized learning environments in the current trends section under two subtitles -components of personalized learning models and systems- and tools and systems.

The review's discussion is presented in the discussion section, followed by future research direction and conclusion.

Literature Review

Boeree (2000) suggested that individuals can generate their own learning experiences and interpret information in the same or different ways as others, as each person has a unique interpretation and perspective on the world. Personalized learning (Yang et al., 2010; Chatti & Muslim, 2019; Peng et al., 2019) has been implemented by the support of intelligent learning systems that mostly consider integrating learners' preferences, analyzing individual learning data, creating learner profiles, etc. by dynamically facilitate the learning process.

The United States National Education Technology Plan 2017 defines personalized learning as instruction that allows adjusting the pacing of learning and the instructional approach to optimize each learner's needs (U.S. Department of Education, 2017). Indeed, pacing is one of the main components of the personalized learning but is not the only one for a holistic, personalized learning experience that provides a unique learning experience to all according to their needs, skills, interests, and goals. Furthermore, Peng et al. (2019) claimed that personalized learning has gradually become more complicated with technology development.

Peng et al. (2019) defined personalized learning as a technology-empowered effective pedagogy that can adaptively modify teaching strategies based on real-time monitoring, enabled by smart technology that considers learners' differences in individual characteristics, individual performance, and personal development.

The increased interest in personalized learning can result from the acceptance of learning as a unique experience, and acquired knowledge is unique to individuals. According to Xie et al. (2019), it has been commonly acknowledged in various learning/psychological theories that learning experiences and acquired knowledge are unique. To analyze the studies on personalized learning components, researchers thoroughly analyzed those components to provide a comprehensive analysis of personalized learning components that provide unique learning experiences.

Current Trends

This study includes different components used for personalized learning models and systems, the systems and tools are available to personalize learning experience and the differences and similarities of each of those models and systems.

Components of Personalized Learning Models and Systems

Most personalized learning approaches focus on learner needs and previous knowledge and aim to provide content accordingly. Erumit and Cetin (2020) created a table to display design features of adaptive intelligent tutoring systems to list their features by the dates that they were developed and found that the last three systems are developed after 2015 focused on adapting content according to the learner responses, allows the learner to interact and choose the content. These components seem to align with Peng et al.'s (2019) definition of personalized learning.

Learning Styles

Tseng et al. (2008) believed that integrating two data sources of individual learning styles and learning behaviors such as learning effectiveness, concentration degree, and learning achievement can be used as the key parameters to determine the individual learners' personalized learning materials. However, Hwang et al. (2013) argued that even though learning styles are considered one of the most common factors that need to be considered in developing adaptive learning systems, few studies have been conducted to investigate if students can choose the best-fit learning systems or content presentation styles for themselves in terms of learning style perspective. Therefore, Hwang et al. (2013) investigated students' perceptions of the most beneficial educational systems from the perspective of learning styles. Their study findings showed that: (a) Students learn better with the version designed for their learning style. This demonstrates the importance of adaptive learning systems, which are based on learning styles. (b) Students do not necessarily choose the version which has been designed for their learning style. This is very important because most adaptive systems create an initial user model based on individual students' answers to a questionnaire or choices of a set of parameters that are always assumed to be "reasonable." The experiment's results demonstrated that this might be untrue in some cases since user choices can be irrelevant to their learning performance. Hwang et al.

(2013) claimed this could significantly impact the design of adaptive learning systems that model needs to be refined and updated in an adaptive approach, which is inherently dynamic and subject to ongoing refinement.

Cognitive Styles

On the other hand, the results of research on learning profiles that considered personality and cognitive styles (Triantafillou et al., 2003) to determine the correlation between learning profile and ability, academic performance or the atmosphere of teaching and learning in the classroom, (Ehrman, 2001; Ehrman & Oxford, 1995; Reiff, 1992) showed the importance of including personality and cognitive styles in personalized learning approaches. However, a robust learner profile is also likely to change with time as learner interests and competence change as they mature and have more experience.

Self-Reflection and Self-Regulated Learning

Furthermore, Chatti (2010) argued that progressive development learning is a complex activity that involves self-reflection and self-regulation. Panadero (2017) claimed that self-regulated learning (SRL) is one of the most critical research areas in education over the last two decades, including the cognitive, metacognitive, behavioral, motivational, and emotional/affective aspects of learning which increase the data available to researchers. Following the lead, a unified evolving personalized learning model can be generated to provide learners with a more satisfied and engaging learning experience that considers diverse needs and goals. With our current teacher-student ratio to provide instruction according to each student's needs seems not to be possible; Chatti and Muslim (2019) and Peng et al. (2019) suggested that SLEs are needed to support personalized learning by helping learners to achieve their learning goals by providing tools that promote awareness, recommendation, self-reflection, assessment, feedback, and motivation. There are indeed many personalized learning models and systems available to both researchers and educators; however, as in the example of SRL, there is no defined age or learner `preparation considered to ensure the learner is ready to self-regulate their learning experience.

Flexible Pacing

One of the components that most educators and researchers agreed upon is allowing students to learn at their own pace is a strength and advantage that personalized learning provides. Sturgis and Patrick (2010, as cited in Lee et al., 2018) explained that well-designed technology systems allow personalized learning to be operational by monitoring individual progress, suggest personalized learning paths, and allowing students to move at their paces.

Also, Wang and Liao (2011) used four components: gender (Chen et al., 2016), learning motivation, cognitive type (Triantafillou et al., 2003), and learning style as different learning characteristics. Wang and Liao (2011) aimed to propose an algorithm to determine optimal adaptive learning sequences for instruction that accommodate a variety of individual differences by using a survey of the literature as a basis; four factors were derived and selected as the variables to be used for the learners' characteristics in the experiment that included 295 first-year students in Taiwan. Wang and Liao (2011) defined learning profiles as a preference for specific ways of learning to suggest optimal way to support learning, as Curry; Shaughnessy (1991; 1998, as cited in Wang & Liao, 2011) explained that a combination of one's motivation, engagement, and cognitive processing habits, that shows distinctive and habitual ways in which people proceed to concentrate on and interact with instructional content presented in a learning environment. Besides, Scanlon et al. (2012, as cited in FitzGerald et al., 2018) explained that issues that affect learners' lives, in the classroom, on field trips, and in their homes could support learning; as a result, they identified three aspects of personalization: personal relevance, choice and learner responsibility. Scanlon et al. (2012, as cited in FitzGerald et al., 2018) also mentioned that systems could capture learner data and model their emotions via facial recognition, processing voice recorded data, sentiment analysis of student comments, heart rate detection using video cameras, and so forth (see, e.g., Calvo & D'Mello, 2010). This would be exemplified by the "whole person" personalization element and have a high level of sophistication, considering many learning characteristics.

Furthermore, Lee et al. (2018) pointed out that to take advantage of technology, it is essential to have a technological system that collects learners' data and seamlessly feeds the data into each function. Learners' data collected in the assessment function should flow into the recordkeeping function, where the data are analyzed with the previous history of each student's data. The learning analytics (LA) should flow into the planning function to prepare personalized learning plans. Based on these LA data, artificial intelligence can suggest a project that may be interesting to the student and meet their learning needs in the instruction function and guide it. The assessment function should be fully integrated with the instructional function through just-in-time tutorials that entail each student practicing each competency until the criterion for mastery has been reached.

Chen et al. (2016) suggested considering the gender (Wang & Liao,2011) component for personalized learning. Chen et al. (2016) identified that the learners' gender differences, cognitive styles, and prior knowledge would lead to different reactions to personalized or non-personalized systems during the learning process. For example, female learners achieved better performance than male learners in the personalized scenario, whereas male learners outperformed females in the non-personalized learning scenario. Furthermore, Atkinson (2006) found a significant difference in learning achievement between male and female students and students who used different learning styles.

Liu and Yu (2011) added mood to personalized learning components and defined personalized learning as a service that provides learning content to fit learners' differences. Learning achievements are influenced by cognitive and non-cognitive factors such as mood, motivation, interest, and personal styles. Liu and Yu (2011) also suggested that teachers and educational designers need to understand the variations in students' attitudes, motivation, and style and their ability using Item Response Theory (IRT) model to understand the learners' abilities.

Li et al. (2013) pointed out the importance of knowing the learning habits. They developed a SCROLL system (System for Capturing and Reminding of Learning Log) that allows learners to log their learning experiences with photos, audios, videos, location and share and reuse them with others. The goals of SCROLL are lying in helping users efficiently record their learning experiences and recall them via the context, recommending other learners' learning experiences for them, finding out individuals' learning habits, and supporting their learning per personal learning habits.

Tools and Systems

There are many tools and systems available that can provide a unique learning experience for all. Chatti and Muslim (2019) and Peng et al. (2019) suggested that SLEs and LA are essential tools to allow learners to meet their learning goals by providing tools that promote awareness, recommendation, self-reflection, assessment, feedback, and motivation, which are essential components of personalized learning.

Smart Learning Environments

Chatti and Muslim (2019) brought attention to the necessity of SLE to support personalized learning by providing systems that foster awareness, recommendation, self-reflections, assessment, feedback, and motivation. Hwang (2014, as cited in Zhang et al., 2018) argued that an SLE could offer instant and adaptive support to learners by immediate analysis of individual learners' needs from different perspectives.

Intelligent Tutoring Systems

Another system that supports personalized learning experience is intelligent tutoring systems (ITS), which employ computational algorithms or models to deliver immediate feedback and learning instructions to learners without human teachers (Psotka et al., 1988). ITS incorporates built-in expert systems to monitor a learner's performance and personalize instructions based on adaptation to the learners' learning style, current knowledge level, and appropriate teaching strategies in e-learning systems (Phobun & Vicheanpanya, 2010). Walonoski and Heffernan (2006, as cited in Hwang et al., 2012) pointed out that Intelligent tutoring systems are such learning systems that provide personalized learning supports or feedback to help individual students improve their learning performance based on their personal information, such as the records in their profiles or learning portfolios. They discussed the adaptive learning systems could be viewed as a special intelligent tutoring system that adapts the presentation of educational materials to students' needs.

Canfield; Kaklauskas et al., Woo et al. (2001;2006; 2006 as cited in Wang & Liao, 2011) explained that adaptive learning systems that are implemented in the context of computer-mediated instruction are called intelligent tutoring systems (ITSs), and ITSs dynamically adapt the learning content, the pedagogical model, and human-computer interaction to the objectives, needs, and preferences of individual users for effective learning and teaching. However, they do not explain why they needed to differ ITS instead of claiming it as a supportive tool to adapt/personalize the learning. By collecting students' learning styles, preferences, and performances by tracking their knowledge, work, and feedback, the system can make inferences from students' learning strengths and weaknesses to suggest additional work (Kaklauskas et al., 2006; Woo et al., 2006). Furthermore, ITS has always been used in e-learning and long-distance learning, not in blended classroom instruction. We do not see a need for separating a learning approach for distance learning versus in-class learning anymore.

Data Mining and Learning Analytics

Zhu and Guan (2013) suggested that two applications that provide big data in education are data mining and learning analysis. These two applications are expected to collaborate on promoting learning by using registered learning data more effectively in evaluating learning methods, predicting anticipated performance, and identifying possible problems.

LA can play an essential role in examining data collected from multiple learning environments, promoting customized activities according to different learners' needs and goals, contributing insights and perception into how learners function in these environments and supporting the learners best in the process. LA allows promoting personalization by providing insights and understanding how learners learn and meet their goals and needs. Chatti and Muslim (2019) also pointed out the increased interest in LA to promote personalized learning. Siemens (2010, as cited in Zhang et al., 2018) defined learning analytics (LA) as the use of learners' data and analysis models to identify information and social connections and predict and guide learning. Zhang et al. (2018) supported the idea of LA and SLEs.

Another approach that allows personalizing the learning is learner profiles, which aim to portray the individual characteristics of each learners' strengths, preferences, motivations, etc.; competency-based progression evaluates the learners' progress by continuously measuring the proper completion of the learner's learning objectives; personal learning is to provide a learner with a path to personal advancement; flexible learning environment as a flexible and intelligent learning environment can provide adequate support for the adaptive modification of teaching strategies.

Wearable Devices

Borthwick et al. (2015, as cited in Xie et al., 2019) brought up that wearable personal learning, which aims to collect data from the person wearing the device or from the surrounding environment to enhance differentiation of instruction and student engagement, will become a new trend with the development of information technologies for learning applications deployed on mobile and wearable devices. For the learning content in adaptive/personalized systems, individual learning data acquisition can be used for artificial intelligence to acquire content-specific knowledge and skills. They also pointed out that higher order thinking skills and communication have attracted little attention in terms of both learning outcomes and the process of personalized learning due to the difficulty of measurement and the limited learning support types (Shemshack & Spector, 2020). Recently, virtual reality techniques have started to support collaborative and immersive learning environments, which will increase the possibility of cultivating higher order thinking skills and communication in personalized systems soon.

Moreover, all these systems assert the goal-driven personalized learning that is a cyclical process and composed of different dynamic phases. Although using different labels, all approaches share typically identifiable phases that include goal setting by analyzing tasks, planning, activating goals, self-motivation, executing performance, and evaluating through self-reflection, feedback, monitoring, controlling, appraisal, regulating, adapting, reacting (Panadero, 2017).

Discussion

Current personalized learning models heavily rely on technology, which allows us to implement personalized learning in our current learning environments with less effort. Machine learning, data mining, and human behavior are determining factors that shape personalized learning. Among many different models and systems that focus on personalized learning experiences for all, it is found that they all based on each human being is unique, so their needs are. As a result, there have been attempts to personalize the learning by considering individuals' specific differences (Shemshack & Spector, 2020). The most used component for personalized learning is learning style. Graf et al. (2009) argued that even though learning styles have been a controversial topic, the learning style models agree that learners have different ways in which they prefer to learn.

Furthermore, many educational theorists and researchers consider learning styles as an essential factor in the learning process. They agree that incorporating learning styles in education has the potential to facilitate learning for students. Graf and Kinshuk (2006) suggested that detecting learners' needs (learning style) is challenging but essential for providing learning adaptivity. While Hwang et al. (2013) found that even learning style improves learning, it was observed that if the choice was given to learners, they did not choose the learning style that helped them learn better.

This finding raises the question that should control over their learning style be given to learners, or should the data collected from learners determine the learning style? Several studies and learning theories showed that when the learner was given control over their learning, they learned better; however, we need to define what it means to give control to the learner. Self-pacing learning is one way to give control to the learner, which found to improve learning while giving control over how to learn did not end up with learners to choose the right learning style for themselves.

As a result of the focus of this study what components need to be included in a comprehensive, personalized learning approach, it was concluded that one of the components that most educators and researchers agreed upon is allowing students to learn at their own pace, which is a strength and advantage that personalized learning provides. While self-pacing learning seems to be one of the critical components of personalized learning systems, which has been proven to increase learning, learner needs, and previous knowledge are the main goals to provide content accordingly to learners. Adapting content according to the learner's responses allows the learner to interact and choose the content. Furthermore, learning profiles that considered personality and cognitive styles showed the importance of including personality and cognitive styles in personalized learning approaches. Panadero (2017) claimed that self-regulated learning (SRL) is one of the most critical areas in education; however, there is no clear definition of how SRL should look and how to empower the learner self-organize the learning materials. Cognitive type; engagement, cognitive processing habits, personal relevance, choice, and learner responsibility, cognitive styles; prior knowledge, learning style, and non-cognitive factors such as gender, mood, learning motivation, interest, learning habits, and personal styles are other learning characteristics that have been considered for different personalized learning systems.

Similarly, as different personalized systems were analyzed to find out the similarities and differences of used components of personalized learning approaches, it was found that while at first cognitive components were the focus of for personalized learning systems such as learning styles and self-pacing were main components considered, the focus of researchers have broadened to non-cognitive components as we learned more about human learning. The cognitive and non-cognitive components used for personalized learning are listed in Table 3.1, to provide a more systemically presentation of the results described and evaluated.

Table 3.1

Summary of Cognitive vs Non-Cognitive Components Used for Personalized Learning

Component	References
Cognitive	
assessment	Chatti and Muslim (2019), Peng et al. (2019)
ability	Ehrman (2001), Ehrman & Oxford (1995), Liu and Yu (2011), Reiff (1992)
feedback	Chatti and Muslim (2019), Curry (1991), Kaklauskas et al. (2006), Peng et al. (2019), Psotka et al. (1988), Shaughnessy (1998), Walonoski and Heffernan (2006), Wang & Liao (2011)
adaptive content delivery	Canfield (2001), Kaklauskas et al. (2006), Lee et al. (2018), Miliband (2006), Phobun & Vicheanpanya (2010), U.S. Department of Education (2017), Woo et al. (2006)
learner engagement	Borthwick et al. (2015), Curry (1991), Erumit and Cetin (2020), Panadero (2017), Shaughnessy (1998), Wang & Liao (2011)
cognitive processing habits	Curry (1991), Panadero (2017), Shaughnessy (1998), Wang & Liao (2011)
learning styles	Atkinson (2006), Graf and Kinshuk (2006), Hwang et al. (2013), Kaklauskas et al. (2006), Panadero (2017), Phobun & Vicheanpanya (2010), Tseng et al. (2008), Wang and Liao (2011)
cognitive styles	Chen et al. (2016), Panadero (2017), Triantafillou et al., 2003, Wang and Liao (2011)
learner choice	Erumit and Cetin (2020), FitzGerald et al. (2018), Panadero (2017), Scanlon et al. (2012)
personal relevance	FitzGerald et al. (2018), Panadero (2017), Scanlon et al. (2012)
learner responsibility	FitzGerald et al. (2018), Panadero (2017), Scanlon et al. (2012)
self-reflection and self-regulation	Canfield (2001), Chatti (2010), Chatti and Muslim (2019), Kaklauskas et al. (2006), Woo et al. (2006), Peng et al. (2019), Panadero (2017)
prior knowledge	Chen et al. (2016), Kaklauskas et al., (2006), Panadero (2017), Phobun & Vicheanpanya (2010)
flexible pacing	Sturgis and Patrick (2010), Lee et al. (2018), Miliband (2006), U.S. Department of Education (2017)

(table continues)

Component	References
Non-Cognitive	
gender	Atkinson (2006), Chen et al., (2016), Panadero (2017), Wang and Liao (2011)
learning motivation, concentration degree	Chatti and Muslim (2019), Curry (1991), Liu and Yu (2011), Panadero (2017), Peng et al. (2019), Shaughnessy (1998), Tseng et al. (2008), Wang and Liao (2011)
mood	Liu and Yu (2011), Panadero (2017)
learning habits	Li et al. (2013), Panadero (2017)
interest, emotions; confusion, engagement, frustration, boredom, curiosity, etc., preferences	Calvo and D'Mello (2010), Canfield (2001), FitzGerald et al. (2018), Kaklauskas et al. (2006), Lee et al. (2018), Liu and Yu (2011), Miliband (2006), Panadero (2017), Scanlon et al. (2012), Woo et al. (2006)
personal styles, individual characteristics, personality, learner profiles	Gomez et al. (2014), Lee et al (2018), Miliband (2006), Liu and Yu (2011), Panadero (2017), Peng et al. (2019), Triantafillou et al. (2003), Walonoski and Heffernan (2006)
individual academic performance	Ehrman, (2001), Ehrman & Oxford (1995), Reiff (1992), Kaklauskas et al. (2006), Peng et al. (2019), Sturgis and Patrick (2010), Tseng et al. (2008), Walonoski and Heffernan (2006)
needs	Canfield (2001), Gomez et al. (2014), Graf and Kinshuk (2006), Hwang (2014), Kaklauskas et al. (2006), U.S. Department of Education (2017), Woo et al. (2006)
awareness	Chatti and Muslim (2019), Peng et al. (2019)
personalized recommendation	Chatti and Muslim (2019), Peng et al. (2019)
personalized learning path	Sturgis and Patrick (2010)

Furthermore, the following analysis helped compare different personalized learning models, so any relationship between used systems/models and components could be identified. Peng et al. (2019) 's definition of personalized learning as a technology-empowered effective pedagogy that can adaptively modify teaching strategies timely based on real-time monitoring, which is enabled by smart technology that considers learners' differences changes in individual characteristics, individual performance, and personal development summarizes the components and elements of personalized learning very well. This definition clarifies that technology tools have a significant role in personalized learning systems by collecting learners' data and seamlessly feeding the data into each function.

SLEs and LA are essential tools to allow learners to meet their learning goals by providing tools that promote awareness, recommendation, self-reflection, assessment, feedback, and motivation, which are essential components of personalized learning. Also, LA can play an essential role in examining data collected from multiple learning environments, supporting customized activities according to different learners' needs and goals, contributing insights and perception into how learners function in these environments, and how to empower the learners best in the learning process. LA allows personalization by providing insights and understanding how learners learn and meet their goals and needs by connecting the previous history of each learner's data.

Another system that supports personalized learning experience is intelligent tutoring systems (ITS), which employ computational algorithms or models to deliver immediate feedback and learning instructions to learners without human teachers (Psotka et al., 1988). Intelligent tutoring systems (ITSs) dynamically adapt the learning content, the pedagogical model, and human-computer interaction to the objectives, needs, and preferences of individual users for effective learning and teaching by collecting students' learning styles, preferences, and performances by tracking their knowledge.

Two main applications that provide big data in education are data mining and learning analysis. These are two approaches that allow personalizing the learning by using learner profiles, which aim to portray the individual characteristics of each learners' strengths, preferences, motivations, etc.; competency-based progression evaluates the learners' progress by continuously measuring the proper completion of the learner's learning objectives; personal learning is to provide a learner with a path to personal advancement; flexible learning environment as a flexible and intelligent learning environment can provide adequate support for the adaptive modification of teaching strategies.

All these systems and tools would be exemplified by the holistic personalization element and have a high level of sophistication, considering many learning characteristics that can help personalized learning by capturing learner data and modeling their emotions via facial recognition, processing voice recorded data, sentiment analysis of student comments, and heart rate detection using video cameras.

It is observed that, as Miliband (2006, as cited in Lee et al., 2018) argued, the goal of personalized learning is to help and support everyone to reach their maximum potential by customizing instruction, including content, instruction delivery, and the pace at which it is learned, to meet unique needs, such as diverse student characteristics and interests of learners by considering the most common components have been used for different personalized learning systems.

Furthermore, ITS provide significant support to create dynamic, evolving personalized learning environments that are cyclical and gather data from learner by creating learning profiles that are created by learning analytics. Ongoing input from learner attitudes and patterns allows ITS to adjust the learning activity and content to be adjusted according to the data collected, such as the learner's mood, previous knowledge, skills, motivation, gender, interests, abilities, learning pace, and learning behaviors.

Gomez et al. (2014) stated that the key benefits of a personalized learning approach are that learners are provided with adaptive and personalized learning experiences tailored to their educational needs and personal characteristics to maximize their satisfaction, learning speed, and learning effectiveness. Learning effectiveness is one of the results we have been hoping for, for centuries, and improvements in learning effectiveness motivate us to look for how to improve it more. The research progress in personalized learning shows that as technology develops, personalized learning takes advantage of the benefits technology can offer that increase the components that can be considered to personalize the learning. However, some concerns need to be considered while collecting data from learners, such as privacy concerns and keeping the data collected from individuals safe.

Chatti and Muslim (2019) pointed out that personalized learning models are labeled differently; they all in core assert the goal-driven nature of personalized learning and view personalized learning as a cyclical process composed of different phases.

Limitations

This study had several shortcomings during the review and in its attempt to answer all the research questions. The literature review is a time-consuming process and labor-intensive approach, and especially with personalized learning, there is an enormous number of studies available. The tremendous number of published papers might lead to missing relevant papers as many literature review studies face this problem. Moreover, the extensive effort to construct a search by identifying relevant keywords is critical for the search process. The keyword determination process was conducted using a snowballing process from related studies to identify the reflections or keywords relevant to this study, and it might be subjective. Overlooking articles by omitting important information or keyword combinations is likewise possible due to the authors' limited time frame and misinterpretations.

Nonetheless, this study also confronts the possible limitation originated by the selection criteria. For example, this study focused on only journal articles and was limited to only documents written in English and studies published between 2010 and 2020. Therefore, other pertinent articles that are not written in English and were not published in selected journals or within the same timeline might not have included.

Future Research Directions and Conclusion

Our findings revealed that the range of components being used to personalize learning is widening as technology develops. As we learn more about human learning and what technology can provide us to personalize learning experience, such as gathering data of learners' emotions by using bio-trackers, which might bring up some privacy concerns, we are redefining our understanding of personalized learning. Future research can focus on what privacy concerns we might face and address those concerns and protect learners' privacy.

In conclusion, this study found that a unified evolving personalized learning approach would consider four main components; learner profiles, previous knowledge, personalized learning, and a flexible self-paced learning environment that generates a personalized learning path according to provided dynamic learning analytics. This paper presents a clear understanding of personalized learning components, models, and approaches. This study serves to contribute to future studies and practices on personalized learning and learning in general.

This study's findings support that personalized learning has become a fundamental learning paradigm in the research community of educational technologies. Firstly, the current trends are presented as they relate to the Research Questions; then, the future direction and limitations are discussed. The study shows that using personality traits and their identification techniques has an enormously positive influence in personalized learning environments.

This study is related to several significant psychology, education, educational, and computer science domains. Likewise, it reveals the integration of personal traits in the adaptive learning environment, which involves many personality traits and identification techniques that can improve learning. Also, it found that there is an increase of interest in two areas that are oriented towards the incorporation and exploration of significant data capabilities in education: Educational Data Mining (EDM) (Shemshack & Spector, 2020) and LA. According to Papamitsiou and Economides (2014), EDM and LA communities seem to add another approach to personalized learning and make it easier modify the learning according to individuals.

Personalized learning for everyone looks different according to the needs, goals, interests, skills (Shemshack & Spector, 2020), and many other individual components throughout the paper. Ennouamani et al. (2020) argued that learners are diverse in terms of their needs, knowledge, personality, behavior (Shemshack & Spector, 2020; Pliakos et al.,2019), preferences, learning style, culture, and the parameters of the mobile devices that they use.

This study has answered some critical research questions, including different components used with personalized learning and systems and models that lead to efficient, effortless personalized learning. Also, some research issues and potential future development directions are presented. According to the discussions and current trends, it was found that personalized learning systems seem to evolve as technology develops. These components may evolve as we learn more about human-machine interaction and learn to use technology to improve learning experiences (Shemshack & Spector, 2020). We suggest that researchers use the components reviewed in this study to guide future studies on the impact of personalized learning on student learning and performance.

To sum up, this study discussed different components used for personalized learning models in detail and how personalized learning evolves as technology develops, and we learn more about human-machine interaction.

Chapter References

Atkinson, S. (2006). Factors influencing successful achievement in contrasting design and technology activities in higher education. *International Journal of Technology and Design Education, 16,* 193–213.

Boeree, C. G. (2000). Gestalt psychology. http://webspace.ship.edu/cgboer/gestalt.html

Calvo, R. A., & D' mello, S. (2010). Affect detection: an interdisciplinary review of models, methods, and their applications. *IEEE Transactions on Affective Computing, 57*, 18–37.

Canfield, W. (2001). ALEKS: A web-based intelligent tutoring system. Mathematics and *Computer Education, 35,* 152–158.

Chatti, M. A. (2010*). Personalization in technology enhanced learning: A social software perspective.* Aachen: Shaker Verlag.

Chatti, M. A., & Muslim, A. (2019). The PERLA framework: Blending personalization and learning analytics. *International Review of Research in Open and Distance Learning*, *20*(1), 244–261. https://doi.org/10.19173/irrodl.v20i1.3936

Chen, S. Y., Huang, P. R., Shih, Y. C., & Chang, L. P. (2016). Investigation of multiple human factors in personalized learning. *Interactive Learning Environments, 24*(1), 119–141.

Curry, L. (1991). Patterns of learning style across selected medical specialties. *Educational Psychology, 11*(3–4), 247–277. https:// doi.org/10.1080/0144341910110304.

Ehrman, M. E. (2001). Bringing learning strategies to the learner: the FSI language learning consultation service. In J. E. Alatis & A. Tan (Eds*), language in our time: bilingual education and official English, Ebonics and standard English, immigration and the Unz initiative* (pp. 41–58). Washington, DC: Georgetown University.

Ehrman, M. E., & Oxford, R. L., (1995). Cognition plus: correlates of language learning success. *Modern Language Journal, 79*, 67–89.

Ennouamani, S., Mahani, Z., & Akharraz, L. (2020). A context-aware mobile learning system for adapt-ing learning content and format of presentation: Design, validation, and evaluation. *Education and Information Technologies, 25,* 3919–3955. https://doi.org/10.1007/s10639- 020-10149-9.

Erümit, A. K., & Çetin, İ. (2020). Design framework of adaptive intelligent tutoring systems. *Education and Information Technologies*. https://doi.org/10.1007/s10639-020-10182-8

FitzGerald, E., Kucirkova, N., Jones, A., Cross, S., Ferguson, R., Herodotou, C., Hillaire, G., & Scanlon, E. (2018). Dimensions of personalisation in technology-enhanced learning: A framework and implications for design. *British Journal of Educational Technology*, *49*(1), 165–181. https://doi.org/10.1111/bjet.12534

Graf, S., Kinshuk, & Liu, T.-C. (2009). Supporting Teachers in Identifying Students' Learning Styles in Learning Management Systems: An Automatic Student Modelling Approach. *Educational Technology & Society, 12* (4), 3–14.

Graf, S., & Kinshuk. (2006). An approach for detecting learning styles in learning management systems. *Proceedings - Sixth International Conference on Advanced Learning Technologies, ICALT 2006*, *2006*, 161–163. https://doi.org/10.1109/icalt.2006.1652395

Gómez, S., Zervas, P., Sampson, D. G., & Fabregat, R. (2014). Context-aware adaptive and personalized mobile learning delivery supported by UoLmP. *Journal of King Saud University - Computer and Information Sciences*, *26*(1), 47–61. https://doi.org/10.1016/j.jksuci.2013.10.008

Hwang, G. J., Sung, H. Y., Hung, C. M., & Huang, I. (2013). A learning style perspective to investigate the necessity of developing adaptive learning systems. *Educational Technology and Society*, *16*(2), 188–197.

Hwang, G. J., Sung, H. Y., Hung, C. M., Huang, I., & Tsai, C. C. (2012). Development of a personalized educational computer game based on students' learning styles. *Educational Technology Research and Development*, *60*(4), 623–638. https://doi.org/10.1007/s11423-012-9241-x

Kaklauskas, A., Ditkevicius, R. & Gargasaite, L. (2006). Intelligent tutoring system for real estate management. *International Journal of Strategic Property Management, 10,* 113–130.

Kinshuk, Huang, H.-W., Sampson, D., & Chen, N.-S. (2013). Trends in Educational Technology through the Lens of the Highly Cited Articles Published in the Journal of Educational Technology and Society. Educational Technology & Society, 16 (2), 3–20.

Lee, D., Huh, Y., Lin, C. Y., & Reigeluth, C. M. (2018). Technology functions for personalized learning in learner-centered schools. In *Educational Technology Research and Development* (Vol. 66, Issue 5). Springer US. https://doi.org/10.1007/s11423-018-9615-9

Li, M., Ogata, H., Hou, B., Uosaki, N., & Mouri, K. (2013). Context-aware and personalization method in ubiquitous learning log system. *Educational Technology and Society*, *16*(3), 362–373.

Liu, M.-T., & Yu, P.-T. (2011). International Forum of Educational Technology & Society Aberrant Learning Achievement Detection Based on Person-fit Statistics in Personalized e-Learning Systems. *Source: Journal of Educational Technology & Society*, *14*(1), 107–120. https://doi.org/10.2307/jeductechsoci.14.1.107

Miliband, D. (2006). Choice and voice in personalised learning. In OECD (Ed.). *Schooling for Tomorrow: Personalising education* (pp. 21–30). Paris: OECD Publishing.

Okoli, C. (2015). A guide to conducting a standalone systematic literature review. *Communications of the Association for Information Systems*, *37*(1), 879–910. https://doi.org/10.17705/1cais.03743.

Panadero, E. (2017). A review of self-regulated learning: Six models and four directions for research. *Frontiers in Psychology, 8*(422). https://doi.org/10.3389/fpsyg.2017.00422

Papamitsiou, Z., & Economides, A. A. (2014). Learning analytics and educational data mining in practice: A systemic literature review of empirical evidence. *Educational Technology & Society, 17*(4), 49–64.

Peng, H., Ma, S., & Spector, J. M. (2019). Personalized learning: An emerging pedagogical approach enabled by a smart learning environment. *Lecture Notes in Educational Technology*, 171–176. https://doi.org/10.1007/978-981-13-6908-7_24

Phobun, P., & Vicheanpanya, J. (2010). Adaptive intelligent tutoring systems for e-learning systems. *Procedia-Social and Behavioral Sciences, 2*, 4064–4069.

Pliakos, K., Joo, S. H., Park, J. Y., Cornillie, F., Vens, C., & Van den Noortgate, W. (2019). Integrating machine learning into item response theory for addressing the cold start problem in adaptive learning systems. *Computers & Education, 137*(April), 91–103. https://doi.org/10.1016/j.compedu.2019.04.009.

Psotka, J., Massey, L. D., & Mutter, S. A. (Eds.). (1988). *Intelligent tutoring systems: Lessons learned.* Psychology Press.

Reiff, J. (1992). *What research says to the teacher: learning styles*. Washington, DC: National Education Association.

Scanlon, E., Anastopoulou, S., & Kerawalla, L. (2012). Inquiry learning reconsidered: Contexts, representations, and challenges. In K. Littleton, E. Scanlon & M. Sharples (Eds.), *Orchestrating inquiry learning*. Abingdon, England: Routledge.

Shemshack, A., & Spector, J.M. (2020). A systematic literature review of personalized learning terms. *Smart Learning Environments. 7*(33). https://doi.org/10.1186/s40561-020-00140-9

Shaughnessy, M. (1998). An interview with Rita Dunn about learning styles. *The Clearing House, 71,* 141–145.

Spector, J. M. (2012;2013;). Foundations of educational technology: Integrative approaches and interdisciplinary perspectives. London: Routledge. https://doi.org/10.4324/9780203814192

Sturgis, C., & Patrick, S. (2010). *When success is the only option: Designing competency-based pathways for next generation learning.* Retrieved from Quincy, MA.

Triantafillou, E., Pomportsis, A. & Demetriadis, S. (2003). The design and the formative evaluation of an adaptive educational system based on cognitive styles. *Computers & Education, 41,* 87–103

Tseng, J. C., Chu, H. C., Hwang, G. J., & Tsai, C. C. (2008). Development of an adaptive learning system with two sources of personalization information. *Computers & Education, 51*(2), 776–786.

U.S. Department of Education, Office of Educational Technology (2017). *Reimagining the role of technology in education: 2017 national education technology plan update*. Available at: https://tech.ed.gov/files/2017/01/NETP17.pdf.

Yang, G., Kinshuk, & Graf, S. (2010). A practical student model for a location-aware and context-sensitive personalized learning system. 2010 International Conference on Technology for Education, T4E 2010 (pp. 130–133). https://doi.org/10.1109/T4E.2010.5550048

Walonoski, J. A., & Heffernan, N. T. (2006). Detection and analysis of off-task gaming behavior in intelligent tutoring systems. *In Intelligent tutoring systems* (pp. 382–391). Springer.

Wang, Y. H., & Liao, H. C. (2011). Adaptive learning for ESL based on computation. *British Journal of Educational Technology*, *42*(1), 66–87. https://doi.org/10.1111/j.1467-8535.2009.00981.x

Woo, W., Evens, M.W., Freedman, P., Glass, M., Shim, L. S., Zhang, Y., et al. (2006). An intelligent tutoring system that generates a natural language dialogue using dynamic multi-level planning. *Artificial Intelligence in Medicine, 36,* 85–117.

Xie, H., Chu, H. C., Hwang, G. J., & Wang, C. C. (2019). Trends and development in technology-enhanced adaptive/personalized learning: A systematic review of journal publications from 2007 to 2017. *Computers and Education*, *140*(June), 103599. https://doi.org/10.1016/j.compedu.2019.103599

Vandewaetere, M., Vandercruysse, S., & Clarebout, G. (2012). Learners' perceptions and illusions of adaptivity in computer-based learning environments. *Educational Technology Research and Development*, *60*(2), 307–324. https://doi.org/10.1007/s11423-011-9225-2

Zhang, J. H., Zhang, Y. X., Zou, Q., & Huang, S. (2018). What learning analytics tells us: Group behavior analysis and individual learning diagnosis based on long-term and large-scale data. *Educational Technology and Society*, *21*(2), 245–258.

Zhu, Z.T., Guan, J.Q. (2013) The construction framework of "Network Learning Space for Everyone." *Educ. Technol. (10)*, 1–7.

CHAPTER 4

FACTORS CONTRIBUTING TO TEACHER SELF-EFFICACY IN DISTANCE LEARNING*

Abstract

Inefficient teacher training and lack of successful technology integration have been an issue in public education settings that need researchers' and policymakers' attention. Knowing the factors that help teachers improve their distance teaching practices and build confidence in distance learning becomes an essential component of efficient teaching. Measuring the impact of the support teachers receive from their administrators during distance learning is an essential first step toward enhancing efficient distance learning practices that support teachers and administrators in increasing teachers' confidence in distance learning practices. This study collected information regarding the support teachers received from their administrators during COVID-19 distance learning using the DLS (Distance Learning Support) (Shemshack & Davis, 2020) instrument. The instrument produced three scales consisting of topics ranging from access to materials and training directly tied to distance learning and teachers' confidence during distance learning. This paper's findings shed light on the underlining questions, what factors help increase teachers' confidence with distance learning, how administrator support can be improved, and which teacher demographics have the highest confidence regarding online learning. In attempting to answer these questions, administrators need reliable instruments assessing the support teachers need for distance teaching to make professional development decisions using relevant data.

Keywords*: distance learning, administrator support, teacher training, COVID-19, online education, teacher self-efficacy*

---

* This chapter is reproduced from Shemshack, A., Davis, T., Knezek & Kinshuk. *Factors Contributing to Teacher Self Efficacy in Distance Learning.* Manuscript submitted for publication.

Introduction

Administrators need reliable instruments to measure the support teachers need for distance learning to make data-based professional development decisions to enhance the educational environment in current and future classrooms. Educators and students in schools worldwide, including the United States, have faced sweeping, unprecedented shifts in teaching and learning due to the coronavirus disease 2019 (COVID-19) pandemic, which shuttered school buildings and forced schools to plan for distance learning (Hamilton & Hunter, 2019). Even before the pandemic, higher education has been offering distance learning programs to the individuals who work full time to earn their degrees and advance in their careers through flexible and convenient online programs; however, K-12 schools are still trying to find the right practices aligned with younger students' needs and abilities. Hrastinski (2008) suggested that for distance learning to be effective and efficient, teachers, organizations, and institutions must have a comprehensive understanding of the benefits and limitations. Knowing the limitations and benefits of distance learning can help school districts and administrators to support teachers more intentionally.

This study aims to compare teachers' confidence in distance learning verse support they have received from their administrators, materials provided to them, and the training they received to measure what helps teachers increase their self-efficacy for distance learning. Shemshack and Davis (2020) stated that this unprecedented time calls for education administrators to review their professional development and support practices to meet quality distance learning's future demands. Furthermore, this study aims to add value to the existing literature on distance learning and teacher support systems by providing more specific data on teachers' beliefs on the support they have received. Measuring the impact of the support teachers receive from their administrators during distance learning is an essential first step toward enhancing efficient distance learning practices that support teachers and administrators in increasing self-efficacy in teachers' distance learning practices.

This paper's findings shed light on the underlining questions, what factors help improve teachers' self-efficacy with distance learning, how administrator support can be improved, and which teacher demographics have the highest self-efficacy regarding online learning. Furthermore, the study investigated if the DLS instrument is reliable for identifying factors contributing to the teacher's self-efficacy. In attempting to answer these questions, administrators need reliable instruments assessing the support teachers need for distance teaching to make professional development decisions using relevant data.

Researchers presented previous work on factors contributing to teacher self-efficacy in distance learning in the background section according to their alignments with the DLS instrument's subscales. The background section is followed by the methods section that provides detailed information on the study's structure, instrumentation, and participants. The validation of the DLS provides information regarding the reliability and validity of the DLS instrument. This study's findings are provided under the discussion section, followed by the limitations and future research section within the conclusion.

Background

Christensen and Knezek (2011) pointed out that teachers' proficiency in using technology and teaching with technology usually increases over time. School districts planned for fall distance learning during the summer of 2019 and trained teachers on distance learning, with the expectation to increase teachers' competency and confidence in distance learning. According to Christensen and Knezek (2017), as the school district focuses on preparing teachers to use technology and supporting the teachers with tools and infrastructure, teachers reported increased self-efficacy. What follows are the themes found in relevant research associated with distance learning support.

Administrative Support

Principals are decision-makers at the campus level when it comes to budgeting and instructional purchase decisions. Leithwood and Riehl (2003) claimed that the most effective principals develop a vision and use this vision to develop a supportive learning community. Furthermore, according to Machado and Chung (2015), principals who created a school vision for effective technology integration and provided teachers with on-going supportive professional development were most effective. While an individual school's tone is a synthesis of its entire staff, the overall focus of instruction and lessons comes from the campus principal. Consequently, the attitudes toward and the practical instruction in classrooms are undoubtedly affected by the principal's vision for their school. When it comes to technology usage, research shows that principals do have a trickledown effect of influence. In a study of 1,000 Taiwanese elementary school teachers, their principals' leadership was significantly affected. It found that "principals' technological leadership improves teachers' technological literacy and directly encourages teachers to integrate technology into their teaching" (Chang, 2012, p. 328).

Teacher Training

Novak (2018) suggested that professional development plans should provide sustained learning experiences with scaffolding, reflection, and coaching for educators who are new to distance teaching. Furthermore, Christensen and Alexander (2020) pointed out that a well-planned teacher professional development on technology tools and online pedagogy is critical for high-quality online teaching and learning. Teacher preparation is critical, especially the pedagogy of teaching online rather than emergency teaching (Hodges et al., 2020). Furthermore, Christensen and Knezek (2017) suggested that understanding teacher confidence and competence in distance learning is essential in designing appropriate professional development. Moreover, Hamilton and Hunter (2019) suggested that school districts might want to emphasize professional development opportunities for teachers serving student populations who are particularly disadvantaged during this time and consider serving them better.

Teachers Access to Resources and Materials

According to Hamilton and Hunter's (2019) study, most respondents indicated that lack of teachers' access to the internet and technology was a limiting factor during distance learning for teachers working in schools in rural areas or towns. Hamilton and Hunter (2019) claimed that some teachers do not have the internet to support students learning online. Adedoyin and Soykan (2020) suggested that since online learning in its entirety is dependent on technological devices and the internet, instructors, and students with lousy internet connections are liable to be denied access to online learning. The dependency of online learning on technological equipment and the equipment provision was a significant challenge for institutions, faculty, and learners. Furthermore, Christensen and Alexander (2020) reported that teacher proficiency increased when technology tools for instruction were provided to teachers to get prepared to use them. Thus, first and foremost, school districts need to ensure all teachers have access to internet connection and resources that need for efficient distance learning.

Teacher Self-Efficacy

Bandura (1982) explained that self-efficacy is concerned with judgments of how well one can execute courses of action required to deal with prospective situations. Furthermore, Bandura (1982) suggested that self-efficacy judgments also determine how much effort people will expend and how long they will persevere in the face of obstacles or aversive experiences. When beset with difficulties, people who entertain severe doubts about their capabilities slacken their efforts or give up altogether. In contrast, those who have a strong sense of efficacy exert significant effort to master the challenges. High perseverance usually produces high-performance attainments. Understanding teacher confidence and competence in learning technology is essential in designing appropriate professional development for teachers (Christensen & Knezek, 2017). According to their individual needs and level, supporting teachers allows confidence to grow over time and motivates teachers to try more challenging activities during distance learning (Avci et al., 2020). Moreover, Christensen and Alexander (2020) suggested that teachers who were already confident with technology only needed additional tools to support their ideas, reminding us of the importance of teachers' support to be intentional and need-based instead of a one-model fits all.

To identify factors that help teachers improve their distance teaching practices and build self-efficacy, instruments need to measure the impact of support teachers receive from their administrators during distance learning. The methods section discusses the previous techniques to gather data to investigate the support teachers receive from their administrators to increase the self-efficacy in teachers' distance learning practices.

Methods

The DLS (Shemshack & Davis, 2020) instrument was used to assess teachers' self-efficacy and beliefs about administrators' support during distance learning to collect information regarding the support teachers received. The instrument items are related to access to materials, training tied to distance learning, and teachers' confidence during distance learning. The DLS instrument's purpose is to measure the support teachers received during distance learning from their administration, assess their access to materials and training, and analyze how these factors support teachers' confidence.

The Study

This study's primary goal was to determine the Distance Learning Support (DLS) instrument's reliability and validity to address the current needs and issues associated with distance learning. Furthermore, this study collected information regarding the support teachers received from their administrators during COVID-19 distance, to compare teachers' confidence in distance learning verse support they have received from their administrators, the training they received, and materials provided to them to measure what helps teachers increase their self-efficacy for distance learning. A valid and reliable instrument is critical to collect grounded data from concluding. The following research questions aim to ensure the instrument is reliable and valid by asking:

1. To what extent are the DLS items/scales reliable and valid?

To further analyze the reliability of the items listed under the instrument and ensure each subscale helps us to identify the specific component that contributes to teachers' confidence.

We also wanted to investigate that even though the DLS instrument is reliable and valid, is it an instrument that does help us to identify factors that contribute to teachers' self-efficacy by asking:

2. Is DLS reliable at identifying factors that contribute to the teacher's self-efficacy?

Furthermore, finally, we investigated if DLS is an instrument that can be used by school districts to collect data on how to support and train their teachers for distance learning by asking:

3. Can the DLS help school districts to support and train teachers for distance learning?

Instrumentation

The survey study was created to collect information regarding the support teachers received from their administrators, their access to materials and training, and how these factors support teachers' self-efficacy. Google Forms was used to create the DLS instrument; it consists of four demographic items and 18 Likert type items. In the demographics section, data was collected based on teachers' age, gender, experience, and grade level they teach. The 18 Likert type items are rated on a 6-point scale (1 = *completely disagree*; 2 = *very much disagree*; 3 = *somewhat disagree*; 4 = *somewhat agree*; 5 = *very much agree*; 6 = *completely agree*) to investigate teacher's perception of administrator support during distance learning. This paper analyzes data from the 18 Likert-type items, highlighting the instrument's reliability, the constructs measured, and any possible correlation among scales produced to represent the constructs and targeted background variables.

Participants

This study collected data from 385 teachers in an urban K-12 Texas School district who taught during the COVID-19 pandemic in the fall of 2020. Teachers had to verify that they taught online in a K-12 setting and consent to the survey. The demographics of the respondents were 75.6% females and 23.1% males. Participants also had to identify their teaching experience, which documented many inexperienced (1-5 years) teachers responding to the survey. 35.3% of the respondents had 1-5 years of teaching experience, while only 15.6 % had more than 20 years of teaching experience.

Validation of the Distance Learning Support Scale.

This section describes the Distance Learning Support (DLS) Scale's reliability and factor analysis. Further inquiry examines hierarchical cluster analysis, followed by discussions on possible correlations among the emerging constructs and background variables (i.e., administrator support, training support, access to materials, and teacher self-efficacy).

Reliability

The output for Cronbach's alpha was .938 for the participants (385) that completed the 18 Likert items. According to DeVellis (1991) guidelines listed in Table 4.1 this is excellent. Item statistics from SPSS indicate that removing only one item, Item 12, would increase Cronbach's alpha by .001, concluding that 18 items selected for this study would make a reliable scale.

Table 4.1

DeVellis Reliability Guidelines

Cronbach's Alpha Output	Rating
Below .60	Unacceptable
Between .60 and .65	Undesirable
Between .65 and .70	Minimally acceptable
Between .70 and .80	Respectable
Between .80 and .90	Very good
Much above .90	Excellent (consider shortening the scale)

Source: DeVellis, 1991, p. 85.

Construct Validity through Factor Analysis

Exploratory factor analysis (principal components, varimax rotation) determined the number of constructs assessed by the survey instrument. The eigenvalue = 1 cutoff default resulted in three factors extracted and produced some cross-loading shown in Table 4.2.

Examination of the scree plot indicated that two or three factors were possibly present in the data, an iterative process of content validity checks conducted concurrently with Cronbach's alpha assessments for items extracted for each factor solution resulted in the selection of the three-factor solution accounting for 77% of the common variance.

Table 4.2

Results of Factor Analysis for Survey Items in Factor Loading Order

	1	2	3
Q9. If my administration does not have an answer to my question related to distance learning, they will find someone who does.	.814		
Q2. I am able to reach out to my administrators to get help/support whenever I needed it.	.813		
Q14. I believe my administrators have efficient systems in place to support teachers for distance learning.	.757	.442	
Q15. I feel my social and emotional needs are being considered by my administrators during distance learning.	.754	.315	
Q11. There is an effort by my administrators to improve my distance teaching practice.	.751		
Q7. I have support from my administration on best practices regarding out of class communication for distance learning.	.740	.377	
Q4. The number of meetings administrators are asking for during distance learning is reasonable.	.637	.358	
Q5. I have received adequate training on distance learning management systems (Google Classroom, Canvas, Blackboard, Schoology, etc.).		.818	
Q6. Video I have received adequate training on synchronous video software (Zoom, Google Meet, Microsoft Teams, Etc.).		.753	
Q3. I feel confident in my ability to teach online using solely distance learning.		.708	
Q10. The training I have received helped me improve my distance teaching practices.	.424	.643	
Q18. I have received professional learning opportunities for distance learning that promote students' academic learning to providing engaging and motivating distance learning opportunities.	.380	.634	.322
Q8. I have received adequate training in grading procedures for distance learning.	.497	.588	
Q13. I have received training on distance learning based on issues that emerged during previous semesters during distance learning.	.404	.581	.302
Q1. I have access to instructional technology devices and materials for me to teach.			.761
Q16. I am provided with Internet access and other technology devices needed for online instruction.			.705
Q12. I try to improve my skills in distance teaching to prepare myself for distance learning.			.563
Q17. I am provided with high-quality materials to support online instruction.	.366	.465	.546

Extraction method: principal component analysis. Rotation method: Varimax with Kaiser normalization. Rotated component matrix converged in 6 iterations.

Each factor produced a "very good" to "excellent" Cronbach's alpha of .920, .890, and .879, respectively. There are cross-loading of certain items; this makes it difficult to explain what construct each item belongs to; for example, Items 10, 8, 13, and 17 displayed cross-loading even when forced into three factors. Most of the cross-loading is between Factors 1 and 2; this is most likely explained by the interdependence of Scale 1 (administration support) and Scale 2 (distance learning training and self-efficacy).

The factors representing the constructs assessed by the instrument appear as follows:

- Factor 1 Administrator Support Scale (Items 9, 2, 14, 15, 11, 7, 4; highlighted in gold on Table 4.2) measures the support teachers received from their administration during distance learning.
- Factor 2 Training and Confidence Scale (Items 5, 6, 3, 10, 18, 8, 13; highlighted in green on Table 4.2) measures the distance learning training provided to teachers and teachers' confidence in their abilities to teach online.
- Factor 3 Access & Materials Scale (Items 1, 16, 12, 17; highlighted in blue on Table 4.2) including items that investigate teachers' access to materials and resources to teach online.

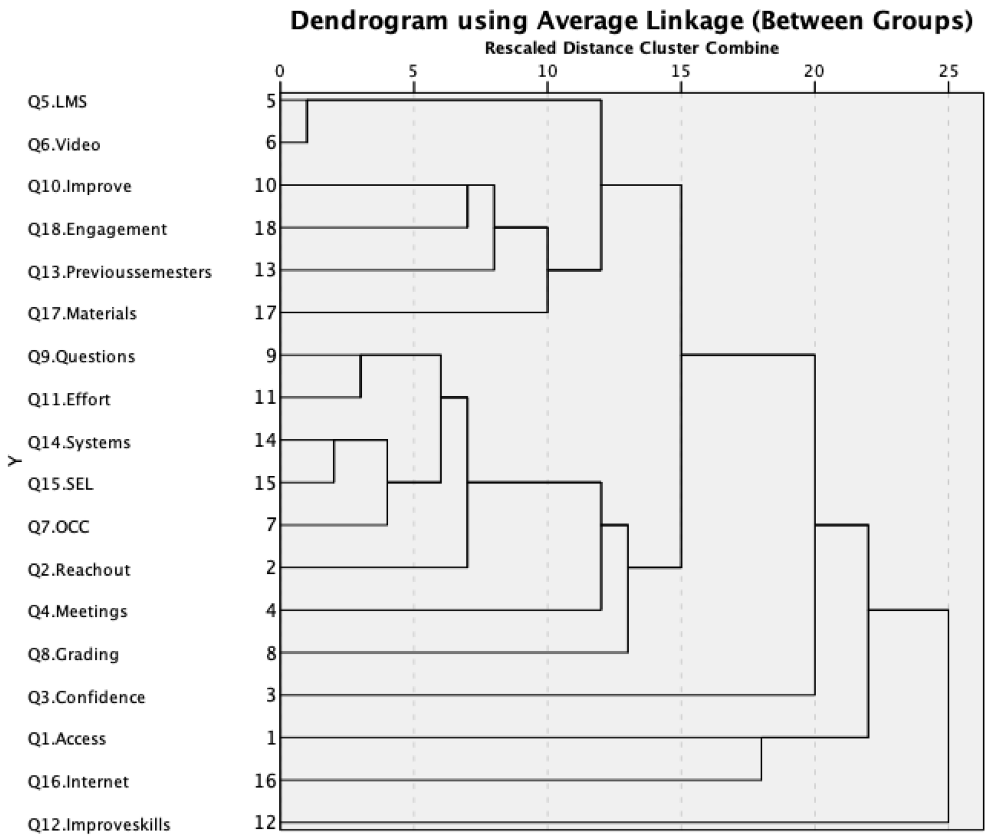
The KMO Measure of Sampling Accuracy yielded a statistic of 0.942; the value is considered excellent. With a value above .90, this indicates that factor analysis will be useful when interpreting the data set. This also indicated that a significant proportion of variance among the survey items is potentially common variance.

Construct Validity through Hierarchical Cluster Analysis

Hierarchical cluster analysis examined the possible constructs measured by three scales. Figure 4.1 shows that the items' strong linkages are consistent with the structure derived through exploratory factor analysis (Table 4.2). When analyzing the dendrogram's cluster analysis (between-groups linkage, z-score standardization) for each survey item (see Figure 4.1), similar groupings to each scale produced through factor analysis can be observed. The three major groupings in Figure 4.1 align with the three factors extracted in Table 4.2.

Figure 4.1

Hierarchical Cluster Analysis Dendrogram Showing Strengths of Associations among Survey Items



A hierarchical cluster analysis using the three scales identified in lower-order factor analysis indicated a strong linkage between Factors 1 and 2 (see Figure 4.2). It is important to note that both the higher-order factor analysis and the cluster analysis indicated that access to materials was separate from the other two scales (admin support, training, and confidence). It appears that teachers had a positive perception of the materials, such as internet access and technology they received but had mixed feelings about administrative support, training, and confidence. This could potentially explain the strong linkage between administrator support, training, and confidence.

Figure 4.2

Hierarchical Cluster Analysis Dendrogram Showing Relative Strengths of Associations among Scales

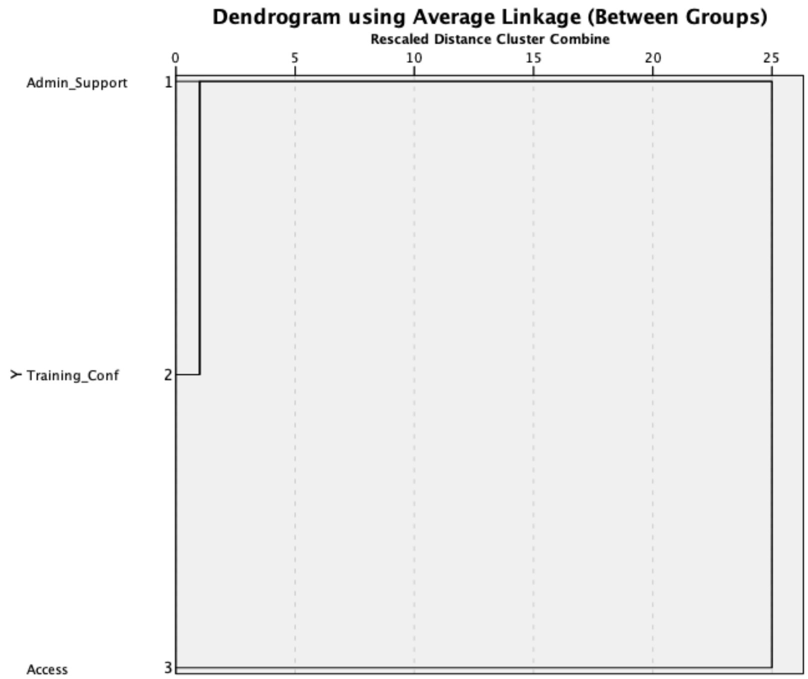
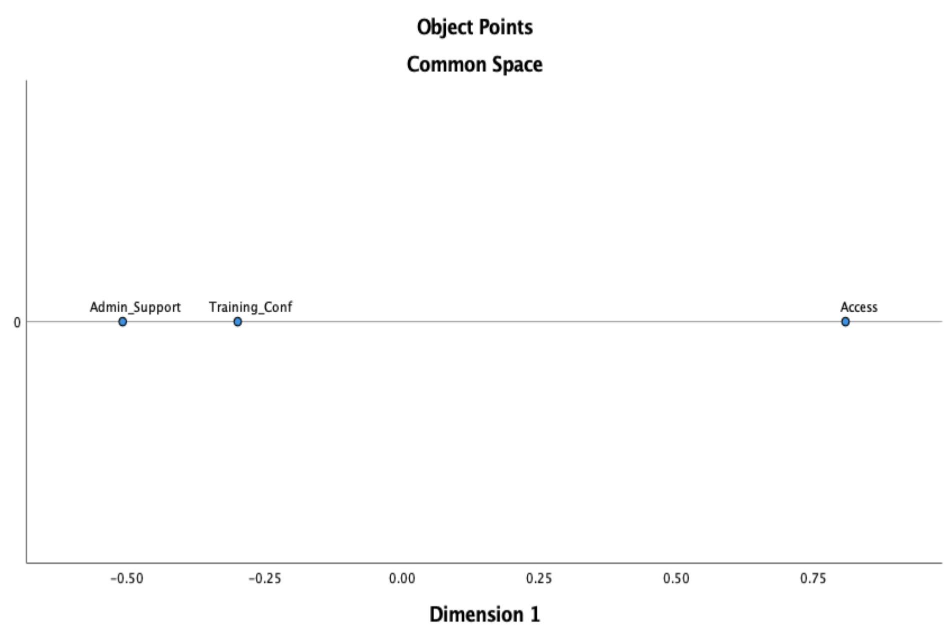


Figure 4.3

PROXSCAL Forced 1 to 1 Dimension



Multidimensional Scaling

A multidimensional scaling analysis using the SPSS procedure PROXSCAL (Euclidean distance, z-score standardization) compared the distances and relationships among the three scales identified through higher-order factor analysis and hierarchical cluster analysis. Figure 4.3 shows that the administrator support scale and training & confidence scale are closely linked together when forced to one dimension. In contrast, the access to material scale remains the outlier.

Findings from the Distance Learning Support Scales

A one-way ANOVA was run (using SPSS software) on four varied factors (gender, age, grade level, and years teaching) [see Tables 4.2, 4.3, and 4.4; also see Appendix 4.3 for descriptive statistics]. In terms of gender, there were no significant findings based on a $p < .05$ threshold, which could be due to the low number of male participants (87) in the study compared to female participants (289). Contrasting scale scores based on the age of teachers produced significant findings for each scale (Table 4.3): Factor 1 administrator support (p-value .014); Factor 2 training and confidence (p-value .048); and Factor 3 access to materials (p-value .010). Since the data was initially gathered based on five separate age groups, the variance and Cohen's d effect size were calculated based on re-coded groups; Group 1 teachers were between the ages of 20-39, and Group 2 teachers were 40+ years old. The effect size ((4.87-4.61)/1.02) for administrator support was Cohen's d = .254, which is considered a small effect size, according to Cohen (1988). The remaining findings also produced small effect sizes of Cohen's d = .197 for training & confidence and Cohen's d = .275 for access to materials.

Table 4.3

Results of One-way ANOVA based on Teacher's Age

		Sum of Squares	df	Mean Square	F	Sig.
Admin_Support	Between Groups	6.315	1	6.315	6.078	**.014**
	Within Groups	393.731	379	1.039		
	Total	400.045	380			
Training_Conf	Between Groups	3.258	1	3.258	3.938	**.048**
	Within Groups	313.527	379	.827		
	Total	316.785	380			
Access	Between Groups	3.140	1	3.140	6.698	**.010**
	Within Groups	177.661	379	.469		
	Total	180.801	380			

Table 4.4

Results of One-way ANOVA based on Years of Experience

		Sum of Squares	df	Mean Square	F	Sig.
Admin_Support	Between Groups	.738	1	.738	.701	.403
	Within Groups	399.307	379	1.054		
	Total	400.045	380			
Training_Conf	Between Groups	1.947	1	1.947	2.344	.127
	Within Groups	314.837	379	.831		
	Total	316.785	380			

(table continues)

		Sum of Squares	df	Mean Square	F	Sig.
Access	Between Groups	3.087	1	3.087	6.584	**.011**
	Within Groups	177.713	379	.469		
	Total	180.801	380			

Table 4.5

Results of One-way ANOVA based on Grade Level

		Sum of Squares	df	Mean Square	F	Sig.
Admin_Support	Between Groups	20.399	2	10.199	10.485	**.000**
	Within Groups	363.793	374	.973		
	Total	384.191	376			
Training_Conf	Between Groups	2.185	2	1.093	1.303	.273
	Within Groups	313.722	374	.839		
	Total	315.907	376			
Access	Between Groups	1.880	2	.940	1.974	.140
	Within Groups	178.144	374	.476		
	Total	180.024	376			

Years of teaching experience also produced a significant finding for scale 3 (access to materials) with a p-value of .011, shown in Table 4.4. Like teachers' age groups, the years of experience were re-coded into two groups to calculate an effect size; Group 1 teachers had 1-10 years of experience, and Group 2 teachers had 11+ years of experience. This result also produced a small effect size of Cohen's $d = .257$. Lastly, a one-way ANOVA was run based on grade level (see Table 4.5) and produced a significant finding for Scale 1 (administrator support) with a *p*-value of .000. The effect size between the upper-level teachers (high school and middle school) and the low-level teachers (elementary school) resulted in a moderate effect size of Cohen's $d = .544$. Based on the ANOVA findings and descriptive statistics, age, years of experience, and grade level taught all appear to be significant factors in teachers' perceptions of the level of support they receive from their administration, training, and access to materials.

Addressing the Research Questions

The findings help address each of the research questions in this paper. First, Question 1; is the DLS survey reliable and valid to be used? The outcomes suggested that the DLS survey is reliable based on the high-reliability statistics for each factor and a high Cronbach's alpha score of .938 for the survey items. This finding, along with the limited cross-loading in lower-order factor analysis without forcing factors, demonstrates the instrument's excellent reliability. It is significant that high order factor analysis, cluster analysis, and multidimensional scaling each grouped the administrator support scale and the training and confidence scale and left the access to materials scale independently. These findings bolster the DLS survey's validity because it consistently measures the interrelated nature between administrator support, training, and teacher confidence.

It is also important to mention that only one item if deleted, would increase the survey's reliability (Item 12), and it would narrowly increase Cronbach's alpha by .001. Furthermore, when analyzing the Likert items' wording after the exploratory factor analysis (Table 4.2) and cluster analysis (Figure 4.1), it produced compelling observations. Scale 1 (administrator support) deals with distance learning support directly tied to administrator actions, such as the number of meetings administrators asked for or if administrators met teachers' social and emotional needs, while Scale 2 (training and confidence) primarily focused on training to prepare teachers for distance learning and the level of confidence they felt in teaching online. For example, did teachers feel they received adequate online learning and learning management systems training that increased teachers' confidence? Using this scale, administrators can determine which teacher demographics felt the most supported in the shift to online learning. Lastly, Scale 3 (access to materials) consisted of items related to access to materials, for example, access to the internet and online materials. The only concern is Item 12, which seems to be an outlier "I try to improve my skills in distance teaching to prepare myself for distance learning." Ideally, with more participants, this item would fall solely into Scale 2 (training & confidence) related to training and teacher's confidence to teach online.

Next Question 2, is DLS reliable at identifying factors that contribute to the teacher's confidence? The study results revealed that the more training teachers receive, the more confident they feel teaching online. Exploratory lower-order factor analysis (see Table 4.1) grouped training and teacher confidence items on Scale 2. One can assume that this is because the more training teachers receive, the more confident they become teaching online. Hierarchical cluster analysis (see Figure 4.1) also grouped training and teacher confidence items. For example, Item 3, "I feel confident in my ability to teaching online using solely distance learning," was grouped with Items 5 and 6, which mention training related to learning management systems and synchronous video software. Hence, one could argue that additional training in these areas would increase teacher confidence. Also, Item 10, "The training I have received helped me improve my distance teaching practices," was linked to Items 13 and 18, that feature training to engage students online and address prior issues related to online learning. Again, these items provide insight into how administrators intentionally plan to increase teachers' confidence in distance learning.

Finally, to address Question 3, can the DLS help school districts to support and train teachers for distance learning? The findings in higher-order factors analysis, cluster analysis, and multidimensional scaling consistently showed a strong connection between the administrator support scale and the training and confidence scales. It is possible that teachers perceived the level of support from their administrators as connected to the training they received. This is essential data for administrators since they are often the catalysts for training and professional development decisions. When considering each survey item's frequencies in Appendix 4.2, administrators can use each item's mean and standard deviation to determine teachers' perceptions of their training to isolate critical areas for growth. For example, the support teachers received regarding social, emotional learning, and the frequencies of meetings were rated lower than all other items. In contrast, teachers rated their access to the materials they need to teach online and their ability to reach out to their administrators as very high. When considering the practical use of each survey item's frequencies, administrators can tailor future supports to meet the needs of their teaching staff.

In terms of criterion-related validity, what can the DLS survey measure? The ANOVA results produce significant findings that can help administrators determine the best course of action when developing support systems and training for their teaching staff. Based on this research's findings, it appears that younger teachers (see Table 4.3) did not feel as supported compared to teachers over 40 years old. Furthermore, younger teachers feel less confident with their ability to teach online. Based on these findings, it would be interesting to collect a larger sample size and look specifically at how administrators could better support younger teachers with less experience, which might help administrators reflect on their support systems for younger teachers. It is also interesting to note that the findings' largest effect size is related to grade level. The ANOVA results (see Table 4.5) and the descriptive statistics (see Appendix 4.3) suggest that elementary school teachers viewed their administrator support favorably than their middle school and high school counterparts. Based on the Likert items' means, elementary teachers also perceived training and access to materials more favorably, which could explain some correlations in the three scales identified by exploratory factor analysis. This is significant because this drastically increased the confidence of elementary school teachers and should bring about interesting conversations regarding what elementary school administrators are doing differently from secondary-level administrators to support distance learning instruction.

Conclusions

This study aims to provide a reliable and valid instrument to school administrators to support their teachers to successfully integrate technology by providing them with need-based training and support. Having tools and intentional support to help teachers improve their distance teaching practices and build confidence in distance learning becomes an essential component of efficient teaching. This study collected information regarding the support teachers received from their administrators during COVID-19 distance learning and how it impacted teachers' self-efficacy regarding distance teaching. This paper's findings shed light on the underlining questions, what factors help improve teachers' confidence with distance learning, how administrator support can be improved, and which teacher demographics have the highest confidence regarding online learning. Also, it is essential to note that elementary teachers perceived training and access to materials more positively.

In contrast, younger teachers did not feel as supported compared to teachers over 40 years old. This information is valuable for administrators to reflect on their support systems for new teachers. Furthermore, this study's limitations and future research are discussed in this section to guide future studies.

Limitations and Future Research

This study's limitations include the limited sample size (385 participants), some cross-loading items, and the small effect size of the significant findings related to the teacher's age. Items 10, 8, 13, and 17 all display cross-loading even when forced into three factors. A larger sample size would be beneficial and potentially produce additional significant findings with a larger effect size. However, even with a small sample size, the findings suggest that teachers' perceptions of their support during the shift to full-time distance learning vary based on teachers' age and years of experience. Recent studies have explored best practices for online learning preparation, such as Christensen and Alexander's (2020) study that found teachers preferred professional development to post and edit various resources into a digital format.

Furthermore, future research should focus on personalizing teacher training and support according to their needs and goals. For example, our study revealed that the more training teachers receive, the more confidence in distance learning abilities. Other studies pointed out the challenge's teachers faced when communicating with students during distance learning. Clausen et al. (2020) found in a limited survey that 59% of teachers were unsuccessful in contacting their students. This is an important avenue for future research because communication between teachers, students, and families is vital for positive learning outcomes (Akcaoglu & Lee, 2018). This paper's findings shed light on the DLS instrument as a reliable and valid instrument to identify factors that support teacher confidence with distance learning. This study's findings aim to help school districts support and train teachers for distance learning by using the data collected with the DLS instrument to plan effective and efficient teacher supports in distance learning.

Chapter References

Adedoyin, O. B., & Soykan, E. (2020). Covid-19 pandemic and online learning: the challenges and opportunities. *Interactive Learning Environments*, *0*(0), 1–13. https://doi.org/10.1080/10494820.2020.1813180

Akcaoglu, M., & Lee, E. (2018). Using Facebook groups to support social presence in online learning. *Distance Learning, 39*(3), 334-352.

Avci, Z. Y., O'Dwyer, L. M., & Lawson, J. (2020). Designing effective professional development for technology integration in schools. *Journal of Computer Assisted Learning, 36*(20), 160-199. https://doi.org/10.1111/jcal.12394

Bandura, A. (1982). Self-efficacy mechanism in human agency. *American Psychologist*, *37*(2), 122–147. https://doi.org/10.1037/0003-066X.37.2.122

Chang, I. H. (2012). The effect of principals' technological leadership on teachers' technological literacy and teaching effectiveness in Taiwanese elementary schools. *Educational Technology & Society, 15*(2), 328-340.

Christensen, R., & Alexander, C. (2020). Preparing K-12 Schools for a Pandemic Before It Occurs. *Journal of Technology and Teacher Education*, *28*(2), 261-272.

Christensen, R., & Knezek, G. (2011). Carrollton Farmers Branch teacher annual needs assessment. Denton, TX: Institute for the Integration of Technology into Teaching and Learning.

Christensen, R., & Knezek, G. (2017). Validating the Technology Proficiency Self-Assessment Questionnaire for 21st Century Learning (TPSA C-21). *Journal of Digital Learning in Teacher Education*, *33*(1), 20–31. https://doi.org/10.1080/21532974.2016.1242391

Clausen, J. M., Bunte, B., & Robertson, E. T. (2020). Professional development to improve communication and reduce the homework gap in grades 7-12 during COVID-19 transition to remote learning. *Journal of Technology and Teacher Education*, *28*(2), 443-451.

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences.* (2nd ed.). Hillsdale, NJ: L. Erlbaum associates.

DeVellis, R. F. (1991). *Scale development: theory and applications*. Applied social research methods series, vol. 26. *Newbury park, CA: Sage publications*.

Hamilton, L. S., & Hunter, G. P. (2019). Insights from the American Educator Panels. *Insights from the American Educator Panels*, 1–6.

Hodges, C. B., Moore, S., Lockee, B. B., Trust, T., & Bond, A. (2020). The difference between emergency remote teaching and online learning. *EduCause Review.* https://er.educause.edu/articles/2020/3/the-difference-between- emergency-remote-teaching-and-online-learning.

Hrastinski, S. (2008). Asynchronous and synchronous e-learning. *Educause Quarterly, 31*(4), 51–55.

Leithwood, K. A., & Riehl, C. (2003). *What we know about successful school leadership*. Philadelphia, PA: Laboratory for Student Success, Temple University.

Machado, L. J., & Chung, C. J. (2015). Integrating technology: The principals' role and effect. *International Education Studies*, *8*(5), 43–53. https://doi.org/10.5539/ies.v8n5p43

Novak, A. (2018). What works in professional learning. In Novak & Weber [Eds.] Best Practices in Professional Learning and Teacher Preparation. Waco, TX: Prufrock Press.

Shemshack, A., & Davis, T. (2020). Validating the Distance Learning Support Survey. In E. Langran (Ed.), *Proceedings of SITE Interactive 2020 Online Conference* (pp. 282-293). Online: Association for the Advancement of Computing in Education (AACE). Retrieved November 21, 2020, from https://www.learntechlib.org/primary/p/218159/.

Appendix 4.1: Distance Learning Support Instrument

Demographic Variables

1. Your age: Category choices (20-29:**1**, 30-39: **2**, 40-49: **3**, 50-59: **4**, 60+: **5**) or two groups (**1:** 20-39, **2:** 40-60+)

2. Gender: Female, Male, non-binary, or prefer not to say (Female: **1**, Male: **2**, non-binary: **3**, prefer not to say: **4**)

3. Years of experience as a teacher: Category choices (1-5 :**1**,6-10:**2**,11-15: **3**,15-20: **4,** 20+: **5**) or two groups (**1:** 1-10, **2:** 11-20+)

4. What grade level you teach: Category choices (Pre-K-2: **1**,3-5: **2,** 6-8:**3,** 9-12:**4)**

Likert Items
(1 = strongly disagree; 2 = disagree; 3 = somewhat disagree; 4 = somewhat agree; 5 = agree; 6 = strongly agree)

1 I have access to instructional technology devices and materials for me to teach online.

2. I am able to reach out to my administrators to get help/support whenever I needed it.

3. I feel confident in my ability to teaching online using solely distance learning.

4. The number of meetings administrators are asking for during distance learning is reasonable.

5. I have received adequate training on distance learning management systems (Google Classroom, Canvas, Blackboard, Schoology, Etc.).

6. I have received adequate training on synchronous video software (Zoom, Google Meet, Microsoft Teams, Etc.).

7. I have support from my administration on best practices regarding out of class communication for distance learning.

8. I have received adequate training in grading procedures for distance learning.

9. If my administration does not have an answer to my question related to distance learning they will find someone who does.

10. The training I have received helped me improve my distance teaching practices.

11. There is an effort by my administrators to improve my distance teaching practice.

12. I try to improve my skills in distance teaching to prepare myself for distance learning.

13. I have received training on distance learning based on issues that emerged during previous semesters during distance learning.

14. I believe my administrators have efficient systems in place to support teachers for distance learning.

15. I feel my social and emotional needs are being considered by my administrators during distance learning.

16. I am provided with Internet access and other technology devices needed for online instruction.

17. I am provided with high-quality materials to support online instruction.

18. I have received professional learning opportunities for distance learning that promote students' academic learning by providing engaging and motivating distance learning opportunities.

Appendix 4.2: Item Descriptive Statistics Descriptive Statistics

	N	Mean	Std. Dev	Var
Q1. Access	381	5.32	.822	.676
Q2. Reach out	381	5.25	1.030	1.060
Q3. Confidence	381	4.73	1.103	1.218
Q4. Meetings	381	4.27	1.510	2.281
Q5. LMS	381	4.60	1.205	1.451
Q6. Video	381	4.79	1.130	1.277
Q7. OCC.	381	4.81	1.171	1.371
Q8. Grading	381	4.34	1.358	1.845
Q9. Questions	381	5.05	1.094	1.197
Q10. Improve	381	4.69	1.116	1.246
Q11. Effort	381	4.94	1.036	1.073
Q12. Improve skills	381	5.54	.613	.376
Q13. Previous semesters	381	4.62	1.255	1.574
Q14. Systems	381	4.59	1.282	1.642
Q15. SEL	381	4.16	1.535	2.358
Q16. Internet	381	5.10	1.046	1.094
Q17. Materials	381	4.62	1.205	1.453
Q18. Engagement	381	4.78	1.055	1.113

Appendix 4.3: One-Way ANOVA Descriptive Statistics

Combined

		N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Min.	Max.
						Lower Bound	Upper Bound		
Admin_ Support	1	89	4.71	.99511	.10548	4.50	4.9207	1.71	6.00
	2	129	4.54	1.07496	.09464	4.35	4.7321	1.14	6.00
	3	73	4.98	.94027	.11005	4.76	5.2037	1.00	6.00
	4	56	4.82	1.04187	.13923	4.54	5.1055	1.71	6.00
	5	33	4.69	.99601	.17338	4.34	5.0501	2.29	6.00
	Total	380	4.72	1.02716	.05269	4.61	4.8265	1.00	6.00
Training_ Conf	1	89	4.44	.84125	.08917	4.26	4.6234	1.86	6.00
	2	129	4.65	.97754	.08607	4.48	4.8248	1.71	6.00
	3	73	4.80	.79664	.09324	4.61	4.9902	2.86	6.00
	4	56	4.79	.92773	.12397	4.55	5.0469	2.57	6.00
	5	33	4.57	1.00255	.17452	4.21	4.9269	2.71	5.86
	Total	380	4.64	.91407	.04689	4.55	4.7407	1.71	6.00
Access	1	89	5.08	.68043	.07213	4.94	5.2276	2.50	6.00
	2	129	5.05	.71736	.06316	4.92	5.1792	2.25	6.00
	3	73	5.28	.61049	.07145	5.14	5.4301	3.75	6.00
	4	56	5.25	.69085	.09232	5.06	5.4350	2.75	6.00
	5	33	5.18	.73759	.12840	4.92	5.4434	3.50	6.00
	Total	380	5.14	.69039	.03542	5.07	5.2157	2.25	6.00

Age (2 groups): Code sheet: (**1**: 20-39/ **2**: 40-60+)

		N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Min.	Max.
						Lower Bound	Upper Bound		
Admin_ Support	1	218	4.61	1.04398	.07071	4.47	4.7521	1.14	6.00
	2	163	4.87	.98515	.07716	4.72	5.0253	1.00	6.00
	Total	381	4.72	1.02604	.05257	4.62	4.8274	1.00	6.00
Training_ Conf	1	218	4.56	.92800	.06285	4.44	4.693	1.71	6.00
	2	163	4.75	.88419	.06926	4.61	4.8931	2.57	6.00
	Total	381	4.64	.91304	.04678	4.55	4.7414	1.71	6.00
Access	1	218	5.06	.70109	.04748	4.97	5.1601	2.25	6.00
	2	163	5.25	.66202	.05185	5.14	5.3524	2.75	6.00
	Total	381	5.14	.68978	.03534	5.07	5.2145	2.25	6.00

Years Teaching (2 groups): Code sheet: (**1**: 1-10/ **2**: 11+)

		N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Min.	Max.
						Lower Bound	Upper Bound		
Admin_ Support	1	228	4.68	.98145	.06500	4.55	4.8160	1.43	6.00
	2	153	4.77	1.09017	.08814	4.60	4.9519	1.00	6.00
	Total	381	4.72	1.02604	.05257	4.62	4.8274	1.00	6.00
Training_ Conf	1	228	4.59	.90960	.06024	4.47	4.7096	1.71	6.00
	2	153	4.73	.91416	.07391	4.59	4.8827	2.57	6.00
	Total	381	4.64	.91304	.04678	4.55	4.7414	1.71	6.00

(table continues)

		N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean Lower Bound	95% Confidence Interval for Mean Upper Bound	Min.	Max.
Access	1	228	5.07	.70564	.04673	4.97	5.1634	2.25	6.00
	2	153	5.25	.65234	.05274	5.15	5.3591	2.75	6.00
	Total	381	5.14	.68978	.03534	5.07	5.2145	2.25	6.00

Grade Level (4 groups): Code sheet: (**1**: Pre-K-2/ **2**: 3-5/ **3**: 6-8/ **4**: 9-12)

		N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean Lower Bound	95% Confidence Interval for Mean Upper Bound	Min.	Max.
Admin_ Support	1	244	4.89	.93102	.05960	4.77	5.0144	1.14	6.00
	2	65	4.49	.99619	.12356	4.24	4.7413	1.71	6.00
	3	68	4.34	1.15672	.14027	4.06	4.6266	1.71	6.00
	Total	377	4.72	1.01083	.05206	4.62	4.8307	1.14	6.00

CHAPTER 5

DEVELOPING A FRAMEWORK FOR PERSONALIZED ADAPTIVE TEACHER EDUCATION TO IMPROVE TEACHERS' SELF-EFFICACY*

Abstract

Technology-supported personalized adaptive learning environments have become a popular research topic focusing on developing more efficient learning environments. However, despite the rapid progress of personalized adaptive learning (PAL), very little research has explicitly looked at personalized adaptive preservice teacher education to provide better support according to their diverse needs and skills to improve their self-efficacy. We need to focus on preservice teacher education as growing data has shown that efforts to improve preservice teacher education can significantly impact student learning. In this regard, this paper analyzed current literature on PAL, PAL tools and systems, preservice teacher education, and self-efficacy. Based on the literature, a framework was proposed to personalize and adapt preservice teacher education to increase their self-efficacy. The proposed framework suggests dynamic data collection on preservice teachers' skills, knowledge and affective states, and the ability to adapt the content, activities, and content delivery to increase preservice teachers' self-efficacy.

Keywords*: Preservice teacher, personalized adaptive learning, teacher education, self-efficacy, personalized learning*

Introduction

Technology-supported personalized adaptive learning (PAL) has been one of the hot topics in learning research for a long time (Xie et al., 2019) that is believed started with theories that are inspired by educational theories from the progressive era in the earlier century

---

* This chapter is reproduced from Shemshack, A & Kinshuk. *Developing a framework for PAL Preservice Teacher Education to Improve Self-efficacy.* Manuscript submitted for publication.

(Shemshack & Spector, 2020). Especially John Dewey's (1915, 1998) emphasis on experiential, learner-centered education tailored to each learner's needs, interests, and abilities and then followed by constructivism theory that points out the need for personalized adaptive learning according to skill levels and needs of individuals. Technology-supported learning environments keep increasing in educational settings, including preservice teacher education institutions. Technology-supported learning systems provide an opportunity for preservice teachers to continue learning without time and space limitations. In addition to content knowledge and pedagogical knowledge, these technology-supported learning environments allow preservice teachers to practice skills they will need in the classroom, such as practicing classroom management skills in a simulated classroom environment.

Nevertheless, technology developments make it easier to adapt the learning content and activities according to individual needs and skills. As a result, learning environments have changed drastically in the recent decade, primarily due to information and communication technologies (Dawson et al., 2010; Spector, 2014; Xie et al., 2019). Current technologies allow the systems to provide services according to user's search history, preferences that encourage learning technologies researchers to imitate these systems for learning systems, moreover, consider learners' abilities and prior knowledge. Xie et al. (2019) stated that personalized adaptive learning has become possible by implementing intelligent learning systems, integrating learners' preferences, analyzing individual learning data, and many more components studied to improve the learning experience. Furthermore, Pane et al. (2015) shared their findings that suggest the effects of personalized learning on learner achievement are promising, which will increase the interest and demand in personalized adaptive learning systems.

Despite the rapid progress of personalized adaptive learning, very little research has explicitly looked at personalized adaptive preservice teacher education to provide teachers with resources according to their diverse needs and skills to improve their self-efficacy. Teachers' professional proficiency is composed of cognitive professional knowledge and affective professional belief components, which are generally assumed to be related and impact instructional practice (Avalos, 2011; Depaepe & König, 2018). To provide meaningful learning opportunities for students, meaningful learning opportunities need to be also offered for teachers (Natividad Beltrán del Río, 2021; Nel, 2017; Siko & Hess, 2014; Thoma et al., 2017). However, studies simultaneously relating cognitive and affective components to instructional practice are limited (Depaepe & König, 2018). Preservice teacher education is a complex process that requires teachers' cognitive and emotional involvement. It requires the willingness to examine where each teacher stands and provide personalized adaptive tools for improvement or change (Depaepe & König, 2018) according to their diverse goals and needs. While many studies analyzed preservice teacher education and current practices, there is limited research investigating personalized adaptive preservice teacher education to improve their self-efficacy. This study aims to address this need by proposing a framework for personalized adaptive preservice teacher education to improve preservice teachers' self-efficacy and, as a result, improve preservice teachers' learning experience and further improve learning experience for students.

According to Bandura (1994), providing content according to learners' skill levels and knowledge is expected to increase self-efficacy. Thus, the relationship between PAL and self-efficacy is analyzed to develop a framework that can be used for preservice teacher education to improve teachers' self-efficacy.

The following section presents a comprehensive review of existing work in the literature on personalized adaptive learning (PAL), PAL tools and systems, preservice teacher education, and self-efficacy. Each component listed component's possible contributions to the personalized adaptive preservice teacher education to improve self-efficacy frameworks' development are discussed in each subsection. Based on the literature, a framework is proposed to personalize and adapt preservice teacher education to increase their self-efficacy in the framework development section. Each component of the framework is discussed in detail; furthermore, their contributions to the framework are discussed. This follows a practical, real-life scenario to provide a better picture of its practical use. This study's findings are then provided under the discussion section, followed by the limitations and future research section within the conclusion.

Personalized Adaptive Learning

Personalized adaptive learning (PAL) is one of the main paradigms of the framework proposed in this study. PAL research literature is analyzed to present its possible impact on preservice teacher education and how it could be used to improve preservice teachers' self-efficacy. PAL does not have a unified definition; however, in this study, our definition is mainly evolving around Peng et al.'s (2019) definition and enriched with components from a few other definitions. Peng et al. (2019) defined personalized adaptive learning as "a technology-empowered effective pedagogy which can adaptively adjust teaching strategies timely based on real-time monitored (enabled by smart technology) learners' differences and changes in individual characteristics, individual performance, and personal development." Furthermore, learning objectives, instructional approaches, and instructional content, and its sequencing may all vary based on learner needs (Chen et al., 2005; Klašnja-Milićević et al., 2011). Also, learning activities are meaningful and relevant to learners, driven by their interests, and often self-initiated (US Department of Education, 2017, p. 9). For the purpose of this research, PAL is defined as a technology-empowered pedagogy that identifies learners' cognitive and affective states by considering their current skill level, prior knowledge, interests, and adapts the content and content delivery accordingly to challenge the learners enough to evoke deep thinking by providing them with relevant material that will keep them motivated in learning and help them to become lifelong learners.

Personalized adaptive learning systems require the use of several tools and theories to build adaptive and meaningful learning systems according to individuals' needs and skills. Item response theory (IRT) is one of the main theories that has been used to create personalized adaptive learning systems (Chen & Chung, 2008; Chen et al., 2005; Pliakos et al., 2019). IRT is a robust theory in education measurement to select the most appropriate items for learners based on individual learner ability; also, difficulties of course materials are simultaneously considered when implementing the proposed dynamic personalization mechanism (Chen et al., 2005; Pliakos et al., 2019). Chen et al. (2005) and Pliakos et al. (2019) suggested that the systems based on IRT provide learning paths adapted to various levels of difficulty of course materials and consider learners' diverse abilities and skills. Furthermore, Pliakos et al. (2019) suggested that not only IRT but also machine learning techniques can be valuable for adaptive item selection. Response predictions for new preservice teachers can be made by addressing the ability estimation as a regression task based on machine learning. The system can predict the new learner's responses by using first a machine learning model to estimate this new learner's ability parameter and then use it to predict the responses with IRT. These systems prevent the learner from becoming lost in the course materials; by providing personalized learning, filtering out unsuitable course materials to reduce cognitive load, and providing an adequate learning diagnosis based on an individual's user profile to help them to learn effortlessly (Pliakos et al., 2019).

Moreover, to make predictions about preservice teachers' cognitive and affective states, their data need to be collected through ongoing assessments blended into the learning process. Assessment and data collection will be the main components of the framework for personalized adaptive preservice teacher education to improve teachers' self-efficacy. Assessment and data collection are discussed more in detail in the following section.

Assessment and Data Collection

Dynamic assessment and data collection are the cornerstones of a dynamic, personalized adaptive learning system (Pardo et al., 2017; Tetzlaff et al., 2020; Troussas et al., 2019). Adaptive formative assessment is an ongoing dynamic learner monitoring process to provide ongoing feedback and support to adapt content according to individual needs to improve the learning experience based on collected data (Tetzlaff et al., 2020). The studies related to self-efficacy have shown that when individuals are provided feedback and support at the right time (Tang & McCalla, 2005, as cited in Klašnja-Milicevic et al., 2015), that helps to increase self-efficacy (Bandura, 1994). This study's focus is developing a framework for personalized and adaptive preservice teacher education to increase teachers' self-efficacy; therefore, we need systems that will help identify the need for help and support during the preservice teacher education. Louhab et al. (2018) referred to adaptive formative assessment as a compass to guide learning and provide instructors with data to guide and support learners, modify instruction, and suggest a learning path. The goal of adaptive formative assessment is to dynamically diagnose and support prescription of what content and support to provide to learners according to their needs and skill levels. Several methods and systems are available to collect data and assess learners' knowledge and skills; however, they are outside of this study's scope.

Figure 5.1

Assessment and Adaptation in Personalized Adaptive Learning (PAL)

Additionally, it is also essential to point out that Item response theory (IRT) has been dominant in adaptive formative assessment systems. In many forms, as suggested by Bennett and Davier (2017), IRT is the most used model in large-scale operational assessment programs. Furthermore, Bennett and Davier (2017) suggested that perhaps an essential feature leading to the dominance of IRT in operational programs is the characteristic of estimating individual item difficulties and test-taker abilities independently on the same scale, which is a feature that is not possible with classical measurement models. This feature allows for tailoring assessments through judicious item selection to achieve precise measurement for individual learners or defining important cut points on an assessment scale, enabling personalized support to all learners. Figure 5.1 shows a possible general dynamic cycle of personalized adaptive learning according to ongoing assessment and data collection for both cognitive and affective states of preservice teacher education that also can be used in different learning environments with different learner groups.

This study's focus on developing a framework for personalized adaptive preservice teacher education to improve preservice teachers' self-efficacy brings up the need for considering emotion and affect in preservice teacher education (Avalos, 2011; Depaepe & König, 2018). Furthermore, Avalos (2011) and Depaepe and König (2018) pointed out the scarcity of studies that have considered cognitive and affective components. Thus, emotion and affect components of personalized adaptive teacher education are discussed in the following section to analyze the impact of considering emotion and affect as an extension of the data collection process in personalized adaptive preservice teacher education to improve teachers' self-efficacy.

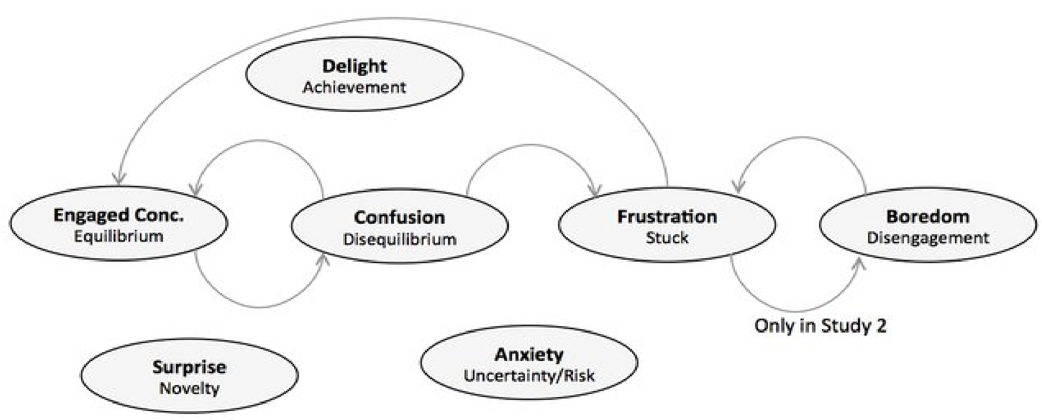
Emotion/Affect

The integration of emotion with learning technologies has been investigated in literature to determine how a computer can sense human emotions and systems that detect and respond to users' emotions to produce more engaging and fulfilling interactions. D'Mello et al. (2010) pointed out that confusion, frustration, engagement, curiosity, delight, anxiety, and boredom tend to be the most observed states, resulting in the context of several learning environments and activities that have been studied. Calvo and D'Mello (2010) stated that systems automatically identifying and responding to a user's affective states during interactions with a computer can enhance the interaction's quality and learning, thereby making a computer interface more usable, enjoyable, and effective (Santos et al., 2014). To improve the learning experience, we need to consider the affective states of preservice teachers to help them stay engaged in learning activities; thus, affective states are included in Figure 1 as part of ongoing data collection and personalized adaptive learning. Assessment and adaptation in the PAL model ensure that data collection focuses on current skills, knowledge, and affective states of the preservice teachers.

Additionally, Santos (2016) pointed out that current literature reports an interplay between the cognitive aspects of learning and affect (Santos et al., 2014), which implies the need to detect and then, through appropriate feedback, affect-related strategies to improve the learning experience. Figure 5.2 is a model of affect dynamics by D'Mello and Graesser (2012), representing how each affective state impacts the learning experience. Model of affect dynamics predicts learners' affective state and suggests learning environments need to substantially challenge learners at the right time to evoke critical thought and deep inquiry through collected data regarding learners' affective state.

Figure 5.2

Model of Affect Dynamics



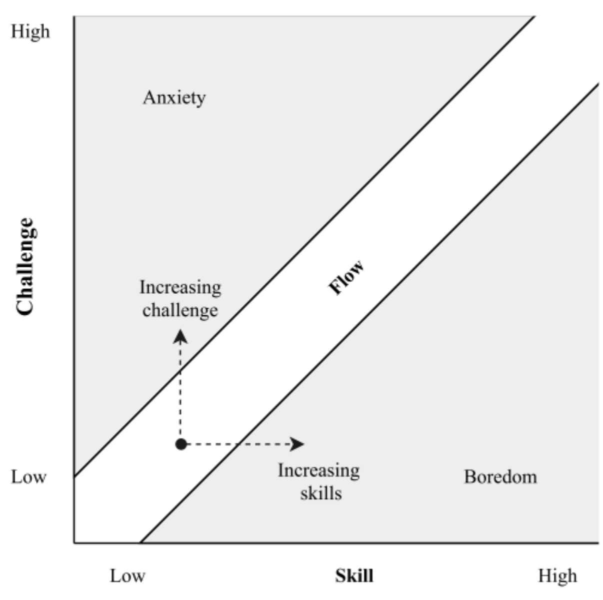
Source: D'Mello and Graesser, 2012.

As presented in Figure 5.2, the model of affect dynamics by D'Mello and Graesser (2012) predicts that learners in a state of engagement/flow will encounter cognitive imbalance and confusion when facing contradictions and obstacles to goals and other impasses.

Furthermore, learners revert into the engaged/flow state if an imbalance is restored through thought, reflection, and problem-solving. However, failure to restore imbalance and obstacles that block goals trigger frustration, which, if unresolved, will eventually lead to boredom. Thus, it is essential to have systems assess the preservice teachers' state of affect and cognition to adapt the content accordingly, so learning environments substantially challenge preservice teachers enough to evoke critical thought and deep inquiry (D'Mello & Graesser, 2012). Furthermore, Figure 5.3 represents the flow channel by Csikszentmihalyi (1990), representing four combinations of high/low skills and high/low challenges, representing a state equilibrium that the model of affect dynamics (D'Mello & Graesser, 2012) supports.

Figure 5.3

Flow Channel



Source: Csikszentmihalyi, 1990.

As presented in Figures 5.2 and 5.3, assessment and data collection of cognitive and affective state is essential to adjust instructional content according to preservice teachers' current states to ensure they are challenged enough to evoke critical thinking and deep inquiry.

According to collected data, predicting learners' current skills, knowledge, and affective state, the systems and tools are available that can be used to develop personalized adaptive learning environments that allow more enjoyable and compelling learning experiences (D'Mello & Graesser, 2012; Santos et al., 2014). Thus, the following subsection focuses on the systems and tools available to adapt and personalize learning. Furthermore, it provides insight on how these tools and systems might impact personalized adaptive preservice teacher education and analyzes the detection of the affective states of preservice teachers and supporting them at the right time might improve their self-efficacy.

Systems and Tools for Personalized Adaptive Learning

We need tools and systems to provide personalized adaptive education to preservice teachers to improve their self-efficacy. As technology develops, the tools and systems available increase; additionally, existing tools and systems evolve as we learn more about machine learning, AI, human-machine interaction, data collection, and data usage. A few systems and tools are discussed in the following sections to present how they might contribute to personalized adaptive preservice teacher education.

Intelligent Tutoring Systems

ITSs is one of the systems that aim to provide direct, dynamic, personalized instruction and feedback by assessing learners' knowledge at a granular level to help learners learn new skills (Weitekamp et al., 2020), usually without a human teacher's intervention (Niculescu, 2016) through mechanisms such as scaffolded practice problems and correctness feedback, next-step hints, and adaptive feedback messages (VanLehn, 2006). ITSs can be used in preservice teacher education to provide education according to teachers' cognitive and affective state to improve their self-efficacy (Bandura, 1994).

Many ITSs in the literature have been developed based on mastery learning theory, which is the primary learning theory in our current education system. Preservice teachers' performance determines what they work on next; based on their skill profiles' dynamic measurements, and intelligent tutors can help institutions effectively teach an academically diverse set of preservice teachers (Bloom, 1968; Kulik et al., 1990; Sales & Pane, 2017). As an essential part of the ITSs, when learners interact with learning materials, ITSs track their progress and adapt their interaction, such as correcting learners' possible misconceptions, providing personalized feedback, and suggesting learning a unique project that suits learners' current knowledge (Wu, 2020) which, as suggested by Bandura (1994), is expected to increase self-efficacy of preservice teachers. The tutor's ability to diagnose what a learner knows and does not know, and the ability to select relevant interventions given this diagnosis, are pivotal to good teaching. Another critical feature is ITSs' ability to infer, from preservice teachers' problem-solving actions and answers, what is likely well understood or mastered, and what is not, from only a few observations, and to move on in the curriculum at the right pace for that specific preservice teacher to provide support and intervention according to their unique needs (Desmarais & Baker, 2012).

Learning analytics (LA) is another set of techniques that promotes personalization by providing insights and understanding of how learners learn and support personalized learning experiences that meet learners' goals and needs (Chatti & Muslim, 2019). In the following section, learning analytics is discussed to explore how LA can personalize and adapt preservice teacher education to improve their self-efficacy.

Learning Analytics

According to Perez-Berenguer et al. (2020), learning analytics is widely recognized to improve the learning/teaching processes. LA allows for learner data dashboard customization and improves the efficiency of the analysis of learners' interaction data. One of the techniques of LA that can be used for preservice teacher education is that events resulting from learners' interaction are captured and stored in Caliper standard format to be further processed incrementally to allow data dashboards to be shown without delay to instructors. LA data dashboard increases access to learner data, which is also more nuanced and fine-grained than ever before, allowing institutions to respond with personalized feedback and support for preservice teachers according to their diverse needs.

Moreover, Chatti and Muslim (2019) pointed out that LA opens new opportunities for advancing personalization by providing insights and perception into how learners learn and support customized learning experiences that meet their goals and needs. LA can play an essential role by analyzing data collected from multiple learning environments for preservice teacher education by supporting customized activities that meet the diverse teachers' needs and goals. Furthermore, LA can provide insights into understanding how preservice teachers perform in PAL environments to best support them according to their diverse needs and skills.

LA systems can analyze and measure learners' data to infer competence, meta-competence, and confidence measures. These measures enable the learning analytics systems to auto-configure and auto-customize to personalized instruction and optimal learning pathways for preservice teachers (Govindarajan et al., 2017). Systems developed based on the LA techniques can auto-configure and auto-customize to offering personalized and adaptive education and calculating an optimal learning pathway for preservice teachers. Furthermore, LA systems provide on-demand and adaptive support for learners based on their needs (Ifenthaler & Yau, 2020; Perez-Berenguer et al., 2020).

Also, adaptive and intelligent web-based educational systems have been a solution to personalized adaptive learning environments through smart learning environments (Peng et al., 2019). The vast amount of data produced by educational technologies can be used to understand preservice teacher education better and, as a result, provide more intelligent, interactive, engaging, and efficient learning to preservice teachers (Koedinger et al., 2013). Various data mining approaches can be used to provide personalized adaptive preservice teacher education to increase their self-efficacy, as explored in the next section.

Data Mining for Personalized Adaptive Learning

Data mining (DM) techniques can identify valuable information that can help preservice teacher education instructors establish a pedagogical basis for designing or modifying an environment or teaching approach. The application of data mining in educational systems is an iterative cycle of hypothesis formation, testing, and refinement (Romero & Ventura, 2007) to get the most out of the data collected.

Peña-Ayala (2014) pointed out that data mining pursues to find out data patterns, organize information of hidden relationships, structure association rules, and estimate unknown items' values to classify objects, compose clusters of homogenous objects, and unveil many kinds of findings that are not quickly produced by a traditional computer-based information system. Using data mining technology, valuable and regular information can be extracted from massive data collected from preservice teachers to recommend learning activities according to their cognitive and affective state. Thereby, DM outcomes represent valuable support for decision-making for efficient learning activities for preservice teachers to increase their self-efficacy. Moreover, as one of the most critical technologies in personalized service, collaborative filtering recommendation is another successful technology currently applied to recommend products (Wang & Fu, 2020) based on information of interest to a specific user by using the user group preference with the shared experience. Moreover, users' preference information in the group is recorded to help other users filter information (Shu et al., 2018).

Also, recommender systems (RSs) are another system used to provide personalized support in learning. The following section analyzes RSs to discuss their possible uses for personalized adaptive preservice teacher education to increase teachers' self-efficacy.

Recommender Systems

Recommendations from RSs require a decision-making process such as deciding on learning objects that are most appropriate according to learners' characteristics. Since novice learners do not have enough knowledge to decide or evaluate objects of interest, RSs can be very beneficial (Klašnja-Milićević et al., 2015). RSs can suggest learning content according to preservice teachers learning characteristics to personalize their learning material to increase their self-efficacy. According to Wang and Fu (2020), personalized services learn users' interests and behaviors by collecting and analyzing user information, mine the hidden interests and behavior rules of user groups, formulate corresponding information filtering strategies, and provide personalized active recommendation services that can improve learning experience.

RSs can collect information according to various preservice teachers' attributes, such as their knowledge level, cultural level, personal learning interest, and learning needs. RSs can recommend learning resources to preservice teachers to provide personalized suggestions and support according to their various attributes, combined with their current knowledge and ability. Furthermore, since RSs stimulate learners' enthusiasm for learning to learn independently and efficiently to achieve the best learning effect (Shu et al., 2018), increasing their self-efficacy (Bandura, 1994), their use with preservice teachers can be very helpful.

Tang and McCalla (2005, as cited in Klašnja-Milicevic et al., 2015) suggested that ideally, RSs should assist learners in discovering relevant learning actions that match their profile, at the right time, in the proper context, and in the right way. RSs should keep the preservice teachers motivated and enable them to complete their learning activities effectively and efficiently (Bandura, 1994).

From the discussion till now, it is clear that several systems and techniques are available in the literature to provide adaptive and personalized support to the preservice teachers to increase their self-efficacy. However, Kumar et al. (2015) noted that no matter how data is processed, the point is that learners and instructors should control the choice of analyses and corresponding methods and use it to improve learning environments' adaptivity according to individuals' unique needs.

With the overview of various systems and techniques becoming available to provide personalized and adaptive support in education, this research aims to develop a framework for personalized adaptive preservice teacher education to improve self-efficacy. The following section looks at preservice teacher education and self-efficacy in detail. Furthermore, the impact of increased self-efficacy on teaching is explored to build a base for a proposed framework for personalized adaptive preservice teacher education to increase self-efficacy.

Preservice Teacher Education and Improving Preservice Teachers' Self-Efficacy

Current studies have repeatedly pointed out that teachers are the main determinants of instructional practice and student learning outcomes (Colson et al., 2018; Darling-Hammond, 2000; Depaepe & König, 2018; Jenset et al., 2018; Schleicher, 2016). Therefore, teachers need to be adequately prepared by providing them with personalized adaptive preservice teacher education to improve their self-efficacy regarding their teaching skills.

Teachers shape their teaching practices by filtering interpretations, framing situations or problems, and guiding actions (Fives & Gill, 2015; Heinonen et al., 2019; Kagan, 1992; Pajares, 1992; Tondeur et al., 2017). Considering Bandura's (1994) suggestion, self-efficacy determines how people feel, think, motivate themselves, and perform. Thus, it is paramount that preservice teachers have a strong sense of self-efficacy to help them maintain their interest in teaching and use those skills to help all students they teach (Gedzune, 2015, as cited in Colson et al., 2018). Teaching is a stressful and high workload profession that will benefit from having good stress management skills. Bandura (1997) pointed out that preservice teachers who have repeated feelings of success more successfully manage teaching stress. Preservice teachers need to feel connected and have a sense of self-efficacy for the responsibilities they face when teaching (Ryel et al., 2001, as cited in Colson et al., 2018).

Bandura (1982, 1994) described self-efficacy as people's beliefs about their capabilities to produce designated performance levels that regulate events that influence their lives. Moreover, a strong sense of efficacy enhances human accomplishment and personal well-being. Also, self-efficacy perceptions affect the reception of change, the presence of knowledge, and the acquisition of skills. A higher self-efficacy level will produce more significant effort toward developing new skills (Bandura, 1994; Ertmer et al., 2012; Howard et al., 2015; Ottenbreit-Leftwich et al., 2018; Shen et al., 2013). Correspondingly, self-efficacy dictates what activities individuals choose to pursue and the level of effort they will put forth (Bandura, 1977, 1982). Thus, self-efficacy has been a critical component in motivation and learning theories in varied contexts (Artino, 2012; Bandura, 1997). Bandura (1977) claimed that one's efforts' cumulative effects alter one's performance. The number of tasks completed by one reflects the degree of perseverance.

Moreover, Hall and Trespalacios (2019) and Henson (2001) pointed out that the concept that self-efficacy impacts behavior and attitude for change is transferrable among all disciplines, including preservice teacher education. One makes decisions often based on their perceived capabilities or self-efficacy (Bandura, 2012). Regarding teachers, self-efficacy is the strongest predictor of experimentation and implementation of new interventions and approaches in the classroom (Hall & Trespalacios, 2019; Henson, 2001). Additionally, teachers' self-efficacy is linked to more significant learning outcomes for learners (Ertmer, 2005; Vieluf et al., 2013).

Self-efficacy is a critical personal resource in personal development and change (Bandura, 1997). Furthermore, Bandura (2006) suggested that learners with high perceived efficacy are the ones who make the best use of information available to them. Moreover, Christensen and Knezek (2017) suggested that understanding teacher confidence and competence in learning is essential in designing appropriate professional development. Preservice teacher education institutions should consider and explicitly address preservice teachers' self-efficacy to provide more engaging and practical education. Self-efficacy is a critically crucial theoretical contribution to the study of academic achievement, motivation, and learning (Bandura, 1977). Furthermore, to be successful at a task, having the requisite knowledge and skills to perform a job is not enough; teachers must also believe they can perform the required behavior(s) under typical and, significantly, under challenging circumstances (Bandura, 1994).

Given that self-efficacy influences one's life paths, teachers with a higher level of perceived self-efficacy more seriously consider the comprehensive range of career development opportunities (Gao et al., 2010; Ottenbreit-Leftwich et al., 2018). Further, they prepare themselves better educationally for the occupational choices, and the greater is their success (Bandura, 1994). Moreover, Bandura (1994) suggested that creating a strong sense of efficacy is the most effective way of mastery experiences, which will allow preservice teachers to stay up to date with developments in technology and teaching strategies. Successes build a robust self-efficacy in one's effectiveness; failures undermine it, mostly if failures occur before a sense of efficacy is firmly established. This aligns well with (Zone of personal development) ZPD theory by Vygotsky (1978) and the flow theory by Csikszentmihalyi (1990) to ensure the educational tasks are challenging enough to keep preservice teachers motivated and not too challenging to cause them to give up.

Studies in the literature have shown that learners with high self-efficacy choose to engage in tasks that promote their knowledge, skills, and abilities, exercise effort in the face of difficulty, and persist longer at challenging tasks (Artino, 2012; Bandura, 1994; Schunk, 1991; Schunk et al., 2008). Teachers need both 'the skill and the will' to function within different domains and under various circumstances. Also, Pajares (1996) pointed out that one cannot accomplish tasks beyond their capabilities by believing that one can. As such, beliefs become the internal rules individuals follow as they determine the effort, persistence, and perseverance required to achieve optimally.

Furthermore, preservice teachers who receive education according to their needs and skills are expected to develop self-efficacy (Bandura, 1994). Challenging enough activities enable keep preservice teachers motivated; however, these activities should not be too hard to cause self-doubts or too easy to cause boredom (Csikszentmihalyi, 1990). According to Bandura (1994), people avoid activities and situations they believe exceed their coping capabilities; however, they readily undertake challenging activities and situations they judge themselves capable of handling. Any factor influencing choice behavior can immensely affect personal development or career development due to the social influences operating in selected environments promote specific competencies (Bandura, 1994). Thus, we need tools that aim to increase teachers' self-efficacy to help them become lifelong learners.

Furthermore, as one of the main focuses of this study's proposed framework, self-efficacy has been studied widely in preservice teacher education for a long time. Based on all this literature, a framework is proposed to include all these components to support preservice teachers learning by providing them personalized adaptive learning to increase their self-efficacy. The following section focuses on developing the framework for personalized adaptive preservice teacher education to improve self-efficacy and analyzes each component of the framework in detail to analyze each component's contribution to the framework's development.

Developing Framework for Personalized Adaptive Preservice Teacher Education to Improve Self-Efficacy

In order for personalized adaptive preservice teacher education to be effective, relevant cognitive and affective states should be assessed to inform the instructional decision-making in personalized adaptive learning systems. Data from the initial assessment can be supplemented and adjusted by repeated measurements and data collection throughout the learning process (Tetzlaff et al., 2020). The framework proposed in Figure 5.4 presents that personalized adaptive preservice teacher education starts with assessing preservice teachers' current knowledge, skills, and affective states to adapt the learning activities, content, and content delivery accordingly. Ongoing assessment and data collection are needed to make decisions according to preservice teachers' cognitive and affective states to adapt the content, content delivery methods. Furthermore, the framework suggests supporting preservice teachers with personalized adaptive support, ongoing intervention, and correctness feedback. Bandura (1994) and Artino (2012) stated that developing self-efficacy helps one set clear and specific goals, assess their skills and knowledge, and adapt it to keep it challenging enough. Preservice teachers do not always have the freedom to choose their own goals; however, they can be supported and guided to construct clear and specific goals aligned with expected attainments, particular skills, and knowledge.

Moreover, goals should be challenging enough, not too demanding, to be out of the range of teachers' capabilities (Bandura, 1977; Csikszentmihalyi, 1990). Challenging but achievable goals allow one to put forth an effort and obtain feedback as preservice teachers proceed toward goal completion. Goals beyond teachers' knowledge or skill levels will likely lead to frustration and degrade self-efficacy (Bandura, 1977; Schunk et al., 2008).

Figure 5.4

Framework for Personalized Adaptive Preservice Teacher Education to Improve Self-Efficacy

Once the initial data is collected, as proposed in Figure 5.4, learning activities are then adapted according to preservice teachers' knowledge, skills, interests, and emotional state.

However, data collection is not a procedure that happens once a while; it is a dynamic process that is built-in in the learning process. Progress towards mastery of learning activities can be continuously measured, and in case of stagnation, content and content delivery adaptation can be implemented. This cycle of assessing the preservice teachers' current cognitive and affective states, setting learning activities and content delivery accordingly, employing assessment and data collection to check whether mastery was achieved (which influences the learning activities for the next cycle) is the backbone of personalized adaptive instruction (Tetzlaff et al., 2020).

According to preservice teachers' cognitive and affective states, adapting content within the proximal development zone (ZPD) of the preservice teachers is the main instructional adaptation of this framework. As suggested in Bloom's mastery learning approach (Bloom, 1968), the PAL system needs to assess previous content/skill mastery before proceeding with the next one. Upon completion of the unit, there needs to be some assessment of the learning gains and subsequent selection/design of the next unit (located in the zone of proximal development and presenting a logical next step on the way to the high-level learning goal). An integral part of designing personalized adaptive preservice teacher education is personalized adaptive content selection based on ongoing collected data on preservice teachers' current cognitive and affective states. Personalizing task selection based on predicted efficiency and learner preference has been shown to increase training and transfer performance (Salden et al., 2006; Tetzlaff et al., 2020) which is expected to increase preservice 'teachers' performance and, as a result, their self-efficacy.

Moreover, data collection allows the system to adapt learning content according to preservice teachers' progress in learning. Simultaneously, data is being collected from teachers' emotional states to ensure they are provided with content delivery methods that align with their interest and their current emotional state. Furthermore, according to Bosch et al. (2016), affect detection is a crucial component for affect-sensitive user interfaces, which aspire to improve learners' engagement and learn by dynamically responding to sensed affect. Figure 2 (D'Mello & Graesser, 2012) represents a model that predicts that learners in a state of engagement/flow will encounter cognitive disequilibrium and confusion when facing contradictions, incongruities, anomalies, obstacles to goals, and other impasses. The flow channel from Csikszentmihalyi (1990) in Figure 5.3 presents that learning environments need to substantially challenge learners enough to evoke critical thought and deep inquiry. It is essential to have systems assess preservice teachers' state of emotion and learning and adapt the content accordingly (Csikszentmihalyi, 1990; D'Mello & Graesser, 2012).

In addition to providing content that is challenging enough to provoke critical thinking, social persuasion through feedback was considered for this framework. Bandura (1977) pointed out that social persuasion promotes strengthening people's beliefs that they have what it takes to succeed, in other words, increasing a sense of self-efficacy. Preservice teachers who are prompted verbally to master given activities are likely to show more significant effort than people who have self-doubts on personal deficiencies when problems arise; as a result, correctness feedback is embedded into this framework right before increased self-efficacy.

According to Bandura (1977), a high sense of perceived self-efficacy leads people to try hard to succeed and develop skills. Moreover, the more robust sense of perceived self-efficacy, the higher the challenges people set for themselves, and the stronger is their commitment to them. Thus, increased self-efficacy leads to the increased effort toward developing new skills, leading to increased perseverance as proposed in the framework in Figure 5.4 for improving preservice teachers' self-efficacy.

Furthermore, self-efficacy increases motivation in several ways, such as determining the goals people set for themselves, how much effort they spend, how long they persist in the face of difficulties, and their resilience to failures. When faced with hindrances and failures, people who withhold self-doubts about their capabilities loosen their efforts or give up quickly (Bandura, 1977). Those who believe in their abilities exert more significant effort when they fail to master the challenge, leading to a strong sense of perseverance. Moreover, strong perseverance contributes to performance accomplishments (Bandura, 1977; Pajares, 1996). Additionally, Pajares (1996) pointed out that self-efficacy is an essential determinant of how well knowledge and skill are acquired in the first place. Self-efficacy influences one's motivation and self-regulation in several ways, such as the choices people make and the actions they take (Bandura, 1977; Pajares, 1996). Pajares (1996) discussed self-efficacy also determines the effort one will expend on an activity, how long one will persevere when confronting obstacles, and how resilient one will prove in the face of adverse situations.

According to Artino (2012), those with higher self-efficacy also tend to be more committed to assigned goals, find, and use better task strategies to attain the plans, and respond more positively to negative feedback than people with low self-efficacy. Artino (2012) pointed out honest and precise feedback contingent upon performance. It provides efficacy information to preservice teachers to calibrate their self-efficacy and encourage them to continue toward goal attainment, proposed in Figure 5.4, after the intervention and adaptation of learning activities. Furthermore, immediate feedback that encourages teachers to shift their focus from actual performance to performance monitoring and evaluation is instrumental in improving self-efficacy calibration (Artino, 2012).

This ongoing support and adaptation is expected to help learners to increase the sense of self-efficacy; as suggested by Bandura (1994), people with high confidence in their capacities approach challenging tasks as challenges to be mastered instead of as threats to be avoided. Such an efficient outlook fosters intrinsic interest and deep focus in activities. People with high confidence set themselves challenging goals and maintain a strong commitment to them, and they show high perseverance. Bandura (1997) and Pajares (1996) have suggested implementing instructional practices that foster knowledge and skill attainment promote the necessary accompanying confidence.

Moreover, Artino (2012) suggested that Bandura (1997) made an argument by stating that formal education's primary goal should be to provide one with the intellectual tools, self-efficacy, and intrinsic interests needed to educate themselves in various pursuits throughout their lifetime. It is also important to note that this framework is not a start to end process; it is an iterative process. The goal of this framework is to support preservice teachers' education by providing them with personalized adaptive education to increase their self-efficacy and, as a result, help them to become lifelong learners to be able to improve the learning experience for themselves and ultimately for students. Moreover, this framework is based on previous studies and has many possible practical uses in educational settings. Primarily it can be used for preservice teacher education, formal teacher education, and many more educational settings. Furthermore, this framework can be used for any educational activities that allow instructors to empower learners to be life-long learners. The following section provides a practical scenario to elaborate the practical use of the framework in preservice education.

An Example of Framework Being Used in Preservice Teacher Education

Suppose a preservice teacher instructor for instructional technology tools course is getting ready to introduce Nearpod and similar interactive tools to preservice teachers. The instructor has read Nearpod usage research to increase student engagement in online environments and wants preservice teachers to feel comfortable using Nearpod or similar tools when they are in the classroom. This instructor could use this framework and follow suggested steps based on this framework as follows.

1. The instructor lists pre-requisite skills and knowledge to efficiently use Nearpod, such as using google slides, embedding videos into google slides, etc.

2. The instructor assesses preservice teachers' skills, knowledge, and affective states before planning the lesson to see if any of them need to learn pre-requisite skills before starting to help them with using Nearpod. Also, some preservice teachers might already know how to use Nearpod; if the instructor has this information, they can develop challenging enough activities for everyone instead of assuming everyone has the same knowledge and skills for this lesson. [Assess current skills, knowledge & affect]

3. According to collected data from the assessment, the instructor adapts learning activities, adapts the learning content, and groups preservice teachers according to their needs. According to the needs of each group, lessons' structure and content differ. Some lessons start with teaching google slides and embedding links for videos. Some lessons directly start with teaching Nearpod since a group of preservice teachers is ready to learn Nearpod. Also, to address the needs of preservice teachers who already know how to use Nearpod, there are activities planned to help them develop activities to explore different usages of Nearpod and how to use it to differentiate the content for students. [Adapt learning activities & content]

4. According to collected data, the instructor provides personalized adaptive support to help the first group of students feel comfortable using google slides before starting using Nearpod. Suppose they had negative beliefs about their instructional technology skills. In that

case, the instructors support them by helping them see if they follow specific steps, get help and support, be more courageous with trying something new, and they eventually will develop these skills. [Personalized adaptive support]

5. The instructor collects data by either walking around the classroom, listen to conversations, or checking preservice teachers' progress on the online platform and intervene as needed. Suppose a preservice teacher is stuck at the stage of embedding a video to google slide and has not figured it out last 5 minutes. The instructor can approach this learner and ask whether they know how to embed a link to any document. If the response is no, the instructor models how they embed a link to a document and asks the preservice teacher how they would try to implement it to google slide. [Dynamic intervention]

6. The instructor would watch preservice teachers' efforts to embed the link and provide correctness feedback as they struggle to embed the link. According to collected data, the instructor will provide correctness feedback to preservice teachers to calibrate their self-efficacy and address any misconceptions. [Correctness feedback]

7. Preservice teachers would feel more empowered by the instructor's support at the right time instead of losing more time on figuring out how to embed a link. Getting help and support simultaneously, receiving challenging enough content is expected to increase preservice teachers' self-efficacy. [Increased self-efficacy]

8. Increased self-efficacy is expected to increase preservice teachers' efforts toward developing new skills and perseverance. Now preservice teachers experienced that after getting help, they were able to embed a link. This experience will allow preservice teachers to learn if they try hard enough to learn new skills and learn anything. This experience is expected to increase preservice teachers' efforts toward learning a new skill and increase perseverance.

[Increased effort toward developing new skills] [Increased perseverance]

9. As a result, preservice teachers develop perseverance and increased effort toward learning new skills. They are expected to be lifelong learners, which is a quality needed for all teachers to keep up with teaching challenges. [Life-long learners]

10. Preservice teachers with increased self-efficacy and have a more positive attitude to learn new skills will always look for opportunities to learn more and improve their students' learning experience. [Improved learning experience for all]

In this scenario, the instructor started planning the learning activity to assess learners' current skills, knowledge, and affective states. Moreover, they planned the learning activities and supported learners according to collected data. It should be noted that this is not a start-to-end process; it is a cyclical process. Before moving to the next learning activity, the instructor would assess preservice teachers' knowledge, skills, and affect to plan learning activities accordingly to support preservice teachers at the right time to improve their self-efficacy, which is ultimately expected to increase their efforts toward learning new skills, increase perseverance. As a result, preservice teachers are becoming life-long learners who will improve the learning experience for both their students and themselves.

Discussion and Conclusion

This study provides an overview of current personalized adaptive learning practices and systems used to personalize and adapt learning and analyses current literature on self-efficacy. Furthermore, it analyzed what factors help increase preservice teachers' self-efficacy. Based on the findings, a conceptual framework for personalized adaptive preservice teacher education is proposed that is expected to guide personalized adaptive preservice teacher education to increase teachers' self-efficacy. The framework is an attempt to address the lack of personalized adaptive preservice teacher education to improve self-efficacy. The proposed framework is expected to be used as a tool to improve teachers' self-efficacy and ultimately improve the learning experience for all.

The proposed framework can be used in different settings with different scenarios. The step-by-step example for preservice teacher education, described in the previous section, reflects its usage in learning environments. In this study, the proposed framework is focused on increasing preservice teachers' self-efficacy by providing personalized adaptive learning support, which is expected to improve self-efficacy and increase perseverance and efforts to learn new skills and acquire new knowledge.

The findings of this study suggest that dynamic data collection requires dynamic adaptation, intervention, and intervention to close any learning gaps or avoid losing interest in learning progress. There is growing data to show that efforts to improve preservice teacher education can significantly impact student learning (Colson et al., 2018; Depaepe & König, 2018; Jenset et al., 2018; Schleicher, 2016). The proposed framework suggests dynamic data collection on preservice teachers' skills, knowledge and affective states, and the ability to adapt the content, activities, and content delivery. This dynamic process is expected to increase preservice teachers' self-efficacy by providing challenging enough content and adapting the resources dynamically according to their needs.

Since this study was built around the current literature of personalized learning tools and components and solely focused on preservice teacher education and how teachers' self-efficacy can be increased by providing personalized adaptive learning, the framework should be useful for preservice teacher education institutions. In addition, it can also be a useful resource K-12 school districts and regional educational centers to provide personalized adaptive teacher education to increase teachers' self-efficacy.

This study has several limitations that are inevitable. The enormous number of published papers might lead to missing relevant papers as many literature review studies face this problem. Furthermore, the framework is based on the synthesis of the studies from the literature and its efficacy has not been measured with any empirical studies. Empirical studies are needed to measure its effectiveness and applicability. Future research can focus on how artificial intelligence (AI) techniques can be used to provide personalized teacher education with less effort and complexity to increase teachers' self-efficacy. Also, such adaptive and personalized systems need to be evaluated to measure their effectiveness and applicability. Teachers face ongoing changes in education that they are expected to keep up with; thus, we need teachers who are willing to learn more and adapt their instructional practices according to changes in schools and society, especially with technology. This proposed conceptual framework for personalized adaptive preservice teacher education to improve self-efficacy can guide future studies to address this need and demand.

Chapter References

Artino, A. R. (2012). Academic self-efficacy: From educational theory to instructional practice. *Perspectives on Medical Education*, *1*(2), 76–85. https://doi.org/10.1007/s40037-012-0012-5

Avalos, B. (2011). Teacher professional development in teaching and teacher education over ten years. *Teaching and Teacher Education*, *27*(1), 10–20. https://doi.org/10.1016/j.tate.2010.08.007

Bandura, A. (1977). Self-efficacy: toward a unifying theory of behavioral change. *Psychological Review, 84*(2), 191-215.

Bandura, A. (1982). Self-efficacy mechanism in human agency. *American Psychologist*, *37*(2), 122–147. https://doi.org/10.1037/0003-066X.37.2.122

Bandura, A. (1994). Self-efficacy. In V. S. Ramachaudran (Ed.), *Encyclopedia of human behavior* (Vol. 4, pp. 71-81). New York: Academic Press. (Reprinted in H. Friedman [Ed.], *Encyclopedia of mental health*. San Diego: Academic Press, 1998).

Bandura, A. (1997). *Self-efficacy: The exercise of control.* New York: W. H. Freeman and Company.

Bandura, A. (2006). Toward a psychology of human agency. *Perspectives on Psychological Science*, *1*(2), 164–180. https://doi.org/10.1111/j.1745-6916.2006.00011.x

Bandura, A. (2012). On the functional properties of perceived self-efficacy revisited. *Journal of Management*, *38*(1), 9–44. https://doi.org/10.1177/0149206311410606

Bennett, R. E., & Davier, M., V. (2017). *Advancing human assessment: The methodological, psychological and policy contributions of ETS*. SpringerOpen.

Bloom, B. (1968). Learning for mastery: Instruction and curriculum. Regional Education Laboratory for the Carolina and Virginia, Topical Papers and Reprints, Number 1. *Evaluation Comment*, 1, n2.

Bosch, N., D'Mello, S. K., Baker, R. S., Ocumpaugh, J., Shute, V., Ventura, M., Wang, L., & Zhao, W. (2016). Detecting learner emotions in computer-enabled classrooms. *IJCAI International Joint Conference on Artificial Intelligence*, *2016-January*, 4125–4129.

Calvo, R. A., & D'Mello, S. (2010). Affect detection: An interdisciplinary review of models, methods, and their applications. *IEEE Transactions on Affective Computing*, *1*(1), 18–37. https://doi.org/10.1109/T-AFFC.2010.1

Chatti, M. A., & Muslim, A. (2019). The PERLA framework: Blending personalization and learning analytics. *International Review of Research in Open and Distance Learning*, *20*(1), 244–261. https://doi.org/10.19173/irrodl.v20i1.3936

Chen, C. M., & Chung, C. J. (2008). Personalized mobile English vocabulary learning system based on item response theory and learning memory cycle. *Computers & Education, 51*(2), 624–645.

Chen, C. M., Lee, H. M., & Chen, Y. H. (2005). Personalized e-learning system using item response theory. *Computers and Education*, *44*(3), 237–255. https://doi.org/10.1016/j.compedu.2004.01.006

Christensen, R., & Knezek, G. (2017). Validating the Technology Proficiency Self-Assessment Questionnaire for 21st Century Learning (TPSA C-21). *Journal of Digital Learning in Teacher Education*, *33*(1), 20–31. https://doi.org/10.1080/21532974.2016.1242391

Colson, T., Sparks, K., Berridge, G., Frimming, R., & Willis, C. (2018). Preservice teachers and self-efficacy: A study in contrast. *Discourse and Communication for Sustainable Education*, *8*(2), 66–76. https://doi.org/10.1515/dcse-2017-0016

Csikszentmihalyi, M. (1990). Flow: The psychology of optimal experience. *The Academy of Management Review 16*(3), 636.

Darling-Hammond, L. (2000). Teacher quality and student achievement: A review of state policy analysis. *Education Policy Analysis Archives, 8*(1) -3 7. http://epaa.asu.edu/epaa/v8n 1 .html

Dawson, S., Heathcote, L., & Poole, G. (2010). Harnessing ICT potential: The adoption and analysis of ICT systems for enhancing the learner learning experience. *International Journal of Educational Management, 24*(2), 116–128.

Depaepe, F., & König, J. (2018). General pedagogical knowledge, self-efficacy, and instructional practice: Disentangling their relationship in preservice teacher education. *Teaching and Teacher Education*, *69*, 177–190. https://doi.org/10.1016/j.tate.2017.10.003

Desmarais, M. C., & Baker, R. S. (2012). A review of recent advances in learner and skill modeling in intelligent learning environments. *User Modeling and User-Adapted Interaction, 22*(1-2), 9-38.

Dewey, J. (1915). *The school and society*. Chicago, IL: Chicago Press.

Dewey, J. (1998). *Experience and education* (60th anniversary ed.). West Lafayette, NY: Kappa Delta.

D’Mello, S., Lehman, B., Sullins, J., Daigle, R., Combs, R., Vogt, K., Perkins, L., & Graesser, A. (2010). A time for emoting: When affect-sensitivity is and isn’t effective at promoting deep learning. *Lecture notes in computer science (including subseries lecture notes in artificial intelligence and lecture notes in bioinformatics)*, *6094 LNCS* (PART 1), 245–254. https://doi.org/10.1007/978-3-642-13388-6_29

D’Mello, S. K., & Graesser, A. (2012). Dynamics of affective states during complex learning. *Learning and Instruction, 22*, 145-157.

Ertmer, P. A. (2005). Teacher pedagogical beliefs: The final frontier in our quest for technology integration? *Educational Technology Research and Development, 53*(4), 25-39.

Ertmer, P. A., Ottenbreit-Leftwich, A. T., Sadik, O., Sendurur, E., & Sendurur, P. (2012). Teacher beliefs and technology integration practices: A critical relationship. *Computers & Education, 59*, 423–435.

Fives, H., & Gill, M. G. (Eds.). (2015). *International handbook of research on teachers’ beliefs.* New York: Routledge, Taylor & Francis.

Gao, P., Wong, A. F., Choy, D., & Wu, J. (2010). Developing leadership potential for technology integration: Perspectives of three beginning teachers. *Australasian Journal of Educational Technology, 26,* 643–658.

Govindarajan, K., Boulanger, D., Seanosky, J., Bell, J., Pinnell, C., & Suresh Kumar, V., & Kinshuk. (2017). Assessing learners' progress in a smart learning environment using bio-inspired clustering mechanism. *Lecture Notes in Educational Technology*, *9789811024184*, 49–58. https://doi.org/10.1007/978-981-10-2419-1_9

Govindarajan, K., & Kumar, V. S., & Kinshuk. (2017). Dynamic learning path prediction: A learning analytics solution. *Proceedings - IEEE 8th International Conference on Technology for Education, T4E 2016*, 188–193. https://doi.org/10.1109/T4E.2016.047

Hall, A. B., & Trespalacios, J. (2019). Personalized professional learning and teacher self-efficacy for integrating technology in K–12 classrooms, *Journal of Digital Learning in Teacher Education, 35*(4), 221-235. https://doi.org/10.1080/21532974.2019.1647579

Heinonen, K., Jaaskela, P., Hakkinen, P., Isomaki, H., & Hamalainen, R. (2019). University teachers as developers of technology-enhanced teaching: Do beliefs matter? *Journal of Research on Technology in Education*, *51*(2), 135–151.

Henson, R. K. (2001). Teacher self-efficacy: Substantive implications and measurement dilemmas. *Annual Meeting of the Educational Research Exchange*, (August 2001), 24.

Howard, S. K., Chan, A., & Caputi, P. (2015). More than beliefs: Subject areas and teachers' integration of laptops in secondary teaching. *British Journal of Educational Technology, 46,* 360–369.

Ifenthaler, D., & Yau, J. Y. K. (2020). Utilising learning analytics to support study success in higher education: A systematic review. In *Educational Technology Research and Development* (Vol. 68, Issue 4). Springer US. https://doi.org/10.1007/s11423-020-09788-z

Jenset, I. S., Klette, K., & Hammerness, K. (2018). Grounding teacher education in practice around the world: An examination of teacher education coursework in teacher education programs in Finland, Norway, and the United States. *Journal of Teacher Education*, *69*(2), 184–197. https://doi.org/10.1177/0022487117728248

Kagan, D. (1992). Professional growth among preservice and beginning teachers. *Review of Educational Research, 62,* 129–169.

Klašnja-Milićević, A., Ivanović, M., & Nanopoulos, A. (2015). Recommender systems in e-learning environments: A survey of the state-of-the-art and possible extensions. *Artificial Intelligence Review, 44*(4), 571-604. https://doi.org/10.1007/s10462-015-9440-z

Klašnja-Milićević, A., Vesin, B., Ivanović, M., & Budimac, Z. (2011). e-Learning personalization based on hybrid recommendation strategy and learning style identification. *Computers & Education, 56*(3), 885–899.

Koedinger, K. R., Brunskill, E., Baker, R. S., McLaughlin, E. A., & Stamper, J. (2013). New potentials for data-driven intelligent tutoring system development and optimization. *AI Magazine, 34*(3), 27-41.

Kulik, C.-L. C., Kulik, J. A., & Bangert-Drowns, R. L. (1990). Effectiveness of mastery learning programs: A meta-analysis. *Review of Educational Research, 60*(2), 265–299.

Kumar, V. S., Kinshuk, Somasundaram, T. S., Boulanger, D., Seanosky, J., & Vilela, M. F. (2015). Big data learning analytics: A new perpsective. In *Ubiquitous learning environments and technologies* (pp. 139-158). https://doi.org/10.1007/978-3-662-44659-1_8

Louhab, F. E., Bahnasse, A., & Talea, M. (2018). Towards an adaptive formative assessment in context-aware mobile learning. *Procedia Computer Science*, *135*(August), 441–448. https://doi.org/10.1016/j.procs.2018.08.195

Natividad Beltrán del Río, G. (2021). A useful framework for teacher professional development for online and blended learning to use as guidance in times of crisis. *Education Tech Research Dev, 69*, 7–9. https://doi.org/10.1007/s11423-021-09953-y

Nel, L. (2017). Students as collaborators in creating meaningful learning experiences in technology-enhanced classrooms: An engaged scholarship approach. *British Journal of Educational Technology, 48*, 1131–1142. https://doi.org/10.1111/bjet.12549.

Niculescu, C. (2016). Intelligent tutoring systems: Trends on design, development, and deployment. *eLearning Vision 2020! Vol III*, 280–285.

Ottenbreit-Leftwich, A., Liao, J. Y. C., Sadik, O., & Ertmer, P. (2018). Evolution of teachers' technology integration knowledge, beliefs, and practices: How can we support beginning teachers use of technology? *Journal of Research on Technology in Education*, *50*(4), 282–304. https://doi.org/10.1080/15391523.2018.1487350

Pajares, F. (1996). Self-efficacy beliefs in academic settings. *Review of Educational Research*, *66*(4), 543-578.

Pajares, M. (1992). Teachers' beliefs and educational research: cleaning up a messy construct. *Review of Educational Research, 62,* 307–332.

Pane, J. F., Steiner, E. D., Baird, M. D., & Hamilton, L. S. (2015). *Continued progress: Promising evidence on personalized learning.* Rand Corporation, ERIC, https://eric.ed.gov/?id=ED571009

Pardo, A., Han, F., & Ellis, R. A. (2017). Combining university student self-regulated learning indicators and engagement with online learning events to predict academic performance. *IEEE Transactions on Learning Technologies*, *10*(1), 82-92. https://doi.org/10.1109/TLT.2016.2639508.

Peña-Ayala, A. (2014). Educational data mining: A survey and a data mining-based analysis of recent works. *Expert Systems with Applications, 41*(4), 1432–1462.

Peng, H., Ma, S., & Spector, J. M. (2019). Personalized learning: An emerging pedagogical approach enabled by a smart learning environment. *Lecture Notes in Educational Technology*, 171–176. https://doi.org/10.1007/978-981-13-6908-7_24

Perez-Berenguer, D., Kessler, M., & Garcia-Molina, J. (2020). A customizable and incremental processing approach for learning analytics. *IEEE Access*, *8*, 36350–36362. https://doi.org/10.1109/ACCESS.2020.2975384

Pliakos, K., Joo, S. H., Park, J. Y., Cornillie, F., Vens, C., & Van den Noortgate, W. (2019). Integrating machine learning into item response theory for addressing the cold start problem in adaptive learning systems. *Computers and Education*, *137*(April), 91–103. https://doi.org/10.1016/j.compedu.2019.04.009

Romero, C., & Ventura, S. (2007). Educational data mining: A survey from 1995 to 2005. *Expert Systems with Applications, 33*(1), 135-146. https://doi.org/10.1016/j.eswa.2006.04.005

Salden, R. J. C. M., Paas, F., & Van Merrienboer, J. J. G. (2006). Personalised adaptive task selection in air traffic control: Effects on training efficiency and transfer. *Learning and Instruction, 16*, 350–362.

Sales, A. C., & Pane, J. F. (2017). The role of mastery learning in intelligent tutoring systems: Principal stratification on a latent variable. *Annals of Applied Statistics*.

Santos, O. C. (2016). Emotions and personality in adaptive e-learning systems: An affective computing perspective. 10.1007/978-3-319-31413-6_13.

Santos, O. C., Boticario, J. G., & Manjarrés-Riesco, Á. (2014). An approach for an affective educational recommendation model. 123-143. https://doi.org/10.1007/978-1-4939-0530-0-6

Schleicher, A. (2016). *Teaching excellence through professional learning and policy reform.* Paris, France: OECD.

Schunk, D. H. (1991). Self-efficacy and academic motivation. *Educational Psychology. 26,* 207–31.

Schunk, D. H., Pintrich, P. R., & Meece, J. L. (2008). *Motivation in education: Theory, research, and applications.* Upper Saddle River: Pearson Education.

Shemshack, A., & Spector, J. M. (2020). A systematic literature review of personalized learning terms. *Smart Learning Environments, 7*(1). Springer. https://doi.org/10.1186/s40561-020-00140-9

Shen, D., Cho, M.-H., Tsai, C.-L., & Marra, R. (2013). Unpacking online learning experiences: Online learning self-efficacy and learning satisfaction. *Internet and Higher Education*, *19*, 10–17. https://doi.org/10.1016/j.iheduc.2013.04.001

Shu, J., Shen, X., Liu, H., Yi, B., & Zhang, Z. (2018). A content-based recommendation algorithm for learning resources. *Multimedia Systems 24*(2):163–173.

Siko, J. P., & Hess, A. N. (2014). Win-win professional development: Providing meaningful professional development while meeting the needs of all stakeholders. *TechTrends, 58*, 99–108. https://doi.org/10.1007/s11528-014-0809-7.

Spector, J. M. (2014). Conceptualizing the emerging field of smart learning environments. *Smart Learn. Environ, 1*(2). https://doi.org/10.1186/s40561-014-0002-7

Tetzlaff, L., Schmiedek, F., & Brod, G. (2020). Developing personalized education: A dynamic framework. *Educational Psychology Review*. https://doi.org/10.1007/s10648-020-09570-w

Thoma, J., Johnson, D., Johnson, K., & Stromer, E. (2017). Planning for technology integration in a professional learning community. *The Reading Teacher, 71*(2), 167–175. https://doi.org/10.1002/trtr.1604.

Tondeur, J., van Braak, J., Ertmer, P. A., & Ottenbreit-Leftwich, A. (2017). Understanding the relationship between teachers' pedagogical beliefs and technology use in education: A systematic review of qualitative evidence. *Educational Technology Research and Development*, *65*(3), 555–575. https://doi.org/10.1007/s11423-016-9481-2

Troussas, C., Krouska, A., & Virvou, M. (2019). Adaptive e-learning interactions using dynamic clustering of learners' characteristics. *10th International Conference on Information,* Intelligence, Systems and Applications, IISA 2019, July. https://doi.org/10.1109/IISA.2019.8900722

US Department of Education, Office of Educational Technology. (2017). Reimagining the role of technology in education: 2017 national education technology plan update. Available at: *https://tech.ed.gov/files/2017/01/NETP17.pdf*.

VanLehn, K. (2006). The behavior of tutoring systems. *International Journal of Artificial Intelligence in Education*, *16*(3), 227-265.

Vieluf, S., Kunter, M., & Van De Vijver, F. J. R. (2013). Teacher self-efficacy in cross-national perspective. *Teaching and Teacher Education*, *35*, 92–103. https://doi.org/10.1016/j.tate.2013.05.006

Vygotsky, L. S. (1978). *Mind in society: The development of higher psychological processes*. Cambridge, MA: Harvard University Press.

Wang, H., & Fu, W. (2020). Personalized learning resource recommendation method based on dynamic collaborative filtering. *Mobile Networks and Applications*. https://doi.org/10.1007/s11036-020-01673-6

Weitekamp, D., Harpstead, E., & Koedinger, K. R. (2020). An interaction design for machine teaching to develop AI tutors. *Conference on Human Factors in Computing Systems - Proceedings*, 1–11.

Wu, L. (2020). Learner model construction of intelligent teaching system based on Bayesian network. *Personal and Ubiquitous Computing, 24*, 419–428.

Xie, H., Chu, H. C., Hwang, G. J., & Wang, C. C. (2019). Trends and development in technology-enhanced adaptive/personalized learning: A systematic review of journal publications from 2007 to 2017. *Computers and Education*, *140*(June), 103599. https://doi.org/10.1016/j.compedu.2019.103599

CHAPTER 6

EMPIRICAL STUDY TO VALIDATE THE PERSONALIZED ADAPTIVE TEACHER EDUCATION TO INCREASE SELF EFFICACY FRAMEWORK

Abstract

The profession of teaching is filled with various challenges, and teachers have faced these challenges for centuries. These challenges in education have caused teachers to leave the profession, especially the first three years of their teaching career. It is observed that teachers have higher self-efficacy, deal with teaching stress better, and stay in the profession. Thus, we created a framework that guides teacher education to be personalized and adapted according to teachers' needs and skills to increase their self-efficacy and as result, to keep them in the teaching profession. The purpose of this study is to validate the Personalized Adaptive Learning (PAL) framework's impact on improving teachers' self-efficacy to have teachers stay in the teaching profession. However, COVID-19 impacted our education system magnificently, and we were not able to measure truly to see if training were delivered by using framework were effective. Teachers' self-efficacy from pre-service training to two weeks after school started decreased significantly and teachers stated the workload and students significant learning loss due to COVID-19 caused many teachers lose their self-efficacy. We held interviews to discuss findings of the study and many teachers stated due to COVID-19, they do not feel competent anymore due to changes COVID-19 bring in education system, and that uncertainty is causing self-doubt. A future study can assess the long-term impact of personalized adaptive pre-service teacher education and compare these teachers' resiliency and turnover rate with teachers who did have an opportunity for personalized adaptive pre-service education to validate the framework or develop it further.

Keywords: *Personalized learning, adaptive learning, pre-service, teacher, self-efficacy*

Introduction

The profession of teaching is filled with various challenges, and teachers have faced these challenges for centuries. These challenges in teaching have caused teacher turnover (Ingersoll R. M., 2001). Therefore, it is essential to discover the constructs that influence the resolution to the problem known as teacher retention in recognizing this issue. Teaching is a stressful and high workload profession (Jomuad et al., 2021) that will benefit from having good stress management skills and perseverance. Bandura (1997) pointed out that teachers who have repeated feelings of achievement more successfully manage stress, and stay in the teaching profession (Herman et al., 2018). Teachers need to feel connected and have a sense of self-efficacy for their responsibilities when teaching (Ryel et al., 2001, as cited in Colson et al., 2018) to stay motivated in learning new skills to meet the needs of all students. As a result, this study focuses on validating the PAL framework's impact on improving teacher self-efficacy to promote perseverance and keep teachers in the profession.

Furthermore, self-efficacy determines how people feel, think, motivate themselves, and perform. Bandura (1982, 1994) outlined self-efficacy as people's beliefs about their capabilities to perform designated performance levels that regulate events that influence their lives (Panadero et al., 2017). Moreover, a strong sense of efficacy enhances personal accomplishment and personal well-being. Also, self-efficacy perceptions affect the reception of change, the presence of knowledge, and the acquisition of skills. A higher self-efficacy level will produce more significant effort toward developing new skills (Bandura, 1994; Ertmer et al., 2012; Howard et al., 2015; Ottenbreit-Leftwich et al., 2018; Shen et al., 2013). Correspondingly, self-efficacy dictates what activities individuals choose to pursue and the level of effort they will put forth (Bandura, 1977, 1982; Ottenbreit-Leftwich et al., 2018). Thus, self-efficacy has been a critical component in motivation and learning theories in varied contexts (Artino, 2012; Bandura, 1997). Bandura (1977) claimed that one's efforts' cumulative effects alter one's performance. The number of tasks completed by one reflects the degree of perseverance (Ottenbreit-Leftwich et al., 2018).

Thus, we need to focus on teachers' self-efficacy as growing data has shown that improving pre-service teacher education can significantly impact learning (Colson et al., 2018; Depaepe & König, 2018; Jenset et al., 2018; Schleicher, 2016). Therefore, it is predominant that teachers have a strong sense of self-efficacy to help them maintain their interest in teaching and use those skills to help all students (Gedzune, 2015, as cited in Colson et al., 2018).

Moreover, although teacher education and self-efficacy have been studied for years, insufficient attention has been paid to personalized adaptive teacher education to increase self-efficacy (Hall & Trespalacios, 2019). The main focus is primarily to provide meaningful learning opportunities for students; however, it is essential to remember that to provide meaningful learning opportunities for students, meaningful learning opportunities need to be also offered for teachers (Natividad Beltrán del Río, 2021; Siko & Hess, 2014). As a result, this study emphasizes the importance of personalized adaptive teacher education to ensure that teachers' education reflects their needs and skill sets to increase their self-efficacy. Teachers' professional proficiency comprises cognitive professional knowledge and affective professional belief components, which are generally assumed to be related and impact instructional practice (Depaepe & König, 2018). However, studies simultaneously relating cognitive and affective components to instructional practice are limited (Depaepe & König, 2018). Teacher education is a complex process that requires teachers' cognitive and emotional involvement. It requires the willingness to examine where each teacher stands and provide personalized adaptive tools for improvement or change (Depaepe & König, 2018) according to their diverse goals and needs. While many studies analyzed pre-service teacher education and current practices, limited research investigated personalized adaptive teacher education to improve their self-efficacy. A framework for personalized adaptive teacher education was developed to address this need to increase teachers' self-efficacy. An expected result is PAL framework will improve teachers' learning experience, which is expected to enhance the learning experience for students and increase teachers' self-efficacy. Furthermore, the purpose of this study is to validate the PAL framework's impact on improving teachers' self-efficacy. The PAL framework focuses on components that identify teachers' needs to educate them according to their specific needs to increase teachers' self-efficacy and perseverance to decrease teacher turnover.

The following section presents a comprehensive review of existing work in the literature on personalized adaptive learning, teacher education, self-efficacy, and teacher retention to layout current studies. This follows the study and study methods. This study's findings are then provided under the discussion section, followed by the conclusion, study's limitations, and future research directions that have emerged from this research.

Background

The following section presents a comprehensive review of existing work in the literature on personalized adaptive learning (PAL), Teacher education and self-efficacy, and teacher retention to provide a foundation to the study and identify previous studies to build on them and prevent duplication.

Personalized Adaptive Learning

Personalized learning has been a research topic for a long time (Xie et al., 2019). However, the meaning has changed over time; currently, personalized adaptive learning primarily implies an automated system that can respond to a learner's progress in real-time without the assistance of a live teacher or tutor and make content and content delivery relevant to the learner by assessing their skills and being intentional about their needs (Shemshack & Spector, 2020).

Personalized adaptive learning systems require using several tools and theories to build adaptive and meaningful learning systems according to individuals' needs and skills (Kinshuk et al., 2016). These systems prevent the learner from becoming lost in the course materials; by providing personalized adaptive learning, filtering out unsuitable course materials to reduce cognitive load, and providing an adequate learning diagnosis based on an individual's user profile to help them learn effortlessly (Pliakos et al., 2019). Peng et al. (2019) suggested that personalized adaptive learning could be constructed with the following aspects: learner profiles and attitudes, previous knowledge and beliefs, competency-based progression, personal learning, and flexible learning environments that are generated by learning analytics (Shemshack & Spector, 2020). Current technologies allow the systems to provide services according to user's search history, preferences that encourage learning technologies researchers to imitate these systems for learning systems; moreover, consider learners abilities and prior knowledge.

The review of literature identified overemphasis on personalized adaptive learning but nothing practical for pre-service teacher education (Hall & Trespalacios, 2019). The literature findings support that personalized adaptive learning has become a fundamental learning paradigm in the research community of educational technologies (Peng et al., 2019; Xie et al., 2019). The previous research suggested that personalized adaptive learning models have gained more attention from governments and policymakers than educators and researchers (FitzGerald et al., 2018; Shemshack & Spector, 2020). However, personalized adaptive teacher education has not gained as much attention.

Even though the literature findings are not directly tied to teacher education, this literature review leads that personalized adaptive learning can be an approach for pre-service teacher education due to the increased use of personalized adaptive learning approaches and their favorable impact on learning (Pane et al., 2015). Furthermore, literature findings revealed that although so many terms are used in education settings by policymakers and cooperate settings, in the research field, the terms used for personalized learning are unified, and mostly personalized learning and/or adaptive learning are being used (Shemshack & Spector, 2020). Peng et al. (2019) put the two most common terms used for personalized learning together and started to use "personalized adaptive learning," which seems like a good lead for future studies. Developing learning approaches that build on students' current abilities and supporting efficacy beliefs allows learner autonomy and with a proper challenge promotes academic attainment (Foshee et al., 2016; Xie et al., 2019).

Also, it is essential to note that machine learning, data mining, and human behavior determine factors that shape personalized adaptive learning. Among many different models and systems that focus on personalized learning experiences for all, it is found that they are all based on the fact that each human being is unique, so their needs are (Shemshack & Spector, 2020). Furthermore, with all these resources available, it will be easy to use technology to provide teachers with personalized adaptive learning experiences to focus on their needs and skillsets, which is expected to increase their self-efficacy, that will lead to increased perseverance and ultimately decrease in teacher turnover.

Teacher Education and Self-Efficacy

Pre-service teacher education is crucial in producing quality inservice teachers (Levine, 2006; Mergler & Spooner-Lane, 2012; Wright & Wilson, 2005). Meaningful learning opportunities need to be offered to pre-service teachers to prepare them for teaching better (Natividad Beltrán del Río, 2021; Nel, 2017; Siko & Hess, 2014**;** Thoma et al., 2017). By exploring teachers' sense of efficacy, administrative leaders can take the initiative to boost individual characteristics of teachers, including teacher self-efficacy, through experience, and professional development. Teacher self-efficacy influences the course of instruction, problem-solving, and decision-making within the classroom. Growing evidence has suggested that efforts to tie teacher preparation more closely to practice can significantly impact inservice teachers' impact on student learning (Colson et al., 2018; Depaepe & König, 2018; Jenset et al., 2018; Schleicher, 2016).

As Bandura (1977) states, the stronger someone's perceived self-efficacy, the more effort they expend and persist longer in the face of difficulties than those who are unsure of their capabilities. (Komarraju & Nadler, 2013). A teacher's sense of efficacy influences persistence and determination in the face of obstacles and adverse experiences (Artino, 2012; Bandura, 1977). As many school administrators and leaders know, retaining effective, quality teachers are an integral part of school achievement for both students and teachers (van Tonder, 2021). As Cavanagh and Dellar (1997) affirmed, school leaders need to create a culture that builds collaboration, achievement, and effective instructional strategies while building competence in their capabilities to achieve success in the field (Norman, 2019).

Furthermore, Bandura (1977) explains, "Efficacy expectations determine how much effort people will expend and how long they will persist in the face of obstacles and aversive experiences" (Komarraju & Nadler, 2013). An individual teacher with high levels of self-efficacy empowers creativity for creating new teaching strategies, effective methods and is not surprised or taken back by adverse situations (Norman, 2019).

Holmes et al. (2019) found that teacher retention is a function of teacher's characteristics, educational preparation, initial commitment, first years teaching experience, professional and social integration, and external factors. Therefore, teacher self-efficacy is crucial in understanding teacher retention and an individual teacher's intent to remain in the profession. Teachers' professional proficiency is composed of professional cognitive knowledge and affective professional belief components, which are generally assumed to be related and impact instructional practice (Colson et al., 2018; Depaepe & König, 2018; Jenset et al., 2018; Schleicher, 2016).

A variety of researchers have discussed self-efficacy regarding the profession of teaching and how this construct can highly influence a teacher's intent to remain in the profession (Bandura, 1993; Herman et al., 2018). It is observed (Bandura, 1993) that increased self-efficacy increases resiliency which is observed to decrease teacher turnover (Herman et al., 2018). Due to this, it is essential to focus on increasing teachers' self-efficacy to keep them in the profession and motivate them to improve their instructional practices.

Teacher Retention

The profession of teaching is filled with various challenges, and teachers have faced these challenges for centuries (Jomuad et al., 2021). These challenges in teaching have created an interesting phenomenon known as teacher turnover (Herman et al., 2018; Ingersoll, 2001). Therefore, it is essential to discover the constructs that influence the resolution to the problem known as teacher retention in recognizing this issue.

Within the first three years of teaching, one-third of new teachers leave the profession (Carr et al., 2017). Once prospective teachers are hired, some districts offer induction or new teacher training. These efforts cost U.S billion dollars a year. The self-efficacy theory suggests that people only attempt doing things they can accomplish (Ware & Kitsantas, 2007). However, individuals who lack self-efficacy doubt their abilities and see complicated tasks as a threat. This can lead to giving up quickly and, in this case, could lead to teacher turnover. When new teachers experience more failures early on in their career and do not feel supported, it can result in them leaving the profession (Grant, 2006; Pedota, 2015).

Supporting teachers through various types of structures and professional development could increase teacher self-efficacy, leading to teacher retention (Grant, 2006; Ware & Kitsantas, 2007). Studies on pre-service teacher education that simultaneously relate cognitive and affective components to instructional practice are limited (Depaepe & König, 2018). When a system that supports teachers is in place and includes activities and programs that directly influence self-efficacy, this could create a positive correlation between persistence and teacher retention (Brown et al., 2013; Grant, 2006; Pedota, 2015). There is a need to develop an understanding of which supports, and other programs help retain teachers. Most school districts provide a combination of support, such as mentoring and instructional coaching, with varying frequencies (Edwards & Nuttall, 2015).

Teacher self-efficacy is pointed out to be vital in understanding teacher retention and an individual's intent to remain in the profession (Norman, 2019). This study helped narrow the focus and reveal how specific educational support can increase staying power in education and impact teacher self-efficacy. School districts can use the results of this study to help improve educational support, such as mentoring programs, instructional coaching, professional learning communities, and professional development programs that are currently in place for teachers.

Methods

The self-efficacy instrument was used to assess teachers' self-efficacy. The values and descriptors presented in the instrument enabled researchers to observe shifts in teachers' self-efficacy from before pre-service training and two weeks into school after entering the pre-service training to validate the PAL framework to measure its impact on teacher self-efficacy. The self-efficacy questionnaire instrument was distributed to teachers using Google forms before the pre-service training to measure their self-efficacy. Pre-service training sessions were planned according to the PAL framework to personalize and adapt sessions according to teachers' skills sets and knowledge. After pre-service training was done, school started, and teachers had two weeks to practice skills they were introduced during the pre-service training. The second self-efficacy questionnaire instrument was distributed to teachers using Google forms to observe the teachers' self-efficacy shifts. The findings of the study brought up a need for further investigation on teacher self-efficacy. As a result, teachers' efficacy results were investigated further through interviews to investigate the significant decrease in teachers' self-efficacy after school started to measure the impact of PAL framework on teacher self-efficacy.

The Study

To serve the purpose of this study and address the gaps identified in the introduction section, this study explores the following research question:

> *How can the PAL framework be used to personalize and adapt professional development programs to address teachers' diverse needs and skills to improve their self-efficacy?*

Furthermore, to analyze the effectiveness and impact of PAL framework the following sub-questions were asked: Was personalized adaptive teacher education framework effective to improve teachers' self-efficacy?

a. What impacts teachers' self-efficacy?

b. Why did teachers' self-efficacy decrease after school started?

These sub-questions narrowed the focus of the study on PAL framework's impact on teachers' self-efficacy.

Instrumentation

An empirical study was conducted to analyze the impact of PAL framework on teachers' self-efficacy. For this purpose, a Teacher Self-Efficacy Questionnaire instrument was designed and developed by analyzing and adapting several existing surveys components, the instrument is in Appendix 6.1 (Bandura, 2006; Roth et al., 2007; Schwarzer et al., 1999; Shemshack & Davis, 2020). The values and descriptors presented in the instrument enabled researchers to observe shifts in teachers' self-efficacy from before and after the pre-service training. The self-efficacy questionnaire instrument was distributed to teachers using Google forms before summer preservice training to measure their self-efficacy. It consisted of two sections: a demographics section consisting of five demographic items and a teacher self-efficacy section consisting of 23 Likert-type items. In the demographics section, data was collected on teachers' age, gender, experience, the subject they teach, and grade level they teach. The 23 Likert type items in teacher self-efficacy section were rated on a 6-point scale (1 = *completely disagree*; 2 = *very much disagree*; 3 = *somewhat disagree*; 4 = *somewhat agree*; 5 = *very much agree*; 6 = *completely agree*) to investigate teachers' self-efficacy before and after the trainings. This paper analyzes data from the teacher self-efficacy section, highlighting the instrument's reliability, change in teachers' self-efficacy, and further data analysis investigation. Furthermore, participants were invited to share their input to validate the study's findings through interviews to get a more holistic picture of components that play a role in teachers' self-efficacy. Interview questions focused on survey items that decreased significantly and the one only item that increased, to understand why. During the interviews, the findings of the first part of the study were discussed with the participants and asked why they think these items significantly decreased. Also, the only one increased item was explained to interview participants, and they were asked why they think that item increased while all other items decreased. Interview questions are in Appendix 6.2.

Participants

This study collected data in the summer of 2021 from 127 (pre-survey) and 124 (post-survey) Texas teachers in an urban K-12 Texas School district who attended pre-service training designed according to the PAL framework. Teachers were requested to consent to the survey through google form before being presented with demographics questions and Teacher Self-Efficacy instrument. The demographics of the respondents identified 78% as females, 19% as males, and about 3% who preferred not to say. Also, participants provided their teaching experience, which documented many inexperienced (0-7 years) teachers responding to the survey. 26.4% of the respondents had 0-3 years of teaching experience, 25.6% had 4-7 years of experience, while only 7.2 % had more than 20 years of teaching experience. The respondents were well spread out among grade levels and subjects they teach. Interviews were held to validate the initial study's findings, and they consisted of 15 participants. Teachers invited to interviews were from across the district to ensure a good representation of each campus.

Pre-service Training

Based on the literature review, a conceptual framework for personalized adaptive preservice teacher education was developed in a previous study that is expected to guide personalized adaptive teacher education to increase teachers' self-efficacy. The PAL framework is based on an analysis of what factors help increase teachers' self-efficacy. The PAL framework is an attempt to address the lack of personalized adaptive preservice teacher education to improve self-efficacy. The PAL framework, located in Appendix 6.1, is a tool to improve teachers' self-efficacy and ultimately improve the learning experience for all.

The PAL framework is focused on increasing preservice teachers' self-efficacy by providing personalized adaptive learning support, which is expected to improve self-efficacy and increase perseverance and efforts to learn new skills and acquire new knowledge. The PAL framework suggests that dynamic data collection requires dynamic adaptation, intervention, and intervention to close any learning gaps or avoid losing interest in learning progress. There is growing data to show that efforts to improve teacher education can significantly impact student learning. The PAL framework suggests dynamic data collection on teachers' skills, knowledge, and affective states, and the ability to adapt the content, activities, and content delivery. This dynamic process is expected to increase teachers' self-efficacy by providing challenging enough content and adapting the resources dynamically according to their needs.

The summer pre-service training facilitators of an urban K-12 Texas school district started planning the learning activity by using the PAL framework as a guide. Moreover, they designed the learning activities and supported teachers according to their needs and skill levels. It should be noted that this is not a start-to-end process; this is a cyclical process where facilitators observe teachers' learning and accordingly provide help and support.

This was a 10-day pre-service training. Teachers were more engaged for the first three days; however, as new topics were being introduced to the teachers and the first day of the school got closer, teachers' engagement decreased. Facilitators could not change the number of topics to be presented as the topics were presented by the district academic team. As many new topics were introduced to teachers, they lost their motivation since, according to three teachers interviewed, they did not have a chance to practice newly acquired skills before moving on to the next new topic. Challenging but achievable goals allow one to try and obtain feedback as teachers proceed toward goal completion. Goals beyond teachers' knowledge or skill levels will likely lead to frustration and degrade self-efficacy (Bandura, 1977; Schunk et al., 2008).

Summer pre-service training started with training new teachers to pre-teach the main concepts covered during summer PD, at this Texas urban school district. Schedule is located in Appendix 6.2. Facilitators already had data on current teachers' knowledge and skills as they worked with teachers as curriculum coordinators. This is aligned with PAL framework under assess current skills, knowledge & affect component.

During pre-service training, teachers were grouped by their subject areas and grade level, so they attended sessions addressing needs specific to their teaching. Facilitators planned their sessions based on data they had on teachers' current knowledge, skills, and affective states to adapt the learning activities, content, and content delivery accordingly. This is aligned with the PAL framework under the adapt learning activities & content component.

Unfortunately, the sessions were virtual due to COVID-19 safety measures, so it was hard to observe teachers' behaviors and collect informal data to adapt the content and delivery accordingly, as suggested by the PAL framework. Even though facilitators stated it was hard to monitor each teacher's emotional states and learning, facilitators still attempted to collect data on teachers during the sessions based on their questions and engagements to adapt and personalize their sessions accordingly, as outlined in PAL framework under personalized adaptive support component.

Interventions and corrective feedback were provided to teachers throughout the sessions, and the objective of each session was communicated with teachers before the sessions, during the sessions, and in the end, to ensure teachers know the expected outcome for each session as suggested by the PAL framework. As outlined in PAL framework under dynamic intervention and correctness feedback components.

As suggested by the PAL framework, facilitators were collecting informal data on teachers' emotional states by monitoring their engagement, their comments in zoom chat, and their facial expressions. Facilitators observed that teachers were getting overwhelmed by many topics that were being introduced. However, they could not make changes to it as suggested by PAL framework. Literature suggests that it is essential to have systems assess teachers' state of emotion and learning and adapt the content accordingly (Csikszentmihalyi, 1990; D'Mello & Graesser, 2012). However, facilitators were not able to make changes to new topics that needed to be introduced due to the preset schedule that was given to facilitators for the pre-service training.

Before moving to the next learning activity, the facilitators observed teachers' knowledge, skills, and guided learning activities to support teachers at the right time to improve their self-efficacy that is ultimately expected to increase their efforts toward learning new skills and increase perseverance. As a result of such personalized support, teachers are expected to become life-long learners who will improve the learning experience for both their students and them.

Reliability and Validity of the Self-Efficacy Instrument

Before disseminating the survey to participants, a pilot study was administered to validate the instrument for the actual study. The output for Cronbach's Alpha of the pilot study was .924, which is excellent, according to DeVellis (1991). The actual study took place in August 2021 with 127 (pre-survey) and 124 (post-survey) participants. The outcome of Cronbach's Alpha for the main study was .949 for the participants (124) that completed the 23 Likert items to measure teachers' self-efficacy. According to DeVellis (1991), this is "Excellent." Exploratory factor analysis (principal components, varimax rotation) determined the number of constructs assessed by the survey instrument. The eigenvalue = 1 cutoff default resulted in two factors. One factor consisted of items related to teachers' ability, while the second one was teachers' motivation for teaching and educating themselves to improve their instructional practices.

The factors representing the constructs assessed by the instrument appear as follows:

- Factor 1 Teachers' Ability Scale (Items 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 17, 18, 19, 20, 21, 22, and 23 in the survey) measures teachers' self-efficacy regarding their ability to teach and help their students.
- Factor 2 Teachers' Motivation Scale (Items 12, 13, 14, 15, and 16 in the survey) measures teachers' motivation for teaching and educating themselves to improve their instructional practices.

The KMO Measure of Sampling Accuracy yielded a statistical value of 0.905, which is considered excellent (Kaiser, 1974). A value above .90 indicates that factor analysis will be helpful when interpreting the data set. This also indicated that a significant proportion of variance among the survey items is potentially a common variance.

Findings from the Self-Efficacy Scale and Interviews

This study investigated teachers' self-efficacy before pre-service training in the summer of 2021 and compared it with changes in self-efficacy two weeks after school started to validate the PAL framework used for pre-service training. Teachers' self-efficacy declined significantly for all items except for one item where it increased. The most significant decline was in Item 20, which is "I believe my administrators have efficient systems in place to support teachers in using instructional software effectively." The findings of the empirical study brought up a need for further investigation on teacher self-efficacy. As a result, interviews were subsequently conducted to investigate the decrease in teachers' self-efficacy. Teachers shared that before school started, they trusted that there were good plans developed during the summer by their administrators due to the information that was provided to them by their administrators. However, once school started, most teachers did not know what to do. Administrators kept asking teachers to do more compliance requirements without paying attention to the stress teachers were going through due to a lack of time to get everything that was being asked.

Item 8 was further analyzed for any increase due to chance by using a binomial (sign test) of all but one increase. As a result, a sign test was conducted. If the probability of "success" in each trial or subject is 0.500, then:

- The one-tail p-value is < 0.0001: this is the chance of observing 22 or more successes in 23 trials.
- The two-tail p-value is < 0.0001: this is the chance of observing either 22 or more successes, or one or fewer successes, in 23 trials which shows that it is scarce to have less than 0.0001 by chance for this item to increase.

The mean of pre-survey and post-survey helped to see the difference in each item's means. The mean of the pre-survey group is 5.24 out of 6, which shows a great alignment across items. One might even argue that these items during the pre-survey were overinflated. This can be due to teachers not trusting that the survey data was anonymous and having suspicion that it could be used against them since it focuses on their confidence in their skills and ability as a teacher. During interviews, teachers were asked about this, and they stated that they did not feel comfortable that they did not have control over how data is collected and how much information their administrators have access to. They stated that if the survey was sent through a third-party company, they would feel more comfortable responding to the survey questions.

The mean of pre-survey shows that teachers' self-efficacy was very high in summer before they started training. However, post-survey was given two weeks after school started-three weeks after pre-survey, and the mean is 5.11, which while still is high, we observed a decrease in teachers self-efficacy. While the mean of all items decreased, there is one item that teachers reported as increased self-efficacy. The item has increased self-efficacy reports that teachers' self-efficacy increased for their confidence in helping their students to close the support gap from home by using instructional tools. Cohen's *d* effect size was analyzed for each item and the whole group to investigate changes in self-efficacy and how they relate to each other (Lenhard & Lenhard, 2016). Effect size (Cohen's d) for the whole study is 0.52, which is educationally meaningful according to Cohen (1988) (see Table 6.2).

Table 6.1

Effect Size (Cohen's d*)*

	Pre-survey	**Post-survey**
Mean	5.24	5.11
Standard Deviation	.27	.26
Sample Size (N)	127	124
Effect Size Cohen's *d*	**-0.52**	

Table 6.2

Effect Size (Cohen's d*) Guidelines*

Significance	**Value**
Small	0.2
Medium	0.5
Large	0.8

Each item's Cohen's *d* was calculated and educationally meaningful, and large ones were Items 2, 5,19, and 20. When comparing means of Factors 1 and 2, the decline in Factor 1, which is teachers' confidence in their ability, is more significant than Factor 2, teachers' motivation to do the job. That finding can be interpreted as even though teachers' self-efficacy declined due to COVID-19 learning loss and the requirements of the job, their motivation did not decline at the same rate. As Henson (2001) suggested, teacher motivation is mainly defined as a desire to help children learn and become productive citizens. The decline in teachers' motivation was not correlational with their confidence in their abilities to teach their students where they are at, which can be a significant finding for administrators to understand the importance of helping their teachers according to their needs to help them increase their self-efficacy to teach no matter where students are at. Shemshack et al. (2021) suggested that it is essential for administrators to have tools and intentional support to help teachers improve their teaching practices, and building confidence in teaching becomes an essential component of efficient teaching.

As an extension of the empirical study, interviews were held to validate the findings of the empirical study. During interviews, teachers were asked why they think teachers' self-efficacy went down after school started. Participants shared that before school started, they were all motivated and ready to teach like before COVID-19 times. However, the policies and uncertainties due to COVID-19 caused them to struggle to reach their students, and they lost confidence that they could help their students to close the learning gap of two years. One participant stated, "students' scores are low; it is going to be a long year. Everybody feels like first-year teacher."

Also, the item in the survey that decreased significantly, "I believe my administrators have efficient systems in place to support teachers in using instructional software effectively," was discussed and investigated by asking why that would happen. What do they think led to this decrease in confidence that administrators are supporting teachers to be more efficient?" The reflections during interviews showed that teachers observed that not only their workload increased, but their administrator's workload increased as well. Due to increased workload, they are not getting the support and help they need from their administrators, which caused losing confidence in their administrators; as reflected by one of the teachers, “Expectations from teachers are too high, there is a disconnect between administrators and teachers.” Another teacher said that they are looking into other professions as “it is not worth being a teacher anymore.” Yet another teacher stated, “I do not feel I can stay in the teaching profession more than one year.”

The interview participants were also asked that since the items that went down significantly are the ones that mention administration support, why do they think teachers’ confidence in administration support declined after school started? Or whether they believe it is related to what happened during these two weeks of school? If so, how?” Teachers stated that they feel administrators are not seeing them as human beings anymore due to disconnectedness. Everybody is focused on compliance items and there are no personal connections anymore which have caused separation between teachers and administrators. One of the interview participants stated, “there is no time to get everything done.”

The direction of discussion during interviews changed by getting participants’ attention to the only increased item: “I am convinced that I can promote learning by using instructional tools when there is a lack of support from home for the student.” During the interview, teachers were asked to reflect on these findings by asking them, “Why do you think that would be an item teachers’ confidence increased? Why do you think teachers’ confidence in helping students decreased while their confidence in closing lack of support from home increased?” Teachers stated that due to COVID-19, they had to learn using many instructional tools and now they feel more comfortable with abilities to help their students to keep learning at home even though there is no parental support since they know possibilities of tools available.

Participants stated that lack of training and support to acknowledge the gap caused by

Covid-19 and not to provide resources to address the learning loss during COVID-19 have been huge obstacles for them. Teachers stated that they feel everybody pretends that students did not go through a pandemic and expects the same outcome data for student learning as years before COVID-19. Teachers feel that this is not fair to teachers as they are so worried about teaching their students grade level standards while trying to teach them the standards from previous two years to ensure they are closing learning gaps caused by COVID-19. After school started, teachers realized that they were not as ready as they thought, and they did not have time to complete all tasks they were asked to do.

Addressing the Research Questions

The above discussion sets the scene to help address each of the research questions of this research. The first research question of this research is: *How can the PAL framework be used to personalize according to professional development programs to address teachers' diverse needs and skills to improve their self-efficacy?* The PAL framework can be used to improve teachers' self-efficacy and ultimately improve the learning experience for all. It can be used in different settings with different scenarios. The framework is focused on increasing teachers' self-efficacy by providing personalized adaptive learning support, which is expected to improve self-efficacy and increase perseverance and efforts to learn new skills and acquire new knowledge.

The literature suggests that dynamic data collection requires dynamic adaptation, intervention, and correctness feedback to close any learning gaps and to avoid losing interest in learning progress. There is growing data to show that efforts to improve teacher education can significantly impact student learning. The PAL framework suggests dynamic data collection on teachers' skills, knowledge, and affective states, and the ability to adapt the content, activities, and content delivery. This dynamic process is expected to increase teachers' self-efficacy by providing challenging enough content and adapting the resources dynamically according to their needs. For personalized adaptive teacher education to be effective, relevant cognitive and affective states should be assessed to inform the instructional decision-making in personalized adaptive learning systems. Data from the initial assessment can be supplemented and adjusted by repeated measurements and data collection throughout the learning process (Tetzlaff et al., 2020).

According to the PAL framework, personalized adaptive teacher education starts with assessing teachers' current knowledge, skills, and affective states to adapt the learning activities, content, and content delivery. Ongoing assessment and data collection are needed to make decisions according to teachers' cognitive and affective states to adapt the content and content delivery methods. Furthermore, the framework suggests supporting teachers with personalized adaptive support, ongoing intervention, and corrective feedback. However, data collection is not a procedure that happens occasionally; it is a dynamic process built into the learning process. Progress towards mastery of learning activities can be continuously measured, and in case of stagnation, content and content delivery adaptation can be implemented. This cycle of assessing teachers' current cognitive and affective states, setting learning activities and content delivery accordingly, and employing assessment and data collection to check whether mastery was achieved (which influences the learning activities for the next cycle) is the backbone of personalized adaptive instruction (Tetzlaff et al., 2020).

According to teachers' cognitive and affective states, adapting content within the teachers' proximal development zone (ZPD) is the main instructional adaptation of this framework. As suggested in Bloom's mastery learning approach (Bloom, 1968), the PAL system needs to assess previous content/skill mastery before proceeding with the next one. Upon completion of the unit, there needs to be some assessment of the learning gains and subsequent selection/design of the next unit (located in the zone of proximal development and presenting a logical next step on the way to the high-level learning goal). An integral part of designing personalized adaptive teacher education is personalized adaptive content selection based on ongoing collected data on teachers' current cognitive and affective states. Personalizing task selection based on predicted efficiency and learner preference has been shown to increase training and transfer performance (Tetzlaff et al., 2020) which is expected to increase teachers' performance and, as a result, their self-efficacy.

Since the PAL framework was built around the current literature of personalized learning tools and components, and solely focused on teacher education and how teachers' self-efficacy can be increased by providing personalized adaptive learning, the framework should be useful for any teacher education institution. In addition, it can also be a helpful resource for K-12 school districts and regional educational centers to provide personalized adaptive teacher education to increase teachers' self-efficacy. Teachers face ongoing changes in education that they are expected to keep up with; thus, we need teachers who are willing to learn more and adapt their instructional practices according to changes in schools and society, especially with technology. The PAL framework for personalized adaptive teacher education can guide future studies to address this need and demand.

The outcomes suggested that even though a framework was used to personalize the teachers' learning experience, having so many components and different professional development topics made it complex for teachers and facilitators, as noted by teachers interviewed. During interviews, the participants suggested that planned learning opportunities need to be focused and new topics should be presented one at a time to allow teachers to practice and feel confident in implementing it before moving into a new skill set acquisition.

The next question was a sub-question of the first question that focused on effectiveness of personalized adaptive teacher education framework to improve teachers' self-efficacy: *Was personalized adaptive teacher education framework effective to improve teachers' self-efficacy?* The study results revealed that even though facilitators used the framework to personalize and adapt the learning experience of teachers, time constraints and variety of the topics needed to be covered were obstacles as teachers were not able to practice their skills to test their proficiency and investigate their skill gaps to get further help and support. Teacher self-efficacy did not show an increase because of training, except for only one item. Teachers felt confident; they can promote learning by using instructional tools when there is a lack of support from home for the student. So, it is suggested that the focus should not only be on delivery format but also that teachers are given time to practice the newly acquired skills, feel confident in new skills, and be aware of areas of need to get further help and support before moving on to introduce a new topic.

The framework was used to assess teachers' learning throughout the sessions and adapt as needed and group them according to their needs. However, having the sessions virtually was an obstacle, and the facilitators were not able to walk around the room to listen to conversations and see teachers progress as they were having them practice specific skills. Future studies are needed to analyze the impact of the framework being used through computer software programs that are programmed to use the framework and adapt the learning according to collected data and also use the framework for regular in-person sessions after COVID-19 to measure the ability to walk around the room to observe teachers progress, listening to their conversations to gauge their understanding and adapt the content and content delivery accordingly, to measure frameworks impact on teachers self-efficacy.

Another sub question was: *What impacts teachers' self-efficacy?* According to the teachers who attended interviews, teachers need more time to plan and prepare their lessons and have access to their administrators to get more help and support, so they know that if they need help, their administrators have resources and time to help them.

Teachers responded to the decrease in teachers' self-efficacy after school started by pointing out that they thought they knew how to help and support their students without really knowing how far their students were and what obstacles COVID-19 carry over from previous school years. Once they assessed their students, they realized that their students are way behind than what teachers thought, and students forgot school procedures and routines as they were out of school for about two years. Teachers stated that they have behavior issues that they are trying to get resolved while trying to teach students the grade level standards and trying to teach them what they missed in last two years to ensure they are not missing foundational skills.

Discussion and Conclusions

Very little research in the literature has explicitly looked at personalized adaptive pre-service teacher education to improve inservice teachers' self-efficacy. Thus, this research is expected to be the foundation for future studies on personalized adaptive pre-service teacher education to improve teachers' self-efficacy. Current studies point out that teachers are the main determinants of instructional practices and student learning outcomes (Colson et al., 2018; Darling-Hammond, 2000; Depaepe & König, 2018; Jenset et al., 2018; Schleicher, 2016). Teachers' beliefs shape their teaching practices by filtering interpretations, framing situations or problems, and guiding actions (Heinonen et al., 2019).

Teachers have a strong sense of self-efficacy to help them maintain their interest in the profession of teaching and use those skills to help the students they teach (Gedzune, 2015, as cited in Colson et al., 2018).

Teachers' self-efficacy from pre-service training to two weeks after school started to decrease significantly. Teachers stated that the workload and students' significant learning loss due to COVID-19 caused many teachers to lose their self-efficacy. We held interviews to discuss the study's findings, and many teachers stated that due to COVID-19, they do not feel competent anymore due to changes COVID-19 has brought in the education system, and that uncertainty is causing self-doubt.

Demographic questions were asked to analyze trends and patterns according to each demographic; however, teachers of all demographics have reported decreased self-efficacy. Items 1-6 in the survey aimed to measure teachers' confidence in instructional software tools and their abilities to reach struggling students; their self-efficacy decreased. Furthermore, this group of questions has one of the most decreased self-efficacy items that is "I am responsive to my students' needs by using several different tools available to me."

Items 6-11 focus on measuring teachers' confidence to use tools and resources available to motivate students to keep learning. This group of questions included one of the most decreased self-efficacy items as well the only increased item that teachers stated, "I am convinced that I can promote learning by using instructional tools when there is a lack of support from home for the student."

Items 12-16 focus on measuring teachers' motivation, whether intrinsic or extrinsic, which, while they all decreased, their decrease was not significant.

Items 17-23 focus on measuring teachers' confidence in resources and support systems available to them, and this group of questions has the largest decrease in teachers' self-efficacy. This aligns with the comment made by one of the teachers interviewed," administrators have too many expectations, students' data was expected to be normal; however, we realized there is a huge learning loss due to Covid-19. " Also, another participant stated that changes in administrator team brought a change in rules and expectations, which brought uncertainty and caused loss of trust in support systems since teachers did not know if any were available to them: "Teaching is overwhelming; especially this year is more challenging than last year when we had Virtual learning due to Covid-19. Everybody is expecting normalcy while there is normalcy; Covid-19 carried over so many issues in teaching, not only learning loss and behavior issues.

Pre- and post-survey were administered with a two-week window to ensure teachers have time to use the skills and strategies obtained during pre-service training. Post survey was administered after the second week of the school that students returned from summer break. So, teachers were able to use these skills and observe their abilities and self-efficacy and have an opportunity to interact with their students to understand their needs and current ability levels.

Furthermore, participants were invited to share their input to validate the study's findings through interviews to get a more holistic picture of components that play a role in teachers' self-efficacy. Interview questions are in Appendix 6.3.

Limitations and Future Research

The initial focus of this study was the induction year teachers. However, the number of participants was low, which required the focus to be widened to all teachers at urban school district in Texas. A future study should concentrate only on the induction year teachers to measure the impacts of personalized adaptive learning on induction year teachers since the highest turnover is with this group of teachers (Ingersoll, 2001; Norman, 2019)

A future study should also assess the long-term effects of personalized adaptive pre-service teacher education in a more holistic approach for induction year teachers since the highest turnover is with this group of teachers (Ingersoll, 2001; Norman, 2019). This study could compare the resiliency and turnover rate of teachers who did not have an opportunity for personalized adaptive pre-service education with teachers who did have an opportunity for personalized adaptive pre-service education. The small sample size is another limitation of the study. There were 124 survey responses collected and 15 teachers interviewed. Also, regional bias might be an obstacle to generalizing the study since participants were only Texas teachers.

This study was planned for two different school districts. However, one of the school districts had many changes in their administration team, and the research team could not reach out to them to plan for the study. This change resulted in holding the study only with one school district in Texas, which is considered a limitation. We could not analyze and compare different school districts to see if results impact the study or a specific district's approach to teacher professional development might affect the study's findings.

Pre-service training sessions were virtual, and we could not observe teachers figure out their progress and understanding and need for help. Also, it is essential to mention that teachers had different trainers during these sessions, and trainers' ability to personalize and adapt to the content might have differed from trainer to trainer, which might affect the study results. Also, it is important to note that teachers stated that the amount of information given to them in a short time was an obstacle for them to retain the information.

The way the study was conducted, it could not be ensured that it was the same participants taking pre-and post-survey. Participants were indeed asked to take post-survey only if they took the pre-survey. However, there is a remote possibility that some post-survey participants were those who had not taken pre-survey. Due to this, a one-to-one data analysis could not be conducted to see changes in individual teachers' self-efficacy. Instead, the means of the groups were compared. Demographics information of pre- and post-survey respondents were compared, and they seem to be highly aligned (about 114 out of 124). Further studies can use an analysis approach that ensures that the same participants take both pre- and post-surveys to provide one-to-one comparison without losing anonymity.

Due to high self-efficacy being reported in pre-survey, there is another possible limitation of the study: teachers do not trust anonymous surveys. They might have thought that the district is collecting data on their skills and abilities, and results might be used against them. So, a self-reported self-efficacy survey might not be a true reflection of their self-efficacy, which is usually a possibility with self-reporting. However, teachers stated that the survey can be distributed by a third-party company to help teachers feel more comfortable about the anonymity of the reporting of their self-efficacy regarding their skills and motivation.

Future studies can explore self-efficacy directly compared to teacher retention with longitudinal studies to study the direct link between teachers' self-efficacy and teacher retention.

The data of this study were collected through a series of surveys of teacher perceptions. Therefore, there was an assumption that participants were reasonably honest in their perceptions of their school environments, and such an assumption may be a limitation of the study. Focusing on teacher education to improve the learning experience for students and inservice teachers needs to be explored further.

Chapter References

Artino, A. R. (2012). Academic self-efficacy: from educational theory to instructional practice. *Perspectives on Medical Education*, *1*(2), 76–85. https://doi.org/10.1007/s40037-012-0012-5

Bandura, A. (1977). Self-efficacy: toward a unifying theory of behavioral change. Psychological Review, *84*(2), 191-215.

Bandura, A. (1982). Self-efficacy mechanism in human agency. *American Psychologist*, *37*(2), 122–147. https://doi.org/10.1037/0003-066X.37.2.122

Bandura, A. (1993). Perceived self-efficacy in cognitive development and functioning. *Educational Psychologist, 28*(2), 117–148. https://doi.org/10.1207/s15326985ep2802_3

Bandura, A. (1994). Self-efficacy. In V. S. Ramachaudran (Ed.), Encyclopedia of human behavior (Vol. 4, pp. 71-81). New York: Academic Press. (Reprinted in H. Friedman [Ed.], Encyclopedia of mental health. San Diego: Academic Press, 1998).

Bandura, A. (1997). *Self-efficacy: the exercise of control.* New York: W. H. Freeman and Company.

Bandura, A. (2006). *Guide for constructing self-efficacy scales*. In T. Urdan & F. Pajares (Eds.), Self-efficacy beliefs of adolescents (pp.307–337).

Bloom, B. (1968). Learning for mastery. Evaluation Comment, 1(4), 1–12. https://doi.org/10.1021/ed063p318.

Brown, L. J., Malouff, J. M., & Schutte, N. S. (2013). *Self-Efficacy Theory.* Armidale, NSW: University of New England.

Carr, M. L., Holmes, W., & Flynn, K. (2017). Using Mentoring, Coaching, and Self-Mentoring to Support Public School Educators, The Clearing House: *A Journal of Educational Strategies, Issues, and Ideas, 90(*4), 116-124. https://doi.org/10.1080/00098655.2017.1316624

Cavanagh, R. F., & Dellar, G. B. (1997). "School culture: A quantitative perspective on a subjective phenomenon." Paper presented at the Annual Meeting of the American Educational Research Association.: Chicago, IL, March 24-28, 1997.

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences.* (2nd ed.). Hillsdale, NJ: L. Erlbaum associates.

Colson, T., Sparks, K., Berridge, G., Frimming, R., & Willis, C. (2018). Pre-service Teachers and Self-Efficacy: A Study in Contrast. *Discourse and Communication for Sustainable Education*, *8*(2), 66–76. https://doi.org/10.1515/dcse-2017-0016

Csikszentmihalyi, M. (1990). Flow: The Psychology of Optimal Experience. *The Academy of Management Review 16*(3), 636.

Darling-Hammond, L. (2000). Teacher quality and student achievement: A review of state policy analysis. *Education Policy Analysis Archives, 8*(1) -3 7. http://epaa.asu.edu/epaa/v8n 1 .html

Depaepe, F., & König, J. (2018). General pedagogical knowledge, self-efficacy, and instructional practice: Disentangling their relationship in pre-service teacher education. *Teaching and Teacher Education*, *69*, 177–190. https://doi.org/10.1016/j.tate.2017.10.003

DeVellis, R. F. (1991). *Scale development: theory and applications*. Applied social research methods series, vol. 26. *Newbury Park, CA: Sage publications*.D'Mello, S. K., & Graesser, A. (2012). Dynamics of affective states during complex learning. *Learning and Instruction, 22*, 145-157.

Edwards, S., & Nuttall, J. (2015). Beginning teachers: issues and experiences. *Asia-Pacific Journal of Teacher Education, 43*(1), 1–3. https://doi-org.libproxy.library.unt.edu/10.1080/1359866X.2014.969415

Ertmer, P. A., Ottenbreit-Leftwich, A. T., Sadik, O., Sendurur, E., & Sendurur, P. (2012). Teacher beliefs and technology integration practices: A critical relationship. *Computers & Education, 59*, 423–435.

FitzGerald, E., Kucirkova, N., Jones, A., Cross, S., Ferguson, R., Herodotou, C., Hillaire, G., & Scanlon, E. (2018). Dimensions of personalisation in technology-enhanced learning: A framework and implications for design. *British Journal of Educational Technology, 49*(1), 165–181. https://doi.org/10.1111/bjet.12534.v

Foshee, C. M., Elliott, S. N., & Atkinson, R. K. (2016). Technology-enhanced learning in college mathematics remediation. *British Journal of Educational Technology*, *47*(5), 893–905. https://doi.org/10.1111/bjet.12285

Grant, L. W. (2006). Persistence and Self-Efficacy: A Key to Understanding Teacher Turnover. *Delta Kappa Gamma Bulletin, 72*(2), 50–54.

Hall, A. B., & Trespalacios, J. (2019). Personalized Professional Learning and Teacher Self-Efficacy for Integrating Technology in K–12 Classrooms. *Journal of Digital Learning in Teacher Education*, *35*(4), 221–235. https://doi.org/10.1080/21532974.2019.1647579

Heinonen, K., Jaaskela, P., Hakkinen, P., Isomaki, H., & Hamalainen, R. (2019). University Teachers as Developers of Technology-Enhanced Teaching: Do Beliefs Matter? *Journal of Research on Technology in Education*, *51*(2), 135–151.

Henson, R. K. (2001). The effects of participation in teacher research on teacher efficacy. *Teaching and Teacher Education, 17*(7), 819-836. https://doi.org/10.1016/S0742-051X(01)00033-6

Herman, K. C., Hickmon-Rosa, J., & Reinke, W. M. (2018). Empirically Derived Profiles of Teacher Stress, Burnout, Self-Efficacy, and Coping and Associated Student Outcomes. *Journal of Positive Behavior Interventions*, *20*(2), 90–100. https://doi.org/10.1177/1098300717732066

Holmes, B., Parker, D., & Gibson, J. (2019). Rethinking Teacher Retention in Hard-To-Staff Schools. *Contemporary Issues in Education Research (CIER)*, *12*(1), 27–32. https://doi.org/10.19030/cier.v12i1.10260

Howard, S. K., Chan, A., & Caputi, P. (2015). More than beliefs: Subject areas and teachers' integration of laptops in secondary teaching. *British Journal of Educational Technology, 46,* 360–369.

Ingersoll, R. M. (2001). Teacher turnover and teacher shortages: An organizational analysis. *American Educational Research Journal, 38*(3), 499–534. https://doi.org/10.3102/00028312038003499

Jenset, I. S., Klette, K., & Hammerness, K. (2018). Grounding Teacher Education in Practice Around the World: An Examination of Teacher Education Coursework in Teacher Education Programs in Finland, Norway, and the United States. *Journal of Teacher Education*, *69*(2), 184–197. https://doi.org/10.1177/0022487117728248

Jomuad, P. D., Mabelle Antiquina, L. M., Cericos, E. U., Bacus, J. A., Vallejo, J. H., Dionio, B. B., Bazar, J. S., Cocolan, J. V., & Clarin, A. S. (2021). Teachers' workload in relation to burnout and work performance*. International Journal of Educational Policy Research and Review, 8*(2), 48–53.

Kaiser, H. F. (1974). An index of factorial simplicity. *Psychometrika, 39*(1), 31-36

Kinshuk, Chen, N. S., Cheng, I. L., & Chew, S. W. (2016). Evolution is not enough: Revolutionizing Current learning environments to smart learning environments. International Journal of Artificial Intelligence in Education, 26(2), 561-581. https://doi.org/10.1007/s40593-016-0108-x

Komarraju, M., & Nadler, D. (2013). Self-efficacy and academic achievement: Why do implicit beliefs, goals, and effort regulation matter? *Learning and Individual Differences*, *25*, 67–72. https://doi.org/10.1016/j.lindif.2013.01.005

Lenhard, W., & Lenhard, A. (2016). *Calculation of Effect Sizes.* Retrieved from: https://www.psychometrica.de/effect_size.html. Dettelbach (Germany): Psychometrica. https://doi.org/10.13140/RG.2.2.17823.92329

Levine, A. (2006). *Educating School Teachers.* Retrieved 16 August 2008 from http: www.edschools.org/pdf/Educating_Teachers_Report.pdf.

Mergler, A. G., & Spooner-Lane, R. (2012). What pre-service teachers need to know to be effective at values-based education. *Australian Journal of Teacher Education*, *37*(8), 66–81. https://doi.org/10.14221/ajte.2012v37n8.5

Natividad Beltrán del Río, G. (2021). A useful framework for teacher professional development for online and blended learning to use as guidance in times of crisis. Education Tech Research Dev 69, 7–9. https://doi.org/10.1007/s11423-021-09953-y

Nel, L. (2017). Students as collaborators in creating meaningful learning experiences in technology-enhanced classrooms: An engaged scholarship approach. British Journal of Educational Technology, 48, 1131–1142. https://doi.org/10.1111/bjet.12549.

Norman, L. B. (2019). *The Revolving Door of Teacher Turnover: Examining the Influence of Teacher Self-Efficacy, Locus of Control, and School Culture on Teacher Retention*., search.proquest.com, https://search.proquest.com/openview/cb48f75956cad867dac6aed65362905a/1?pq-origsite=gscholar&cbl=18750&diss=y

Ottenbreit-Leftwich, A., Liao, J. Y. C., Sadik, O., & Ertmer, P. (2018). Evolution of Teachers' Technology Integration Knowledge, Beliefs, and Practices: How Can We Support Beginning Teachers Use of Technology? *Journal of Research on Technology in Education*, *50*(4), 282–304. https://doi.org/10.1080/15391523.2018.1487350

Panadero, E., Jonsson, A., & Botella, J. (2017). Effects of self-assessment on self-regulated learning and self-efficacy: Four meta-analyses. *Educational Research Review*, *22*, 74–98. https://doi.org/10.1016/j.edurev.2017.08.004

Pane, J. F., Steiner, E. D., Baird, M. D., & Hamilton, L. S. (2015). Continued Progress: Promising Evidence on Personalized Learning. *Rand Corporation*, ERIC, https://eric.ed.gov/?id=ED571009

Pedota, P. J. (2015). How can student success support teacher self-efficacy and retention? *Clearing House, 88*(2), 54–61. https://doi.org/10.1080/00098655.2014.998600

Peng, H., Ma, S., & Spector, J. M. (2019). Personalized Adaptive Learning: An Emerging Pedagogical Approach Enabled by a Smart Learning Environment. *Lecture Notes in Educational Technology*, 171–176. https://doi.org/10.1007/978-981-13-6908-7_24

Pliakos, K., Joo, S. H., Park, J. Y., Cornillie, F., Evans, C., & Van den Noortgate, W. (2019). Integrating machine learning into item response theory for addressing the cold start problem in adaptive learning systems. *Computers and Education, 137*(April), 91–103. https://doi.org/10.1016/j.compedu.2019.04.009

Roth, G., Assor, A., Kanat-Maymon, Y., & Kaplan, H. (2007). Autonomous motivations for teaching: how self-determined teaching may lead to self-determined learning. *J. Educ. Psychol.* 99, 761–774. https://doi.org/10.1037/0022-0663.99.4.761

Schleicher, A. (2016). *Teaching excellence through professional learning and policy reform.* Paris, France: OECD.

Schunk, D. H., Pintrich, P. R., & Meece, J. L. (2008). *Motivation in education: theory, research, and applications.* Upper Saddle River: Pearson Education.

Schwarzer, R., Mueller, J., & Greenglass, E. (1999). Assessment of perceived general self-efficacy on the internet: Data collection in cyberspace. *Anxiety, Stress, and Coping, 12*(2), 145-161. https://doi.org/10.1080/10615809908248327

Shemshack, A., & Davis, T. (2020). What Supports Do Teachers Need from Administrators for Distance Learning. In E. Langran (Ed.), *Proceedings of SITE Interactive 2020 Online Conference* (pp. 294-295). Online: Association for the Advancement of Computing in

Education (AACE). Retrieved September 26, 2021, from https://www.learntechlib.org/primary/p/218160/.

Shemshack, A., Davis, T., Knezek & Kinshuk. *Factors contributing to teacher self-efficacy in distance learning.* [Manuscript submitted for publication].

Shemshack, A., & Spector, J. M. (2020). A systematic literature review of personalized learning terms. *Smart Learning Environments, 7*(1). Springer. https://doi.org/10.1186/s40561-020-00140-9

Shen, D., Cho, M.-H., Tsai, C.-L., & Marra, R. (2013). Unpacking online learning experiences: Online learning self-efficacy and learning satisfaction. *Internet and Higher Education*, *19*, 10–17. https://doi.org/10.1016/j.iheduc.2013.04.001

Siko, J. P., & Hess, A. N. (2014). Win-win professional development: Providing meaningful professional development while meeting the needs of all stakeholders. *TechTrends, 58*, 99–108. https://doi.org/10.1007/s11528-014-0809-7.

Tetzlaff, L., Schmiedek, F., & Brod, G. (2020). Developing Personalized Education: A Dynamic Framework. *Educational Psychology Review*. https://doi.org/10.1007/s10648-020-09570-w

Thoma, J., Johnson, D., Johnson, K., & Stromer, E. (2017). Planning for technology integration in a professional learning community. *The Reading Teacher, 71*(2), 167–175. https://doi.org/10.1002/trtr.1604.

van Tonder, G. P. (2021). A multimodal induction model for beginning teachers: a narrative approach. *International Journal of Educational Management*, *35*(4), 879–896. https://doi.org/10.1108/IJEM-08-2020-0389

Ware, H., & Kitsantas, A. (2007). Teacher and Collective Efficacy Beliefs as Predictors of Professional Commitment, *The Journal of Educational Research, 100(*5), 303-310. https://doi.org/10.3200/JOER.100.5.303-310.

Wright, V. H., & Wilson, E. K. (2005). From pre-service to inservice teaching: A study of technology integration. *Journal of Computing in teacher Education*, *22*(2), 49-55.

Xie, H., Chu, H. C., Hwang, G. J., & Wang, C. C. (2019). Trends and development in technology-enhanced adaptive/personalized learning: A systematic review of journal publications from 2007 to 2017. *Computers and Education*, *140*(June), 103599. https://doi.org/10.1016/j.compedu.2019.103599

Appendix 6.1: PAL Framework

Appendix 6.2: Pre-Service Training Schedule

2021-2022 Summer New Teacher Orientation		
Facilitators Names Teachers grouped by their needs and skill levels	Wednesday, July 28	Thursday, July 29
	New Teacher* Orientation	
9:00 am - 12:00 pm	GROUP A (Full)	GROUP C
1:00 pm - 4:00 pm	GROUP B	GROUP D

K-2 Schedule

WEEK 1	Tuesday, August 3	Wednesday, August 4	Thursday, August 5
Morning Session	9:00-10:00 AM Introduction to K-2 Curriculum Conducted by ... Recording Link Passcode: .K	8:00 - 9:00 AM Balanced Literacy Refresher **Returning Teachers Only** Conducted by ... Recording Link Passcode: %+Vhwb1f	9:00 - 10:00 Science Curriculum Conducted by ../ Recording Link Passcode: Y
	10:30 - 12:00 Math Curriculum Conducted by .. Recording Link Passcode: b	9:15 - 12:00 Balanced Literacy Overview **New Teachers Only** Conducted by ... Recording Link Passcode: %	10:30 - 12:00 STEMscopes Science Conducted by ... Passcode: PK-2 Recording Link Passcode: Y.
Lunch 12:00 - 1:00			
Afternoon Session	1:15 - 4:30 Math Workshop Framework Conducted by ... Passcode: PK-2 Recording Link Passcode: a	1:00 - 2:15 ELAR Curriculum Conducted by... Recording Link Passcode: @	1:00 - 3:00 PM HMH Into Reading Overview, Password: 09gj&5XH8 New Teachers Only Conducted by Becky Giles, HMH Recording Coming Soon
		2:30-4:30 The Science of Teaching Reading: Where do we go from Here? Conducted by (Recording Not Available)	3:00 - 5:00 HMH Updates, Password: 0 Returning Teachers Only Conducted by .. Recording Coming Soon
WEEK 2	**Monday, August 9**	**Tuesday, August 10**	**Wednesday, August 11**
Morning Session	9:00 - 12:00 Stemscopes Math Conducted by...	8:00 - 9:30 Heggerty Phonemic Awareness Conducted by... Recording Link	Office Hours 10:00 - 12:00 Passcode: ..
		10:00 - 12:00 NEW Studies Weekly Conducted by ... Recording Link	
Lunch 12:00 - 1:00			
Afternoon Session	1:00 - 3:00 Reading A-Z Conducted by .... Recording Link	3:00 - 4:00 Social Studies Curriculum Conducted By ... Passcode: P.	
	3:00 - 4:00 SORA Digital Library Conducted by .. Recording Link	4:00 - 5:00 Fact Fluency and Daily Numeracy Conducted by Instructional Leadership Team Members Passcode: ..	

3-5 ELAR PD Schedule

WEEK 1	Tuesday, August 3	Wednesday, August 4	Thursday, August 5
Morning Session	Overview ELAR Curriculum 8:30-11:30	Independent Reading 8:30 - 11:30	HMH Notice and Note 9-11 AM Meeting Code: Passcode: @Literacy1
Afternoon Session	**The afternoon will be reserved for teachers to:** - engage with instructional materials - ensure you have access to all programs (Schoology, HMH, Amplify, ThinkUp) -lesson planning time		
WEEK 2	**Monday, August 9**	**Tuesday, August 10**	**Wednesday, August 11**
Morning Session	HMH Writer's Workshop 9-11	Social Studies Curriculum Overview 9	
Afternoon Session	Flocabulary (self paced) 12-2:30	Studies Weekly 3-5 1-3 PM	
	Think Up & iReady 3-4:30	SORA - 3:00-4:00	

6-8 ELAR Schedule

WEEK 1	Tuesday, August 3	Wednesday, August 4	Thursday, August 5
Morning Session	Introduction to ELAR Curriculum (8:30 - 11:30 AM)	Notice & Note Independent Reading (8:30-10:30 AM)	Amplify Training: 6th Grade ONLY (8:30 - 10:30 AM)
			Lesson Planning: 8th Grade ONLY (8:40 - 10:30 AM)
		Lesson Planning: 7th Grade ONLY (10:45 - 12:30 AM)	Amplify Training: 7th Grade ONLY (11:00 AM - 1:00 PM)
			Lesson Planning: 6th Grade ONLY (11:10 - 1:00 PM)
Afternoon Session	The afternoon will be reserved for teachers to: - engage with instructional materials - ensure you have access to Schoology		Amplify Training: 8th Grade ONLY (1:30 - 3:30 AM)
WEEK 2	**Monday, August 9**	**Tuesday, August 10**	**Wednesday, August 11**
Morning Session	HMH: Into Literature Training (10:30 - 12:30 PM)	Region 20: STAAR Assessment Updates & Discussion in a Secondary Classroom (8:30 AM - 11:30 AM)	
Afternoon Session	ThinkUp/iReady Training (1:00 - 2:30 PM) Demo Account: https://pd.i-ready.com. Username: C08P Password: Dem	Sora: Digital Library (3:00 - 4:00 PM)	

3-5 Math Schedule

WEEK 1	Tuesday, August 3	Wednesday, August 4	Thursday, August 5
Morning Session 8:30-11:30	Introduction to 3-5 Math Curriculum	3-5 Math Instructional Practices	3-5 Math Deep Dive & Lesson Planning by Grade Level
Afternoon Session 1:00-4:00	The afternoons will be reserved for 3-5 math teachers to: - Engage with instructional materials and lesson preparation - Ensure you have access to programs: Schoology, STEMscopes Math, ThinkUp and ST Math (Demo accounts will available for upcoming training purposes if needed)		
WEEK 2	**Monday, August 9**	**Tuesday, August 10**	**Wednesday, August 11**
Morning Session 8:30-11:30	Think-Up & iReady (10:00 - 11:30) See below for iReady Demo Accounts	ST Math (New Teachers) The Essentials Course 1: Getting Started ST Math (Returning Teachers) Focus On	Office Hours
Afternoon Session 1:00-4:00	STEMscopes 3-5 Math	ALEKS (5th grade only) 1:00 - 2:30	
Updated on 8/9/21			

	iReady Demo Account Information	STEMscopes Math Demo Account
	Please read the Using iReady Sample Account	Website: https://login.acceleratelearning.com/?to=n11061d165062

6-8 Math & Math Interventionists Schedule

WEEK 1	Tuesday, August 3	Wednesday, August 4	Thursday, August 5
Morning Session 8:30-11:30	The mornings will be reserved for 6-8 math teachers to: - Engage with instructional materials and lesson preparation - Ensure you have access to all programs: Schoology, McGraw Hill, ThinkUp, and ALEKS (Demo accounts will available for upcoming training purposes if needed)		
Afternoon Session 1:00-4:00	Introduction to 6-8 Math Curriculum (and Math Interventionists)	6-8 Math Instructional Practices (and Math Interventionists)	6-8 Math Deep Dive & Lesson Planning by Grade Level (and Math Interventionists)
WEEK 2	**Monday, August 9**	**Tuesday, August 10**	**Wednesday, August 11**
Morning Session 8:30-11:30	McGraw Hill - Texas Math (8:30 - 10:00) Registration Link	Advance 8th Grade - Algebra 1 Curriculum Overview	
Afternoon Session 1:00-4:00	Think Up and iReady (1:00 - 2:30) (and Math Interventionists)	ALEKS (1:00 - 2:30)	

	iReady Demo Account Information	Texas Math Demo Account	
	Please read the Using iReady Sample Account followed by the Getting Started with Teacher Toolbox prior to training	Website: https://my.mheducation.com/login Username: math4texas Password: 15	McGraw Hill - Texas Math Back-up link if you have any difficulties registering for today's session

2021-2022 Summer Teacher Training- Science

WEEK 1	Monday, August 2	Tuesday, August 3	Wednesday, August 4	Thursday, August 5	Friday, August 6
	ALL Teachers				
Session 1 8:30-10:00am		Introduction to Science Curriculum	3rd Grade	STEMscopes Science	
Session 2 10:15am-12:00pm			4th Grade		
12:00-1:15	Lunch				
Session 3 1:15-2:30pm		Gizmos 3rd Grade- High School	5th Grade	7th Grade	
Session 4 2:45-4:00pm			6th Grade	8th Grade	

WEEK 2	Monday, August 9	Tuesday, August 10	Wednesday, August 11	Thursday, August 12	Friday, August 13
	ALL teachers unless listed otherwise				
Session 1 8:30-9:10am	Flocabulary (self-paced)	Science Best Practices			
Session 2 9:15-9:55am	BrainPOP (self-paced)				
Session 3 10:00-11:30am	ThinkUp! (5th & 8th ONLY)				
11:45-1:15	Lunch				
Session 4 1:15-4:00pm	Legends of Learning	Planning With Your ILT			

All trainings are TBD and may change prior to the beginning of training due to the ever changing daily information. Please email me with any specific questions or suggestions. Thank you!
-Facilitator

Quick Links
PD Recordings
Schoology Curriculum Group Access
Lesson Plan Template
Instructional Software Access
Instructional Playbook
Sample Lesson Plans
PD Presentations
Planning With Your ILT Zoom Links

6-8 Social Studies Schedule

WEEK 1	Tuesday, August 3	Wednesday, August 4	Thursday, August 5
Morning Session	The morning will be reserved for teachers to engage with instructional materials and ensure they have access.		
Afternoon Session	Introduction to Social Studies Curriculum (1:00 - 4:00 PM)	1:00 - 4:00 PM Region 20: Social Studies Professional Development	1:00 - 4:00 PM Region 20: Social Studies Professional Development
WEEK 2	**Monday, August 9**	**Tuesday, August 10**	**Wednesday, August 11**
Morning Session	McGraw-Hill Training (8:30 - 10:00 AM) My.mheducation.com Demo Account TEACHER USERNAME: s PASSWORD: 1	The morning will be reserved for teachers to engage with instructional materials and ensure you have access	
Afternoon Session	6th & 7th Grade Lesson Planning (2:30 - 4:00 PM)	8th Grade Lesson Planning (1:00 - 3:00 PM)	

Appendix 6.3:Teacher Interview Questions

1. We looked at teachers' self-efficacy before training and compared it with two weeks after school. Teachers' self-efficacy went down for all items except for one item going up. Why do you think that is? Why would teachers' self-efficacy about their ability to help their students decrease instead of increasing with training?

2. One of the items that decreased significantly is "I believe my administrators have efficient systems in place to support teachers in using instructional software effectively." Why would that happen? What do you think led to this decrease in confidence that administrators are supporting teachers to be more efficient?

3. Items that went down significantly are the ones that mention administration support; why do you think teachers' confidence in administration support declined after school started? Or do you believe it is related to what happened during these weeks of school? If so, how?

4. The only item increased is " I am convinced that I can promote learning by using instructional tools when there is a lack of support from home for the student." Why do you think that would be an item teachers' confidence increased? Why do you think teachers' confidence in helping students decreased while their confidence in closing lack of support from home increased?

5. Data show patterns for both decreases in motivation and confidence in teachers' skillset. What do you interpret from this finding?

6. Is there anything you think we should consider when we are trying to figure out data and trying to understand why teachers' self-efficacy decreased after the training or school started? What do you think is the impact on the decrease?

Note: Follow-up questions were asked as deemed to get more clarification.

Appendix 6.4: Item by Item Change in Means

Survey Items	Survey Items	Pre-Survey Means	Post-Survey Means	Diff
1. When I try hard enough, I can reach even the most struggling students by using the tools with which I am provided.	1	5	4.93	-0.07
2. As time goes by, I will continue to become more capable of helping to address my students' needs.	2	5.59	5.38	-0.21
3. I can successfully teach all relevant subject content to even the most struggling students.	3	5.09	4.94	-0.15
4. I can effectively use the instructional tools with which I am provided.	4	5.2	5.07	-0.13
5. I am responsive to my students' needs by using several different tools available to me.	5	5.46	5.23	-0.23
6. I know that I can motivate my students to use instructional tools to keep learning at their own pace.	6	5.29	5.1	-0.19
7. I know that I can carry out innovative ideas for using instructional tools.	7	5.28	5.21	-0.07
8. I am convinced that I can promote learning by using instructional tools, when there is a lack of support from home for the student.	8	4.87	4.9	0.03
9. I am confident in my ability to keep students on the task on complex assignments by using instructional tools.	9	5.2	5.07	-0.13
10. I am confident in my ability to motivate students who show little interest in schoolwork by using instructional tools.	10	5.07	5.02	-0.05
11. I am convinced that I can help students enjoy coming to school by using instructional tools.	11	5.24	5.18	-0.06
12. When I try to find interesting topics and new ways of teaching, I do so because it is important for me to keep up with innovations in teaching.	12	5.61	5.47	-0.14
13. When I invest effort in my work as a teacher, I do so because it is important for me to feel that I can help people.	13	5.7	5.6	-0.1
14. When I try to find exciting tools and new ways of teaching, I do so because it is fun to create new things.	14	5.65	5.49	-0.16
15. When I invest effort in my work as a teacher, I do so because I enjoy finding unique solutions for students.	15	5.65	5.51	-0.14
16. When I devote time to individual talks with students, I do so because I like being in touch with children and adolescents.	16	5.57	5.39	-0.18
17. I have received adequate training on instructional tools available to me.	17	4.84	4.8	-0.04
18. The training I have received helped me to use instructional tools available to me more efficiently.	18	4.94	4.86	-0.08
19. There is an effort by my administrators to help me use instructional tools available to me efficiently.	19	5.19	4.87	-0.32
20.I believe my administrators have efficient systems in place to support teachers in using instructional software effectively.	20	5.04	4.67	-0.37
21. I am provided with high-quality instructional software programs to support my instruction.	21	4.97	4.94	-0.03
22. I have received professional learning opportunities to promote student engagement and motivation.	22	5.05	4.82	-0.23
23.I have the necessary skills to effectively teach and use instructional tools available to me efficiently.	23	5.24	5.1	-0.14

Appendix 6.5: Item by Item Cohen's *d*

Survey Items	Pre mean	SD	Post mean	SD	Effect Size Cohen's *d*
1. When I try hard enough, I can reach even the most struggling students by using the tools with which I am provided.	5	0.873	4.93	0.939	-0.077
2. As time goes by, I will continue to become more capable of helping to address my students' needs.	5.59	0.525	5.38	0.761	-0.322
3. I can successfully teach all relevant subject content to even the most struggling students.	5.09	0.817	4.94	0.943	-0.17
4. I can effectively use the instructional tools with which I am provided.	5.2	0.787	5.07	0.903	-0.154
5. I am responsive to my students' needs by using several different tools available to me.	5.46	0.687	5.23	0.766	-0.316
6. I know that I can motivate my students to use instructional tools to keep learning at their own pace.	5.29	0.68	5.1	0.859	-0.246
7. I know that I can carry out innovative ideas for using instructional tools.	5.28	0.744	5.21	0.886	-0.086
8. I am convinced that I can promote learning by using instructional tools, when there is a lack of support from home for the student.	4.87	0.946	4.9	1.058	0.03
9. I am confident in my ability to keep students on the task on complex assignments by using instructional tools.	5.2	0.724	5.07	0.808	-0.17
10. I am confident in my ability to motivate students who show little interest in schoolwork by using instructional tools.	5.07	0.799	5.02	0.879	-0.06
11. I am convinced that I can help students enjoy coming to school by using instructional tools.	5.24	0.729	5.18	0.837	-0.077
12. When I try to find interesting topics and new ways of teaching, I do so because it is important for me to keep up with innovations in teaching.	5.61	0.606	5.47	0.604	-0.231
13. When I invest effort in my work as a teacher, I do so because it is important for me to feel that I can help people.	5.7	0.509	5.6	0.523	-0.194
14. When I try to find exciting tools and new ways of teaching, I do so because it is fun to create new things.	5.65	0.585	5.49	0.749	-0.238
15. When I invest effort in my work as a teacher, I do so because I enjoy finding unique solutions for students.	5.65	0.557	5.51	0.618	-0.238
16. When I devote time to individual talks with students, I do so because I like being in touch with children and adolescents.	5.57	0.611	5.39	0.793	-0.255
17. I have received adequate training on instructional tools available to me.	4.84	0.971	4.8	0.928	-0.042
18. The training I have received helped me to use instructional tools available to me more efficiently.	4.94	0.924	4.86	0.868	-0.089
19. There is an effort by my administrators to help me use instructional tools available to me efficiently.	5.19	0.932	4.87	0.945	-0.341
20.I believe my administrators have efficient systems in place to support teachers in using instructional software effectively.	5.04	0.971	4.67	0.994	-0.377
21. I am provided with high-quality instructional software programs to support my instruction.	4.97	0.999	4.94	0.957	-0.031
22. I have received professional learning opportunities to promote student engagement and motivation.	5.05	0.967	4.82	0.98	-0.236
23.I have the necessary skills to effectively teach and use instructional tools available to me efficiently.	5.24	0.75	5.1	0.805	-0.18

CHAPTER 7

DISCUSSION AND CONCLUSION

To investigate the impact of personalized adaptive teacher education on increasing teachers' self-efficacy, this dissertation used a manuscript style format to address the scarcity of research on personalized adaptive teacher education to increase teachers' self-efficacy and decrease teacher turnover. To provide meaningful learning opportunities to students, meaningful learning opportunities also need to be offered to teachers to prepare them for teaching better (Natividad Beltrán del Río, 2021; Nel, 2017; Siko & Hess, 2014; Thoma et al., 2017). However, studies on teacher education that simultaneously relate cognitive and affective components to instructional practice are limited (Depaepe & König, 2018). This research is anticipated to be the foundation for future studies on personalized adaptive preservice teacher education to improve teachers' self-efficacy.

Research has shown that teachers are key to enhancing learning in schools (National Research Council, 2000). Therefore, it is imperative to prepare our preservice teachers properly and support them with personalized adaptive education that focuses on their diverse needs. Preparing preservice teachers according to their needs is expected to prepare teachers to support and help their students better.

Numerous studies investigated teachers' impact on student learning and found that teachers are the main determinants of instructional practice and student learning outcomes (Colson et al., 2018; Darling-Hammond, 2000; Depaepe & König, 2018; Jenset et al., 2018; Schleicher, 2016). Hence, teachers need to be prepared by providing personalized adaptive preservice teacher education to improve their self-efficacy. Teachers' views shape their instructional practices by refining interpretations, framing situations or difficulties, and guiding actions (Heinonen et al., 2019). Reflecting on Bandura's (1994) suggestion, self-efficacy beliefs determine how people feel, think, motivate themselves, and perform; it is predominant that teachers have a strong sense of self-efficacy to help them sustain their interest in the teaching profession (Gedzune, 2015, as cited in Colson et al., 2018).

Teaching is a demanding, stressful, and high workload profession that requires good stress management skills. As pointed out by Bandura (1997), preservice teachers with recurred success feelings are more successful with managing the stress caused by the demands of the teaching job. Thus, preservice teachers need to have a sense of self-efficacy for teaching responsibilities (Ryel et al., 2001, as cited in Colson et al., 2018) to deal with the daily stress.

The first paper in this dissertation provides literature review and the findings revealed the existence of a high rate of personalized adaptive learning studies but a lack of connection for personalized adaptive learning and preservice teacher education to increase teachers' self-efficacy. While findings pointed out that personalized adaptive learning has become a significant learning model in the research community, there is no concise and unified definition for personalized adaptive learning. Also, the literature pointed out that personalized adaptive learning systems seem to evolve as technology develops, and machine learning, data mining, and human behavior seem to be primary determinants that shape personalized adaptive learning. Although this study was solely focused on personalized adaptive learning, it provided a foundation for understanding the strengths of personalized adaptive learning. Hence, this systematic literature review built a path to personalized adaptive learning for preservice teacher education as personalized adaptive learning approaches increase and their favorable impact on learning (Pane et al., 2015). Also, as mentioned earlier, the gap for analyzing components used for personalized adaptive learning was identified because of this literature review.

The second paper examined common elements that have been used for personalized adaptive learning to determine what components would be suitable for personalized adaptive preservice teacher education. The results demonstrated two things. First, the variety of components being used for personalized adaptive learning is increasing as technology develops. Second, using personality traits and their identification techniques has enormously positively influenced personalized adaptive learning environments. Furthermore, it is also essential to point out that Smart Learning Environments (SLEs) and Learning Analytics (LA) are determined to be fundamental tools to allow learners to meet their learning goals by promoting awareness, recommendation, self-reflection, assessment, feedback, and motivation, which are essential components of personalized adaptive learning. Furthermore, because of the focus of this study, it was concluded that a united evolving personalized adaptive learning approach would consider four main components; learner profiles, previous knowledge, personalized adaptive learning, and a flexible self-paced learning environment that develops a personalized learning path according to provided dynamic learning analytics.

The third paper focused on assessing inservice teachers' needs to identify how administrator support, inservice teacher training, and access to materials can help teachers increase their self-efficacy to determine components that help improve teachers' self-efficacy. This research was developed based on Bandura's (1982) suggestion that self-efficacy determines how much effort one will expend and persevere in the face of obstacles or aversive experiences. Thus, this study gathered data on the support teachers received from their administrators and how it impacted their self-efficacy. The results of this study suggested that the more training teachers receive, the more confident they feel. Furthermore, this paper's findings shed light on factors that improve teachers' self-efficacy and contribute to this dissertation on factors that improve teachers' self-efficacy.

As this study investigated the impact of the support teachers receive from their administrators, which is an essential first step toward enhancing efficient practices that support both teachers and administrators to increase teachers' self-efficacy, the findings of this study can guide preservice teacher education institutions and decision-makers of teacher education to assess inservice teachers' needs and self-efficacy to help and support them with a more personalized adaptive education to improve their self-efficacy.

Teachers deal with ongoing changes in education that they are expected to keep up with; therefore, we need teachers who are willing to learn more and adapt their instructional practices according to changes in schools and society, especially with technology. As a result, the fourth paper focused on a conceptual framework developed based on the literature review and in-depth analysis of personalized adaptive learning components that can be used for teacher education to improve teachers' self-efficacy. Furthermore, the proposed framework for personalized adaptive preservice teacher education can be used as a tool for teacher education to improve teachers' self-efficacy and ultimately improve teachers' and students' learning experiences.

Moreover, this framework can be used in different settings with various scenarios. A step-by-step illustration for preservice teacher education is provided in this study to reflect its usage in learning environments. This framework is expected to improve teachers' self-efficacy by providing personalized adaptive learning support, resulting in improved self-efficacy and increased perseverance to learn new skills and acquire new knowledge. This study can be used as a reference for future research and teacher education.

This study's findings revealed that dynamic data collection requires dynamic adaptation, intervention, and correctness feedback to close any learning gaps or prevent teachers from losing interest in learning. This study is foundational as growing data has shown that improving preservice teacher education can significantly impact student learning.

The fifth paper is an empirical study that focuses on validating the framework proposed in this research by using the framework to analyze the pre and post-self-efficacy of a teacher group before and after personalized adaptive training. The values and descriptors presented in the self-efficacy instrument allowed researchers to observe changes in teachers' self-efficacy from before summer preservice training and two weeks into school to validate the PAL framework to measure its impact on teacher self-efficacy. Summer preservice training sessions were planned according to the PAL framework to personalize and adapt sessions according to teachers' skills sets and knowledge. After summer preservice training was done, school started, and teachers had two weeks to practice skills they were introduced to during summer preservice training. The second self-efficacy questionnaire instrument allowed observation of the teachers' self-efficacy shifts.

The findings of the study brought up a need for further investigation on teacher self-efficacy. As a result, teachers' efficacy results were investigated further through interviews to investigate the significant decrease in teachers' self-efficacy after school started to measure the impact of the PAL framework on teacher self-efficacy.

Teachers shared that before school started, they trusted that there were good plans developed during the summer by their administrators, based on the information provided to them by their administrators. However, once school started, most teachers did not know what to do. Administrators kept asking teachers to do more compliance requirements without paying attention to the stress teachers were going through due to a lack of time to get everything done.

Very little research in the literature has explicitly looked at personalized adaptive preservice teacher education to improve inservice teachers' self-efficacy. This research expands that research and is expected to be the foundation for future studies on personalized adaptive preservice teacher education to improve teachers' self-efficacy. Although this study's findings revealed the existence of a high rate of personalized adaptive learning studies, there is still a lack of connection between personalized adaptive learning and preservice teacher education to increase teachers' self-efficacy. While findings pointed out that personalized adaptive learning has become a significant learning model in the research community, there is no concise and unified definition for personalized adaptive learning. Also, the literature pointed out that personalized adaptive learning systems seem to evolve as technology develops, and machine learning, data mining, and human behavior seem to be primary determinants that shape personalized adaptive learning. This study built a path to personalized adaptive learning for preservice teacher education as personalized adaptive learning approaches increase and as well as their favorable impact on learning. Also, as mentioned earlier, the results of this study suggested that the more training teachers receive, the more confident they feel. Furthermore, this study's findings shed light on factors that improve teachers' self-efficacy and contribute to enhancing teachers' self-efficacy. Current studies point out that teachers are the main factors of instructional practice and student learning outcomes (Colson et al., 2018; Darling-Hammond, 2000; Depaepe & König, 2018; Jenset et al., 2018; Schleicher, 2016). Moreover, teachers' beliefs shape their teaching practices by filtering interpretations, framing situations or problems, and guiding actions (Heinonen et al., 2019). Teachers have a strong sense of self-efficacy to help them maintain their interest in the profession of teaching and use those skills to help all students they teach (Gedzune, 2015, as cited in Colson et al., 2018).

This preliminary study can lead to future studies and implications of preservice teacher education and inservice teacher education to understand the importance of being aware of teachers' needs and accordingly provide them with personalized adaptive support that focuses on their needs. Personalized adaptive teacher support is expected to increase teachers' self-efficacy, resiliency, and teacher retention. Preservice teacher education institutes, regional educational centers, and school districts can benefit from this study and similar studies to prepare teachers for the teacher profession and the challenges it brings to ensure higher teacher retention rates. Increased teacher retention rate will help us keep educated trained teachers in the profession, so we do not need to start from scratch every year with new teachers. First-year teachers are primarily in survival mode compared to veteran teachers; they need more mentoring and support, which costs money to school districts and loss of instructional time for students they serve.

Overall Limitations

This study has several limitations that are inevitable. While a comprehensive review of literature was conducted as part of this research, the immense number of papers published in this area means the literature review in this research might have missed some relevant papers. This is a problem many studies face.

Lack of access to many induction year teachers was a limitation of this study, as the initial intention was indeed to focus on induction year teachers. This resulted in including teachers with varied years of experience, which shifted the focus of the study from induction year teachers to all teachers. Therefore, the impact of the PAL training on induction year teachers was not measured.

Changes in schools' administrator teams were another limitation of this study as it caused obstacles to access to more teachers and school districts.

The small sample size is another limitation of the study. A total of 385 teachers were surveyed for one of the studies, and 124 teachers were surveyed, and 15 teachers were interviewed for empirical study. Although there were enough number of participants to achieve valid and reliable results through the instrument used, collecting more data would provide more generalizable results. Also, regional bias might be an obstacle to generalizing the study since participants were only Texas teachers; as the education systems vary across states in the United States and worldwide, teachers' self-efficacy levels might be different as expectations and job requirements differ. The findings might be limited to the sampled population. Future studies can scale it up to include more participants from other regions for a large-scale investigation.

Summer preservice training sessions were virtual, so observing teachers determine their progress, understanding, and the need for help could not be accommodated as much as it would be in the in-person training.

Recommendations for Future Studies

This study solely focused on summer preservice training designed using the PAL framework and did not have enough participants to have control groups to compare teacher retention rates. Future research could compare different preservice teacher education practices and measure their impacts on teacher self-efficacy and retention. Current studies reported that higher teacher self-efficacy rates result in higher teacher retention rates to study the correlation between teachers' self-efficacy and retention rates.

This study could not measure the long-term impact of the PAL support as only two weeks were given to teachers before sending out the post-survey. Hence it is essential to measure the long-term effect of ongoing PAL opportunities to measure teachers' self-efficacy and its impact on teacher retention. A future study should assess the long-term effects of personalized adaptive preservice teacher education in a more comprehensive approach over three years of teaching since the highest turnover is with induction year teachers (Ingersoll, 2001; Norman, 2019).

Future studies should also look into the pre-service education practices of other professionals and compare their self-efficacy with teachers to analyze if professionals given more time to practice during pre-service education has a positive impact on self-efficacy.

As the PAL framework suggested that based on literature, PAL opportunities will increase teachers' self-efficacy and, because of increased self-efficacy, teachers' resiliency will increase as they face challenging issues, decreasing teacher turnover. Hence, future studies can compare the resiliency and turnover rate of teachers who did not have an opportunity for personalized adaptive preservice education with teachers who did have an opportunity for personalized adaptive preservice education. Furthermore, future studies can explore self-efficacy directly compared to teacher retention with longitudinal studies to study the direct link between teachers' self-efficacy and teacher retention rates.

Chapter References

Bandura, A. (1982). Self-efficacy mechanism in human agency. *American Psychologist*, *37*(2), 122–147. https://doi.org/10.1037/0003-066X.37.2.122

Bandura, A. (1994). Self-efficacy. In V. S. Ramachaudran (Ed.), *Encyclopedia of human behavior* (Vol. 4, pp. 71-81). New York: Academic Press. (Reprinted in H. Friedman [Ed.], Encyclopedia of mental health. San Diego: Academic Press, 1998).

Bandura, A. (1997). *Self-efficacy: The exercise of control.* New York: W. H. Freeman and Company.

Colson, T., Sparks, K., Berridge, G., Frimming, R., & Willis, C. (2018). Preservice teachers and self-efficacy: A study in contrast. *Discourse and Communication for Sustainable Education*, *8*(2), 66–76. https://doi.org/10.1515/dcse-2017-0016

Darling-Hammond, L. (2000). Teacher quality and student achievement: A review of state policy analysis. *Education Policy Analysis Archives, 8*(1) -3 7. http://epaa.asu.edu/epaa/v8n 1 .html

Depaepe, F., & König, J. (2018). General pedagogical knowledge, self-efficacy, and instructional practice: Disentangling their relationship in preservice teacher education. *Teaching and Teacher Education*, *69*, 177–190. https://doi.org/10.1016/j.tate.2017.10.003

Heinonen, K., Jaaskela, P., Hakkinen, P., Isomaki, H., & Hamalainen, R. (2019). University teachers as developers of technology-enhanced teaching: Do beliefs matter? *Journal of Research on Technology in Education*, *51*(2), 135–151.

Ingersoll, R. M. (2001). Teacher turnover and teacher shortages: An organizational analysis. *American Educational Research Journal, 38*(3), 499-534.

Norman, L. B. (2019). *The revolving door of teacher turnover: Examining the influence of teacher self-efficacy, locus of control, and school culture on teacher retention.* https://search.proquest.com/openview/cb48f75956cad867dac6aed65362905a/1?pq-origsite=gscholar&cbl=18750&diss=y

Jenset, I. S., Klette, K., & Hammerness, K. (2018). Grounding Teacher education in practice around the world: An examination of teacher education coursework in teacher education programs in Finland, Norway, and the United States. *Journal of Teacher Education*, *69*(2), 184–197. https://doi.org/10.1177/0022487117728248

National Research Council. (2000). In M. S. Donovan, J. D. Bransford, & J. W. Pellegrino (Eds.), *How people learn: Bridging research and practice.* Washington, DC: National Research Council, Committee on Developments in the Science of Learning.

Natividad Beltrán del Río, G. (2021). A useful framework for teacher professional development for online and blended learning to use as guidance in times of crisis. *Education Tech Research Dev 69*, 7–9. https://doi.org/10.1007/s11423-021-09953-y

Nel, L. (2017). Students as collaborators in creating meaningful learning experiences in technology-enhanced classrooms: An engaged scholarship approach. *British Journal of Educational Technology, 48,* 1131–1142. https://doi.org/10.1111/bjet.12549.

Pane, J. F., Steiner, E. D., Baird, M. D., & Hamilton, L. S. (2015). *Continued progress: Promising evidence on personalized learning*. Rand Corporation, ERIC, https://eric.ed.gov/?id=ED571009

Schleicher, A. (2016). *Teaching excellence through professional learning and policy reform.* Paris, France: OECD.

Siko, J. P., & Hess, A. N. (2014). Win-win professional development: Providing meaningful professional development while meeting the needs of all stakeholders. *TechTrends, 58*, 99–108. https://doi.org/10.1007/s11528-014-0809-7.

Thoma, J., Johnson, D., Johnson, K., & Stromer, E. (2017). Planning for technology integration in a professional learning community. *The Reading Teacher, 71*(2), 167–175. https://doi.org/10.1002/trtr.1604.