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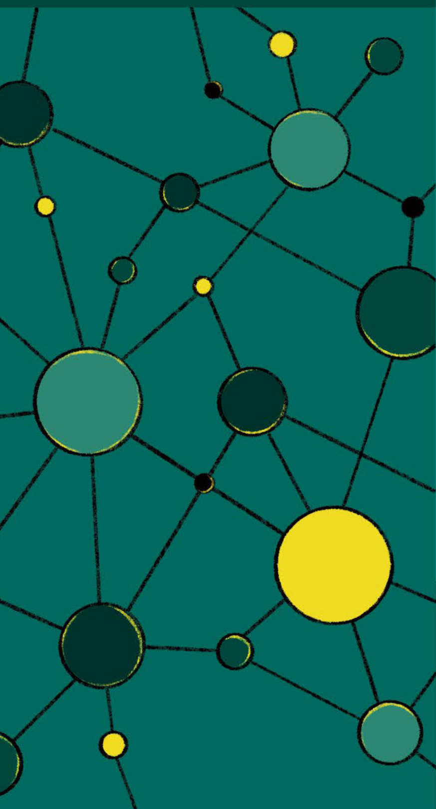
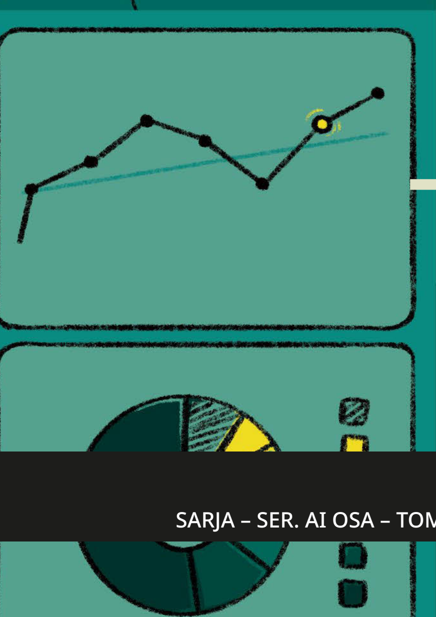
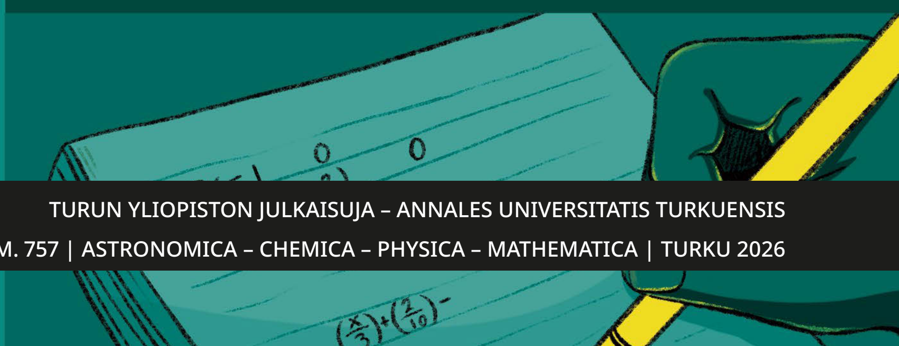


Personalizing K–12 STEM Education through Technology-Enhanced Learning and Learning Analytics

Umar Bin Qushem





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PERSONALIZING K–12 STEM EDUCATION THROUGH TECHNOLOGY-ENHANCED LEARNING AND LEARNING ANALYTICS

Umar Bin Qushem

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I dedicate this dissertation work to my parents, Mr. Kazi and Mrs. Yasmin who raised me with discipline, imparted life lessons, shaped my curiosity beyond beneficiary knowledge, and offered unwavering support through their prayers.

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ABSTRACT

Science, Technology, Engineering and Mathematics (STEM) education has been widely recognized as a priority area over the last decade. Despite global recognition of STEM literacy as essential for problem-solving and addressing societal challenges, traditional classrooms often struggle to address individual student's learning needs in core subjects such as mathematics and life sciences. In addition, integrated intervention approaches for achieving STEM-skills and enhancing motivation towards STEM in K-12 settings remain underexplored compared to Higher Education applications.

The present Doctoral research, therefore, tackles a pressing challenge in K-12 STEM education: *"How to effectively personalize learning for diverse student needs?"*. The research develops and tests a framework that integrates Technology-Enhanced Learning (TEL) platforms with Learning Analytics (LA) to create adaptive, data-informed educational experiences for diverse groups of K-12 learners. The study employs a Mixed-Methods Research (MMR) design divided into three phases: (1) a synthesis phase (2) an intervention phase; and (3) a reflection phase. Data were collected from two interventions: one involving 720 primary and lower-secondary students (4^{th}-6^{th} grade) who took personalized lessons on arithmetic operations over 9 months using ViLLE-tool; and another one involving 70 upper-secondary students (10^{th}-12^{th} grade) who took supplementary lessons on 'Life and Evolution' over 5 weeks using VR-tool. Data were analyzed through exploratory data analysis and statistical methods.

The research work contributes to the field by advancing theoretical understanding of personalized education, providing empirical evidence from authentic classroom settings, and demonstrating how adaptive learning technologies and LA can foster personalized learning in K-12 STEM. The work addresses critical gaps in the literature by developing an empirically grounded, theory-informed adaptive and context-sensitive personalized learning interventions framework in addition to offering a methodological blueprint for future research in the Educational Sciences.

KEYWORDS: Technology-Enhanced Learning; Learning Analytics; Personalized STEM Learning; Precision Education; Intervention; Learning Management Systems; Virtual Reality; K-12.

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TIIVISTELMÄ

Luonnontieteiden, teknologian, tekniikan ja matematiikan (engl. Science, Technology, Engineering and Mathematics, STEM) eli LUMA-aineiden opetusta on pidetty keskeisenä kehitysalueena viimeisen vuosikymmenen aikana. Vaikka STEM-osaamisen merkitys on globaalisti tunnustettu tärkeäksi ongelmanratkaisun ja yhteiskunnallisten haasteiden näkökulmasta, perinteiset opetustavat eivät aina pysty vastaamaan oppilaiden yksilöllisiin tarpeisiin keskeisissä oppiaineissa, kuten matematiikassa ja luonnontieteissä. Lisäksi interventiomenetelmiä, joiden tavoite on lisätä motivaatiota ja parantaa LUMA-aineiden taitoja, on kuitenkin tutkittu selvästi vähemmän peruskouluissa ja lukioissa kuin korkeakoulutuksessa.

Tämä väitöstutkimus tarttuu ajankohtaiseen kysymykseen K–12 LUMA -opetuksessa: kuinka oppiminen voidaan yksilöllistää tehokkaasti siten, että se vastaa erilaisten oppijoiden tarpeisiin? Tässä tutkimuksessa kehitetään ja testataan viitekehystä, joka yhdistää teknologia-avusteisen oppimisen (engl. Technology-Enhanced Learning) alustat oppimisanalytiikkaan (engl. Learning Analytics), jotta voidaan tarjota mukautuvia, dataan perustuvia oppimiskokemuksia K–12-oppilasryhmille. Tutkimus on toteutettu monimenetelmätutkimuksena, joka jakautuu kolmeen vaiheeseen: (1) synteesi-, (2) interventio- ja (3) reflektiovaihe. Aineisto on kerätty kahdesta interventiosta: Ensimmäiseen osallistui 720 4.–6. luokan oppilasta, jotka opiskelivat peruslaskutoimituksia yhdeksän kuukauden ajan ViLLE-oppimisympäristössä. Toiseen osallistui 70 lukio-opiskelijaa (10.–12. luokat), jotka suorittivat Elämä ja evoluutio -aiheisia opintoja VR-työkalun avulla viiden viikon ajan. Aineisto analysoitiin eksploratiivisen data-analyysin ja tilastollisten menetelmien avulla.

Tämän tutkimuksen tavoitteena on syventää teoreettista ymmärrystä yksilöllistetystä opetuksesta, tarjota empiiristä näyttöä autenttisista luokkahuonetilanteista ja osoittaa, miten mukautuvat oppimisteknologiat ja oppimisanalytiikka voivat tukea yksilöllistä LUMA-opetusta K–12-ryhmissä. Tämä tutkimus pyrkii täydentämään aiempaa tutkimusta kehittämällä empiirisesti perustellun, teoriapohjaisen, mukautuvan ja kontekstin huomioivan viitekehyksen kasvatustieteellistä jatkotutkimusta varten.

ASIASANAT: teknologia-avusteinen oppiminen; oppimisanalytiikka; yksilöllinen LUMA-oppiminen; yksilöllinen opetus; interventiosuunnittelu; oppimisalustat; virtuaalitodellisuus; LUMA-opetus; K–12.

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Abbreviations

AI	Artificial Intelligence
ALT	Adaptive Learning Technologies
ALP	Adaptive Learning Platform
ANCOVA	Analysis of Covariance
AR	Augmented Reality
CG	Control Group
CT	Context Personalization
DLE	Digital Learning Environments
EG	Experimental Group
EdTech	Educational Technology
GDPR	General Data Protection Regulation
GFLA	Generic Framework for Learning Analytics
HE	Higher Education
ITS	Intelligent Tutoring Systems
LA	Learning Analytics
LEAF	Learning Evidence Analytics Framework
LMS	Learning Management Systems
MB	Molecular Biology
MMR	Mixed-Methods Research
MOOC	Massive Open Online Courses
OEPS	Online Experimental Psychological System
PE	Precision Education
PL	Personalized Learning
PLD	Personalized Learning Design
PLP	Personalized Learning Path
PSL	Personalized STEM Learning
SLR	Systematic Literature Review
SRL	Self-Regulated Learning
STEM	Science, Technology, Engineering, Mathematics
TA	Technology Affordances
TEL	Technology-Enhanced Learning

TMLE	Technology-Mediated Learning Environments
UAE	United Arab Emirates
VLR	Video Learning Resources
VR	Virtual Reality
ZPD	Zone of Proximal Development

List of Original Publications

This dissertation is based on the following original publications, which are referred to in the text by their Roman numerals I–IV. Copies of the published articles are included in the appendix under the "Original Publications" section.

I Qushem, U. B., Christopoulos, A., Oyelere, S. S., Ogata, H., & Laakso, M. J. Multimodal Technologies in Precision Education: Providing New Opportunities or Adding More Challenges?, *Education Sciences*, 2021; 11(7): 338. https://doi.org/10.3390/educsci11070338.

II Qushem, U. B., Christopoulos, A., Kallisa, R., Khalil, M., Salakoski, T., & Laakso, M. J. Technology-enhanced Learning and Learning Analytics for personalized STEM learning: A scoping review. *International Journal of Educational Research,* 2025; 134(102827). https://doi.org/10.1016/j.ijer.2025.102827.

III Qushem, U. B., Christopoulos, A., & Laakso, M. J. Learning management system analytics on arithmetic fluency performance: A skill development case in K6 education. *Multimodal Technologies and Interaction*, 2022; 6(8): 61. https://doi.org/10.3390/mti6080061

IV Christopoulos, A., Pellas, N., Bin Qushem, U., & Laakso, M. J. Comparing the effectiveness of video and stereoscopic 360° virtual reality-supported instruction in high school biology courses. *British Journal of Educational Technology*, 2023, 54(4): 987–1005. https://doi.org/10.1111/bjet.13306

The original publications have been reproduced with the permission of the copyright holders. In all publications, the author of this dissertation contributed to the study conceptions and designs, data collections, analyses and interpretations; and was responsible for the writing the first drafts of the manuscripts referred in this dissertation. All co-authors participated in the conceptualization, provided critical feedback, and contributed in manuscript's revisions.

1 Introduction

1.1 Background

1.1.1 Challenges in K-12 STEM Education

K-12 STEM (Science, Technology, Engineering, Mathematics) education faces significant challenges in meeting diverse learner needs and preparing students for an increasingly technology-driven society. Despite the acknowledged significance of STEM literacy, traditional classroom approaches often struggle to address individual learning differences and maintain student engagement (Hebebci & Usta, 2022; Yang et al., 2025). At the same time, the increasing demand for STEM-related skills in societies and industries has led to renewed emphasis on STEM education policies, driven by global organizations seeking highly competitive talent with both interpersonal and problem-solving skills to address emerging industry challenges (Elrehail et al., 2018).

Indeed, contemporary K-12 learners must develop critical thinking skills while demonstrating proficiency in essential knowledge areas such as mathematics and life sciences. Mathematical skills serve as a foundation for daily life, professional development, and technological advancement (Saffrina & Baidullah, 2024). However, significant achievement gaps persist in STEM education. In mathematics, for instance, 22% of adults lack the proficiency required for many modern jobs, while 76% of high school seniors fail to achieve grade-level competency (Beach, 2013, 2022; Geary et al., 2013; National Center for Education Statistics, 2020). Life science education faces similar challenges, with many students struggling to understand fundamental biological concepts and processes. Such deficits in scientific and mathematical literacy can limit individuals' future employment opportunities and overall quality of life (Cozad & Riccomini, 2016).

1.1.2 The Promise of Personalized Learning in STEM

Personalized Learning (PL) has emerged as a viable approach to address these challenges by tailoring educational experiences to individual learner needs, preferences, and progress rates. In STEM contexts, personalization becomes particularly crucial due to the hierarchical nature of mathematical and scientific concepts, where foundational understanding is essential for advanced learning. The COVID-19 pandemic further highlighted the need for flexible, technology-supported educational approaches that can maintain learning continuity while accommodating diverse learning contexts (Khalid et al., 2024; Park & Doo, 2024). Consequently, educational institutions have increasingly focused on developing Adaptive Learning Platforms (ALPs), individualized feedback integrated within Digital Learning Environments (DLE), and differentiated instructional approaches to support learners in acquiring necessary STEM knowledge and skills. The shift represents a transformation from traditional educational approaches toward more adaptive, inclusive, learner-centered pedagogies that respond to individual learning trajectories and outcomes. Unlike conventional adaptive learning systems, which primarily adjust content based on predefined learning pathways, Personalized education considers multidimensional learning by analyzing multimodal factors—including learner behaviors, interaction patterns, and knowledge construction processes—thereby positioning PE at the forefront of STEM learning innovation (Lin et al., 2025).

1.1.3 Technology-Enhanced Learning as an Enabler

Technology-Enhanced Learning (TEL) has evolved into a powerful enabler of personalized STEM education. Modern technologies such as Intelligent Tutoring Systems (ITS), Learning Management Systems (LMS) with adaptive learning capabilities, and immersive technologies (e.g., Virtual / Augmented / Mixed Reality) offer new opportunities to tailor learning experiences and provide interactive and engaging content (Lang et al., 2022). Specific applications have shown promise in K-12 contexts; for instance, LabPI was designed to support TEL for school chemistry (Wejner & Wilke, 2022) while MalMath demonstrated effectiveness in increasing student motivation and academic achievement in mathematics (Shurygin et al., 2023). However, technology implementation alone is insufficient. It should coincide with pedagogical enrichment with structured focus on individual learning styles and preferences. Without such profiling, technology could misalign with learners' actual learning journey thus, resulting in suboptimal educational outcomes. Therefore, personalization and adaptiveness in learning requires understanding how students learn, what challenges they face, and how their learning progresses over time within the learning environment. Such need has driven interest in data-driven approaches that can capture and analyze learning processes systematically.

Technology integration in teaching and learning has surged in the last two decades. However, all tools and technologies utilized in instructional design may not be able to meet the personalization demand or possess required features. According to Walkington & Bernacki, the success of learning environment should be grounded in achievement of intended learning outcomes, with the expectation that it will positively impact technology-enhanced STEM learning (Walkington, & Bernacki, 2020). Looking at recent developments, instructional designers and educators have developed Adaptive Learning Technologies (ALT) with human-designed adaptive features, enabling teachers to personalize instruction and task design according to each student's current ability level. These technologies play a prevalent role in shaping blended learning activities, fostering dynamic interactions between teachers and students across diverse educational contexts (Simon & Zeng, 2024). For instance, Wang et al (2020) conducted comparative study between effectiveness of the ALPs and teacher-led instruction among two small and large groups of 8th grade Chinese students. The study reported that the students' gains in their mathematics test due to the use of the Squirrel Adaptive Learning system show the importance of TEL that is adaptive and personalized. Despite the study addressing positive outcomes, researchers have emphasized the need for further studies on developing STEM skills in young learners, particularly in mathematics.

In addition, Artificial Intelligence (AI) is regarded as one of the untapped opportunities for equity and access in STEM education particularly mathematics and science education due to the natural alignment of technological evolutions and innovative characteristics (Kohnke & Zaugg, 2025). In particular, Kohnke & Zaugg (2025) argued that "AI-driven assistive technologies, such as virtual learning environments, ITS, and assistive robotics, further facilitate access to STEM education for students with intellectual disabilities," which ensures the evolving sectors of personalization for inclusive learning. However, authors report that despite advancement, students with disabilities are still falling behind their peers in other settings and require a more inclusive approach to support reducing the gap and have lasting impacts (McLeskey et al., 2014).

1.1.4 Learning Analytics for Personalization

Learning Analytics (LA) represent a data-driven approach to education that involves collecting, analyzing, and interpreting learning data to provide insights to learners, educators, and decision-makers (Lang et al., 2022). Although LA has traditionally been viewed as a data-driven approach—relying on digital trace data such as logs and interactions—recent developments in the field have seen an expansion into theory-driven approaches. This shift aims to reduce misinterpretations of learning patterns and to better understand how these patterns connect with established learning theories (Wang et al., 2020). One of the core theories supporting learning and academic achievement in digital environments is Self-Regulated Learning (SRL), which is defined as the way learners plan, monitor, and reflect on their own learning (Viberg et al., 2020; Lau et al., 2017). Learning Analytics has the potential to provide students with insights into their SRL behaviors and target improvements in learning outcomes. Moreover, SRL-driven LA can enable learners to practice self-regulation, ultimately helping them develop the strategies, skills, and knowledge essential for academic success and future career achievements (Winne, 2017). Learning Analytics practices have shown potential in various STEM contexts, including process mining to analyze student learning behavior in programming (e.g., problem-solving) and engineering (e.g., mobile application development) (Fan et al., 2021; Salehian Kia et al., 2021) and predictive modeling to identify students at risk of underperformance (Cogliano et al., 2022; Hilpert et al., 2023). In K–12 contexts, LA has been applied to advance key educational goals, particularly in enabling personalized support. Notable applications include predicting student dropout (Baker et al., 2020), using Lag sequential analysis to examine the learning processes of Taiwanese high school students (Wen et al., 2018) and analyzing log data to evaluate student participation in computational thinking activities (Grover et al., 2017).

Learning Analytics has also emerged as a powerful tool for enhancing PL by leveraging student data to tailor instruction, provide real-time feedback, and optimize learning outcomes. This data-driven approach enhances teachers' capability to facilitate personalizing leaning paths, adapting instructional strategies to meet diverse learner needs. Wong et al. (2023) indicated that while LA has been increasingly used for PL experiences, most studies lack empirical validation as they rely primarily on theoretical frameworks and small-scale interventions. Other studies (e.g., Larrabee Sønderlund et al., 2019; van Haastrecht et al., 2024) have assessed the effectiveness of LA interventions, but questions remain about how these interventions can be integrated into existing educational practices to provide data-driven support for PSL. Li and Wong (2020) also explored the role of LA in Personalized Learning Environments (PLE) and concluded that LA techniques—such as data mining, clustering, and predictive modelling—have been used to track student progress and recommend PL pathways, but few studies have systematically assessed their long-term impact on student engagement and achievement. Xu et al. (2022) examined LA in adaptive learning and identified several key challenges, including data privacy concerns, limited scalability of personalization algorithms, and difficulty integrating LA into traditional instructional practices. As part of the concluding remarks, the authors suggest that while LA holds promise for PL, more research is needed to understand its effectiveness in diverse learning contexts with special emphasis in STEM disciplines. Sharif and Atif (2024) discussed the evolution of classrooms through LA and their role in the educational transformation. They argued that LA could effectively identify students encountering difficulties in learning to the degree that it puts them at risk of discontinuing studies.

1.1.5 Research Gaps in K-12 TEL-LA Integration

Despite the potential of both TEL and LA individually, their integration remains underdeveloped, especially in K-12 STEM contexts. Three key gaps exist in current research and practice.

First, many educational strategies remain fragmented rather than integrated, particularly those aimed at enhancing individual learners' outcomes in STEM subjects (van Haastrecht et al., 2024; Wong et al., 2023; Zhang et al., 2020). The fragmentation stems from the challenges educators face in capturing deeper insights into students' cognitive abilities and the underlying factors that shape their learning strategies (Popenici & Kerr, 2017). The present doctoral research addresses this gap by fostering the integration of TEL and LA to develop advanced Personalized STEM Learning (PSL) approaches that both deliver adaptive content and continuously assess learning progress. The integration empowers stakeholders to gather and analyze diverse learning data, leading to deeper understanding of student learning processes (Spikol et al., 2017; Qushem et al., 2022).

Second, there is a lack of adequate environmental and pedagogical support systems for assessing whether learners have truly progressed in their knowledge and skills (Riquelme et al., 2019). The assessment challenge is particularly acute in STEM fields, where conceptual understanding must be distinguished from procedural knowledge. Given that PL relies on effective identification of individual learning needs, studying diverse learning factors in interventional settings from early stages is essential to identify student learning improvement. The doctoral research addresses this gap by demonstrating how adaptive learning experiences through technology components such as Learning Management Systems (LMS) and Virtual Reality (VR) enable continuous monitoring of student academic performance and learning behavior using LA tools thus, facilitating systematic evaluation of key learning outcomes.

Third, research has not yet fully explored how integrated TEL-LA approaches can be developed and implemented to enhance K-12 STEM education. Personalized STEM learning in the K-12 sector remains under-researched compared to Higher Education (HE) contexts (Alamri et al., 2021; Barbosa et al., 2024; Dunn & Kennedy, 2019). Researchers attribute this gap to the need for comprehensive interventions utilizing multiple ALT and techniques for assessing student STEM learning over sustained periods (Li & Wong, 2023; Moelans et al., 2024). The complexity of developing and evaluating such integrated approaches presents substantial technical and methodological challenges that require systematic investigation. The doctoral research addresses this gap through systematic exploration of diverse technological tools and adaptive learning strategies, incorporating data-driven technologies and techniques to generate evidence for supporting K-12 learners. The process informed the selection and design of a comprehensive set of intervention practices, culminating in the implementation of a TEL-LA-PSL integrated framework aimed at advancing STEM learning in K-12 education.

The gaps underscore the need for comprehensive research that examines how TEL-LA integration can support designing, evaluating and applying methodological approaches in K-12 learning contexts, providing both theoretical understanding and practical implementation guidance for educators and stakeholders.

1.2 Problem Statement

In a typical scenario of a classroom, STEM concepts are typically introduced to a large group of students, yet their complexity requires strong foundations and problem-solving skills, making it challenging for some learners to comprehend immediately. This is when individuals pretend to grasp the idea but expose themselves later in the test or perform poorly in the exam. This introduces the need to support students with TEL and track student engagement as well as progress through LA. Modern technologies like LMS and VR have been useful to support tailoring students' needs and customized yet interactive learning. On the other hand, LA is, in a simplistic form, a data-driven approach—collect data, analyze, and provide unexplored results to students, educators, and decision-makers—that has been useful in personalization (Lang et al., 2022).

There are efforts to support K-12 learners' knowledge acquisition and learning improvement in STEM using technologies. For instance, LabPI was designed and placed to support TEL for school chemistry (Wejner & Wilke, 2022), and MalMath enabled increasing student motivations and academic achievement in school math (Shurygin et al., 2023). Besides the practical use of TEL, an increasing number of studies also demonstrated the adoption of LA practices in personalization. For instance, several studies utilizing various forms of LA practices, such as process mining (Fan et al., 2021; Salehian Kia et al., 2021), have been utilized to analyze student learning behaviors and tactics in improving SRL. Likewise, predictive modelling has aided the process of identifying students at risk of underperformance (Cogliano et al., 2022; Hilpert et al., 2023). This shared an enormous opportunity in adapting LA practice into TEL for designing and supporting PSL.

Despite two decades of research on digitalized education and pedagogy, ongoing challenges persist regarding: 1) learners' needs for personalized support in knowledge acquisition (Tabesh, 2018), and 2) the identification of effective instructional approaches that sustain learner motivation in STEM education (Alamri et al., 2021; Sáinz et al., 2022). K-12 educators are increasingly exploring alternative instructional approaches, such as adapting curriculum to enhance problem-solving abilities and critical thinking skills within STEM and related paradigms (Capraro et al., 2021). However, instructional approaches for complex STEM concepts require greater personalization and integrated frameworks are still needed to maximize learning performance, build sustained motivation, and better understand learner behaviors.

As outlined in Section 1.1.5, despite current efforts in TEL and LA within K-12 education, there remains a critical need for interventions that utilize multiple ALT and techniques to assess student STEM learning over extended periods.

1.3 Research Aims and Scope

The integration of TEL with LA for multimodal evidence-based learning demonstrates significant potential for supporting PSL. Such integration enables educational stakeholders to systematically gather and analyze diverse learning data and facilitates deeper understanding of individual student learning processes (Qushem et al., 2022; Spikol et al., 2017). The present doctoral research investigates the theoretical foundations and practical applications of ALT and data-driven methodologies as tools for measuring academic factors that influence student learning outcomes. The scope of the investigation extends beyond traditional academic performance assessment to encompass behavioral indicators—including student engagement and motivation—that demonstrably impact learning effectiveness. By adopting such a comprehensive approach, it acknowledges the multifaceted nature of learning processes and the need for holistic assessment frameworks in contemporary educational contexts.

Two primary objectives guide the research work: first, synthesizing existing literature through a systematic review to examine how ALT and data-driven practices within TEL and LA interventions support PSL in K-12 contexts and, second, empirically investigating through controlled experiments how TEL-LA interventions influence academic learning outcomes in STEM education. The rationale behind the adoption of a Mixed-Methods Research (MMR) design can help to provide evidence-based recommendations for scalable implementation in diverse educational settings (Caruth, 2013).

The research addresses critical gaps in current literature by proposing a comprehensive TEL-LA model specifically designed for K-12 educational contexts. The model advances beyond existing frameworks by simultaneously supporting individualized learning pathways and enabling sophisticated assessment of complex learning trajectories. The approach builds upon established research demonstrating the effectiveness of integrative learning designs in cultivating foundational knowledge and transferable competencies (Müller et al., 2023). Furthermore, the work contributes to the emerging field of PE by developing systematic approaches for analyzing individual learning patterns through integrated technologies and multimodal analytics (Watters, 2021; Lin et al., 2025).

1.4 Research Questions and Objectives

The doctoral research focuses on examining how TEL and LA approaches can support PSL in K-12 contexts. So, the overarching research question that governs the doctoral research is: *How can integrated Technology-Enhanced Learning and Learning Analytics interventions transform personalized STEM learning outcomes in K-12 education?*

That leads to the dissertation' overarching objective involves investigating how TEL-LA interventions, supported by adaptive tools and LA practices, can facilitate PSL, capture learning trajectories, and assess their impact on academic outcomes in K-12 STEM education. Accordingly, three primary research questions guide the investigation:

RQ1: How can Technology-Enhanced Learning and Learning Analytics support Precision Education and personalized STEM learning?

The question is addressed through two studies: (a) Study I identifies diverse multimodal technologies utilized in PL contexts, and (b) Study II examines intervention practices employing TEL and LA that effectively support PSL. The studies adopt a granular approach to exploring both general and ALT within personalized learning frameworks, with particular attention to their application in supporting individual learners. The analysis includes a scoping review of personalized practices incorporating TEL and LA within empirical studies, exploring how PL manifests in STEM education and examining how current literature supports or challenges these approaches prior to designing TEL-LA intervention studies.

RQ2: How do Technology-Enhanced Learning and Learning Analytics-based interventions influence academic learning outcomes in personalized STEM learning?

Two empirical studies, Study III and Study IV, address this question by demonstrating the effectiveness of interventions in K-12 blended learning environments. Both interventions utilize TEL and LA technologies to improve academic learning outcomes: (a) the mathematics intervention (Study III) measures academic performance and associated behaviors in arithmetic operations learning, and (b) the science intervention (Study IV) assesses academic performance and motivation in biology concept acquisition.

RQ3: What theoretical constructs and learning factors can be leveraged to improve learning outcomes through Technology-Enhanced Learning and LA-based interventions for personalized STEM learning?

The research question generates lessons learned from the TEL-LA interventions implemented in PSL. The objective is to identify underlying theoretical constructs and learning factors—derived from PL theories—that impact academic learning outcomes in K-12 STEM education. The insights guide the design of practical implications for educators and stakeholders to provide tailored support in PSL. Studies II, III, and IV collectively address this research question through their theoretical analyses and empirical findings.

1.5 Significance and Expected Contributions

This dissertation aims to present significant theoretical, empirical, and methodological contributions to the field of educational technology (EdTech) and personalized learning.

Theoretical Contributions: The doctoral research contributes theoretically by developing an integrated TEL-LA model demonstrated to be effective for PSL in K-12 contexts. The model represents a novel synthesis that extends beyond existing frameworks (Ogata et al., 2018; Walkington & Bernacki, 2014) by systematically integrating TEL and LA components to support personalized STEM learning. By bridging these previously disparate areas, the work opens new research avenues that can advance understanding of how technology-mediated adaptive learning functions in practice, particularly within the complex dynamics of K-12 educational environments.

Empirical Contributions: The doctoral research contributes empirically by presenting TEL-LA interventions deployable across multimodal contexts, incorporating ALT that enable systematic measurement and analysis of diverse learning trajectories. The interventions target performance indicators, behavioral patterns, and motivational factors that influence learning outcomes. Additionally, the research provides empirical evidence from mathematics and science interventions that inform practitioners about how ALT can enhance students' academic learning outcomes. The evidence base generated through these interventions offers concrete guidance for educators seeking to implement technology-enhanced PL approaches in their own contexts.

Methodological Contributions: Finally, the doctoral research also contributes methodologically by introducing a customized three-phase MMR design that advances PL toward outcome-based assessment. This approach represents an important shift in EdTech research by emphasizing measurable learning outcomes rather than focusing solely on technology adoption or user satisfaction metrics. Furthermore, the research expands intervention approaches within EdTech by providing robust methodological frameworks for future investigations in the domain. The methodological innovations developed through this work offer researchers new tools for examining the complex relationships between technology, pedagogy, and learning outcomes in personalized educational contexts.

1.6 Dissertation Structure

The dissertation consists of five chapters that constitute the research work conducted in the context of this doctoral research.

Chapter 1 provides a general introduction to the background and rationale behind the dissertation. Particular focus is given to the socioeconomic demands and drivers behind the transformation that the STEM education field has undergone. The chapter outlines research problems along with aims and objectives to be addressed through the research questions. The chapter concludes with the significance and expected contributions of the study.

Chapter 2 provides a theoretical foundation and conceptual framework connecting existing personalization and technology practices in educational contexts. Related literature is reviewed to identify the philosophical context of PE and practical applications associated with TEL-LA interventions. The conceptual framework integrates TEL and LA practices grounded in learning theories and existing PL process designs to support PSL. Since the doctoral research' aim is to develop a next-generation PE solution in STEM, it is important to identify empirical evidence from existing work. In the subsequent section, empirical evidence on PSL covering mathematics and science educational contexts is presented to connect theories and practices. The chapter concludes by underscoring the current research gap to provide the basis for the subsequent research positioning.

Chapter 3 explains the overall dissertation's research methodology. Building on the theoretical foundation and conceptual framework established in the previous chapter, a philosophical underpinning behind the research paradigms is presented to support the dissertation's research design based on MMR. The section also highlights the research process unfolding across three phases that accommodates the rationale behind the reviews and empirical studies. Since the subsequent part of the dissertation draws from published studies, an overview of each study and its methodological choices is summarized, including data collection, processing, analysis strategies, ethical considerations, quality criteria, and validity measures.

Finally, limitations and methodological reflections are presented at the end of the chapter.

Chapter 4 provides an overview of the publication portfolio and a summary of the main findings from studies (I-IV), including each study's research context, objectives, key findings, and contribution to the dissertation. The chapter concludes with a cross-study synthesis integrating all studies included in this dissertation.

Chapter 5 provides a summary of the dissertation, reflecting on how the research studies contribute to addressing the dissertations' research questions. In addition, a synopsis of the doctoral research's contribution to advancing theoretical, empirical, and methodological understanding is discussed. Furthermore, practical implications are suggested for stakeholders. The section also presents the dissertation's limitations along with future directions to support ongoing research. The chapter concludes with a final reflection presenting the overall conclusions and research journey.

2 Theoretical and Conceptual Foundations

2.1 Introduction to Personalized Learning in Educational Contexts

The concept of PL has recently re-emerged as one of the major instructional practices in the educational sector (Pane et al., 2015; Zhang et al., 2020). Despite the recent attention, historically, the fundamental concept had existed and was used by educators as 'individualized instruction' based on learners' needs (Drumheller, 1971; Keller, 2010). With personal computers emerging in the mid-1970s, educators have been able to pursue rich, PL experiences and opportunities to explore customized and tailored support began to flourish. This is when technology companies like IBM, Apple, and Microsoft started to revolutionize society through innovations and bringing personal computers to homes. Many technology companies, philanthropists, and governments have provided support to develop educational technologies particularly web-based learning (McKimm et al., 2003), and assessment technologies (Pirnay-Dummer et al., 2010) and PL platforms like Khan Academy and DreamBox Learning among others (Brass & Lynch, 2020).

Personalized Learning has been defined in various forms, influenced by policies and contexts ranging from the national to the local level, despite being characterized as complex and diverse. Regardless of the specific context, PL centers around the learner's interests and needs. As an approach it aligns with one of the most frequently cited definitions of personalization, which describes it as "instruction that is paced to learning needs, tailored to learning preferences, and tailored to the specific interests of different learners" (US Department of Education, 2010). Furthermore, Larry Cuban has contextualized PL within the school environment suggesting that PL becomes truly distinctive only when customized lessons are combined with strategies such as setting and achieving both short- and long-term goals for school learners (Bernacki et al., 2021).

Educational transformation in the last two decades also contributed to the evolution of PL. Personalization of instruction and learning started to become a part of the school, and flexible instructional practices are considered and supported within the learning environment (Keefe & Jenkins, 2008). In the context of K-12, there has been increasing demand for education reform, urging numerous schools to adopt PL systems, as it is believed to improve academic learning achievement (Basham et al., 2016). That also reflects the recently adopted policies by US states to deliver PL opportunities to K-12 students (Zhang et al., 2020).

Leading global education systems such as the United States, the United Kingdom, Finland and Canada, have made sustainable efforts to personalize learning in hope to address the growing student diversity and provide quality education for all students (Peterson, 2016). Different approaches have also been observed, especially those adopted by leading K-12 education systems in countries such as Finland, which are renowned for their comprehensive, non-personalized methods that emphasize equality over individualization (Harju-Luukkainen, 2023; Paavola & Pesonen, 2021). Similarly, some developed nations like Japan deliberately reject overly personalized education systems in line with their collectivist values (e.g., Japanese collective learning) (Ishii, 2022) and East Asian mastery methods (Boylan et al., 2018). The contemporary understanding of PL arises from convergence of advancements in educational research, the learning sciences, and technology-driven innovations (Basham et al., 2017). Various researchers and educators, regardless of domains and settings, have been conducting interdisciplinary studies to explore different designs of PL and explore whether it holds what it takes "to transform traditional education systems and provide more equitable outcomes for all learners" (Zhang et al., 2020).

2.2 Theoretical Foundations

In this section the main theoretical paradigms that underpin this research—*Context Personalization (CP)*, *Technology Affordances (TA)*, and *Zone of Proximal Development (ZPD)*—are defined and discussed. The paradigms are presented in thematic order to establish a coherent theoretical foundation that connects learning theories relevant to personalization, TA, and learning outcomes (**Figure 1**). The theoretical pillars demonstrate how these interconnected theories collectively inform our understanding of outcome-based PL in technology-enhanced environments. On the whole, PL thrives when all the three elements work in harmony. Context Personalization lays the groundwork by aligning tasks with learners' interests and goals. Technology Affordances then amplify that personalization, adapting interactions in real time. Finally, ZPD-based assessment closes the loop by measuring growth and guiding further intervention. Context Personalization serves as the foundation where tailoring learning tasks to each learner's interests, backgrounds, and goals ensures relevance from the very start. By mapping individualized or group-specific learning paths before instruction, educators spark motivation and lay the groundwork for adaptive support. Technology Affordances enable real-time adaptation. Digital tools—such as simulations, adaptive quizzes, and collaborative platforms—translate personalized contexts into dynamic experiences. By reflecting learners' physical interactions and social motivations, these affordances adjust difficulty, feedback, and collaboration modes on the fly. With personalized contexts and ALT in place, the final imperative is to measure learning gains. The ZPD pinpoints the gap between independent learning performance and potential achievement with guidance. Integrating ZPD-based diagnostics into PL systems reveals where scaffolds are needed, quantifies growth, and informs the next cycle of personalization.

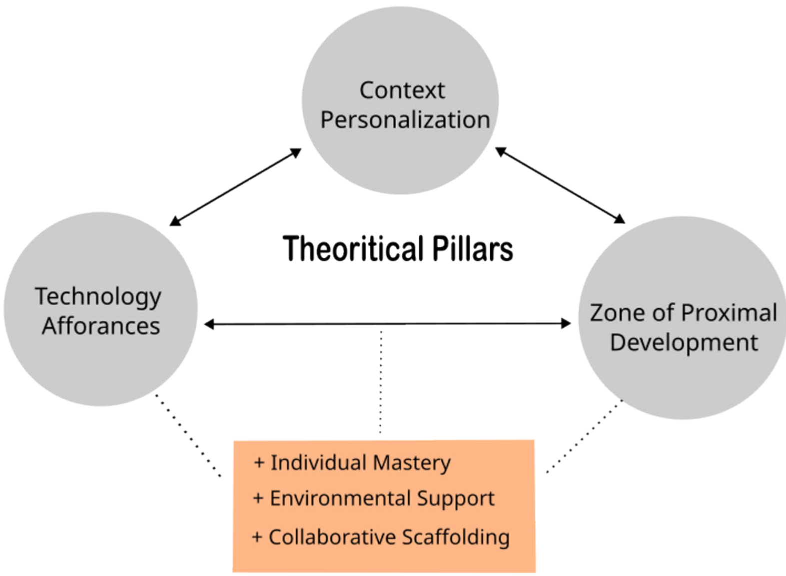

Figure 1. Theoretical pillars of outcome-based personalized education.

2.2.1 Context Personalization Theory

Personalization in learning is deeply connected to various educational theories that explain how learners engage with content, receive support, and develop skills. One closely connected theory that focuses specifically on personalization is *Context Personalization* (Walkington & Bernacki, 2014). The theory introduces a method for addressing learning differences, accommodating student interests, and aligning each learning task with learners' individual interests. The theory has been expanded through practical applications in the context of PL, particularly in mathematics (Walkington & Bernacki, 2018; Walkington & Bernacki, 2019). The developments highlighted that this method could leverage situational interest and learners' depth of knowledge about problem contexts. Therefore, learners are capable of demonstrating enhanced proficiency in tackling complex task and solving problems more swiftly. Consequently, the research emphasized how learning contexts—including accommodating learning characteristics, multiple dimensions of interests, fine-grained personalization, diversification in problem definitions, and ownership of the problem—should be directed towards the learner and serve the learners' best interests. A single approach to personalizing learner tasks could promote inclusivity, yet it may not deliver the depth and flexibility essential for individual-centered learning, which relies on a comprehensive framework of varied, evidence-based, design choices. Based on these considerations, Walkington & Bernacki (2020) concluded that "multi-component methods of personalizing learning that are commonly adopted in schools thus need to be designed with multiple learning theories in mind and in response to a specifically selected set of learner characteristics that are to be accommodated".

2.2.2 Technology Affordances Theory

To support the rationale of Walkington & Bernacki's argument (2020) of personalization, other learning theories are essential. When considering personalization of learning task features (learning characteristics), learning environments, more precisely TEL, seem to be one of the key determinant factors. Technology Affordances should be placed as a unifier between personalization and learning assessment. Originally from the theory of affordances proposed by Gibson and attributed to his work (Gibson, 1977), the concept of affordance is perceived as a powerful lens for studying the co-constitutive relations between technology and humans in organizations (Fayard & Weeks, 2014). Gibson originally saw affordances as objective features of an environment tied to an organism's capabilities. Gaver (1991) reintroduced the idea of affordances through technology, and he suggested that the concept of affordances can be considered a useful metaphor for user-centered analysis of technologies. Later, Norman (2013) showed that in interactive technologies, what truly matters is how users perceive and interpret those features. Today, most TEL-LA researchers treat affordances as emerging from the interaction between a tool's design, user intentions, and social conventions. As such, effective learning tools combine clear interface cues with supportive elements (icons, tutorials, social hints) to help educators and students recognize and act on digital possibilities in STEM settings. Gaver (1991) deepens this view by emphasizing the perceptible cues in interface design that guide user behavior, while Fayard & Weeks (2014) argue for a sociomaterial entanglement of social and technical affordances, where platforms and communities co-shape each other. Though the concept has been used in the business and organization domain, the rationale of the theory has remained significant in interpreting educational contexts. Notably, it allows educators "to examine how people's practices and their use of technology in a setting is shaped, but never fully determined, by the setting's physical and social characteristics" (Faryard & Weeks, 2014). Rooted in Gibson's ecological notion of affordance, as the relational properties between actor and environment, digital tools provide functionalities—like adaptive sequencing, real-time feedback, and multimodal interfaces—that learners can comprehend and act upon to advance their goals.

2.2.3 Zone of Proximal Development Theory

Despite the use of technology in many contexts, including education, if the personalization or technological support is not producing impact, it will raise concerns for all parties involved in the educational process. It is, therefore, highly vital for education, particularly K-12, to integrate multiple learning approaches that support learners in interaction, gaining motivation, and enhancing learning outcomes. The ZPD theory, conceptualized by Vygotsky (1978), is highly instrumental in guiding in this context with stressing inherently social and collaborative dimension of learning. ZPD offers a framework for studying the relationship between learning development through collaborative activities and educational intervention for ensuring right amount of support one requires to achieve targeted competencies (Allal & Ducrey, 2000). ZPD's effort is primarily regarded as a way of linking instruction and assessment with regulation, thereby supporting advancement in the K12 school settings. Thus, the concept of ZPD therefore formed a strategic theoretical baseline with affordances (i.e., technology) influencing school learners' learning development and learning assessment.

While these theories originated from distinct ontological perspectives—individual, technological, and collaborative—they collectively form the core foundation of an interconnected, outcome-based approach to PL. In reconciling these theoretical perspectives, the dissertation aimed at proposing a framework where personalization is both an individual and a collaboratively scaffolded process, operationalized through the affordances of adaptive learning technologies. The proposed integrated model supports and measures learner outcomes by ensuring that PE in technology-ehanced environments is both adaptive and equitable.

2.3 Conceptual Framework

As outlined in the Introduction section, the PE dimension integrates learning theories grounded in cognitive processes, teaching approaches, and the ZPD. This dimension consists of two components: first, key technology practices of TEL and LA; and second, the educational sector where these practices are applied to maximize impact. In this doctoral research, PE is applied to facilitate PSL through an integrated TEL-LA intervention model in mathematics and science education. The PE conceptual framework thus accommodates ALT and data-driven practices for PSL, emphasizing learning characteristics, active engagement, and adaptive learning experiences toward specific learning outcomes.

The present framework (**Figure 2**) builds upon and extends the foundational Personalized Learning Design (PLD) model proposed by Walkington and Bernacki (2020). While their model positioned learning characteristics at the forefront of PLD, it lacked specificity regarding the practices needed to transform data—such as motivation and metacognition—into structured, meaningful constructs for instructional decision-making. Compared to this framework, learning characteristics includes not only traditional digital learning (engagement) data—such as logins, clicks, and time on tasks—but also latent constructs like motivation and metacognition. These indirect indicators help infer various aspects of learners' motivational and metacognitive strategies. While these constructs are not directly observed as raw data, they can be modeled and approximated through careful analysis of learner behaviors and interactions within digital environments (Lau et al., 2017).

The present framework addresses the gap by integrating LA strategies specifically personalization and evaluation into adaptive and immersive learning environments to systematically analyze learning data and measure learning outcomes. Specifically, it connects personalization concepts with practical applications of TEL and LA, representing an important step toward operationalizing PE. By bridging theoretical constructs of the PLD with empirical evidence, the framework explores how personalization impacts performance and addresses associated challenges in STEM learning.

This section provides a detailed explanation of PE, the key components of the integrated model, and how these components support personalization in STEM learning.

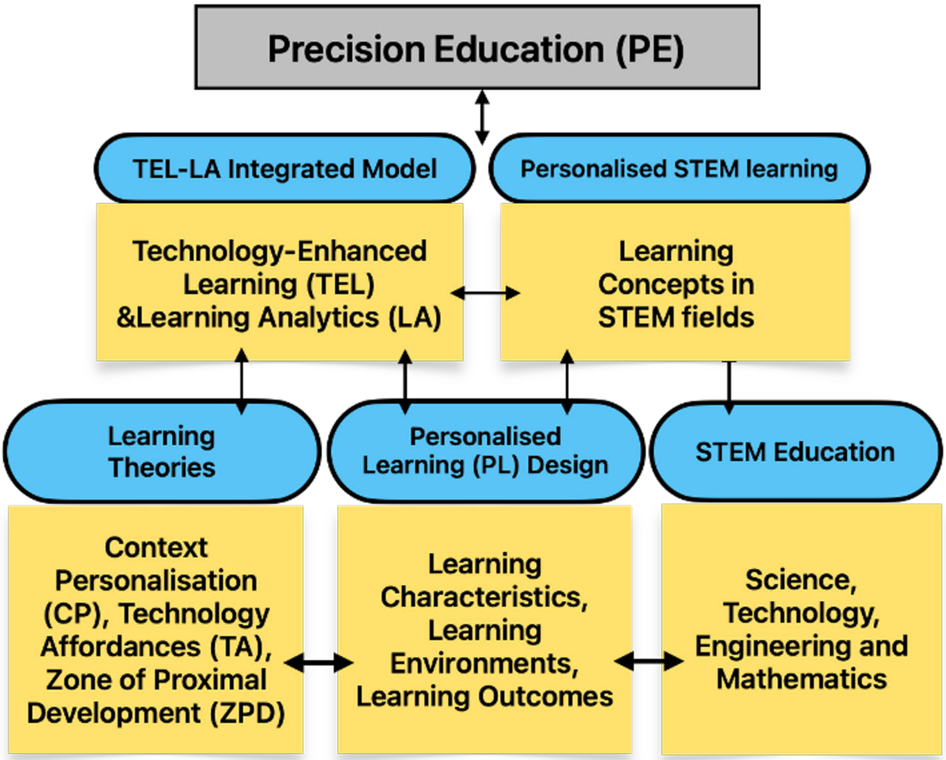

Figure 2. A Precision Education conceptual framework of TEL-LA-PSL.

2.3.1 Defining Precision Education

The term 'precision' is associated with the use of data to evaluate and manage a broad variety of phenomena (Williamson, 2018). Borrowed from medicine, precision in education thereby highlights a shift toward more personalized and data-informed learning and teaching strategies. Unlike medical conditions, learning is culturally situated, value-laden, and resistant to precise measurement. Education researchers use common terminology (e.g., precision, customization, individualization, matching, tailoring) interchangeably to clarify the heterogeneity of individuals with specific difficulties so that they can administer targeted interventions with greater support. This, in a sense, is the core of Precision Education (PE)—to make efforts for the right person, to have the proper intervention in place for the right reason. In other words, precision scholars are not questioning whether an intervention is effective but, instead, they explore what interventions have been performed, for whom, and how. However, PE might be expedited not by treating diverse learners as the problem but by confronting the standardized education system—with its rigid curricula, and uniform assessments—that suppresses individual strengths, stifles creativity, and fails to nurture each student's unique potential.

The PE strategy can be broadly split into two sections: (a) precision teaching and (b) precision learning grounded in behavior-analytic theory, notably in the work of Ogden Lindsley (Evans et al., 2021) and Owen White (White, 1986). While both share a focus on measurement of fluency (rates of correct responding) and decision-making informed by data, they differ in where control and responsibility for progress primarily reside. Emerging areas of interest in PE involve the systematic usage of learner data to implement an individualized curriculum tailored to the individual's learning needs. The steps required in achieving the latter can be paralleled with the 'navigational structure' that Google Maps utilizes. The first target is to help individuals comprehend the end-point learning goals (planned location). This includes the development of a clear understanding related to their current knowledge and competencies (current address) as well as the means to communicate their needs better (mode of transportation). Furthermore, guidance and assistance on how to build on the intermediate success opportunities (pathways to destination) must be disclosed.

Precision Education is, by definition, relying on tremendous ambitions. In a sense, it involves the convergence of genetics, neuroscience, behavioral, and psychological sciences exchanging viewpoints related to the learning process and deciding whether certain learning materials and tools can be integrated to support individuals' needs. The abovementioned further explains why supporters of PE argue that, to personalize the learning experience, advanced computer systems might be needed to process such massive amounts of data. Indeed, the provision of PE includes collecting extensive points of personal data, as indicated by the ongoing research efforts in genomics, psychology, and cognitive science, which explore both individuals' physiological conditions and the internal elements of their minds (Kuch et al., 2020; Williamson, 2018).

It is assumed that the evolution of PE began long before the spotlight on Barack Obama's 2015 speech as President of the USA, where he discussed different precision medicine initiatives (Hart, 2016) and their importance to the societal context (Hart, 2016; Kuch et al., 2020; Wartman & Donald Combs, 2018). Although there is an ongoing debate regarding the origins of PE, examples of ways to support such practices include progress risk prediction and early warning using LA practices. Moreover, the importance of PE has been observed in many contexts of teaching and learning. Lindsley, one of the early PE theorists, discovered and pinpointed from B.F. Skinner's experimental analysis of behavior the notion of precision teaching, identifying that "The Learner Knows Best", which inspired educators to contextualize it into an educational perspective (Lindsley, 1971; White, 1986). The computer-based precision learning system for developing student fluency is an example of how contemporary artifacts may still be discovered (McDade, 1992).

In recent years, several efforts have emerged to draw much needed retention for improvement in this sector. Stephen J. H. Yang of Taiwan National Central University identified four critical PE components related to PE: (a) diagnosis, (b) prognosis, (c) treatment, and (d) prevention (Yang, 2019). Meanwhile, in the sociohistorical context of schooling, Professor Hiroaki Ogata of Kyoto University and his team's educational products were heavily influenced by the essence of PE where data from multivariate sources (e.g., digital logs, student psychiatric data from e-book systems) are utilized to improve K-12 students' learning experiences across the country (Japan, Korea, Taiwan, and Singapore) (Boticki et al., 2019; Ogata et al., 2017).

Anchored in the PE paradigm—the right person, the right intervention, for the right reason—this doctoral research differentiates between traditional learning and targeted learning with appropriate infrastructural and pedagogical support. Targeted learning involves tailoring instruction to each student's unique needs and interests while enabling student voice and choice in what, how, when, and where they learn. So, a PL ecosystem should be driven by two core concepts: personalization, which focuses on identifying the specific "who" for interventions, and adaptivity, which functions as the essential mechanism within technological systems. Adaptivity refers to a platform's capability to monitor user activities, interpret them through domain-specific models, and dynamically adjust content, difficulty, or learning paths based on real-time performance. Together, these concepts form a navigational structure where data identifies students' current knowledge (their "starting address") and guides them precisely toward student's learning goals (their "planned destination").

2.3.2 TEL-LA Integration Model

The integration of EdTech with LA creates compelling opportunities to customize STEM education to individual student needs. Despite persistent challenges around K–12 data privacy, gathering reliable data, algorithmic bias, and the commercialization of education, TEL and LA have become influential fields that empower educators to harness student data for adaptive strategies and deliver truly PL experiences (Wong et al., 2023). As AI-powered assistive technologies become increasingly integrated into education, they serve as a prime example of how AI can transform and enhance the synergy between TEL and LA by enabling learning experiences that are more intelligent, personalized, and attuned to individual needs. When implemented thoughtfully, AI-powered TEL-LA systems can foster learning environments that are not only more responsive and effective, but also more inclusive and equitable. Similarly, further research is needed that examines how PL can be effectively applied through interdisciplinary and integrative frameworks within STE(A)M contexts (Li & Wong, 2023). Thereby, leveraging real-time insights of learner's performance, behaviors and motivation, Technology Enhanced

Learning-Learning Analytics (TEL-LA) based instructional design can facilitate more effective learning pathways, enhance student persistence, and address disparities in educational outcomes.

There are some initiatives, such as the ‘Learning Evidence Analytics Framework (LEAF)’ (Ogata et al., 2018) and ‘Generic Framework for Learning Analytics’ (Greller & Drachsler, 2012), that refer to GFLA. However, LEAF considered integrating various classroom tools and the LA Dashboard to support undergraduate students’ e-learning journey. On the other hand, GFLA mainly discussed the dimensions of learning and highlighted how data collection, interpretation, and learning environment jointly assist educational stakeholders in translating learning into insights. In addition to that, there are ethical dimension such as data privacy and algorithm bias, that require investigations and implementations for success of intervention behind the utilization of TEL and LA. Greller and Drachsler (2012) argued that without clear policy guidelines and stakeholder literacy, student data can be misused or inadequately secured, undermining trust and ethical use. Ogata et al. (2018) extend this critique, proposing an evidence-based TEL framework that embeds data minimization, pseudonymization, and stakeholder consent workflows to protect young learners’ rights. On other hand, Ogata et al. (2018) caution that learning analytics models must integrate socio-cultural parameters to non-targeted generic recommendations that disadvantage certain student groups. Greller and Drachsler (2012) underscore the danger that educators lacking analytics literacy may misinterpret biased outputs as objective, leading to misguided interventions that further marginalize vulnerable learners. Despite the reported research on TEL and LA for personalization and instructional support in STEM, there was not much integrated framework that highlights that integration of TEL with LA features to be utilized as intervention design or used to support intervention outcomes. This brought immense vacuum, and existing research remains fragmented in K-12 settings despite advancements in many TEL-LA integrations in research works.

In this research, TEL provides the essential foundational infrastructure through diverse modalities such as LMS and VR, which serve as the necessary environments to host and deliver personalized interventions. While TEL offers the delivery platforms, LA functions as the critical operational driver that bridges the gap between these technological environments and the overarching paradigm of PE. By extracting and interpreting students' digital traces—such as practicing patterns and interaction logs—LA transforms raw data into actionable insights that inform instructional adaptations, such as Customized Difficulty Levels and Personalized Learning Paths (PLPs). This integration ensures that technological modalities are not merely passive hosts but active components of a data-informed ecosystem designed to identify individual learner characteristics and enhance the overall learning experience.

2.3.3 Empirical Evidences on Personalized STEM Learning

Personalized STEM learning is gaining paramount importance in the area of research, particularly as educators seek to tailor learning experiences to meet the diverse needs of students. Integrating several pedagogical approaches, including blended learning and universal design for learning shows promise in fostering student engagement and improving learning outcomes in STEM fields. In the study of Bernacki et al. (2021), it is pointed out that the dimensions of adaptivity in learning technologies should reflect on learner characteristic(s) to which the technology adapts the learning experience and accommodates learners' various needs (i.e., prior knowledge assessment, error detection strategies, motivation endurance, self-regulated learning strategies, and versatile individual learning style). That also reflects underlying challenges and weaknesses of early-stage learners when learning complex concepts in STEM (i.e., cells, fractions) (Beach, 2022; Tomson et al., 2021) and echoes the need for practices with adaptive features. One of the critical strategies for personalizing STEM learning is the incorporation of blended learning models with learning STEM concepts (Julita et al., 2022). However, targeted learning supported by intervention-based studies could be promising solution tailoring learning experiences to better meet the needs of individual learners. While integration of advanced technologies offers to support PL, individualized learning support through ALP is widely considered as a strategy to enable more students to attain the envisioned level of competence and produce better learning outcomes when it comes to K-12 STEM (Grimm et al., 2023).

2.3.4 Personalization in Mathematics Education

Personalization in mathematics education is increasingly recognized as a pivotal strategy for maximizing student engagement and achievement, particularly in addressing the diverse needs of learners. Evidence supporting the effectiveness of PL in mathematics can be drawn from various studies and analyses focusing on situational interest (Rodríguez-Aflecht et al., 2018), academic grit (Yu et al., 2021), and identity development among students (Radišić et al., 2024). Research shows that personalization can significantly enhance situational interest, utility value, and task effort among students. Bernacki & Walkington (2018) found that while personalization positively affects situational interest in mathematics, this effect diminishes as students' pre-existing interest in mathematics increases. This suggests that tailored educational approaches can be particularly effective for students who may not initially have strong interests in math, making it crucial for educators to leverage PL strategies to spark interest in this subject. Interventions utilizing TEL have shown significant correlations with improved learner performance in mathematics, particularly for students with mathematical disabilities (Benavides-Varela et al., 2020). The importance of instructional design and strategies, such as video modelling (Satsangi et al., 2019), interactive applications (Pitchford et al., 2019), within digital interventions has shown promising results in enhancing student engagement, math understanding, and addressing gender disparities in early-grade mathematics education.

Tailoring educational practices to meet the individual needs of students not only enhances their engagement but also mitigates emotional barriers to learning, ultimately improving their mathematical achievement. By recognizing and utilizing personal identity in educational strategies, teachers can foster an environment where all students feel empowered and connected to the subject matter (Priniski & Thoman, 2020). A number of studies have explored various approaches to improve arithmetic fluency, ranging from traditional instructional methods to the utilisation of LMS and advanced tutoring systems (Roy et al., 2021; Visscher et al., 2018). For example, the Rapid Automated Naming approach, which can examine individual capacity in naming highly recognizable visual information, has been identified as a significant indicator of fluency in basic arithmetic tasks (basic tasks, such as subtraction and addition) when utilized in the Online Experimental Psychological System for 3rd year kindergarten students (Cui et al., 2017). In PLE, mastery is recognized as the demonstrated capability in applying particular knowledge and skillsets to a predetermined standard measured through performance task, adaptive assessments (Corbett & Anderson, 1995; Shute, 2011). However, very limited research has been done to support mathematics learning that ultimately caters to personalized curricula and automatic assessment, leaving a critical gap in empirical evidence to guide assessment design and comparability.

2.3.5 Personalization in Science Education

Personalization in science education is increasingly recognized as a crucial approach to enhance student engagement, motivation, and overall learning outcomes. Evidence from recent research demonstrates that PL experiences, tailored to individual students' interests and needs, can significantly improve their motivation and connection to scientific concepts. One notable study by Loukomies et al. (2013) emphasizes the importance of aligning educational activities with students' personal needs and motivations. The researchers argue that students are more likely to find learning experiences meaningful when these activities reflect their personal interests and autonomy, leading to greater engagement in science learning environments (Loukomies et al. 2013). This perspective supports the notion that personalization can help students perceive science learning as worthwhile and relevant, thus fostering a deeper connection to the subject matter. For instance, SMART (System of Augmented Reality for Teaching) has shown potential in cultivating students' interest and learning motivation in physics (Javaheri et al., 2022), while effective digital games in learning biology content, i.e., photosynthesis, facilitated student engagement and comprehension (Culp et al., 2014).

In science, particularly biology, educators face challenges in supporting both the development of theoretical knowledge and the achievement of conceptual understanding. Video-based instruction has been a provisional remedy to make learning materials more naturalistic and aid in the comprehension of abstract concepts (Lei et al., 2015; Marsetller & Bodzin, 2015; Monkovic et al., 2021). One of the few studies that identified positive effects of video-based multimedia instruction in high school biology education, particularly in Molecular Biology (MB), highlights its role in enhancing learners' procedural understanding (Monkovic et al., 2021) and improving memory retention (Marsetller & Bodzin, 2015). However, a more interactive and comprehensive learning platform is overdue in retaining student interest and motivation, especially for K-12 learners. Recent advancements in VR-based instruction have sparked interest as a viable alternative to video-based instruction due to its interactive nature enhancing users' spatial presence. The integration of VR in educational contexts offers promising avenues for creating engaging learning environments (Uz-Bilgin & Thompson, 2021; Wu et al., 2021) that can lower cognitive effort and enable diverse and logical interpretation of information, particularly for communicating abstract concepts that require critical thinking and analytical skills as well as problem-solving abilities for K-12 learners (Wu et al., 2021). Multiple studies (Subran & Mahmud, 2024; Zafeiropoulou et al., 2021; Chu et al., 2024) have highlighted the emerging outcomes of using VR and AR in science education, such as improved knowledge acquisition, engagement, motivation, and academic achievement due to the high representational fidelity of 3D virtual objects and the opportunity to simulate abstract concepts. Nevertheless, more intervention-based learning and comparative assessment are needed to identify whether a particular instructional platform better serves students' needs.

2.3.6 K-12 versus Higher Education Contexts

The application of PL approaches has primarily focused on adaptive learning technologies, data-driven instructional practices, and individualized feedback systems. A systematic review by Li et al. (2020), in which 798 articles published between 2000 and 2018 were analyzed, found a growing trend in PSL, particularly in HE settings. The findings emphasized the increasing reliance on TEL to design customized learning pathways but further noted that research on PSL at the K-12 levels remains lower especially on intervention-oriented design leveraging TEL-LA (Li et al., 2020; Wong et al., 2023). Therefore, while general K-12 STEM education is prevalent, research on K-12 STEM should be properly investigated. Several significant challenges and limitations have been identified in the implementation of

PSL interventions, particularly within K-12 educational settings. These concerns include heightened ethical demands, complex multi-layered consent processes unique to schools and younger populations, and technical skill gaps of educators, among others. Since individuals in K-12 settings are pupils, authentic learning tasks and disciplinary integration might impose extravagant cognitive load among learners, leading towards negative attitudes on STEM (Kirschner & Hendrick, 2020). Another potential aspect is that teachers who are teaching STEM concepts are not well versed with pedagogy that is required for delivering comprehensive PSL and environmental setup (Chen et al, 2025). A more recent review by Li and Wong (2023) examined 72 studies on PSL (including Arts— STEAM) education published between 2011 and 2020. The analysis revealed that blended learning environments and LA were the most commonly used personalization approaches. However, they also identified a critical gap: while many studies explored specific aspects of personalization, few provided a holistic analysis of how ALT and LA interact to enhance STEM education. Bernacki et al. (2021) reviewed 376 studies conducted between 2010 and 2018 and found that affiliated researchers predominantly focused on the education domain; exceptions persist in STEM. However, when it comes to PSL, Maier & Klotz's study (2022) findings showed more dominance in HE (**Figure 3**), which raises concerns as primary and secondary students seem more vulnerable and need comprehensive personalized support to acquire STEM knowledge and mastery in the early stage of their academic journey.

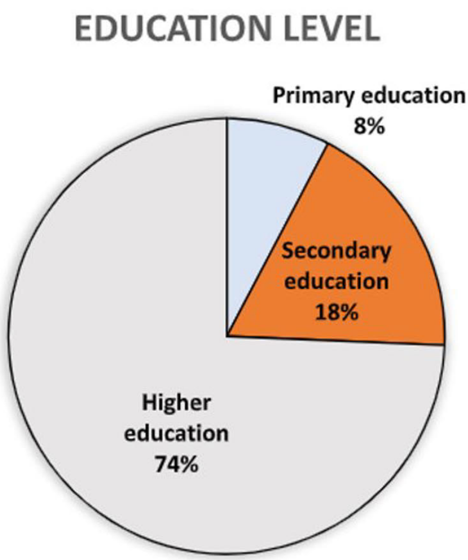

Figure 3. Distribution of captured support of personalized feedback (Maier & Klotz, 2022).

2.4 Identifying the Research Gap and Research Positioning

This chapter introduced learning theories and ALT that have been used in PSL. Based on the literature review on PL with technologies and practices in STEM educational contexts, there are mixed results and significant gaps that despite the growing body of research, studies focusing on the integrated approach or model to provide personalized support and provide alternative pathways in STEM-related disciplines are limited and need more comprehensive studies (Li & Wong, 2023; Xu et al., 2022). Subjects like mathematics and science are complex, whereby teacher-led instructional design is not enough to ensure PL for all level of learners. The researchers identified gaps that lack systematic evaluation with targeted intervention and need more investigation to support PSL in K-12. In order to meet demands of tailored support and interactive learning, TEL and LA are not only essential but also effective, as proven in the earlier research. Despite EdTech and data-driven approaches existing separately, the application in PE context remains under research and more research is needed to build a strong case and foundation with different learning contexts and settings to meet global outreach. In light of this, this dissertation is providing a PE solution with an integrated TEL-LA model for PSL, which is grounded by the learning theories and conceptualized into the K-12 learning settings.

The dissertation is structured around an MMR design, beginning with two exploratory studies to investigate key themes, and extending into two experimental studies aimed at generating empirical evidence to support the findings. Thus, Study I has been conducted through exploring multimodal technologies that are adaptive and supportive of precision-based learning. On the other hand, despite many studies focusing on isolated aspects of PL, there is a critical gap in providing a comprehensive understanding of how TEL-LA interventions function across different educational contexts (Li & Wong, 2020). In addition, PL in STEM is already known and theorized; however, it lacks comprehensive exploration within the context of TEL-LA intervention practices in PSL. This has led Study II to be focused on to broadening the identification of various combinations of digital tools, analytics approaches, and adaptive strategies that transformed specific areas of STEM learning with measurable positive outcomes.

Likewise, empirical evaluations on STEM education's effectiveness are still underdeveloped, especially in K-12 (Wong et al., 2023). Following the review studies (Study I-II), this doctoral research aimed at conducting empirical experimentation with the expense of developing PSL for K-12 learners. Since the methodology is structured to guide better tailoring student needs and enable the production of outcome-based assessments, in Study III, the TEL-LA intervention has been used to experiment on the improvement of arithmetic fluency development as part of PSL, particularly achieving learning outcomes in learning mathematics concepts. On the other hand, in Study IV, TEL-LA intervention has been utilized to inspect learning improvement and motivation while learning STEM concepts, particularly related to science.

3 Research Methodology and Design

3.1 Philosophical Foundations and Research Paradigm

The research adopts a pragmatic approach, a meta-theoretical stance that privileges the practical consequences of research and embraces methodological pluralism. It is particularly prominent in MMR, a research methodology that was established around 2000 (Lund, 2012) and has become increasingly popular in educational sciences. Mixed-Methods Research, defined as “a method of both quantitative and qualitative designs in the same research study, evolved in response to the observed limitations of both quantitative and qualitative designs” (Caruth, 2013). However, when grounded by pragmatism, it contends that the value of any inquiry lies in its ability to solve real-world problems. That embodies the fundamental principle of pragmatism—knowledge is formed through its practical outcomes and priorities “what works” rather than rigid paradigms. It holds that research questions—not methodological dogma—should guide the choice of methods. Thus, MMR can have more leverage over strict adherence to any single philosophical tradition (Morgan, 2014; Creswell & Plano Clark, 2018). Unlike positivism (which favors quantitative methods) or constructivism (which emphasizes qualitative inquiry), pragmatism embraces methodological pluralism, ensuring that research design is dictated by the nature of the problem rather than ideological allegiance.

Pragmatism also demands that insights gleaned from literature translate into practical interventions. Testing review-derived mechanisms—such as ALT or assessment measures—under quasi-experimental or controlled conditions evaluates their causal efficacy in improving K-12 students’ learning outcomes. A pragmatic cycle of “synthesis → intervention → reflection” allows continuous feedback between theory and practice, yielding solutions that are both conceptually robust and contextually viable (Tashakkori & Teddlie, 2003). Hence, the orientation of this design is followed by first conducting systematic reviews to map and synthesize existing evidence, then executing intervention-based studies to test and refine those insights in K-12 educational settings.

Pragmatism allows the research to navigate the tension between technological determinism (the belief that technology automatically causes effects) and pedagogical constructivism by treating the TEL-LA integration instrumentally, assessing the technology's success based purely on its outcomes in promoting active, situated knowledge construction (Oliver, 2011). Therefore, the need for three phase MMR design in this context of the personalized STEM learning is justified because its transactional approach judges the value of technology not on its inherent features, but on the warranted assertions derived from the relationships between actions and consequences in the learning environment (Biesta, 2010). Lastly, as per the research's aim in contributing more guidance to future PE solutions, practical recommendations are necessary to reflect on existing practices and empirical evidence.

3.2 Research Design and Methodological Choice

The research employs an MMR approach by integrating qualitative and quantitative techniques to support PSL in the TEL-LA model. The methodology is designed around three RQs, drawing upon the methods and the findings of the four studies included in this dissertation and executed in three phases (**Figure 4**). Phase 1 includes two systematic reviews; Phase 2 includes two interventional studies; and lastly, Phase 3 includes a reflection from both Phase 1 and Phase 2. Phase 1 systematically identifies "what works" in diverse contexts, captures PL contexts and practices including different educational technologies in use, intervention practices, and under-explored learning factors (e.g., performance, behavior, motivation) that matter for scalable implementations (Bernacki et al., 2021). By aggregating quantitative outcomes with qualitative themes, reviews produce a theory-informed foundation for intervention design thus, ensuring that subsequent experiments address genuine gaps rather than reinventing the wheel (Tanko, 2022). Phase 2 follows the next step, which is to empirically validate through intervention-based studies. That provides practical examples of how to implement PL in K-12 settings through the TEL-LA intervention approach. Studies explore how early-stage learners (K-12) enhanced skill and interest in certain STEM concepts by leveraging adaptive learning technologies, with academic learning outcomes measurable through LA. Building on the findings from earlier phases, Phase 3 redefines the underlying constructs and factors of PL, and formulates recommendations based on observed personalization practices and intervention outcomes.

To address the overarching question, the following three research questions guide the investigation:

RQ1: *How can Technology-enhanced Learning and Learning Analytics support Precision Education and Personalized STEM learning?*

RQ2: *How does technology-enhanced learning with LA-based interventions influence academic learning outcomes in STEM?*

RQ3: *What underlying theoretical constructs and learning factors can we influence through technology-enhanced learning with LA-based interventions in STEM?*

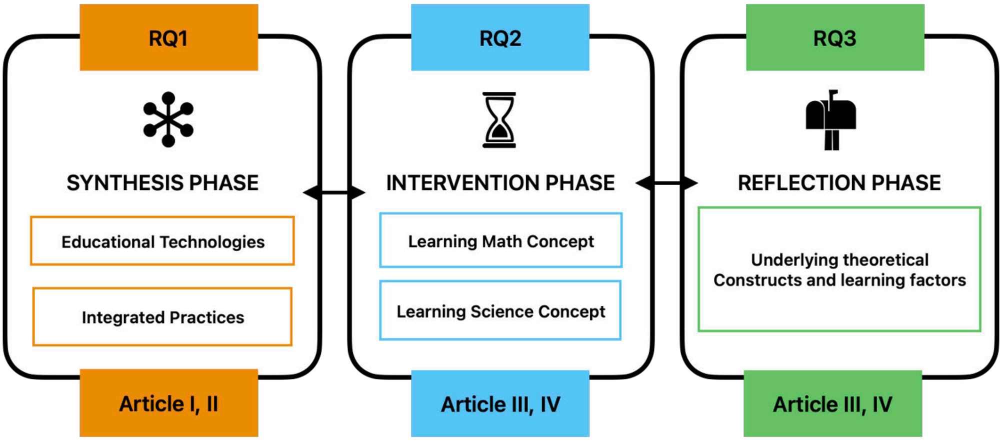

Figure 4. Methodological process of three-phase MMR design.

In addition, each phase of the research design is complementary to the next phase and thus, explained in thematic yet chronological order to get an overview and justification of the methodological choices that were considered across studies (Study I-IV)

3.2.1 Synthesis Phase

3.2.1.1 Choices of Narrative and Scoping Review

The methodological decision to utilize Narrative and Scoping Reviews over traditional Systematic Literature Reviews (SLR) was a strategic response to the nascent stage of PE, a field that necessitates a broad, multidisciplinary synthesis of AI, learning analytics, and neuroscience. A narrative review was chosen to facilitate a comprehensive mapping of PE's multidimensional approaches and to define the theoretical drivers required to tailor experiences to individual strengths and weaknesses. This was followed by a scoping review that functioned as a methodological map to analyze the extent of literature in STEM, identifying significant gaps such as the scarcity of research in K-12 settings and the lack of explicit theoretical grounding in existing personalized interventions supporting STEM literacy.

3.2.1.2 General Contexts and Settings

The first phase includes two review studies (Study I-II) conducted in adherence to the systematic approaches of reporting literature synthesis and findings (i.e., PRISMA in educational and social sciences research). **Table 1** provides an overview of both studies including each study design, research questions, and how this stage explores diverse technologies and intervention practices. The first review (Study I) was conducted on multimodal technologies in PE following a 'narrative review' approach. Although this approach is more informal in processing and interpreting the literature, unlike PRISMA, it is regarded as a comprehensive approach in providing readers a glimpse of an overview and up-to-date information on a related topic or domain (Dixon-Woods et al., 2005). The review aimed to advance the understanding of precision-based educational approaches used in schooling by mapping existing literature. The review identified key findings and explored the different ALT and instructional strategies utilized to support the learning and education sectors. Specifically, the review presented diverse research efforts, including multi-modal technologies facilitating the integration of PE practices. For instance, it explored recent technologies and applications (including MOOC, serious games, AI, LMS, mobile applications, AR/VR, and other classroom-based technologies) that are supportive in the context of PE.

Similarly, to previous research on personalization and theoretically grounded in TA, further exploration of looking at intervention approaches and integrated practices is essential to support PL. The second review (Study II), driven by motivation, was conducted to investigate key interventions supported by TEL-LA practices in STEM education across K-12 to HE. The review has examined intervention characteristics, impact on learning outcomes, and implementation challenges outlined recently in empirical literatures. While Study I informed about technologies and instructional strategies in a broad manner, it was deemed necessary to narrow towards certain fields. As such, STEM fields, particularly understanding of how TEL-LA interventions can effectively support personalized educational experiences, have remained significant gaps according to previous researches (Li & Wong, 2023; Xu et al., 2022). Thus, a thorough exploration of intervention-oriented empirical studies from 2020 to 2024 was done in Study II. The review was performed following the 'scoping review' approach, as presented by Arksey and O'Malley (2005). Scoping review is particularly useful in contexts where the research landscape is broad, emerging, or lacks well-defined parameters (Peters et al., 2021).

This rigorous synthesis phase established the qualitative framework that underpinned an MMR design, thereby transforming the subsequent quantitative interventions into targeted evaluative assessments of the unique PE framework. By categorizing technology modalities into ALPs and Technology-Mediated Learning Environments (TMLE) during the scoping phase, the research strategically justified the deployment of the ViLLE LMS to address cognitive arithmetic fluency and stereoscopic 360° VR to enhance conceptual understanding in abstract biology.

Table 1. Overview of the included reviews.

	Technology Review (Study I)	**Intervention Practice Review (Study II)**
Research Questions	RQ1. How has precision education been viewed or integrated into schooling? RQ2. How have multimodal technologies been facilitated the integration of precision education practices?	RQ1: What are the key characteristics of TEL-LA interventions in PSL? RQ2: What are the key impact areas and learning outcomes associated with TEL-LA interventions in PSL? RQ3: What are the challenges and limitations in implementing TEL-LA interventions for PSL?
Design	Narrative Review	Scoping Review
Methods	Descriptive Literature Analysis	Descriptive Literature Analysis
Database	Web of Science, Science Direct, EBSCO, ERIC, ACM Digital Library, IEEE Xplore, JSTOR, PsycINFO, Scopus, ProQuest	Web of Science, Scopus, and ACM
Search String Keywords	"precision learning", "precise teaching", "personalized learning", "primary education", "secondary education", "K12", "higher education", "tertiary education"	Learning Environment" OR "Learning Intervention" OR "Education* Technology" OR "Learning* Technology") AND ("Learning Analytics") AND ("Science" OR "Technology" OR "Engineering" OR "Math*" OR "STEM* education" OR "STEM* learning"
No of Papers Identified	499	487
Inclusion Criteria	No filters were applied regarding the publication source type (i.e. journal/conference manuscripts, book chapters). Publication must have written in English Publication timespans must have been between from 1 January 2000 to 31 December 2020.	Experimental studies and empirical studies with experiments that were published between 2020 and 2024. Studies in the domain of STEM education. Clearly described as an interventional design or fall under the category of having some interventional effects in STEM-related education using learning platforms and LA practices. Studies published in peer-reviewed journals listed under Web of Science and Scopus Databases and indexed scientific conferences (LAK in ACM).
No of Papers Included	45	31

3.2.2 Intervention Phase

3.2.2.1 Educational Settings and Learner Groups

Reflecting on the Study I and II, which were staged for determining systematically "what works" in diverse contexts and capturing intervention practices for scalable implementations (see 3.2), the Synthesis Phase has provided ALT that are useful in PL, more broadly in PE. It also identified and provided evidence on what intervention practices could be effective for implementation? Accordingly, the Intervention Phase (**Figure 5**) was carried out in four distinct stages to support the learning interventions. Driven by the overarching paradigm of PE, these intervention studies with distinguished group of learners (Study III-IV) were designed to empirically validate PSL in mathematics and science. By targeting 4^{th}–6^{th} grade for foundational arithmetic fluency and 10^{th}–12^{th} grade for abstract science, the research covers both skill acquisition in arithmetic operations (Math) and conceptual understanding in fundamental biology (Science). The particular strategy was to show soundness of personalized intervention in different yet multimodal contexts. Both studies emphasized ecological validity by ensuring interventions were timetable-aligned and curriculum-driven, making them feasible for standard school environments rather than just controlled laboratories.

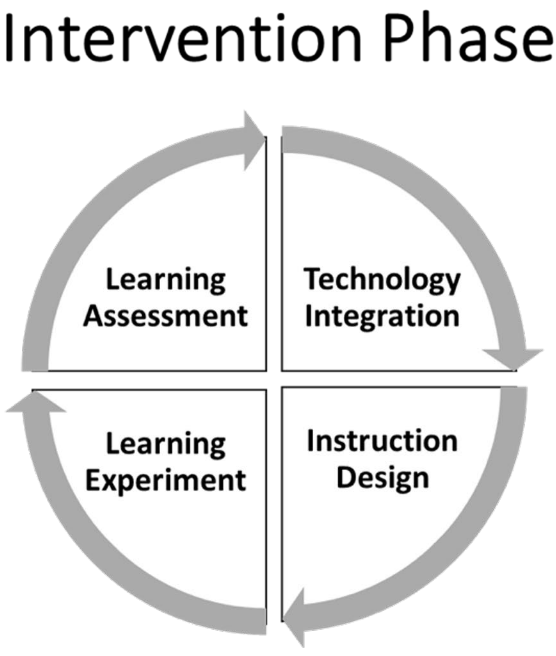

Figure 5. Four stages of intervention phase.

The first stage involved the technology components, which served as the foundation of the learning environment necessary for PL interventions. The study focused on utilizing technologies that are believed to be providing adaptive learning experiences to designated learners. Based on the findings about the ALT and intervention practices in the *Synthesis Phase*, two different technology modalities, such as Learning Management System (LMS) and VR with LA, were identified in supporting diversified yet personalized STEM learning.

The second stage, which refers to the instructional design, started with developing a PLP—supporting students with a personalized experience in learning fundamental concepts in mathematics and science. It guided the creation of intervention processes that inform stakeholders, i.e., teachers, researchers, and students, with their respective activities, such as intervention timeline and personalized support needed before and after the experiment. Researchers were also engaged in all stages throughout the intervention and played an essential role from the experiment to assessment.

In the mathematics intervention (Study III), the research team of the University of Turku collaborated with the local teachers to develop a curriculum-driven, school-grade-specific, PLP (**Table 2**). It considered the integrated 'ViLLE' LMS as the technology platform. The ViLLE is a collaborative digital learning tool (Laakso et al., 2018) utilized in supporting TEL-LA interventions. The platform was initially developed in 2005 as a programming visualization tool aimed at supporting HE Computer Science students. In subsequent years, it was adopted and systematically evaluated across other educational levels (i.e., primary and secondary education) and disciplines (e.g., mathematics, languages) (Kurvinen et al., 2020).

Table 2. Curriculum structure used in mathematics intervention.

Grade	Arithmetic Lessons		Other Featured Lessons
	Additions/Subtractions	Multiplications/Divisions	
4th	Addition and Subtraction; Addition and Subtraction with like fractions; Addition and Subtraction with unlike fractions; Addition and Subtraction with decimal numbers; Decimal numbers: Columnar addition and subtraction, comparing; Addition and subtraction with negative numbers.	Multiplication and division, order of operations; Multiplication tables; Division: partition; Columnar multiplication and long division; Remainders.	Expressions; Geometry: Lines, triangles and quadrilaterals; Coordinate plane; Fractions and mixed numbers; Decimal numbers; Hundredths; Units of length and mass; Time; Comparing and rounding integers; Negative numbers; Charts and graphs; Equations; Large numbers; Calculations with large numbers.
5th	Basic Arithmetic Operations; Reducing fractions, adding and subtracting mixed numbers; Addition and subtraction with decimal numbers.	Multiplication, and Division; Multiplying and dividing fractions; Multiplying and dividing a decimal number.	Equations, problem solving and order of operations; Percentage, Fractions, integers and decimal numbers; Basics of geometry; Circles, and Triangles; Quadrilaterals and solid figures; Large, and mixed numbers; Tables, charts and diagrams; Mean, median and mode; Probability and Statistics; Measurement, Units of mass and volume; Time and speed; Area: Exponents and units; Area: Triangles and parallelograms; Similarity and scale; Reflection, Estimating, Coordinate system and sets.
6th	Basic Arithmetic Operations; Addition and Subtraction with decimal numbers; Racer: Addition and subtraction.	Multiplication, and Division; Multiplication and division with decimal numbers; Multiplication and division with fractions.	Large, decimal numbers and fractions; Scales, geometry, measurement and maps; Triangles and Rectangular cuboids; Quadrilaterals and solid figures; Reducing fractions; Mixed numbers with common denominators; Expanding unlike fractions to common denominators; Calculating percentages; Prices, Time and units of time; Number line and equations; Negative numbers; Integers and the coordinate plane; Divisibility and factors; Functions; Calculating time intervals; Speed and time zones; Tables, graphs and charts; Probability; Racers; Problem solving.

Regarding the science intervention (Study IV), instructional design involved enriched educational content where the instructional materials covered key concepts of fundamental biology as defined in national curriculum by Opetushallitus or Finnish National Agency for Education (**Table 3**), and assessment activities were co-designed with High School teachers and implemented according to the school timetable. For this intervention, a low-end mobile-VR solution (VeeR Mini VR Goggles) has been adopted to support science learning.

Table 3. Overview of the biology concepts as defined in the Opetushallitus curriculum.

Theme	Learning objectives
Cells	Understand the structures and purposes of basic components of prokaryotic and eukaryotic cells, especially macromolecules, membranes and organelles Understand how these cellular components are used to generate and utilise energy in cells Understand the cellular components underlying mitotic cell division
Genetics	Learn the basic principles of inheritance at the molecular, cellular and organismal levels Understand causal relationships between molecule/cell level phenomena ("modern" genetics) and organism-level patterns of heredity ("classical" genetics) Understand the source of genetic variation and how it is shaped in the absence of selection
Evolution	Understand the evidence that living species share descent from common ancestry and how this fact explains the traits of living species Understand that evolution entails changes in the genetic composition of populations

In the third stage, following the finalization of the instructional design procedures and the integration of technologies, the main experiments took place. The mathematics intervention was designed to help pupils develop fluency in arithmetic operations, whereas, the science intervention was designed to support students learning abstract concepts in biology. Following the experimentation, the intervention phase adopted a LA cycle to systematically evaluate the impact of the intervention on key learning outcomes using both quantitative and behaviorally inferred indicators—supported by LA techniques (Qushem et al., 2022). Since the research's objective is to improve academic learning outcomes, learning assessment stage focused on the measurement of student's academic performance in tests (pre-post) associated with learning arithmetic operations and biology concepts. It is also important to mention that student learning involved a complex process and, thus, one measure was not enough in determining student developing fluency and mastery in skill. So, two other measures were also considered: behavior (Study III) and motivation (Study IV) besides learning performance.

In the mathematics intervention (Study III), the research study utilized a single-group quasi-experiment design to investigate the factors influencing arithmetic fluency development among primary school pupils (4^{th}–6^{th} grade). The intervention involved students using ‘ViLLE’ for a total duration of 9 months, with a requirement of using the platform in one weekly in-class lesson and for homework, without further restrictions on additional use. During this period, their academic performance and learning behavior were continuously monitored using the available LA tools.

In the science intervention (Study IV), the research study employed a quasi-experimental design in a physical classroom setting to compare Video Learning Resources (VLR) with stereoscopic 360° VR as supplements to traditional instruction for the ‘Life and Evolution’ module. Students were divided into two groups: the control group used VLR, while the experimental group used low-end mobile VR devices (VeeR Mini VR Goggles). The experiment spanned five weeks, including a pretest on week one, three weeks of instruction using assigned tools with weekly knowledge assessments, and a final post-test and psychometric survey on the last week. Students used their own devices, with the VR group being provided the VR goggles from the research team. It is also important to highlight that classroom session were indeed time restricted and focused exclusively on teaching the selected learning topics designed for the science intervention (**Figure 6**).

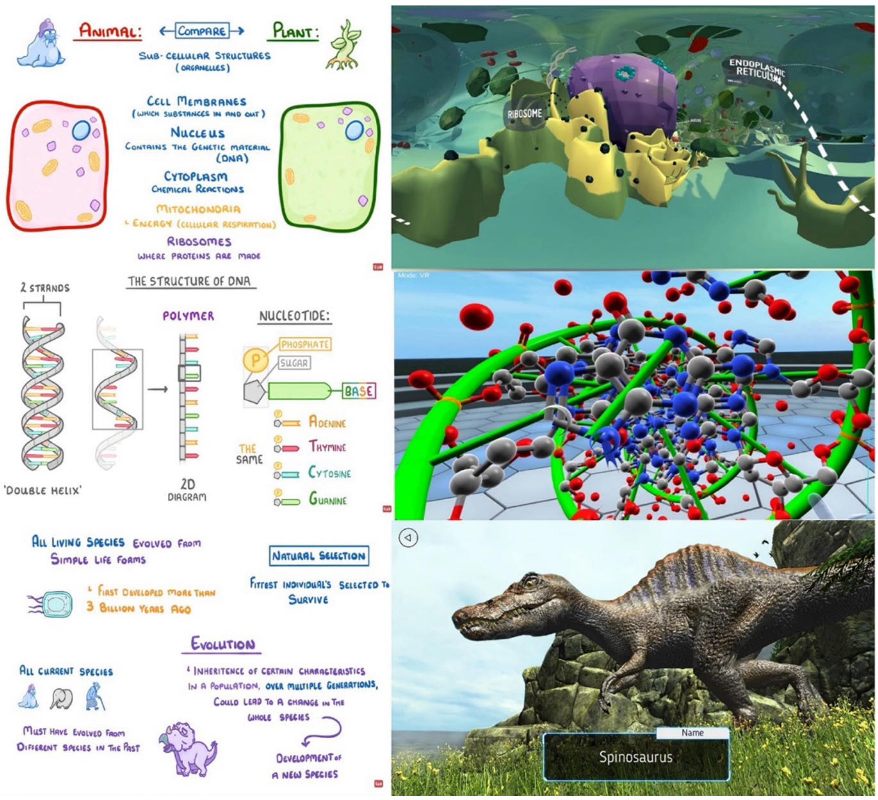

Figure 6. Comparative overview of Learning concepts used in science intervention.

These empirical intervention studies were specifically designed to address the gaps identified in the reviews, moving beyond simple measurement to use LA as a functional driver for real-time instructional adaptation. Ultimately, this research sequence ensures that the transition from broad theoretical concepts to specific classroom applications is grounded in both multidisciplinary theory and a systematic analysis of the existing evidence base.

3.2.2.2 Design, Pedagogical Principles, Roles and Activities

The intervention design for both studies were a collaborative effort with local teachers to ensure that the digital learning paths were curriculum-driven and school-grade-specific. The mathematics intervention utilized the ViLLE Learning Management System as its foundational technology over a full school year, while the science intervention was co-designed to align with the "Life and Evolution" module, utilizing low-end mobile VR (VeeR Mini Goggles) as a supplementary tool over five consecutive weeks. Both designs were structured to integrate seamlessly into existing school timetables, utilizing pre- and post-intervention assessments to measure growth.

The pedagogical principles differ between the two subjects to address specific learning goals. The Study III is grounded in the philosophy of deliberate practice, which focuses on goal-oriented activities and self-regulated learning to provide a precision-based treatment with varying difficulty levels. Conversely, the Study IV is rooted in guided discovery through active exploration and experimentation to narrow the theory–practice gap in molecular biology.

Regarding activities and roles, the technological systems, teachers, and learners function as a data-informed ecosystem. In the mathematics intervention, Learning Analytics functioned as a functional, real-time driver within the ViLLE LMS rather than a post-hoc analysis tool. Evidence of this operationalization is found in the system's ability to automate the grading of 95% of submissions and utilize Machine Learning algorithms to interpret student digital traces to adjust PLP and identify misconceptions (Qushem et al., 2022). The Science intervention leveraged the inherent feedback mechanisms of the stereoscopic VR environment, which provided students with self-paced exploratory learning that served as a form of near-real-time instructional support. This might not have served as embedded LA like ViLLE due to its post-hoc and comparative analysis in nature. However, it still remained a practical and informative method within LA for understanding active learning and positive outcomes through mechanism of guided discovery. This approach bridged the theory–practice gap by providing dynamic 3D visualizations that were tailored to individual exploration speeds, allowing for a depth of study not possible in standard instruction. Learners in the mathematics intervention engage in self-paced yet gamified practice at least 3 minutes daily while in the science intervention they had acquired the learning agency to move forward or backward through immersive scenes in the science intervention. While teachers deliver the curriculum and brief seminars during the mathematics intervention (Study III), but they had primarily used the ViLLE-integrated (LA) dashboard to monitor real-time progress, allowing them to modify courses and identify students requiring additional human intervention. In the case of science intervention (Study IV) teachers work closely with researchers to ensure that all digital instructional materials and assessment tasks are strictly aligned with the teacher's handbook and local school curriculum. They also used the technology as a bridge to communicate abstract concepts—such as molecular structures—that typically require students to use high-level critical thinking and analytical skills

The unique standard practice of these interventions distinguishes them from traditional classroom settings that often average low-performing students with the rest of the class. Instead, these studies provide precision-based treatment tailored to individual learner profiles. In the mathematics intervention, repetitive routines were replaced by gamified, data-driven practice that fosters numeracy skills through individualized feedback. In the science intervention, the intervention supplements or replaces flat textbook instruction with immersive 3D exploration, overcoming traditional barriers such as a lack of laboratory access or high equipment costs.

3.2.2.3 Data Collection, Processing and Analysis Strategies

Despite the research design adhered to the four-stage cycle of the intervention phase, both intervention studies have been done in different time and different place. **Table 4** thus provides an overview of both intervention's methodology including data collection approach, supported learning environments, analytics techniques used to assess student learning trajectories and associated factors.

The mathematics intervention (Study III) involved 720 primary school pupils (4^{th}–6^{th} grade) in the United Arab Emirates (UAE) for over nine months. Primary sources of the data collection involved information from the 'ViLLE' Learning Management System (LMS) for curriculum-driven, PL, with their academic performance and learning behavior continuously being monitored via the integrated Learning Analytics (LA) tools that recorded digital traces. Pre- and post-intervention assessments were conducted using pen-and-paper tests comprising 160 calculations with a 180-second time limit, and total correct answers served as the dependent variable. For data processing, initial participants (776) were filtered to 720 based on inclusion criteria (e.g., participation in both assessments, consistent online practice), and physical tests were marked and linked to students' digital profiles. The gathered data underwent descriptive statistical analysis, and the LMS log data, including student practicing behavior and exercise types, were explored for numeracy skill development and correlations to practice and reflection. The analysis strategy included Exploratory Data Analysis (EDA) to identify learning trends and differences, paired t-tests to examine the statistical significance of pre- and post-intervention performance differences, and Multiple Linear Regression (MLR) to determine the relationship between post-assessment performance improvement and deliberate practice, considering daily practice time, number of exercises, and total practicing days. Student performance was also categorized as improved, unchanged, or decreased based on practicing effort, and cohort-level analysis was performed to compare mathematics fluencies across educational levels, with insights from machine learning and educational data mining algorithms used to interpret real-time practicing data.

Science intervention (Study IV) involved 70 upper secondary school students (10^{th}-12^{th} grade) in Finland split into two groups: a control group using Video Learning Resources (VLR) and an experimental group using stereoscopic 360° VR (VeeR Mini VR Goggles) for five weeks in a high school biology module. Data collection included initial demographic information (gender, prior digital tool experience, cybersickness history, biology interest), pretest, weekly intermediate, and comprehensive posttest knowledge assessments, and a psychometric survey (Instructional Materials Motivation Survey) to gauge motivation, attention, and satisfaction using Likert scales. Data processing involved scoring assessments (0 for incorrect, 0.5 for partial, 1 for correct) and averaging motivation subscale items. The dataset was initially explored with descriptive statistics, and outliers were analyzed using a z-criterion score of 3.29, with normality determined by z-scores of skewness and kurtosis. The analysis strategy primarily used SPSS (version 28), employing one-sample t-tests or non-parametric Wilcoxon Signed Rank tests for comparing assessment scores against a criterion, independent sample t-tests or Mann–Whitney U tests for group comparisons, and Analysis of Covariance (ANCOVA) to control for covariates like gender, interest, familiarity, and pre-assessment scores. Non-parametric Mann–Whitney U tests were specifically used for learning experience comparisons and gender analyses due to deviations from normality, and Spearman rho correlations investigated associations between motivation and familiarity/interest.

Table 4. Overview of the Intervention studies.

	Mathematics Intervention Study III	Science Intervention Study IV
Research Questions	RQ1. How does digital deliberate practice impact student's arithmetic fluency development? RQ2. How does students' digital practice behavior influence arithmetic fluency development?	RQ1: Are students who engage with the stereoscopic 360 VR-supported instructional method performing better in the learning process compared to those who are instructed with the video-based multimedia instruction? RQ2: Are students who engage with the stereoscopic 360° VR-supported instructional method more motivated'
Course/Learning Concepts	Arithmetic Operations	Fundamental Biology Concepts
Domain	Mathematics	Science
Design	Quasi-experimental	Quasi-experimental
Method	Learning Analytics	Statistical Analysis
Population	720 students	70 students
Context	United Arab Emirates (UAE)	Finland
Settings	Primary School (4^{th}-6^{th} grade)	Upper Secondary School (10^{th}-12^{th} grade)
Analysis	Exploratory Data Analysis; Multiple Regression Analysis	Descriptive and Inferential Statistics
Tool	Learning Management System (ViLLE)	Virtual Reality (VeeR Mini VR Goggles) and Video
Assessment Indicator	Academic Performance, Behaviors	Demographics, Academic Performance, Motivation

3.2.3 Reflection Phase

This phase was designed to facilitate the identification of key findings in the form of underlying theoretical constructs and factors of PL, while also delineating recommendations as a foundation for future stakeholders, aligned with the outcomes of the synthesis and intervention phases. This approach was based on the pragmatism philosophy presented by Tashakkori & Teddlie (2003). In this section, empirical findings of the Study (III-IV) have been evaluated critically on what worked, what didn't, and why—transforming experience into actionable knowledge from intervention design to the implementation. It supports the refinement of theoretical models and helps bridge the gap between research and practice (Shin et al., 2023). Recognizing an intervention's context-specific constraints—such as those in science education—enables researchers to determine if, and in what ways, the results may be transferred to new settings in accordance with the dissertation recommendations. Consequently, recognizing both the advantages and challenges of reflective practices is a significant step for designing evidence-based learning approaches in educational interventions, particularly those aimed particularly at PE (Phua et al., 2024). The following **Figure 7** summarizes the evolution of PE utilizing TEL-LA mechanism, moving beyond uniform learner characteristics, standardized pedagogical support, and rigid outcome-based learning.

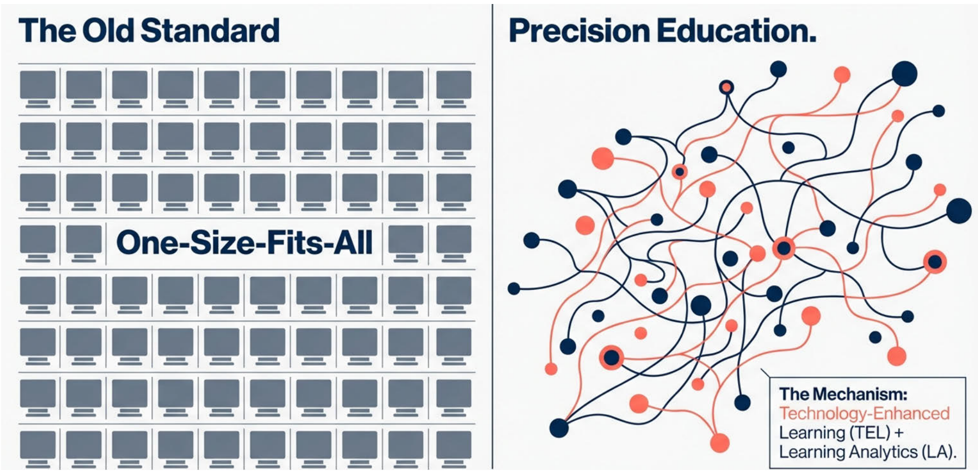

Figure 7. TEL-LA Mechanism as enabler of Precision Education.

In addition, personalization elements were operationalized in tailoring specific educational objectives. For example, the mathematics intervention emphasized elements like content, difficulty, and automated feedback, whereas the science intervention focused on pacing and deep exploration within 360° virtual scenes. These environments were governed by a hybrid decision mechanism that integrates analytics-driven algorithms to interpret student digital traces in real-time, teacher-mediated support where instructors used LA dashboards to identify at-risk students and modified courses, and learner-mediated agency through guided discovery. Finally, learner pathways served as navigational structures that guide students from their current knowledge to their learning goals. These pathways showed a structured, curriculum-driven route such as building arithmetic fluency through deliberate practice or employed cyclical processes designed to increase motivation in science concepts.

3.3 Ethical Considerations

Intervention studies included in this dissertation adhered to established ethical standards and guidelines for responsible research practice, ensuring compliance and upholding ethical safeguards to protect participants and maintain scientific integrity.

In the mathematics intervention (Study III), researchers ensured that necessary approval was obtained from the responsible committee on human experimentation at both institutional and national levels. Prior to the intervention, participating teachers and students received clear information about the study's nature and objectives. Guardians of the students were informed about the consent by countersigning a form that detailed all aspects of the study, including the protection of students' personal information in accordance with General Data Protection Regulation (GDPR) guidelines. All individual identities of 4^{th}-6^{th} grade students were anonymized. Further, the findings of the data and results are made available from the corresponding author upon reasonable request. The authors also explicitly declared no conflicts of interest.

Similarly, to science intervention (Study IV), all necessary permission from the local regional manager of upper secondary schools and the school principal was obtained as part of the standardized practice. Detailed information, both written and verbal, was provided to potential student participants regarding the study's scope and nature, including warnings about known VR side effects such as nausea or epilepsy. Students who agreed to participate provided countersigned informed consent forms, which also outlined the collection and use of their data and explicitly stated their right to withdraw from the study at any point without consequence. All sensitive data was handled in strict accordance with GDPR guidelines, and the lead author processed the data alone to protect individual identities.

3.4 Quality Criteria and Validity Measures

This dissertation followed an MMR research design in line with the pragmatism demanding insights derived from literature translate into actionable insights. The dissertation included qualitative (systematic review) and quantitative (intervention) studies to support the aim of the dissertation examining how TEL-LA intervention enhances PSL and improves academic learning outcomes in K-12. A sequential approach was adopted, beginning with the identification of adaptive tools and practices, followed by their integration into the intervention design—with particular emphasis on empirical validation. The quality criteria in the conducted studies are demonstrated through credibility and transferability in Study (I–II). In the synthesis phase, the anticipated qualities of different learning technologies, particularly their adaptivity and suitability for PL, have been fulfilled. Besides, existing evidence on TEL-LA-based intervention practices has also been characterized including the impact of their learning outcomes. All procedures were undertaken in a structured manner, guided especially by the known methodological approach, i.e. PRISMA.

In the intervention phase, both studies employed robust methodologies to ensure the quality and validity of their findings. In Study III, the quality of the instructional design was underpinned by a curriculum-driven, school-grade-specific PLP developed in collaboration with local teachers. Arithmetic fluency was consistently evaluated using standardized pen-and-paper tests administered with pre- and post-intervention, each with a fixed time limit and a clearly defined scoring protocol. Validity was addressed by strict inclusion criteria for participants to ensure observed improvements were attributable to the intervention, enhancing internal validity. Construct validity was supported by the precise definition and measurement of arithmetic fluency across all basic operations, and effort was operationalized through categorized practicing behavior linked to assessment scores.

In Study IV, key quality criteria included collaborative design of instructional and assessment activities with teachers, diverse knowledge assessment types, and the use of a psychometric survey with excellent internal consistencies for motivation assessment (Cronbach's alpha of 0.95 for Attention, 0.92 for Relevance, and 0.90 for Satisfaction). Validity measures for this study included non-randomized sampling to minimize distribution bias, controlling for gender and other covariates (prior interest, technology familiarity, pre-assessment scores) using ANCOVA, and designing challenging post-test questions to prevent ceiling effects, thereby enhancing construct validity for knowledge gain measurements.

3.5 Methodological Constraints

Like any other studies, intervention studies included limitations in achieving main objectives. Ensuring personalized STEM learning for K-12 is itself a complex phenomenon, provided that the main targets are young learners, i.e., 4^{th}-6^{th} graders, and dealing with learners in diverse contexts or geolocations corresponds to multi-perspective issues. Social disparity and background are often hard to tackle or assess only by small-scale longitudinal study or intervention. In the conduct of the two intervention studies respectively to support math (Study III) and science (Study IV), learning for academic performance improvement has certain limitations by its structure and practicality.

In Study III, a significant methodological challenge encountered was the language barrier for non-native English students in the UAE, which potentially affected their usability of the digital interface. Another practical issue involved difficulties in accurately interpreting physical assessment forms, as some students' personal identification information was unclear, leading to the exclusion of individuals whose data could not be reliably matched to the LMS database. The study's generalizability is further limited by the inclusion of only one cohort of 6^{th} graders, which prevented direct comparisons with other equivalent groups. The single group quasi-experiment design, while longitudinal, means there was no direct control group to compare against, which can make it more challenging to definitively attribute observed improvements solely to the intervention.

In Study IV, several methodological limitations were also identified. First, the generalizability of the results is limited to the local context where the study was conducted, thereby affecting its external validity. Second, the sample size of 70 participants was acknowledged as a limitation, although the researchers argued that a smaller sample allows for a deeper evaluation of student learning performance and motivation. Finally, the study acknowledged the potential for a "novelty effect," where participants' prior norms and perceptions toward the integrated technologies, especially in light of changes due to the Covid-19 pandemic, might have influenced their learning behavior and attitude. While efforts were made to control for factors like gender, prior interest, and technology familiarity using ANCOVA, the initial familiarity with VR was lower in the experimental group compared to VLR in the control group, making it impossible to ensure initial equality in this regard. The quasi-experimental design with non-randomized sampling, though chosen to eliminate distribution bias, inherently lacks the full control of a true experiment.

4 Summary of Studies and Key Findings

In this chapter, a summary of the main findings of the systematic reviews and intervention studies informed by the theoretical and conceptual framework of TEL and LA integration has been presented. While reviews were undertaken to understand the existing research landscape particularly on ALT and intervention practices, the relative novelty of PE highlighted the need for further comprehensive exploration of its adaptiveness and instructional strategies in a highly promising yet complex domain like STEM. Following the practices of converging theory and practices into evidence, the empirical studies were carried out in selective stages, forming part of the broader intervention phase within the overarching MMR design outlined in chapter 3. It underlines how TEL-LA helps conduct experiments and analyze K-12 students' learning performance, behavioral patterns, and underlying motivation associated with STEM learning. Both interventions, supported by findings of reviews, contributed to the overarching dissertation goal of improving K-12 academic learning outcomes and personalized STEM learning. Despite studies added at the end of the dissertation (see Original Publications section) for further reading, a synthesis of the main findings of Study I-IV in line with research questions answered within the research studies collectively guided this dissertation. **Figure 8** provides an overview of studies (Study I-IV) connected using a three-phase customized MMR research design (see Section 3) that informed this dissertation work, connecting theory and practice to empirical validation to knowledge and implication.

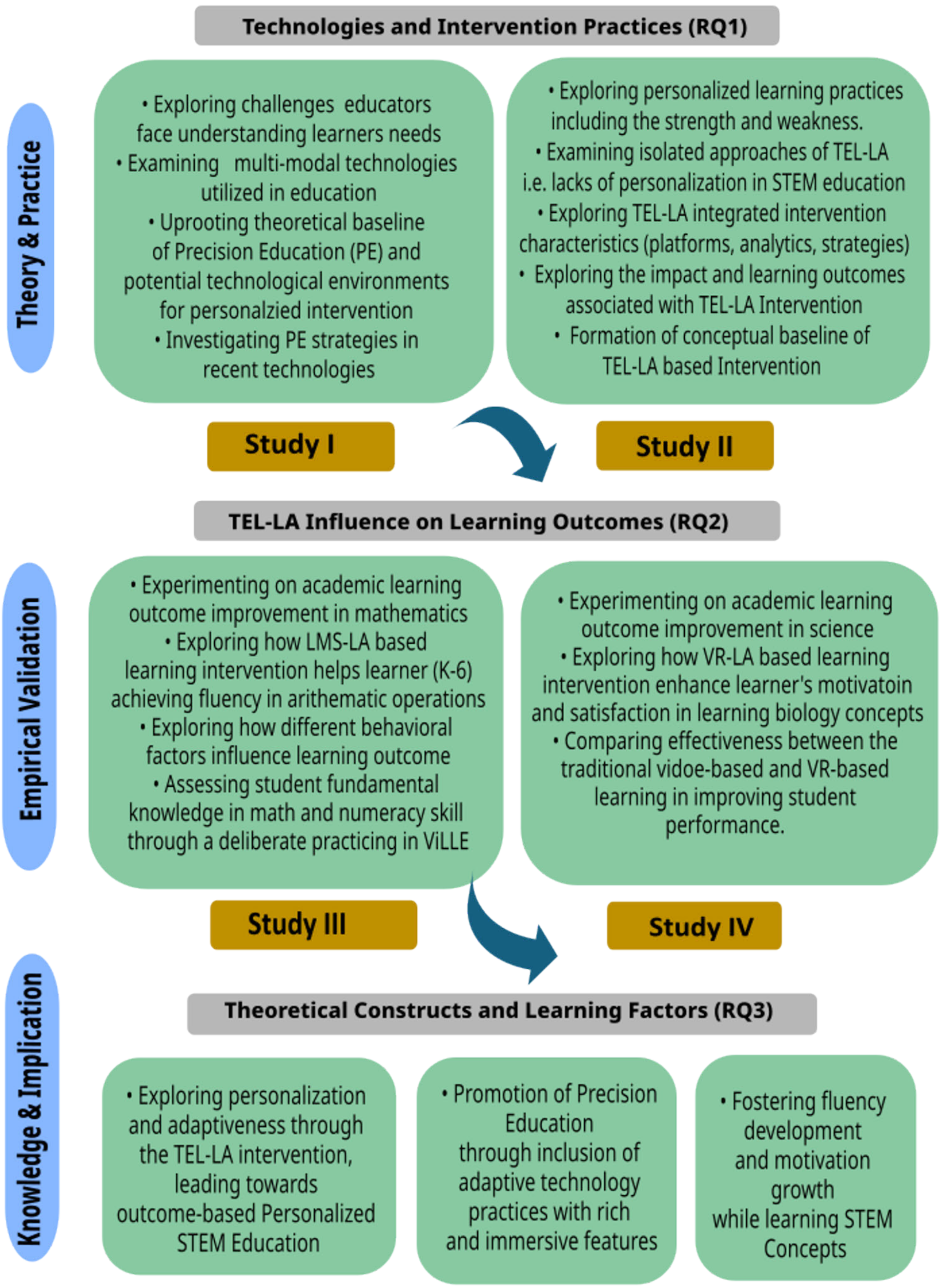

Figure 8. Overview of the publication portfolio.

4.1 Study I: Multimodal Technologies in Precision Education

The paper presents a narrative literature review exploring the integration of multimodal technologies in PE. Since the current doctoral research was influenced by adaptive and PL to support academic performance, this paper aimed to identify how PE has been viewed and integrated into schooling and how diverse technologies have facilitated providing personalized support and adaptive experiences. The researchers conducted a comprehensive keyword-based search in EdTech and related interdisciplinary databases for publications between 2000 and 2020, analyzing 45 articles that met their inclusion criteria. The review discusses various multimodal technologies and their applications within the context of personalized and precise learning approaches across different educational settings.

RQ1. How has precision education been viewed or integrated into schooling?

RQ2. How have multimodal technologies facilitated the integration of precision education practices?

In response to RQ1, the review found that PE is viewed as an approach that utilizes data to evaluate and manage learning in a more personalized way, addressing the heterogeneity of learners with specific difficulties through targeted interventions. PE is broadly split into precision teaching and precision learning, emphasizing the systematic use of learner data to implement individualized curricula. The integration of PE into schooling involves the application of various strategies and tools, such as skill-by-treatment interactions, cognitive behavioral therapy, and learning analytics to improve academic performance and engagement (**Figure 9**). Examples include the use of data from multivariate sources to enhance K-12 students' learning experiences and the development of PLPs facilitated by a clear understanding of learning goals, current knowledge, and available pathways. The study highlights that

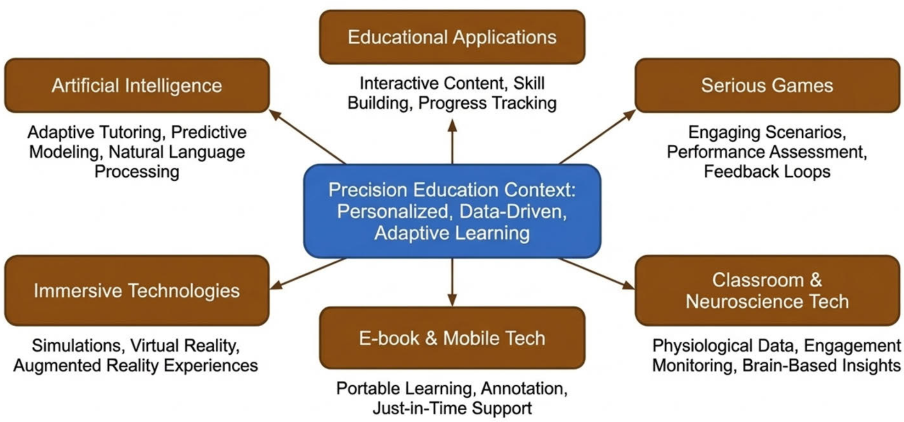

Figure 9. Supporting PE into schooling through diverse Technologies, and Pedagogies.

while the concept of connecting learning with personal life is not new, technology, inspired by its success in fields like medicine (precision medicine), is now beginning to significantly contribute to personalization in education.

In response to RQ2, the study identified numerous multimodal technologies that facilitate the integration of PE practices across various educational levels and contexts (**Figure 10**). These include AI for identifying learning styles, predicting dropouts, and detecting system interactions. Educational applications like ViLLE and iWrite support PL through feedback-based assessment and collaborative writing. Massive Open Online Courses (MOOC) are evolving to offer personalized learning experiences by simplifying content and utilizing curriculum planners and communication tools. Serious games enhance motivation and engagement through immersive learning and adaptive features powered by AI. Mobile applications and e-books provide ubiquitous access to learning materials and enable instructors to evaluate learning inefficiencies through usage logs and offer personalized features. Immersive technologies like VR and AR offer intuitive and appealing content, enhancing interaction, knowledge acquisition, and motivation. Classroom technologies, such as the Cloud Classroom and programs like ISI-Math, facilitate resource sharing, collaborative work, and individualized instruction. The review emphasizes that the adoption of multimodal tools for data collection enables instructors to better understand students' needs and tailor tasks to their competencies, suggesting that a focus on both pedagogical elements and learners' reactions to stimuli is crucial for personalized learning experiences.

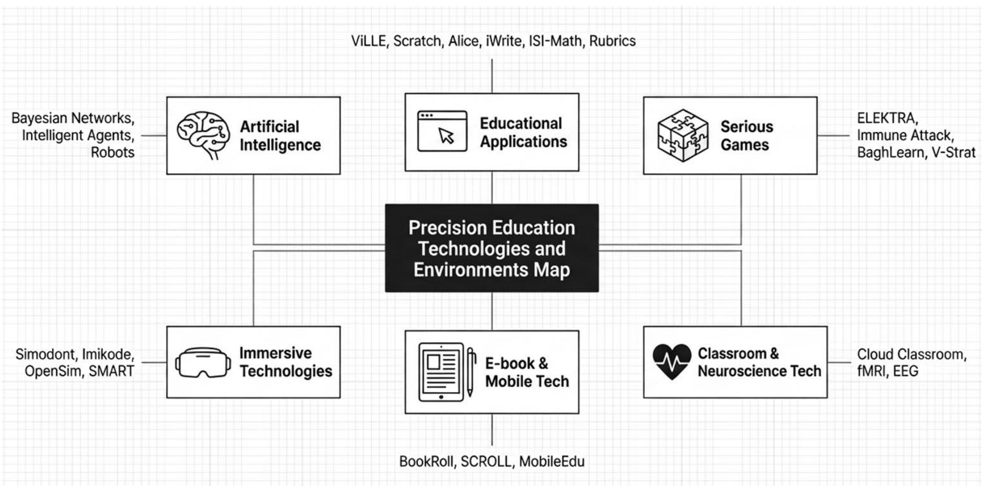

Figure 10. Multimodal Technologies that have been facilitated the integration of PE practices.

4.2 Study II: TEL-LA for Personalized STEM Learning

This study focuses on TEL-LA in PSL. It investigates the key characteristics of TEL-LA interventions in PSL, their impact areas and learning outcomes, and the challenges and limitations associated with their implementation. The field of PSL has seen substantial growth in research, with the number of studies increasing notably from 2020 to 2021. Most interventional studies were conducted in HE, followed by K-12 settings. Most of the reviewed studies were carried out in the USA, with other contributions from Australia, the Netherlands, and several other countries. Sample sizes varied greatly, categorized as small, medium, or large, with small-scale interventions being the most frequent. Interventions predominantly covered mathematics and science disciplines, though some included cross- and/or inter-related fields like computer science, information systems, and data science. The primary research design approach used was quasi-experimental, followed by randomized control trials and true experimental designs. Various learning theories provided foundations for investigating learner behavior, with Self-Regulated Learning (SRL) emerging as a key theoretical framework across several disciplines (Cloude et al., 2024; Molenaar et al., 2021; Cogliano et al., 2022; Hilpert et al., 2023; Fan et al., 2021). Other frameworks included social comparison, social norms, cognitive theory, goal complex theory, planned behavior theory, self-determination theory, metacognition theory, and desirable difficulties theory.

RQ1: What are the key characteristics of TEL-LA interventions in PSL?

RQ2: What are the key impact areas and learning outcomes associated with TEL-LA interventions in PSL?

RQ3: What are the challenges and limitations in implementing TEL-LA interventions for PSL?

In response to RQ1, key characteristics include the increasing frequency of studies in recent years, predominantly in HE and K-12, with the USA leading geographically. Interventions primarily target mathematics and science within STEM, often employing quasi-experimental designs. Theoretical underpinnings frequently involve SRL, alongside other cognitive, motivational, and social theories. Technology platforms are categorized into ALP, DLE, and TMLE, with specific examples like Canvas, MOOC, VR, MOODLE, and ASSISTments ITS being common. Analytics techniques range from various quantitative and qualitative methods to machine learning and Bayesian knowledge tracing. SRL is also the most prominent learning strategy employed, complemented by approaches like problem-based, problem-solving, and mastery-based learning. These characteristics reflect the diverse technological, analytical, theoretical, and pedagogical approaches used to personalize STEM learning (**Figure 11**).

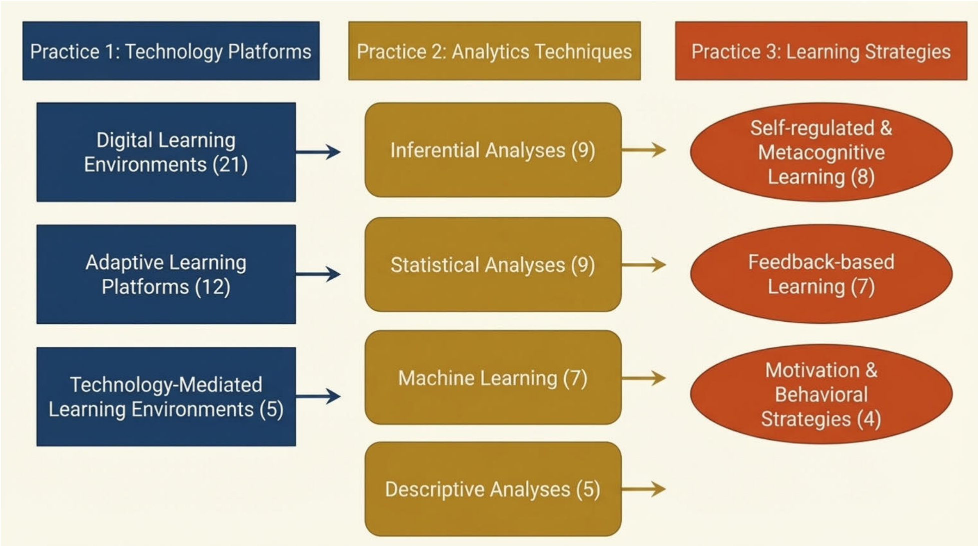

Figure 11. Key characteristics of TEL-LA interventions in PSL with number of frequencies.

In response to RQ2, the majority of studies reported a positive impact on learning performance or learner engagement. Positive performance outcomes were evidenced by improved test scores, higher course grades, increased completion rates, and increased competence. Improved engagement was shown through more regular interaction with resources, enhanced accountability via feedback, increased online active learning time, extended practice time through tutoring, and higher engagement driven by social presence and social identity. Beyond performance and engagement, positive impacts were also found in learning behavior (e.g., help-seeking, increased use of intensive strategies, adjusting video speed), cognition (e.g., enhanced quality judgment using rubrics, structured learning experiences through planning, greater learning effects with higher reflection depth), and motivation. Some studies showed varsatile impacts, including improved predictive capabilities, enhanced observation of learning patterns, more actionable feedback, better identification of at-risk students, more tailored interventions, deeper student understanding, enhanced flow experiences, richer interactions, increased self-efficacy, higher participation levels, and influence on long-term STEM career trajectories through mastery of concepts and affective states. However, the source also notes variation and complexity in outcomes, with studies reporting mixed results across performance, behavior, cognition, engagement, motivation, and emotion. Factors like procrastination, practice behaviors, difficulty adjustment, excessive practice, student motivation, and perceived task difficulty influenced learning outcomes differently. There were instances where expected improvements did not occur, or outcomes decreased, such as resistance to adaptive learning technology. The effectiveness of interventions could also vary based on factors like human support availability and student prior ability.

In response to RQ3, challenges and limitations were reported across several areas. Personalization barriers included difficulties in identifying individuals' experiences and opinions, measuring learning time effectively, and accounting for demographics, achievement goals, and varying levels of content and support. Challenges in capturing learning goals via surveys and ensuring inclusive measurement were noted, as were difficulties in identifying additional support needs and preserving learners' diverse experiences. Studies that did not adequately consider demographics or individual learning characteristics faced challenges in understanding learners and providing personalized support. Methodological constraints encompassed issues from data acquisition to analysis, such as the absence of random assignment, limited content areas or learning approaches, space constraints on instruments, and inaccurate measurement. Biases like selection bias and social desirability bias were identified as potential threats. Implementation fidelity could be challenged when using multiple platforms with different features. Limitations also arose from using quantitative investigations, leading to loss of information or erroneous statistics, and qualitative analysis potentially lacking detailed discussion for generalizable coding schemes. Data quality and validity issues were also significant. Generalizability was limited when interventions were designed with a single learning system or short duration. Sample size and missing data were reported as significant limitations, affecting the execution of interventions and learning assessments and influencing the feasibility of statistical tests. Finally, the quality of trace data from Learning Management Systems (LMS) was sometimes questionable.

4.3 Study III: LMS Analytics for Arithmetic Fluency

In consideration of personalized STEM learning, particularly supporting K-12 learners' mathematics improvement, this intervention study explored the impact of digital deliberate practice using a LMS on the arithmetic fluency performance of 720 primary education students (4^{th}–6^{th} grade) from the UAE. Building on the findings from Study I, which demonstrated useful ALT, participants of the intervention utilized the 'ViLLE' LMS at least once per week for one school year (nine months). The study determined how digital practice affects fluency development and how students' digital practice behavior influences this development. In this study, a PLP for arithmetic fluency development with various exercises was designed in close collaboration with teachers, as recommended by Hoyles (2018), and integrated into the digital learning platform. We explored how students' performance and learning behavior have impacted students developing fluency through pre- and post-intervention assessments supported by the LA practices. The following questions have been asked in attempts to explore the effectiveness of intervention supported by TEL-LA practices in advancing academic performance improvement in arithmetic operations.

RQ1. How does digital deliberate practice impact student's arithmetic fluency development?

RQ2. How does students' digital practice behavior influence arithmetic fluency development?

In response to RQ1, we have monitored 3 school groups belonging to 4th, 5th, and 6th grade, respectively, against their practicing impact from the collected LMS digital traces. Students practicing over the 15 exercises (available in the Learning path Curriculum) during the intervention shared clear indication of student's knowledge development in the arithmetic operations (**Table 5**). For instance, 4th grade students showed a clear preference (54% of the total submissions) for the Mathematics Driller, the Mathematics Quiz, and the Calculation Order exercises. In contrast, exercises like Mathematics Decimals, Calculations Fractions, Cards Game, and Bubble Mathematics were not so appealing to them (less than 1% of the total submissions). Looking into the students practiced exercises (i.e., addition and subtraction) as well as their pre-post assessment results, we found most of the learners were able to significantly improve performance in arithmetic operations, reflected in positive correlations (**Table 6** and **Table 7**).

Table 5. Descriptive statistics of exercises with cumulative percentage scores.

Exercises*	Lessons	4th Grade			5th Grade			6th Grade		
		f	%	Score	*f*	%	Score	*f*	%	Score
Math Quiz	ARI	654	10.09 %	157	4	0.46 %	44	3	0.31 %	26
Math Calculation Forms	NUM	90	1.39 %	184	7	0.81 %	55	103	10.76 %	146
Math Calculation Rows	ADD/SUB	526	8.11 %	202	128	14.87 %	155	124	12.96 %	371
Math Decimals	DEC	3	0.05 %	44	33	3.83 %	130	22	2.30 %	141
Calculation Fractions	FRA	4	0.06 %	59	19	2.21 %	75	57	5.96 %	179
Fill in Exercise	SUB	137	2.11 %	47	0	0.00 %	0	0	0.00 %	0
Audio Arithmetic	ARI	536	8.27 %	179	257	29.85 %	258	68	7.11 %	261
Match Pairs	MAO	122	1.88 %	122	21	2.44 %	45	12	1.25 %	72
Math Driller	QUA	2060	31.78 %	419	133	15.45 %	256	164	17.14 %	644
Cards Game	—	0	0.00 %	0	0	0.00 %	0	1	0.10 %	30
Calculation Order	ARI	777	11.99 %	616	57	6.62 %	122	213	22.26 %	559
Number Exercise	ARI	597	9.21 %	129	27	3.14 %	54	95	9.93 %	36
Bubble Math	—	0	0.00 %	0	0	0.00 %	0	3	0.31 %	22
Runner	ADD/SUB	613	9.46 %	127	131	15.21 %	101	86	8.99 %	89
Number Composition	NUM	363	5.60 %	50	44	5.11 %	87	6	0.63 %	60
Total	—	6482	100.00 %	2331	861	100.00 %	1383	957	100.00 %	2637

*Exercises: (Category 1) ARI: Arithmetic operations, Sum and Difference, Basic Arithmetic operations, Columnar Addition and Subtraction; ADD/SUB: Addition and subtraction; (Category 2) Listen and Visualization; (Category 3) NUM: Fill in missing number, Number identifications, Placing numbers; (Category 4) DEC: Decimals; FRC: Fractions; SUB: Subtractions; (Category 5): MAO: Matching Arithmetic Operations; (Category 6): QUA: Quartiles.

Table 6. Statistical analysis of participants' pre- and post-math assessment results

Cohorts			Pre-assessment		Post-assessment		*t*-test	
School	Grade	N	x̄	s	x̄	s	*t*	*p*
School 1	4	236	46.14	16.97	53.72	16.06	9.20	0.00001
School 2	4	161	44.64	17.53	56.65	19.57	10.9	0.00001
School 4	4	93	46.41	17.65	58.60	19.73	11.19	0.00001
School 1	5	172	53.49	20.64	62.13	17.97	7.58	0.00001
School 3	5	29	50.34	13.80	58.34	17.23	4.97	0.00003
School 3	6	29	57.83	22.35	73.86	28.54	6.80	0.00001

Table 7. Overview of participants' performance associated with arithmetic fluency development.

Evaluation	N	x̄	s	*t-test*	*p*	*Sig.*	Cohen's *d*
Pre-assessment	720	48.24	18.60	19.69	$<2.2e^{-16}$	0.01	0.51
Post-assessment	720	58.01	18.98				

In response to RQ2, we explored whether students' digital practice behavior impacts learning outcomes. Given that students practicing behavior was positively correlated with improvement in learners' fluency performance. We added an additional new measurement to compare students' performance (score) against the practice time. The main objective of this effort was to identify the optimal practice time before no further improvement in participants' fluency skills could be demonstrated. For this comparison, quartiles from the total number of digital submissions were taken into consideration and linked to the individuals' assessment scores. In our observation, students practicing behavior was positively correlated with improvement in their fluency performance (**Figure 12** illustrates the correlation between student performance over time). For example, 6th grade students, who practiced more, showed greater improvement and no performance decrease. The study also categorized students based on their 'effort' (combining practice time and number of exercises completed) and linked it to performance improvement. It was observed that consistent practice over time led to better fluency, although some students who practiced a lot did not show improvement, warranting further investigation. LMS features like gamification and Learning Analytics are suggested to play a role in enhancing numeracy skills through structured and personalized practice.

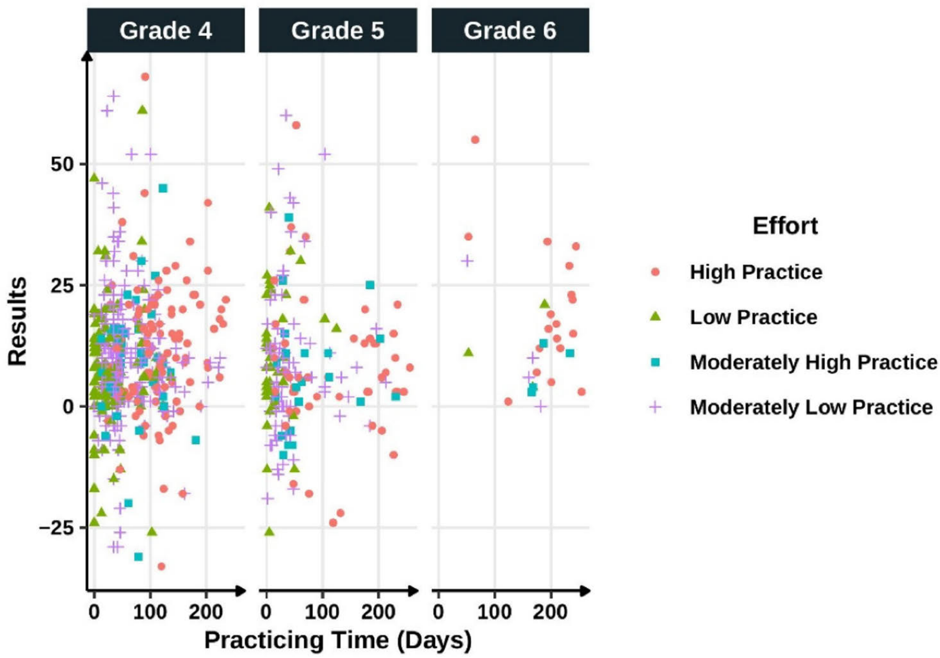

Figure 12. Clusters of effort-performance.

This conclusive analysis of the findings revealed that the vast majority of students (97% of 6th graders, 83% of 4th graders, and 76% of 5th graders) demonstrated a positive improvement in their arithmetic fluency development over the nine-month period of using the LMS. Multiple Linear Regression analysis indicated that students need to practice deliberately for approximately 68 days (a minimum of 3 minutes a day) before seeing any substantial improvement in their performance. The study concluded that there is a positive association between the digital learning platform and students' arithmetic fluency development.

4.4 Study IV: VR versus Video in Biology Education

This intervention study compared the effectiveness of video learning resources (VLR) and stereoscopic 360° VR as supplements to traditional instruction in a high school biology course focusing on the 'Life and Evolution' module. The study involved 70 upper secondary school students who were equally divided into a control group using VLR and an experimental group using low-end mobile VR (VeeR Mini VR Goggles). In this study, an interactive learning approach using VR, substituting traditionally used instruction materials for learning science, was utilized influenced by the intervention approach by Erbas and Demirer (2019). We investigated the impact of different learning approaches on students' academic performance (factual and conceptual knowledge gains measured through pre-, intermediate, and post-assessments) and learning motivation (relevance, attention, and satisfaction measured via a psychometric survey). The educational intervention was conducted over five consecutive weeks. The following questions have been asked in attempts to explore the effectiveness of intervention supported by TEL-LA practices in advancing academic performance improvement in biology concepts learning.

RQ1: Are students who engage with the stereoscopic 360 VR-supported instructional method performing better in the learning process compared to those who are instructed with the video-based multimedia instruction?

RQ2: Are students who engage with the stereoscopic 360° VR-supported instructional method more motivated'?

In response to RQ1, academic performance was evaluated through pre-assessment, intermediate assessment, and post-assessment scores covering topics like cells, genetics, and evolution and explored through descriptive statistics and subsequently analyzed using inferential methods (**Table 8**). At the start of the study (pre-assessment), students in both the VR (Experimental Group—EG) and VLR (Control Group—CG) conditions had similar initial knowledge levels. Their median scores (Table 3) were significantly below 0.50 for Cells and mean scores significantly below 0.50 for Genetics, while scores for Evolution did not significantly differ from 0.50, suggesting Evolution was the topic students knew relatively most about initially. Intermediate assessments, conducted weekly on the subject taught, showed that students in both groups achieved satisfactory scores (above the criterion value of 0.50) for Cells and Evolution. For genetics, only the EG (VR) had a mean significantly higher than 0.50, although the difference between the two groups was small and not statistically significant.

Table 8. Descriptive statistics for the pre- and intermediate biology learning assessment results

	Control group				**Experimental group**				
Test	*M*	*SD*	Test for difference from 0.50	*p*	*M*	*SD*	Test for difference from 0.50	*p*	Condition difference test
Pre-assessment									
Cells	0.41	0.13	$z = -3.53$	< .001	0.39	0.10	$z = -4.52$	< .001	$z = -0.72$, $p = .475$
Genetics	0.35	0.13	$t(34)=-6.70$	< .001	0.35	0.11	$t(34)=-7.52$	< .001	$t(68) = -0.19$, $p = .848$
Evolution	0.48	0.13	$t(34)=-1.05$	.300	0.47	0.09	$t(34)=-1.97$	.058	$t(68) = 0.41$, $p = .828$
Intermediate assessment									
Cells	0.67	0.13	$z = 4.81$	< .001	0.69	0.12	$z = 5.02$	< .001	$z = -0.85$, $p = .394$
Genetics	0.53	0.29	$t(34)=0.70$	.490	0.59	0.20	$t(34)=2.83$	.008	$t(68) = -1.01$, $p = .316$
Evolution	0.64	0.16	$t(34)=5.20$	< .001	0.68	0.14	$t(34)=7.51$	< .001	$t(68) = -1.04$, $p = .303$

The final assessment (posttest) used questions selected as the most challenging from the intermediate tests. Independent sample t-tests revealed no statistically significant differences between the students in the VR condition and the VLR condition for the post-assessment scores on Cells, Genetics, or Evolution. Analysis of Covariance (ANCOVA), which controlled for factors like gender, interest, familiarity, and pre-intervention scores, also found no significant condition effect, gender effect, or interaction effect for the post-assessment scores on any of the topics. Therefore, the study concludes that stereoscopic 360° VR instruction did not result in better learning outcomes than VLR instruction. Equally good and quite similar academic performance results were achieved on both conditions. This aligns with other research indicating that different visualizations can be sufficient for the acquisition of knowledge in biology and molecular topics. In response to RQ2, the study also examined the potential of VR and videos to influence learning motivation. Motivation was evaluated using the Relevance, Attention, and

Satisfaction scales from the Instructional Materials Motivation Survey (Keller, 2010). These scales measure how well the material relates to prior knowledge/needs/future use (relevance), avoids boredom and holds attention (attention), and provides enjoyment/accomplishment (satisfaction). Analysis using Mann–Whitney U tests showed that the experimental group (VR) reported significantly higher relevance, attention, and satisfaction compared to the control group (VLR) in **Table 9**.

Table 9. Descriptive statistics for motivation in learning biology concepts.

	Control group			Experimental group			U	z	p
Test	M	SD	Mdn	M	SD	Mdn			
Relevance	3.14	0.96	2.33	3.97	0.42	4.22	381	2.81	.005
Attention	3.16	0.93	2.42	4.11	0.40	4.17	281	3.98	< .001
Satisfaction	3.05	0.99	2.50	4.17	0.43	4.33	163	5.40	< .001
Total Motivation	3.13	0.95	2.37	4.08	0.41	4.22	233	4.50	< .001

Overall, the motivation was concluded to be higher in the VR group. Separate gender comparisons indicated that there were similar motivational experiences for boys and girls within each condition. Interestingly, familiarity with VLR was negatively associated with motivation in the control group (**Table 10**), meaning students more familiar with videos were less positive about the relevance, attention, and satisfaction they perceived. This association was not found for familiarity with VR, possibly because students were less familiar with this technology. The findings suggest that the use of stereoscopic 360° VR has a considerable advantage in terms of motivating students. This is important because higher motivation can lead to better long-term memory retention and can help students see the utility and relevance of what they are learning.

Table 10. Spearman rho correlations between familiarity and interest and motivation.

	Control group		Experimental group	
Variable	Familiarity	Interest	Familiarity	Interest
Relevance	-.46**	.04	.11	-.19
Attention	-.54***	.04	.01	-.03
Satisfaction	-.43**	.02	.11	-.16
Total Motivation	-.43**	.02	.04	-.06

In summary, while the study found no significant difference in students' academic performance or knowledge gains when comparing stereoscopic 360° VR and video learning resources, the results clearly show that students experienced significantly higher levels of learning motivation, attention, and satisfaction when using stereoscopic 360° VR.

4.5 Cross-Study Synthesis and Integration

Both the systematic reviews and empirical studies addressed on TEL-LA application in PSL highlight numerous practical issues that can profoundly impact early-stage learner's academic learning outcomes. These issues spanned through design, implementation, technological infrastructure, pedagogical approaches, and evaluation methodologies, particularly in the context of personalized learning interventions.

The dissertation's first study (Study I) delved into looking at various technologies that were found useful to support PL in schooling or the education sector in general. While there were diverse technologies that were being identified aligning within the context of personalization, specific technologies like Canvas, MOOC, VR, MOODLE, and ITS were frequently used and pivotal for such cause. VR and AR offer interaction opportunities, appealing content, and contributes in knowledge acquisition, commitment, motivation, and academic achievement through high representational fidelity and simulation of abstract concepts. From the motivation and literature gaps that educational strategies and alternative integrated instructional approaches remain underdeveloped, especially to support complex concepts and applied fields of STEM in K-12, TEL and LA can be highly effective and supportive in personalization. That guided the dissertation's second study (Study II) aimed at looking at what the key characteristics of TEL and LA approaches are and how TEL-LA supports personalized STEM learning. The study expands the corpus of knowledge on how TEL-LA interventions are determining the learning outcomes and measuring the learning impact across education contexts. The review led to the identification of various combinations of digital tools, analytics approaches, and adaptive strategies that transformed specific areas of STEM learning with measurable positive outcomes.

The third and fourth studies (Study III-IV) were conducted not only to support personalized STEM learning initiative in K-12 setting but also to evaluate empirical evidence raised in the previous studies. Intervention design of the experimental studies was supported with the development of PLPs and integration of ALT such as LMS and VR. Simultaneously, valuable learning-related data, particularly time-on-task, behavioral patterns, and self-reported motivation, has been captured through the practice of Learning Analytics. In the third study (Study III), TEL-LA intervention utilizing ViLLE LMS with built-in LA features were adopted to foster arithmetic fluency development. In addition to extend our empirical valuation and successful intervention to support mathematics learning, we aimed at diversifying our attempt to develop approaches to support K-12's personalized learning in science. Therefore, in fourth study (Study IV), intervention study was modified to accommodate immersive technology, particularly VR. Since students traditionally use video-based instruction, we conducted a comparative experiment to see whether VR also can improve student biology learning and have a higher impact on academic performance than traditional video-based learning.

Designing intervention utilizing TEL and LA integrated practices served as a potential personalized learning approach in supporting PSL. Both studies exhibited that leveraging student engagement behaviors and motivation aspects demonstrated not only to be effective learning strategies, but it can guide educators maximizing student learning outcomes leading towards PE.

5 Discussion and Conclusion

This chapter discusses the research findings, guided by the overarching research questions: How can TEL-LA intervention transform personalized STEM learning to improve academic learning outcomes in K-12? The discussion is structured to address the research questions and is followed by sections on theoretical, empirical and methodological contributions. This chapter also reflects on the findings to propose practical implications for teachers and stakeholders with rightful technologies, instructional design, and effective implementation of PSL. The chapter also outlines the overarching limitations, highlighting both theoretical and empirical constraints that inform the proposed future directions. The chapter concludes with a final reflection affirming the dissertation main position towards supporting a timely needed initiative of PSL in revamping the K-12 sectors to encounter the demands of future talents and skill development.

5.1 Addressing the Research Questions

All four studies focus collectively on the integration of ALT and intervention driven outcomes for K-12 STEM learning, with a particular emphasis on the learning performance, behaviors and associated motivation. They offer insights into useful intervention practices designed to support personalized learning approaches for learning mathematics and science. In revisiting the research questions, this study sought to explore how the methodological approaches adopted in the included studies (Study I-IV) aligned with and supported the overarching aims of the dissertation. The first two studies built the foundation of what technology and intervention practices should be utilized for enabling adaptive learning and impact on student learning outcomes, the second two studies showed how those technologies and integrated practices have been implemented throughout intervention studies.

RQ1: How can Technology-Enhanced Learning and Learning Analytics support Precision Education and personalized STEM learning?

RQ1 sought to gain insights into a broader overview of PE inspired by precision medicine as well as how personalized learning and approaches practiced and integrated into school through multimodal technologies (AI, LMS, MOOC, games, mobile, VR/AR, classroom tech). In addition to theoretical underpinnings of PE, RQ1 broadened to explore an integrated approach suitable for measuring the learning outcomes particularly TEL and LA for Personalized STEM learning. This question was motivated by the necessity of uncovering various forms of education and learning technologies as well practices for adaptive intervention design or pioneer in facilitating tailored support on the PL. In answering RQ1, both Study I and Study II investigates and reviews the growing field of PE and PL leveraging technologies and practices from the latest literatures. While Study I contributed to defining the multimodal learning and support and articulated useful technologies like ViLLE, VR and beyond tradition education approaches, Study II demonstrated specifically on TEL-LA intervention practices for personalized STEM learning, detailing characteristics, observed positive/mixed learning impacts, and implementation challenges. These studies built the foundations of what technologies should be utilized and what intervention practices to be applied for experimentations and evaluation of K-12 student academic Learning outcomes in STEM. Both studies highlight the potential of technology and intervention practices to enhance PL while acknowledging inherent complexities and challenges. RQ1 also laid the foundation of theoretical baseline of the dissertation.

RQ2: How do Technology-Enhanced Learning and Learning Analytics-based interventions influence academic learning outcomes in personalized STEM learning?

RQ2 sought to examine the potential of TEL and LA integrated within the intervention design and how they might offer insights into students' learning and support academic learning outcome in mathematics and science. This question was informed by the gaps in the literature on personalized learning approaches and intervention in STEM particularly K-12 settings (Wong et al., 2023). In answering RQ2, ALT i.e. ViLLE and VR played a crucial role in both educational interventions (Study III-IV), though each technology and their primary impacts differed. Complementing the technological tools, various research practices, including aspects of Learning Analytics (LA) through rigorous data collection and analysis, were employed to evaluate the influence on learning outcomes. The mathematics study (Study III) utilized an LMS (ViLLE) with built-in LA features as the core instructional tool for arithmetic operations fluency development. This intervention found a statistically significant positive improvement in arithmetic fluency for the vast majority of students. The LMS design, which included educational games, customized difficulty levels, automated feedback, and PLPs, facilitated deliberate digital practice, which was strongly associated with performance improvements. This demonstrates how the specific technological platform (LMS) and its embedded features (gamification, feedback, personalization) can be designed to influence cognitive outcomes by promoting specific, beneficial learning behaviors like practice. Crucially, deliberate practice within the LMS was identified as a critical factor for substantial improvement in arithmetic fluency, necessitating consistent engagement, exemplified by at least 68 days with a minimum of 3 minutes per day. In the high school biology study (Study IV), the intervention compared stereoscopic 360° VR with Video Learning Resources (VLR) as supplements to traditional instruction for abstract concepts. While this study found no statistically significant difference in academic performance (factual or conceptual knowledge gains) between students using VR and those using video, it revealed a significant positive influence of stereoscopic 360° VR on student motivation, including higher reported relevance, attention, and satisfaction. This suggests that the design of the technology itself – specifically, the immersive and stimulating experience offered by VR, which provides dynamic visualization and a sense of presence – can be a powerful factor for influencing affective outcomes like motivation, even if it doesn't always translate directly to improved knowledge acquisition compared to other visualization methods like video. Thus, while the biology study (Study IV) found VR primarily influenced affective outcomes like motivation, the mathematics study (Study III) demonstrated that the LMS, supported by LA data on practice, directly impacted cognitive outcomes like fluency. RQ2 also helped to showcase empirical baseline of the dissertation.

RQ3: What theoretical constructs and learning factors can be leveraged to improve learning outcomes through Technology-Enhanced Learning and LA-based interventions for personalized STEM learning?

RQ3 sought to generate lessons underlying influential variables of the design and implementation from the TEL-LA supported intervention studies. This research question was motivated by the need of increasing demand for knowing what elements and aspects can be assessed to influence in student academic learning outcomes. It also underscores the concern that many studies focused PL with limited understanding and lack on the diversifying accommodating multimodal technologies and adaptive intervention practices for K-12 STEM learning (Li & Wong, 2023; Li et al., 2020; Simon & Zeng, 2024). The mathematics (Study III) and science (Study IV) interventions provide a comprehensive understanding of underlying theoretical constructs and learning factors, demonstrating how they synergistically contribute to enhanced K-12 STEM education, primarily through the lenses of personalization, TA, and the critical development of fluency and motivation. Personalization serves as a core theoretical driver across both interventions, enabling tailored learning experiences. In Study III, the ViLLE LMS specifically enabled personalized and SRL through curriculum-driven, school-grade-specific PLPs that allowed for customized difficulty levels. While not the primary focus in the Study IV, the ability to enrich educational content, allowing students to delve into topics with greater depth and breadth, contributed to a form of personalization. These personalized approaches were critically supported by diverse TA. Ultimately, these personalized and technologically enhanced learning environments directly contributed to fluency development and motivation growth. In the Study III, the TEL-LA integration fostered significant positive improvement in arithmetic fluency by addressing both motivation and instructional support. The adaptive LMS-based tool, with its gamification elements and PLPs, demonstrably increased student engagement and interest in problem-solving, fostering self-efficacy and self-regulation of learning. In the Study IV, the use of VR significantly enhanced students' learning motivation, confidence, and satisfaction compared to traditional video learning resources. This immersive technology provided a more realistic and stimulating experience that was found to be more pleasurable for students, positively impacting long-term memory retention. The VR-based intervention successfully motivated participants in terms of attention, satisfaction, and perceived relevance. While not directly leading to higher knowledge gains in the VR vs. video comparison, the study emphasized that technology or computer-enhanced learning, to be effective, needs to be systematic and regular, underlining the importance of consistent engagement for optimal outcomes. Thus, both interventions collectively highlight that effective personalized STEM learning in K-12 is a holistic endeavor, integrating curriculum-driven personalization, leveraging specific TA for either skill development or engaging visualization, and fostering both cognitive gains (like fluency) and crucial affective outcomes (such as motivation, self-efficacy, and satisfaction) through structured, deliberate practice and immersive experiences.

5.2 Dissertation Contributions

This dissertation aims to present theoretical, empirical, and methodological significance. The contributions are listed below.

5.2.1 Theoretical Contributions

The *Precision Education Conceptual Framework of TEL-LA-PSL* (**Figure 2**) is one of the theoretical contributions this dissertation makes to the field of Personalized and Intervention Based Learning design in K-12's STEM Education. The framework is characterized by an articulation of an initial design (Walkington & Bernacki (2020) which guided its dimensions, and it stands in contrast to the conventional "one-size-fits-all" education system (Li & Wong, 2020). Thus, *Precision Education Conceptual Framework of TEL-LA-PSL* was developed based on the findings of the problem and needs analysis stages of the PL-inspired process followed in this dissertation. For instance, the findings from the Study I showed that despite the existence of educational technologies to support classroom activities and learning, there were not technologies that are adaptive or interactive, even it does there should be necessary to test in empirically whether technologies are inclined to support and effective in learning. The technologies should consider adaptable features that consider learner’s learning characteristics. Considering these factors, a personalized learning approach should tailor educational experiences to each student’s strengths, needs, and interests (Li & Wong, 2020; Xie et al., 2019) and involve their voices and choices in what, how, when, and where they learn. It should also optimize pacing and instructional strategies to meet their specific requirements (Li & Wong, 2023).

Study II therefore examined the integration of TEL and LA approaches to highlight another essential dimension of PLD: student engagement within learning environments. LA is particularly feasible here because it allows us to capture and measure learning characteristics—learning data—originating from learning environments. Despite extensive research on PL, K–12 STEM education still lacks intervention-based instructional designs. Study II addresses this gap by reviewing literature on TEL and LA, examining ALT and data-driven practices that underpin TEL–LA interventions for PSL.

This dissertation makes also theoretical contributions by re-establishing learning theories into the PE conceptual framework bridging between TEL-LA integration and PL in STEM. This opens new research possibilities by combining personalization learning theories, TA with data and analytics, and educational research into STEM. Supported learning theories have been key driving forces behind personalization in learning, with ALT and assessment techniques playing an integral role. These theories not only help contextualize the phenomenon but also support this dissertation in bridging the design and implementation of personalized learning interventions in K–12 settings, ultimately aiding individual learners in developing scientific literacy in mathematics and science.

Personalized Learning Design often invokes broad constructivist or social-constructivist paradigms to justify learner-centered instruction, yet these frameworks alone lack the granularity needed to guide technology-enhanced interventions. By foregrounding CP, TA, and the ZPD, we move beyond general principles of knowledge construction to a more actionable theoretical foundation. Context Personalization (Walkington & Bernacki, 2020) specifies how learners’ interests and cultural funds of knowledge become levers for engagement, rather than leaving “meaningful contexts” implicitly defined by instructors. Technology Affordances (Gibson, 1977; Gaver, 1991; Fayard & Weeks, 2014) translate constructivist claims about active learning into concrete design criteria—adaptive sequencing, multimodal feedback, and interface cues that learners perceive and act upon and ZPD

(Vygotsky, 1978; Allal & Ducrey, 2000) supplies a developmentally sensitive metric, ensuring that TEL-LA interventions stay in the sweet spot between independent success and mediated challenge. Together, these constructs challenge the field to abandon conventional theories in favor of a layered approach that explicitly connects learner characteristics, digital design, and formative assessment.

Theoretically, privileging these three constructs enriches education research by offering actionable measures for both design and evaluation of personalized STEM interventions. Context Personalization sharpens our understanding of how situational interest evolves into sustained conceptual investment, enabling hypotheses about which cultural frames most effectively bridge students' prior knowledge with STEM abstractions. Technology Affordances refract long-standing debates about active learning into the ALPs, prompting new theory on how PLPs and interactive engagement shape cognitive and motivational processes. Finally, integrating ZPD within TEL-LA intervention closes the loop between design intent and outcome measurement: it not only prescribes how to sequence tasks but also drives real-time analytic models that detect when learners are stretching their capabilities. In sum, this reframing transform constructivist ideals from philosophical groundings into testable, scalable theories—fueling richer, data-driven investigations of personalized STEM education.

5.2.2 Empirical Contributions:

Building on previous discussions and a thorough review of existing literature, it is evident that personalized STEM learning remains a highly demanding and insubstantially explored field in K-12—underscoring the need for continued research and innovation in this area. Reflecting on the suggestion of Grimm et al. (2023) who supports a stronger individualization of STEM learning environments, this research work expanded not only to support theoretically on PE, but also practically empirically testing the integrated approach particularly TEL-LA in PSL. This reflects the core impetus driving the development of the PE conceptual framework, offering a response to both research-based needs and design imperatives. It demonstrated interventions supported by TEL and LA integrated models in mathematics and science learning concepts, contributing on PSL in multi-modal contexts.

Empirical findings from the multi-stage interventions in science (Biology using VR) and mathematics (Arithmetic Fluency using an LMS) provide crucial insights that inform the strategic use of ALT and LA practices. These insights are instrumental in fostering better personalized STEM learning and extending comprehensive support in K-12 settings, directly addressing several identified research gaps. Thereby, the following overarching empirical contributions can be made:

5.2.2.1 Instructional Design in Multimodal Contexts

For abstract subjects like Biology, developing instructional content with multidimensional elements, high-representational fidelity, and acoustic feedback can greatly enhance student experience and promote conceptual understanding. VR, with its ability to render virtual scenes from different angles and foster a sense of physical presence, contributes to spatial awareness and understanding of abstract concepts. Adopting curriculum-driven, school-grade specific PLPs and providing open educational resources are highly recommended when integrating digital learning tools. This approach, coupled with SRL and automatic feedback, can promote competencies and maintain student interest. Not all instructional approaches or exercise types are equally efficient in training a target skill. Therefore, providing a variety of gamified exercises in a structured and personalized form is important for optimal student performance and engagement.

The findings advocate for the systematic introduction of simulations in abstract subjects to facilitate the development of conceptual congruence and aid in knowledge comprehension during scientific discovery. Immersive technologies like stereoscopic 360° VR have a considerable advantage in enhancing learning motivation, confidence, and satisfaction compared to VLR. Students using VR reported significantly higher relevance, attention, and satisfaction. This increased motivation can lead to longer-term memory retention. The perceived relevance, where students felt what they were learning was useful, was also higher with VR, suggesting greater utility and applicability of learned knowledge. Digital Learning Environments integrating gamification elements, immediate feedback, and PLPs significantly increase learners' extrinsic motivation, promote self-efficacy, and facilitate self-regulation of learning. This design compliance in an LMS can directly lead to enhanced numeracy skills and fluency. The studied VR/VLR- and LMS-based instructional approaches appear promising for mitigating the gender gap normally found in STEM subjects, as no significant gender differences were observed in performance or motivation.

5.2.2.2 Addressing K-12 Research Gaps

Review studies indicate that personalized learning interventions are more commonly conducted in HE than in K-12 settings. The inclusion of both primary (mathematics) and secondary (science) interventions directly contributes to the under-represented K-12 empirical base, providing valuable evidence from these crucial educational levels. A significant gap noted in reviews is the tendency of studies to focus solely on academic performance. This design's emphasis on assessing multiple measures, including student behavior (in mathematics) and motivation (in science), in addition to academic performance, provides a more holistic and nuanced understanding of learning outcomes. This addresses the need to understand how interventions impact the entire learning process, not just knowledge acquisition. While LA is used for monitoring, its use for "intervention—the final stage of the learning analytics cycle" for personalized support (e.g., for at-risk learners) has been identified as a significant research gap (Li & Wong, 2020). The mathematics intervention's systematic use of LA to identify the precise amount of deliberate practice needed for fluency improvement (68 days) directly contributes to filling this gap by providing empirical evidence of LA informing tailored interventions. This aligns with PE's aim to use data for "diagnosis, prognosis, treatment, and prevention". While these interventions focused on specific STEM disciplines, their success in personalizing learning through ALT and LA provides a methodological blueprint that can be adapted for more interdisciplinary STE(A)M contexts and integrated with varied pedagogical strategies (e.g., real-life problem-solving, project-based learning) in future studies, an area identified as needing more investigation.

5.2.3 Methodological Contributions

This dissertation advances methodology in personalized STEM learning interventions by proposing a four-stage intervention process that integrates technology, learning design, experiment, and assessment to achieve empirically validated learning outcomes in K–12 mathematics and science. This 4-stage interventional design offers significant value for future research in personalized STEM learning interventions. This methodological design, by detailing the selection and integration of ALT, the personalized instructional design, and the multi-faceted, LA-supported assessment, offers a replicable and adaptable framework for empirically investigating and optimizing personalized STEM learning interventions in diverse educational contexts. These can be summarized into following key takeaways.

1. **Foundation for Adaptive Learning Technology Integration**: The design provides a clear, practical framework for integrating specific ALT (LMS and VR) into PLPs in STEM. Future studies can build on the demonstrated utility of ViLLE for longitudinal skill development and continuous behavioral monitoring, and the effective application of low-end mobile VR for enhancing engagement and understanding of abstract scientific concepts. This offers a scalable and accessible approach for various educational contexts, particularly those with resource constraints.

2. **Scalability and Accessibility of Technologies**: The choice of using an established LMS platform (ViLLE) and accessible low-end mobile VR solutions (VeeR Mini VR Goggles) demonstrates a pragmatic approach to technology integration. This provides valuable insights for future studies seeking to implement cost-effective and widely scalable personalized learning interventions in diverse educational environments.
3. **Integration of LA for Data-Driven Insights**: The systematic adoption of the LA cycle for continuous monitoring and evaluation is a major strength. This enables data-driven insights into student progress, difficulties, and learning behaviors (e.g., practicing behavior in mathematics). This capability informs future research on how LA can be used to refine intervention design, provide real-time adaptive support, and personalize learning experiences even further.
4. **Ecologically Valid and Collaborative Design**: The methodology emphasizes collaboration with local teachers in developing curriculum-driven, school-grade-specific learning paths and co-designing instructional materials and assessments. This ensures that interventions are relevant, practical, and contextually aligned with real classroom needs, thereby enhancing the ecological validity and transferability of findings to actual educational settings.
5. **Comprehensive Multi-Faceted Assessment**: A key contribution is the methodological emphasis on assessing not just academic performance but also learning behavior and motivation. This holistic approach allows researchers to gain a deeper, more nuanced understanding of how interventions impact the entire learning process, moving beyond superficial knowledge acquisition. Future studies can adopt this comprehensive assessment strategy to provide more robust empirical evidence of intervention effectiveness.

In addition, dissertation methodology structured into a three-phase MMR design broadens education-technology research by embedding quantitative and qualitative strands throughout the lifecycle of a personalized STEM intervention. In traditional setting, MMR accommodates qualitative and quantitative methods. This approach is often reflected in study designs that integrate qualitative methods such as interviews or observations, while utilizing surveys or questionnaires for quantitative analysis. Driven by a pragmatic paradigm, this dissertation introduces a flexible and context-responsive research design that extends beyond conventional MMR frameworks to support personalized STEM learning in the TEL- LA integrated model. It reflects two dimensions of PE following the conceptual/thematic organization. That demonstrate a unique contribution where qualitative study is designed based on the systematic reviews and quantitative study were designed based on the intervention design. This eventually help building learning design with ALT and data-driven approaches and conducting interventional studies that can advance PL toward outcome-based learning and assessment. This will also ultimately broaden MMR by weaving these phases together—instead of treating quantitative and qualitative work as separate "moments"—the framework not only delivers empirically grounded personalization insights but also establishes a new standard for customizing STEM education through adaptive alternatives technologies. it forges continuous integration—yielding richer insights, stronger triangulation, and a guiding structure for future studies.

5.3 Practical Implications

Despite the efforts articulated from the intervention literatures and conducted experimental studies in this doctoral research, learning STEM related subjects is not an easy task especially for students like primary and lower-secondary school students. It requires comprehensive support from various actors. In this dissertation, it has been strived at deconstructing the comprehensive support through the practical tools and practices like TEL and LA, and implemented through PSL intervention for academic learning outcomes i.e. performance improvement. Among the actors, teachers and educators are in the closest connection to provide that necessary support; Educational Technologist comes next as personalization and adaptivity plays a significant role in facilitating their support which should be reflected in the design of platforms and tools; Researchers can be perceived as the connector and assessor in this initiative since they often are involved with evaluation of the underlying factors and practical aspects within the process of design, intervention, and the outcome assessment. In parallel with the findings of the intervention studies (conducted as part of the dissertation), there are aspects and practices that were observed in TEL-LA-PSL interventions for greater impact. Thus, these following recommendations (**Table 11**) are prepared to support educators, researchers, and educational technologists regarding the influence of TEL and LA interventions on academic learning outcomes in STEM-related concepts.

Table 11. Stakeholder's recommendations as part of practical implications.

Stakeholders	Recommendations
Educators	Utilize DLE that enable students to work flexibly and independently to promote knowledge advancement and mastering of subjects.
	Consider integrating simulations and "immersive" multimedia tools in abstract subjects like Biology to facilitate conceptual congruence and aid knowledge comprehension during scientific discovery.
	Integrate stereoscopic 360°-VR solutions in conventional classroom settings for study.
	When integrating digital learning tools, especially for mathematics, consider the adoption of a curriculum-driven and school-grade specific PLP.
	Leverage Learning Management Systems (LMS) with features like customized difficulty levels, automated feedback, and PLPs, as these can increase incentives for engagement and interest in problem-solving challenges.
	Note that deliberate and planned practice with self-regulated learning and automatic feedback can promote students'' mathematics competencies and maintain their interest.
	Use systems where a large percentage of submissions are graded automatically (>95% in one described platform), allowing more time for supporting students.
Instructional Designers	Design heuristic data collection instruments with PE in mind to develop new frameworks and models that complement data collected via multimodal tools.
	Design instructional content with multidimensional elements, high-representational fidelity, and acoustic feedback to enhance students'' experience.
	Develop curriculum-driven, school-grade specific PLPs when integrating digital learning tools.
	Establish a validated inventory (battery) of tasks for arithmetic fluency development, especially for primary school students.
	Note that identifying learners'' characteristics and behavioral traits enables the provision of personalized and adaptive instructional paradigms aligned to their competencies and needs, particularly for challenging STEM skills.
	Should ponder upon to include strategic motivation elements like interactivity, personalized feedback, and adaptivity to support student participations.
Education Technologists	Adopt open educational resources aligned to the curriculum of the local context.
	When designing digital learning systems, include strategic motivation elements like interactivity, personalized feedback, automated assessment (correctives), and adaptivity to support student participation.
	Utilize LA features in LMS to explore and identify instructional design strategies and techniques that are more appealing and influential to learners. Machine Learning and Educational Data Mining algorithms can be used to analyze real-time practicing data and interpret student progress, difficulties, and misconceptions.

Stakeholders	Recommendations
	Systematically introduce the adoption of simulations in abstract subjects (like Biology) to facilitate the development of conceptual congruence and aid knowledge comprehension.
	Consider integrating multimodal tools that can gather information related to learners'' visual engagement or kinesthetic reactions to diverse stimuli. This can complement the development of a ''learner profile'' and provide insights into learning strategies, preferences, and styles.
Researchers	Investigate the elements and conditions which influence learners'' arithmetic fluency development and advancement, potentially exploring the relationship between learners'' background, intrinsic motivation, and practicing behaviors using multimodal data.
	Conduct additional research on the instructional design features and respective game elements in digital learning tools, as not all instructional approaches appear equally efficient in training a target skill.
	Perform applied research in real teaching-and-learning contexts (schools, universities) as part of students'' routine practice, using modified tools, adaptive materials, and assessment methods.
	Conduct long-term studies, as information acquired from near-term experiments may hinder the potential of PE.
	Emphasize strategic recruitment of diverse samples and improve physical data collection approaches (e.g., using premade identifiers).
	Conduct follow-up assessments to examine whether observed improvements (e.g., in fluency) are short- or long-term.
	Explore how LMS-generated data and Learning Analytics (LA) can provide insights into learners'' progress, difficulties, and misconceptions, supporting instructional design strategies.
	Support and facilitate multidisciplinary research covering aspects like ethics, security, cultural, and societal norms in PE, especially given its infancy stage.

5.4 Limitations and Future Direction

Despite explicit mention of conceptual framework of TEL-LA-PSL grounded by learning theories and PLD, it is worth mentioning that dissertation indeed is not beyond theoretical and empirical constraints.

In theoretical constraints, learning theories were chosen in close proximity that are best describing the phenomenon for PSL, broadly as an initiative towards PE. However, learning theories (CP, TA, and ZPD) used in contextualizing TEL-LA model may have originally used in different domain like psychology or cognitive science. Given that PE remains a relatively recent concept, the PLD employed within the framework may be open to alternative interpretations or approaches. Besides, there is a lack of combination and validity in the conceptualization and contextualization needed for deciding the required resources, processes, and structures for PE.

Technologies comes as one of the vital resources, however, as far as PE concerns, the collection of complexes, multidimensional data in a systematic and longitudinal way, which presents significant practical challenges. Some of which are already discovered during the interventions. Despite the review of empirical studies identified potential improvement on PSL through TEL-LA interventions, there are still several limitations reflected across studies particularly related to personalization, methodology, and data. Several empirical studies reported reduced sample sizes as a result of incomplete data, missing demographic information, and difficulties in generalizing findings across different contexts were a common phenomenon (Cho et al., 2024). This phenomenon is not just revealed in the review findings of the Study II, but it relates to many studies that utilize ALT and data-driven approaches i.e. LA in educational sciences. Another pressing issue was about generalizability, which indicated that having a positive outcome from a single learning platform and time period may not ensure the effectiveness or efficiency compared to other TEL platforms or domains (Zambrano & Baker, 2024; Khalil & Prinsloo, 2025). Despite this doctoral research attempted utilizing multimodal approaches and technology integration to improve learning outcomes in STEM, future research should focus more conduct more adaptive and integrated intervention approaches to other domains. Furthermore, data collection problems, self-selection bias, and the inherent complexity of human learning pose additional hurdles (Iraj et al., 2020). The reliance on self-reported data can introduce social desirability bias, affecting the accuracy of measurements (Cogliano et al., 2022; Salehian Kia et al., 2021).

In the empirical constraints, High-end technological equipment for immersive technologies is costly and may be inefficient in large group settings. The cost can be a barrier (Study IV). While positive improvement in arithmetic fluency was shown with the LMS intervention, follow-up assessments are needed to determine if this improvement is long-term. Another point to note that the novelty effect of using new technologies can influence students' learning behavior and attitude, making it difficult to isolate the technology's true impact from the excitement of something new. Though media-related factors that positively influence high-end VR solutions (e.g., high graphics quality, multimodal interaction) or negatively impact low-end solutions (e.g., dizziness, fatigue) are considered irrelevant to knowledge acquisition or disciplinary understanding. That also reflect typical challenges i.e. generalization of results that are faced in educational sciences due to experiment conducted in specific contexts (like the UAE study), may be limited (Study III). The study comparing VR and video instruction in high school Biology found no statistically significant difference in factual or conceptual knowledge gains between the two methods, although differences in motivation, confidence, and satisfaction were identified (Study IV). Both methods were found sufficient for knowledge acquisition and academic performance. This suggests that simply using a different technology might not inherently improve knowledge gains beyond traditional video methods.

Moreover, the mathematics intervention presented in this dissertation underscores the importance of deliberate digital practice for skill development—an outcome made possible through the integration of learning analytics (LA) features embedded within Technology-Enhanced Learning (TEL) platforms. The observed improvements in learner performance were closely linked to these in-built LA capabilities, which enabled real-time feedback and adaptive task sequencing. In contrast, such performance gains were less evident in the science intervention, where LA methods were applied primarily in post-hoc analyses to examine academic outcomes and learner motivation. This contrast highlights the potential value of embedding LA modules directly into science learning environments. Future research should therefore prioritize integrating real-time LA through embedded visualization or algorithmic adaption within the immersive tools like VR to trace engagement patterns and respond to student behaviors, offering deeper insights into performance trajectories and supporting more targeted and scaled skill development in science education.

5.5 Final Reflections

This dissertation set out its vision to explore how personalized learning (PL) can be meaningfully designed and evaluated through the integration of Technology-Enhanced Learning (TEL) and Learning Analytics (LA) in K–12 STEM education. It addressed critical research gaps related to the lack of empirically grounded, theory-informed frameworks capable of guiding adaptive and context-sensitive personalized learning interventions. By centering the MMR design around CP, TA, ZPD theories and pragmatism approach, the research moved beyond constructivist paradigms to offer a more actionable and developmentally responsive PE conceptual framework of TEL-LA intervention for PSL.

In the dissertation, studies collectively respond to that gap by offering a structured, empirically grounded approach that bridges theoretical constructs with intervention design and implementation. This has led to broadening the identification of various combinations of digital tools, analytics approaches, and adaptive strategies in Study I-II that transformed PL and specific areas of STEM learning with measurable positive yet mixed outcomes. The empirical findings demonstrated that effective personalized learning should go beyond merely improving academic performance. The Study IV particularly science intervention study underscores the importance of affective outcomes like motivation and engagement. The Study III particularly mathematics intervention study highlighted the critical role of specific learning behaviors, such as deliberate practice, in achieving cognitive skill mastery.

This broader perspective informs instructional designers to personalize not only content and pathways but also motivational elements and practice behaviors. The interventions demonstrated that the choice of ALT should be purpose-driven. VR technology is potent for fostering interest and engagement in visually complex or abstract science topics where hands-on experimentation is limited. On the other hand, LMS platforms, especially those with robust LA and gamification, are highly effective for systematic, long-term skill development in subjects requiring consistent practice, like arithmetic fluency. The rigorous use of LA in the mathematics intervention directly supports the principles of PE by collecting and analyzing multidimensional data (digital traces, practice patterns) to diagnose learners' strengths and weaknesses and provide more personalized or precise support. This enables tailored interventions, such as recommending specific practice duration, or identifying students in need of additional support. Both interventions emphasize curriculum-driven and school-grade specific learning paths developed in collaboration with local teachers, ensuring pedagogical soundness and practical applicability within authentic classroom settings. This collaborative approach makes PL more adaptable and relevant to diverse K-12 contexts.

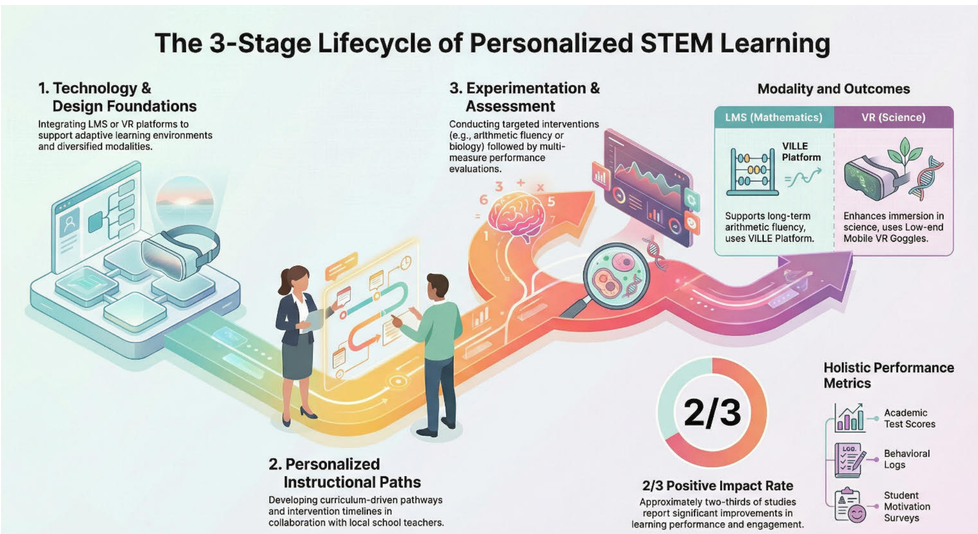

Figure 13. Infographic of PSL Lifecycle.

From the theoretical and empirical findings, the dissertation provides concrete evidence for the strategic application of ALT and LA to foster personalized learning in K-12 STEM (**Figure 13**). They not only validate the potential of these tools but also provide a clearer roadmap for future research and implementation, directly addressing persistent gaps in the EdTech landscape. Besides, the dissertation has also demonstrated a comprehensive PE conceptual framework of TEL-LA-PSL—designed to enhance academic outcomes through personalized learning in STEM that affirms the need for educational research to adopt more integrated, MMR approaches that capture the complexity of personalized learning in data-rich environments for improving mathematics and science learning. However, this also underscores the need for coordinated, cross-sector collaboration. Henceforth, Educational institutions, local municipalities, and funding bodies supporting future of education should work cooperatively to co-develop innovative, scalable solutions that advance K–12 STEM education. Such partnerships are essential to transforming research-driven frameworks into sustainable solutions that are contextually adaptive and pedagogically impactful.

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A passionate Learning Analyst and Educational Sciences Researcher with a keen interest in transforming traditional learning and teaching into more adaptive and context-sensitive digitalized education. Building on my firsthand experience with Finnish education and the closed cooperation with Nordic Educational Institutes, I aim to advance my research in Precision Education while developing inclusive tools and pedagogies to support diverse learners and ensure equitable education for underprivileged learners and educators worldwide.

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