Addanki, Kranthi (2023) *Enhancing learning management systems to support online learning using academagogy.* PhD Thesis, James Cook University.

https://doi.org/10.25903/0ac4%2D2793

Enhancing Learning Management Systems to Support Online Learning Using Academagogy

Kranthi Addanki

Thesis submitted for the degree of Doctor of Philosophy

College of Science and Engineering

James Cook University

October 27, 2023

Declaration of Originality

I declare that this thesis is my own work and has not been submitted in any form for another degree or diploma at any university or other institute of tertiary education. Information derived from the published and unpublished work of others has been acknowledged in the text and a list of references is given.

Acknowledgements

I am grateful to everyone who has helped me successfully complete this research. First, I would like to thank my supervisors, Dr Jason Holdsworth, Dr Dianna Hardy and Prof Trina Myers, for their invaluable support. My special thanks to Jason for his patience and engaging discussions throughout this PhD journey. Many thanks to Dianna for sharing her research methodologies expertise and always encouraging me. I especially thank Trina for her timely insights on research and motivational career advice.

I am thankful to many others who have contributed to the success of my research. I would like to acknowledge the Graduate Research School for organising research workshops. Also, I would like to thank the International Student Support Team for coordinating social and cultural events. I express gratitude to all my lab mates and colleagues. My special thanks to all the students who participated and shared their experiences in the research. I wish you all the best in your future endeavours.

I heartfully acknowledge the support from family members, especially my husband, Narayan Kumar Addanki. I thank you for your unconditional support, love, care and belief. Many thanks to my in-laws, Sushuma and Surya Narayana Addanki, for the encouragement to pursue this PhD degree. I would also thank my daughter Adrija and son Advai for bringing joy and faith in stressful times during my research journey.

I am indebted to my parents, Bharathi and Dharma Raju Jalla, for their support in my life. Your life values of perseverance, discipline, optimism and helping nature have shaped me into the strong person that I am. I also thank my brother Viswa Nadha Varma Jalla, for always being there to guide me through my difficult times. Finally, I would like to dedicate this thesis to my mother, Bharathi. Though you passed away during this research journey, you are in my heart and soul, inspiring me to achieve more.

To my mother, Bharathi.

Statement of the Contribution of Others

Financial Support

James Cook University Post Graduate Research Scholarship with a stipend of $27,596 per annum for three and half years and a tuition fee waiver

Intellectual Support

Dr Jason Holdsworth, Information Technology Academy, James Cook University

Dr Dianna Hardy, Indigenous Education and Research Centre, James Cook University

Prof Trina Myers, School of Information Technology, Deakin University

Editorial Support

Dr Jason Holdsworth

Dr Dianna Hardy

Prof Trina Myers

Ms Kellie Johns, Graduate Research School, James Cook University

Anonymous reviewers of the published papers derived from the thesis

Dr Eileen Siddins for graphic design and editing assistance in compliance with Standards D and E of the Australian Standards for Editing Practice

Publications Created From the Thesis

Conference Papers

Addanki, K., Holdsworth, J., Hardy, D. & Myers, T. (2020, December 12–13). *Academagogy for enhancing adult online learner engagement in higher education* [Paper presentation]. AIS SIGED International Conference on Information Systems Education and Research 2020, Association for Information Systems, United States of America.

Addanki, K., Holdsworth, J., Hardy, D. & Myers, T. (2022, February 14–18). *A preliminary study using academagogy to uncover the problems that block adult online learner engagement* [Paper presentation]. 24th Australasian Computing Education Conference, Association for Computing Machinery, United States of America.

Abstract

Online learning offers enormous opportunities as it can be undertaken anytime, anywhere. However, adult learners (i.e., learners aged 25 and above) have a high attrition rate, attributed to the one-size-fits-all online teaching model. Education literature highlights the benefits of personalising adult learner experience to improve engagement, satisfaction, performance and retention. Learning Management Systems (LMS) used for online education at universities need more support for the personalisation of learning by educators. The personalisation process has been deemed complex for educators due to difficulty understanding learner experiences, choosing appropriate teaching strategies and dealing with scalability issues associated with applying personalisation. This research aims to investigate personalisation enhancements for an LMS using the academagogy framework.

Previous research has shown that using a teaching framework such as academagogy improves educators' ability to meet the needs of individual students. However, the use of this framework is rare in online tertiary teaching. Academagogy allows an educator to choose an appropriate teaching model from the spectrum of pedagogy, andragogy and heutagogy based on the needs of a cohort of learners. Pedagogy is an educator-centred model, where the educator is responsible for the learning content and the delivery. Andragogy is a learner-centred model in which decision making and ownership of learning are shared between the learner and the educator. Heutagogy is a learner-determined model where the learners are mostly autonomous and fill their knowledge gaps through discovery and reflection. A preliminary literature review on academagogy posited the Pedagogy-Andragogy-Heutagogy (PAH) continuum as a promising framework to personalise adult online learner experiences in an LMS.

This research applied a Design-Based Research methodology to investigate personalisation in an LMS through the lens of academagogy. Firstly, an ethnographic pilot study of an online learning environment, including observation of the interactions between adult learners and an educator in a blended subject, showed the potential of using academagogy for personalisation. The pilot study highlighted the significant workload required to conduct a PAH analysis for personalisation by an educator. Secondly, a mock prototype of an Artificial Intelligence (AI) informed system was co-designed with an educator using the Wizard of Oz (WOz) method. WOz is a human–computer interaction technique used to design and test a system at a lower cost by eliciting early iterative feedback regarding capability requirements. Finally, an extended study of user experience feedback with the mock AI prototype revealed that the educator developed an increased awareness of online learner experiences and simplified the tasks required to facilitate the personalisation process in an LMS. Furthermore, increased positive emotions and cognitive abilities to learn independently were identified.

Overall, the key contributions of this research are (a) design principles for applying academagogy to personalise adult learner experiences in an LMS and (b) a refined mock AI prototype to automate the application process. The design principles emphasise self-learning skills and retention of adult online learners. The mock AI prototype is intended as a starting point for further development into a smart learning analytics dashboard that assists educators by reducing their workload and providing just-in-time personalised support for learners. These contributions have broader implications for developing high-quality online learning environments benefitting educators and learners in higher education.

Table of Contents

List of Figures

List of Tables

List of Abbreviations

AI: Artificial Intelligence

API: Application Programming Interface

AR: Action Research

BD: Big Data

CoI: Community of Inquiry

CSE: College of Science and Engineering

DM: Data Mining

DBR: Design-Based Research

DPs: Design Principles

EDM: Educational Data Mining

HCD: Human-Centred Design

HCI: Human-Computer Interaction

ICT: Information and Communication Technology

IT: Information Technology

ITS: Intelligent Tutoring Systems

JCU: James Cook University

LA: Learning Analytics

LAD: Learning Analytics Dashboard

LMS: Learning Management System

ML: Machine Learning

MOOC: Massive Open Online Course

NLP: Natural Language Processing

OSE scale: Online Student Engagement scale

PAH: Pedagogy-Andragogy-Heutagogy

SA: Sentiment Analysis

SPR: Subject Participation Review

UX: User Experience

UI: User Interface

VADER: Valence Aware Dictionary and sEntiment Reasoner

WOz: Wizard of Oz

Chapter 1. Introduction

Online learning is introduced as an overall research field in this chapter. The problem of a high attrition rate for adult online learners is narrowed to the challenges that educators face in personalising learning experiences in Learning Management Systems (LMSs). The main goal of this research is to help educators personalise adult online learner experiences to improve their engagement using a learner-centred teaching model, academagogy.

1.1 Chapter Overview

This chapter outlines the thesis and research question. Section 1.2 describes the background of the research. Section 1.3 highlights the problem statement for the research. Section 1.4 provides the research context. Section 1.5 discusses the research gap, research question and aims. Section 1.6 outlines the methodology to conduct the research, and Section 1.7 explains the significance of the research with contributions. Finally, Section 1.8 provides a concise view of the remaining chapters of the thesis.

1.2 Background

The history and the current trend of online learning is explained in this section. This section also describes adult learners, as they are the primary target group for the research. The motivation and the advantages for which the learners enrol in online learning are presented.

1.2.1 Online Learning

Online learning is a newer form of distance education, where learning occurs over the internet. *Distance education* is often characterised by the geographic separation between learner and educator (Moore, 1989). Distance education originated in the 1970s when education was organised by delivering learning materials in text format using postal services (Moore, 1991).

Also, the content was broadcasted on radio and television programs and electronic recording using audiotape, videotape and computer software (Moore, 1989). Online learning is delivered through LMS through web-related internet services (El Said & Mandl, 2021; Moore et al., 2011).

LMSs are the primary delivery method for teaching face-to-face and distance learners in higher education (Dahlstrom et al., 2014; El Said & Mandl, 2021; McGill & Klobas, 2009). LMS is a software application for processing, storing and disseminating educational materials (McGill & Klobas, 2009). Various LMSs are being used as platforms to deliver learning material via different types of multimedia files that can enable audio, video and text. These LMSs allow the learning process to occur synchronously and asynchronously, with the multimedia files facilitating online learners at universities.

The term online learning is interchangeably referred to blended learning, flipped learning, hybrid learning, open learning, e-learning (electronic learning), web-based learning, technology-mediated learning, virtual learning and distance learning (Bates, 2018; Moore et al., 2011; Rapanta et al., 2020). LMS technology is the common aspect of these learning methods, while the learners' mode of attendance and correspondence are the major differentiating aspects. For instance, a *fully online* learning mode is a classic distance education where the learner completes all the required learning activities at their preferred location and time instead of attending campus based on face-to-face classes (Moore et al., 2011). *Blended learning* is a combination of online learning and traditional campus-based learning where the learner has the flexibility to spend minimum time at the campus for necessary activities like hands-on practical work, and can complete the maximum of the learning activities through online learning mode (Bates, 2018; Bizami et al., 2022). Online and blended learning are the two terms most used in the literature, and there appears to be no clear distinction between the two terms (Bizami et al., 2022; Garrison

& Kanuka, 2004; Moore et al., 2011; Raes, 2021; Singh & Thurman, 2019). In this thesis, these terms are used to describe any combination of fully online and face-to-face learning.

Online learning has proliferated as more universities transform into mega universities using LMSs. A mega university is a university with at least 100,000 learners (Daniel, 1997). Mega universities facilitate many post-secondary learners who would otherwise be unable to continue their education (del Valle & Duffy, 2007). Universities have considered online learning through LMSs a viable option to increase enrolments without increasing the physical infrastructure (del Valle & Duffy, 2007). Some universities are expanding their international learner enrolments by offering lower-cost distance education through Massive Open Online Courses (MOOCs; see Flynn, 2013).

The ever-expanding technological power of the internet, combined with the globalisation of education, continues to enhance the capabilities and the proliferation of online learning environments. For example, online learning enrolment in higher education institutions in the United States increased by 31.6% of all higher education enrolments in 2016 compared to a 4.5% growth rate in 2012 (Martin et al., 2019). Commensurate with the increasing online enrolments in the United States, the self-paced global online learning market had increased at a 7.6% compounded five-year rate, reaching US$51.1 billion in 2016 from US$35.6 billion in 2011 (Colchester et al., 2017). Recent reports have shown that the global online learning market surpassed US$315 billion in 2021 and is projected to reach US$1 trillion by the end of 2028 (Global Market Insights, 2022). The number of external or online learners in Australian universities is increasing (Muir et al., 2019). According to the Australian Government Department of Education, Skills and Employment, the enrolment of online learners in higher education increased by almost 27% compared to internal learners by 7% (Matthews et al., 2017).

Even before the COVID-19 pandemic, online learning was on the rise. Moreover, the pandemic accelerated the use of online learning in higher education (Kandri, 2020). The pandemic caused the mandatory closure of primary, secondary and tertiary institutions worldwide, where it was estimated that almost 90% of all learners could not attend regular face-to-face classes (Kandri, 2020). Consequentially, a widespread shift towards online learning has occurred within the education sector. Higher education is expected not to return to normal face-to-face learning, either by retaining the same level of fully online learning courses or encouraging more online learning activities through blended learning (Azorín, 2020; Cochrane et al., 2021; Murphy, 2020).

Online learning provides flexibility for learners to learn anywhere and anytime, thus providing opportunities for lifelong learning. Online learning is advantageous to a larger population of learners with family life, work and community responsibilities and a lower income (Caruth, 2014; Stone & Springer, 2019). The research depicted in this thesis mainly focused on adult learners who pursue online subjects[1] via universities as formal education.

1.2.2 Adult Learners

The term *adult learner* also refers to 'non-traditional learners' or 'matured-aged learners' in literature (Kahu et al., 2013; Kara et al., 2019; Tilley, 2014). Many characteristics, such as age, the gap between study, work, family and social responsibilities, differentiate adult learners from other learners (Babb et al., 2021; Cercone, 2008; Tilley, 2014). Despite debates relevant to defining adult learners and their age group, this research adopts the prominent notion of adult learners as 25 years and older (Bowden & Merritt, 1995; Cercone, 2008; Morris et al., 2019).

[1] The term *subject* used in this thesis refers to the smallest stand-alone entity, with 13 weeks of learning and teaching activities. A subject is often called a unit, module or course in other contexts.

Adult learners are the largest group of online learners at tertiary institutions (Cercone, 2008; Moore & Shemberger, 2019; Seaman et al., 2018). Industrialisation and globalisation through the advancement of technology have increased the need to upskill adults' digital literacy (Boeren et al., 2020). Also, due to the COVID-19 pandemic, many adults lost jobs, increasing their need to develop skills across the lifespan (Boeren et al., 2020). Adult learners who needed reskilling to survive in the job market at the time chose online learning as a feasible option (Sutton, 2021).

Online learning is a suitable education method for adult learners as it offers reduced transportation costs and flexibility around work, studies and family responsibilities (Cercone, 2008; Morris et al., 2019; Stone & Springer, 2019). Many adult learners enrol in online subjects due to the flexibility of organising learning activities for self-paced learning at any time and place (del Valle & Duffy, 2007; Kara et al., 2019). However, adult education literature posited that these learners have high dropout rates in online university learning (Babb et al., 2021; Kara et al., 2019; Knowles, 1980).

1.3 Problem Statement

Adult learners have high attrition rates at tertiary institutions (Ferreira & MacLean, 2017; Kahu et al., 2013; Morris et al., 2019). For example, a report on a six-year study showed that adult learners (over age 24) at tertiary institutions have completion rates around only 43.5 % when compared to traditional-aged learners (20 and younger), whose completion rate is 68.7% (Shapiro et al., 2018), implying that the adult learners have attrition more than 50% attrition. Moreover, the report revealed that learners who are enrolled part-time have completion rates of only 20.7% when compared to full-time enrolled learners with completion rates of 83.6 % (Shapiro et al., 2018). This indicates the high attrition rate of adults (who are mostly enrolled part-time) in online learning, which varies from 50% to 80% (Ferreira & MacLean, 2017; Morris et al., 2019; Park & Choi, 2009).

Feelings of isolation, lack of interaction with instructors and peers, work–life balance, a lack of digital literacy skills to engage in self-directed learning and conventional models of instruction for online learning are some of the factors that cause high dropout rates for adult online learners (Boeren et al., 2020; Bowden & Merritt, 1995; Kara et al., 2019). These factors vary with the diversity of adult learners' self-learning skills, learning styles and lifelong learning management skills, which an educator may not easily control in an online class except with the traditional teaching model.

The traditional teaching model has been found to hinder the engagement of adult online learners in higher education. In this one-size-fits-all model, the learning is organised and presented similarly to all learners in an LMS, irrespective of adults' learning needs disengaging them from online learning (Bajaj & Sharma, 2018; Demir et al., 2021; Ferreira & MacLean, 2017). *Engagement* is predominantly defined as the time and energy learners invest in educationally purposeful activities, and the effort institutions devote to effective educational practices (Kahu et al., 2013). Studies have found that slower adult learners get overwhelmed while faster adult learners become bored, and in both cases, this tends to decrease learner engagement when using regular teaching methods (Bajaj & Sharma, 2018; Ferreira & MacLean, 2017). Low engagement caused by the one-size-fits-all educational model likely contributes to high dropout rates in adult online learners. The traditional instruction model can be changed according to the individual learner needs with technological and pedagogical support to benefit adult learners (Bowden & Merritt, 1995; Robb, 2013; Singh et al., 2022).

Various theories were explored to understand the psychology of adult learners. Malcolm S. Knowles, an eminent researcher in adult education, recommended four basic assumptions to facilitate adult learners: (1) the self-concept of learners, (2) the role of previous experiences, (3) readiness to learn and (4) orientation to learning (Knowles, 1980). Adult learners are internally motivated and are ready to learn when the online curriculum is tied to their previous experiences and immediately applicable to their practical work or life situations (Chametzky, 2014; Ferreira & MacLean, 2017; Knowles, 1980).

Flow theory was proposed by Csikszentmihalyi in 1975, who defined *flow* as "a psychological state describing the optimal feeling of people who are cognitively efficient, motivated and happy" (Liao, 2006, p. 46). According to Csikszentmihalyi, intrinsic motivation plays a vital role in making humans autotelic (from the Greek words auto = self and telos = goal). He explained that "people pursue certain activities because they derive some satisfaction from them, and this satisfaction itself acts as a reward", which is more than a justification for grades (Csikszentmihalyi, 2000, p. 13). Liao (2006) applied flow theory to understand learner experiences in online learning and showed that learner motivation is subjective according to individual experiences.

Moore defined transactional distance as the physical separation in online education, which leads to a psychological separation and communication gap between the educator and learner (1991). To reduce this transactional distance, Moore suggested more dialogic interaction between educators and learners and a flexible subject structure. Hence, instruction in distance education should accommodate adaptable subject design based on the needs of the learner population and individual learners (Moore, 1991).

The Community of Inquiry model (CoI) is a prominent theory to enhance the learning experience in online learning. According to Garrison et al. (1999), the CoI model consists of three essential elements: cognitive presence, social presence and teacher presence. Cognitive presence is the extent to which participants in a learning community can construct meaning through sustained communication (Garrison et al., 1999). Social presence is defined as the ability of a participant to project their characteristics into the community so that the other participants feel they are present as 'real' people, even though the participants are virtually present in a distance learning mode (Garrison et al., 1999). Teacher presence means providing a flexible structure to the subject or program to enhance cognitive and social presence consistent with educational outcomes (Garrison et al., 1999).

Based on the theories related to adult learners, the traditional online teaching model in LMSs is unsuitable for instructing learners in higher education. Further, several studies have shown that online learning and teaching should consider the personal learning interests of adult learners instead of the rigid model to optimise their learning in LMSs (Bates, 2018; Bowden & Merritt, 1995; Chametzky, 2014; Knowles, 1980; Knowles et al., 2015; Robb, 2013; Singh et al., 2022; Stone & Springer, 2019). Consequently, this thesis focuses on personalising adult learners' experiences in an LMS to improve their engagement and retention in online learning.

1.4 Context

This section discusses the specific concepts related to personalising adult learner experiences in an LMS. Both the technologies and theories that support personalisation in an LMS are briefly described.

1.4.1 Personalisation

Personalisation is defined as the systematic design of the learning process, which focuses on tailoring instruction according to the needs of individual learners (Walkington & Bernacki, 2020). Online and blended learning studies have shown that personalisation can improve learning experiences, engagement, satisfaction, performance and retention (Cardenas et al., 2022; Lim et al., 2020; Murray & Perez, 2015). The learners who received personalised learning instruction performed above two standard deviations better than learners who received traditional instruction (i.e., some average students given one-to-one tutoring performed above 98% of the class; see Bloom, 1984). Though personalisation of instruction seems advantageous, its implementation was found to be complex—possibly due to a lack of properly integrated technological advancements, such as LMS, with current teaching models (Bartolomé et al., 2018; FitzGerald et al., 2018; Mikić et al., 2022).

Personalisation in LMSs is predominantly supported by technologies such as Big Data (BD), Data Mining (DM), Machine Learning (ML), Artificial Intelligence (AI) and Learning Analytics (LA). In an LMS, a learner leaves a vast number of digital footprints or traces, such as clicks, accesses, pauses, submissions, reading habits, writing habits and navigation patterns (Siemens, 2013). The vast variety of data (i.e., BD) is statically analysed using Educational Data Mining (EDM) methods to discover essential knowledge for teaching and learning (Slater et al., 2016). LA has roots in multiple disciplines like BD, EDM, ML and AI. LA is "the measurement, collection, analysis and reporting of data about learners" to understand and optimise the learning environment (Siemens, 2013, p. 1382). The Learning Analytics Dashboard (LAD) is a User Interface (UI) that provides visualisations of LA and indicates the historical and current interactions of a learner in an LMS (Verbert et al., 2013). LADs are widely used for personalisation (Verbert et al., 2020). LADs are mainly used to identify at-risk learners based on numerical quantitative LA data to support educators in designing personalised interventions that improve learner performances (Suero Montero & Suhonen, 2014). Sentiment Analysis (SA) is also used for personalisation and complements LA data in LADs by providing deeper insights into qualitative learner emotions (Ott & Liesaputra, 2022; Verbert et al., 2020). SA is a Natural Language Processing (NLP) technique that analyses "people's opinions, sentiments, evaluations, attitudes and emotions via the computational treatment of subjectivity in text" (Hutto & Gilbert, 2014, p. 217).

Personalisation literature shows the dominance of technologies and their usability in various learning contexts while not considering the experiences of the main stakeholders of LMSs: educators and learners. For instance, a systematic review of personalisation literature in higher education (from 1960 to 2015) revealed the absence of theoretical knowledge that could inform educators on how to use various technologies to conduct their teaching practices (Bartolomé et al., 2018). This knowledge gap in personalisation literature is also supported by other reviews (Mikić et al., 2022; Walkington & Bernacki, 2020). The knowledge gap provides complex challenges for educators choosing technologies to provide supportive interventions for online learners. Studies have reported that a consistent theoretical grounding is necessary to guide the use of digital tools for designing personalised learning environments (Bartolomé et al., 2018; McLoughlin & Lee, 2010; Mikić et al., 2022; Walkington & Bernacki, 2020). Integrating teaching theories that support educators in guiding the personalisation process may help educators decide when, what, where and how the technologies can be used for personalisation (Bartolomé et al., 2018; Ferreira & MacLean, 2017; Winter et al., 2008). Consequently, the academagogy theory was explored for its potential to guide the personalisation process for educators in an LMS and improve adult online learner engagement.

1.4.2 Academagogy

Academagogy is a learner-centred teaching model defined as a meshed model of pedagogy, andragogy and heutagogy (Winter et al., 2008). *Pedagogy* is an educator-centred teaching model where the learner is a passive recipient of information from the educator, and the educator is responsible for arranging learning resources (Luckin et al., 2011). *Andragogy* is a learner-centred teaching model in which the learner and the educator share the decision-making learning process through collaboration (Blaschke, 2016). *Heutagogy* is defined as a self-determined learning model where a learner proactively takes the responsibility to fill in their knowledge gaps through discovery and reflection (Blaschke, 2016). The Pedagogy-Andragogy-Heutagogy (PAH) continuum is a progression of learning and teaching activities from pedagogy to andragogy towards heutagogy (Luckin et al., 2011).

Academagogy allows an educator to select appropriate parts from the model's pedagogy, andragogy and heutagogy, and blend them in a context where they could be effectively used for better learning outcomes (Winter et al., 2008). The educator is responsible for choosing a model that suits specific contexts and provides an effective learning environment (Kennedy, 2018). Hence, the flexibility of the academagogy model discourages the one-size-fits-all model, which is a rigid form of instruction (Kennedy, 2018).

In the context of the Australian Federal Government and Australian universities, academagogy was suggested to improve learning and teaching (Cretchley, 2009). Academagogy emphasises participatory learning through the social constructivism paradigm, which shapes the learning process through context, conversation and collaboration (McAuliffe & Winter, 2014b;

Murthy et al., 2012). Social constructivism theory is derived from the work of Lev Vygotsky as "learning results from social interaction, and that meaning is socially constructed through communication, activity, and interactions with others" (Swan, 2005, p. 4). Academagogy follows Vygotsky's notion of the zone of proximal development (McAuliffe & Winter, 2014b), defined as "the distance between the actual development level as determined by independent problem solving and the level of potential development as determined through problem solving under adult guidance or in collaboration with more capable peers" (Swan, 2005, p. 4). The academagogy model's flexibility, particularly for educators seeking to enhance learners' self-learning skills through social constructivism, was ideal and thus used as a theoretical framework for this research.

1.5 Research Question, Aim and Objectives

LMSs are adequate content repositories, but they are limited in facilitating personalised learning experiences to address the diverse learning needs of adult learners (Bajaj & Sharma, 2018; Dahlstrom et al., 2014; Furini et al., 2022). Adult online learners feel isolated and less engaged due to their limited interactions with educators in LMSs (Kara et al., 2019). In general, learners interact (i.e., reactively communicate) in an LMS in three modes: (1) *learner–content* interaction, (2) *learner–learner* interaction and (3) *learner–educator* interaction (Moore, 1989). Personalisation can be applied in all three modes of interaction using different techniques, models or theories (Shearer et al., 2020). This research concentrated on personalising the learner–educator interaction in an LMS, since adult learners value learner–educator interactions more than learner–learner and learner–content interactions (Martin & Bolliger, 2018; McAuliffe & Winter, 2013). The learner–educator interaction is preferred for its characteristics, such as self-directed learning and autonomy (Moore, 1989). Therefore, the main aim of this research is to improve the personalised interaction between educators and adult online learners in LMSs by using academagogy as a foundation. Based on the background and the motivation to use academagogy for personalisation, the research question, related aim and objectives are presented in Table 1.1.

Table 1.1

Research Question, Aim and Objectives

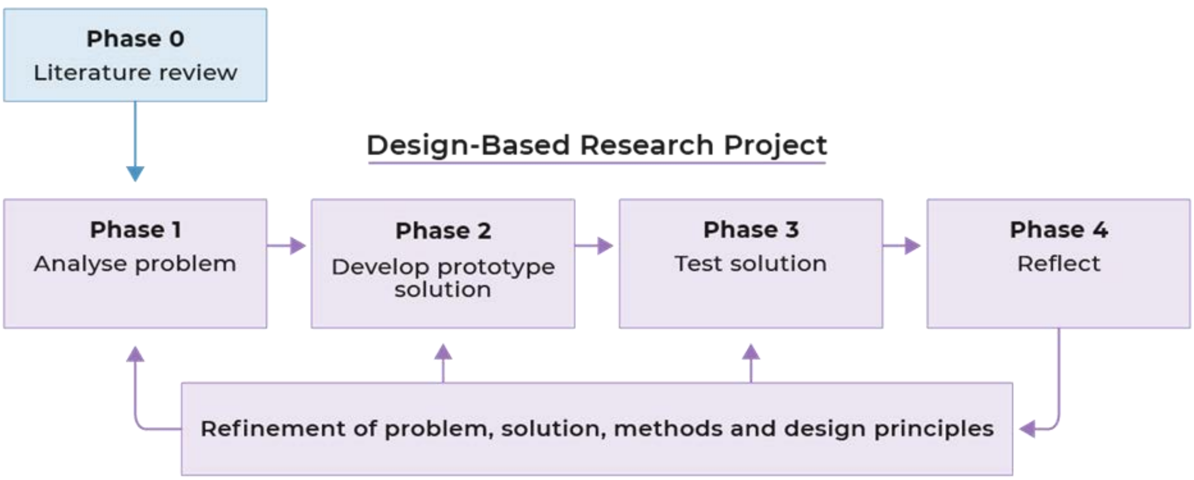
Research question	How can we enhance the capabilities of a Learning Management System to help educators personalise adult online learner experience using academagogy?
Research aim	To improve personalised interaction between educators and adult online learners in Learning Management Systems using academagogy as a foundation.
Research objectives	1. Identify and analyse educators' challenges and obstacles when personalising learning for adult students in a Learning Management System using academagogy. 2. Outline and describe the principles for applying academagogy to facilitate personalisation in a Learning Management System. 3. Provide preliminary insights about the combined impact of academagogy, Learning Analytics and Sentiment Analysis on the engagement of adult online learners. 4. Provide User Experience design concepts for educators and learners focusing on personalisation in a Learning Management System using academagogy.

1.6 Research Methodology

Design-Based Research (DBR) methodology was chosen to study the research question and fulfil the research aims and objectives. DBR is defined as a series of approaches to produce new theories, artefacts and practices that can imply learning and teaching in natural settings (Barab & Squire, 2004). The DBR methodology provided a procedure to analyse, develop, test and refine the academagogy Design Principles (DPs) for personalisation in an LMS. Based on the DBR guidelines for conducting academic research, a mixed methods approach was utilised to rigorously analyse the research data and interpret results (Herrington et al., 2007; Reeves et al., 2005). The original DBR methodology depicted by Herrington et al. (2007) was adapted in this research (otherwise called a DBR project) as shown in Figure 1.1.

Figure 1.1

Design-Based Research Project Informed by Herrington et al. (2007)



The DBR project was conducted in five phases:

- Phase 0 (July 2019–February 2021) involved a preliminary literature review on academagogy applications for adult online learning. The review positioned the PAH continuum as an academagogical framework to personalise adult online learner experiences and improve engagement (Addanki et al., 2020).
- Phase 1 (February 2021–July 2021) consisted of a pilot study using an ethnography approach to investigate adult learner and educator experiences in an LMS, using academagogy. The pilot study showed that the academagogy framework could be potentially used for personalisation in an LMS but identified scalability issues, such as extra time commitment and workload for an educator to apply academagogy. Hence, an

AI system was proposed to help an educator by automating the process of applying academagogy (Addanki et al., 2022).

- Phase 2 (July 2021–February 2022) comprised the development of a prototype solution to address scalability issues in applying academagogy for personalisation in an LMS. In this phase, a lightweight mock AI prototype was co-designed (see Chapter 5 for more details).
- Phase 3 (February 2022–July 2022) involved iteratively testing and refining the prototype solution with an extended study. In this study, the capabilities of the mock AI prototype were tested and refined with three iterations. The results from user experiences with the mock AI prototype are presented in Chapter 5.
- Phase 4 (July 2022–March 2023) included reflection on the research results and advancing the theoretical knowledge of academagogy for personalisation to enhance adult online learner engagement in LMSs. The research outcomes also provided a prototype solution for addressing issues in the practical applications of academagogy with the mock AI prototype, as discussed in Chapter 7.

1.7 Significance

This thesis presents a longitudinal DBR project to enhance the capabilities of an LMS and help educators personalise adult learning experiences using academagogy. Personalisation is a reiterating theme used to enhance online learner engagement, as it can enhance learner performance, satisfaction and retention in higher education (Mikić et al., 2022). Personalisation literature is dominated by the advancement of digital tools (Bartolomé et al., 2018). However, the personalisation process is deemed complex for educators, potentially due to their limited understanding of how to use tools for their teaching practice (Bartolomé et al., 2018; FitzGerald et al., 2018; Mikić et al., 2022). Research highlights the need for understanding pedagogical strategies (teaching and learning theories) to guide the implementation of the personalisation process (Bartolomé et al., 2018). Consequently, this research project used academagogy theory to guide the personalisation process, which can advance the personalisation literature, using technologies such as LMSs, SA and AI (detailed in Chapters 6 and 7).

The high attrition rate of adult learners is a crucial concern in tertiary education (Bowden & Merritt, 1995; Ferreira & MacLean, 2017; Kara et al., 2019; Knowles, 1980; Morris et al., 2019; Park & Choi, 2009). Many factors can cause adult learners' attrition (see Section 1.3) and the standard model for online learning is not feasible for these learners as they have diverse previous experiences, preferences and needs (Caruth, 2014; Smith, 2019). Adult education literature recommends personalisation based on diverse learner characteristics (Knowles, 1980; Moore & Shemberger, 2019; Stone & Springer, 2019). Therefore, this research on personalising adult learner experiences adds to the broad literature on enhancing adult learner engagement to address the research problem.

The online learning market is predicted to grow at an unprecedented rate (see Section 1.2.1). Adult learners also continue to seek lifelong learning due to the affordance of online learning and the requirement of digitalisation in many workplaces. In addition to serving the needs of adult learners, online learning is also helpful for younger learners from primary to secondary school, universities, vocational education and recruits training in corporate settings. Thus, the research on personalising adult learner experiences in an LMS, guided by the theoretical framework of academagogy, clearly contributes to a wider community.

1.7.1 Contribution

Learner engagement is a common concern for stakeholders in the education sector, ranging from primary to higher education (Albinson, 2016; Fredricks et al., 2004; Raes, 2021).

The range of stakeholders for this research includes adult learners, educators, university administrators, MOOC administrators and LMS vendors. By focusing on the improvement capabilities of an LMS to help educators' personalisation using academagogy, this research contributes new knowledge for the major stakeholders: adult learners, educators and university administrators.

Adult learners are the primary stakeholders for this research as they continue to enrol in online subjects offered by universities, either to reskill or upskill. Further, adult learners invest time, energy and money while expecting the best returns on their investment in either grades, degrees or learning satisfaction (Sutton, 2021). Hence, this research on adult online learner engagement aimed to improve self-directed and self-determined skills contributes to lifelong learning.

Educators teaching at universities are also major stakeholders of this research. In a face-to-face class, it is obvious that an educator can adjust instruction based on learners' emotions, behaviours and cognitive levels, while in online learning, observing learners' experiences is challenging and complex (Clarizia et al., 2018). In a larger online class, monitoring enormous volumes of learner data becomes increasingly complex for an educator (Schubert et al., 2018). This research was designed to reduce the workload of educators managing large online classes using LMSs by implementing the personalisation process. The research was purposed to save educators valuable time by reducing their time spent on monitoring online learners' experiences. Educators can therefore focus their time on adapting the content or teaching strategies based on their learners' needs.

University administrators are the secondary stakeholders of this research. Retention and the success rate of learners are major concerns for universities (Stone, 2017). Hence, the research contributions can potentially help university administrators increase the degree completion and enrolment rates of adult learners in online learning. This could help university administrators maintain cost-efficiency measures and, by facilitating a larger learner population, enhance revenue (El Said & Mandl, 2021).

1.7.2 Research Publications

The publications produced during this PhD candidature are presented in Table 1.2, which overviews the papers and their relevance to the research.

Table 1.2

Overview of Research Publications

Publication	Overview	Relevance to thesis
Addanki, K., Holdsworth, J., Hardy, D. & Myers, T. (2020, December 12–13). *Academagogy for enhancing adult online learner engagement in higher education* [Paper presentation]. AIS SIGED International Conference on Information Systems Education and Research 2020, Association for Information Systems, United States of America.	This paper contained a literature review of the academagogy teaching model and its applications. The review highlighted the value of using academagogy to personalise online learning for adult learners.	Literature review (Chapter 2)
Addanki, K., Holdsworth, J., Hardy, D. & Myers, T. (2022, February 14–18). *A preliminary study using academagogy to uncover the problems that block adult online learner engagement* [Paper presentation]. 24^{th} Australasian Computing Education Conference, Association for Computing Machinery, United States of America.	This paper reported on a pilot study that initially explored adult online learner experiences using academagogy. A mixed method analysis of the participants' data revealed: (a) learning trajectories to determine the position of the learner on the Pedagogy-Andragogy-Heutagogy (PAH) continuum; (b) that PAH learning trajectories could be used to encourage the capabilities of learners towards heutagogy and (c) workload for an educator to analyse data, determine the learner's position and encourage the learner on the PAH continuum.	Research Objective 1

1.8 Thesis Structure

The thesis is divided into eight chapters:

- **Chapter 1. Introduction** (this chapter) provided the rationale for the research focusing on the knowledge gap, research question, aim and objectives.
- **Chapter 2. Literature Review** includes a critical description of related literature highlighting the research gap in understanding the use of academagogy for personalisation to improve adult online learner engagement. The content of this chapter was published in the proceedings of the International Conference on Information Systems Education and Research Association for Information Systems (Addanki et al., 2020).
- **Chapter 3. Research Methodology** describes the research paradigm that inspired the selection of the methods informing the overall research design.
- **Chapter 4. Pilot Study** discusses the findings of an ethnographic study where a cohort of blended learners and an educator were observed to explore the details of how academagogy can be applied to personalise adult online learners' experiences in an LMS. A version of this chapter was published and presented at the Australasian Computing Education Conference (Addanki et al., 2022).
- **Chapter 5. Extended Study** discusses the iterative co-design of a mock AI prototype to help educators' personalisation using academagogy in an LMS. This chapter also presents the findings of user experiences on the mock AI prototype from both educator and adult learner perspectives.
- **Chapter 6. Comparative Analysis** presents research findings comparing the learners' data from both the pilot and extended studies. The research findings provide empirical evidence for theory and practical recommendations.

- **Chapter 7. Discussion** reflects on the findings from the DBR project. This chapter further describes the theoretical recommendation as DPs for personalisation using academagogy in an LMS. This chapter also presents practical recommendations for the mock AI prototype.
- **Chapter 8. Conclusion** discusses the significance of the research findings with implications for theory and practice, limitations of the research and future directions.

Chapter 2. Literature Review

This chapter explores previous research on personalisation in LMSs specific to adult online learners and identifies any knowledge gaps to guide the research methods. Past literature related to the research question is described to provide context for this research and determine its relativity to previous works.

2.1 Chapter Overview

Section 2.2 explores personalisation literature regarding LMSs and identifies knowledge gaps. Section 2.3 provides a deeper understanding of the term academagogy with its historical roots. Section 2.4 further describes the research gap in academagogy theory and Section 2.5 provides a glimpse of the state-of-art applications of the academagogy model. Section 2.6 illustrates the rationale for using academagogy to support online adult learners; Section 2.7 describes how the academagogy model can be used as a theory to guide the personalisation of learning experiences of adult learners. Finally, Section 2.8 summarises the chapter.

2.2 Personalisation in Learning Management Systems

An LMS is an information system that facilitates online learning with basic features of processing, storing and disseminating educational materials (McGill & Klobas, 2009). In addition, an LMS supports features like institutional administrative and communication tasks required for online learning and teaching. LMSs first emerged in 1990 and are widely used in primary to K-12 schools, higher education and corporate training (Dahlstrom et al., 2014). Since 1990, different LMSs, such as Blackboard, Moodle, Canvas, Desire2Learn, Sakai and eCollege, have been introduced. Although current LMSs are efficient educational service providers with basic features, they are limited in supporting advanced capabilities like personalisation. Reviews of educators' and learners' experiences with the current LMS ecosystem in higher education show these systems have a limited ability to support personalisation for successful online learning (Cardenas et al., 2022; Dabbagh & Fake, 2017; Dahlstrom et al., 2014; Demir et al., 2021; Šimko et al., 2010).

Personalisation refers to instruction that is paced according to individual learner needs. Online learning studies have shown that personalisation potentially improves learner engagement, participation, performance, experience, satisfaction and retention (Cardenas et al., 2022; Murray & Perez, 2015; Stone & Springer, 2019). However, personalisation literature shows complexity in its implementation as its practice varies broadly in different contexts (FitzGerald et al., 2018; Mikić et al., 2022; Zhang et al., 2022).

Personalisation involves systematic learning design and tailoring instruction to individual learner needs, preferences, interests and goals (Bray & McClaskey, 2010; Bray & McClaskey, 2013; Walkington & Bernacki, 2020). Sometimes, personalisation is interchangeably referred to as differentiation. In *differentiated* learning, each learner has the same learning objectives, but they experience changes in their instructions according to their learning preferences (Bray & McClaskey, 2010). Personalised instruction may include multiple dimensions such as adapting learning content, feedback, assessments, presentation style, navigation paths and interaction based on different factors (FitzGerald et al., 2018; Mikić et al., 2022). These multiple dimensions make it difficult for educators to implement personalisation in a specific context. Hence, the personalisation process in this research is systematically designed by considering the following questions related to the context:

- Where is personalisation occurring?
- Who are the beneficiaries of personalisation?

- What is being personalised?

2.2.1 Where is Personalisation Occurring?

Personalisation can take place in normal face-to-face learning environments or technology-enabled learning environments like online learning. Based on the context of this research (see Section 1.4), the personalisation process for online learning must be conducted in an LMS.

2.2.2 Who Are the Beneficiaries of Personalisation?

The major stakeholders of this research are adult online learners. The problem statement described in Section 1.3 shows that adult learning characteristics, such as autonomy, motivation, previous learning experiences and future learning applications are considered to create personalised learning.

2.2.3 What is Being Personalised?

In general, learners interact with the LMS in three modes: (1) learner–content interaction, (2) learner–learner interaction and (3) learner–educator interaction (Moore, 1989; see also Section 1.5.1). Personalising learner–content interaction in an LMS focuses on changing the learning content or the presentation style based on the targeted learners' preferences. Some researchers have used learners' visual, auditory, reading, writing and kinesthetic learning styles to adapt or change the content in LMSs (Aeiad & Meziane, 2018). Personalisation of content by including gamification elements was also demonstrated to improve learner achievement (FitzGerald et al., 2018). Adaptive learning techniques using ML algorithms, DM and LA to personalise the content for learners are increasing (Bartolomé et al., 2018). Intelligent Tutoring Systems (ITS) are widely used for personalising the navigation paths for learning content based on learners' existing knowledge about a particular topic (FitzGerald et al., 2018). Based on the context of this research (personalisation of adult learner experiences in an LMS) the interaction between educator and learner was prioritised because adult learners prefer collaboration with the educator rather than just learning content (McAuliffe & Winter, 2013). Personalising learner–learner interaction in an LMS focuses on group-based activities by pairing learners with similar or different learning styles and forming communities of practice using social media platforms including Facebook, Twitter, Wikis et cetera (FitzGerald et al., 2018; McLoughlin & Lee, 2010). This type of personalisation is not feasible for adult learners since they prefer more dialogic and meaningful feedback from an educator rather than their peers (Jaggars & Xu, 2016; Kara et al., 2019; Moore, 1989). Learner–educator interaction is vital in adult education because of characteristics, such as self-directed learning guided by an educator (Moore, 1989). To add value to the personalisation process, researchers have suggested a delicate balance between promoting learners' self-learning skills and the facilitation process by educators in online learning (McLoughlin & Lee, 2010). Thus, the aim of the research is to personalise learner–educator interactions.

As mentioned in Section 1.7.1, an educator can adjust instruction based on the visual cues of learners' emotions, behaviours and cognitive levels in a face-to-face class. However, in online learning, observing learners' experiences is challenging (Clarizia et al., 2018). Different technologies such as LA, BD, ML, AI and ITS are used to observe learner experiences and help educators reduce the workload involved in analysing learner data (FitzGerald et al., 2018; Mikić et al., 2022). However, educators face challenges when using different technologies due to their limited theoretical understanding of personalisation in LMSs (see Section 1.4.1). Hence, academagogy theory was applied to guide the personalisation process in an LMS in this thesis.

2.3 Academagogy

The term academagogy is defined as ‘scholarly leading’ and comes from the Greek words academy (place or community of scholarship or learning) and agogus (leader; see also Cretchley, 2009; Winter et al., 2008). As mentioned in Section 1.4.2, academagogy is also defined as a meshed model of pedagogy (educator-centred model), andragogy (learner-centred model) and heutagogy (self-determined model), as shown in Figure 2.1. The academagogy model can be used to facilitate learners of diverse cultural, generational and disciplinary backgrounds and prior knowledge (Cretchley, 2009; Oliver, 2015; Winter et al., 2008).

Figure 2.1

Academagogy Model

Content has been removed due to copyright restrictions

Note. The colours red for Pedagogy, amber for Andragogy and green for Heutagogy are intentionally chosen based on the traffic light signal mechanism. These colours are used as a hint to educators about a learner’s performance for personalisation in a Learning Management System (Arnold & Pistilli, 2012). Adapted from “The transition to academagogy”, by A. Winter, M. McAuliffe, D. Hargreaves and G. Chadwick, 2008, *Philosophy of Education Society of Australasia (PESA) Conference 2008*, Brisbane, Queensland.

2.3.1 Pedagogy

Pedagogy comes from the Greek words paid (child) and agogus (leader of) and is defined as the art and science of teaching children (Holmes & Abington-Cooper, 2000). Pedagogy originated from monastic schools in Europe between the 7th and 12th centuries, where monks used to teach simple skills to children (McAuliffe et al., 2008). In the pedagogy model, a learner is externally motivated depending on the institutional or educator-defined goals for learning.

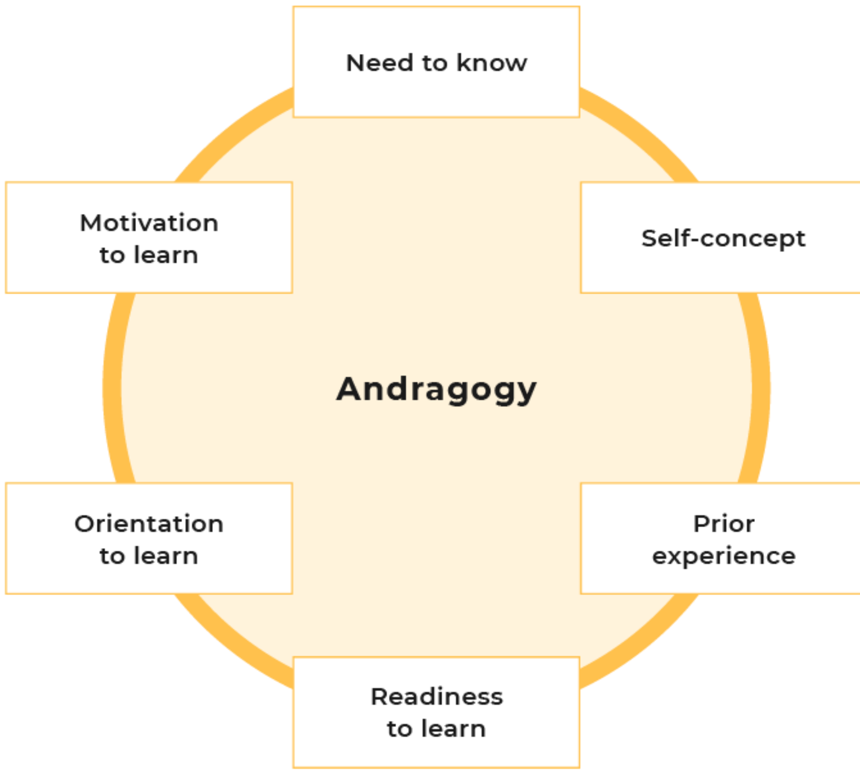
2.3.2 Andragogy

Andragogy originates from the Greek words aner (adult) and agogus (leader of) and is defined as the art and science of teaching adults. Malcolm S. Knowles, the father of andragogy, posited that adults learn differently from children (Knowles, 1980; Knowles et al., 2015). The principles for andragogy are defined below (Knowles, 1980; Knowles et al., 2015; see also Figure 2.2):

- **Need to know**. Adult learners need to know the reason (why, what and how) to learn.
- **Self-concept**. Adult learners are highly self-directed and autonomous by being involved in decisions for education while practising self-conceptualisation.
- **Prior experiences**. Adult learners' previous experiences form a foundation for their learning activities.
- **Readiness to learn**. Adult learners are interested in learning activities that have immediate relevance to their work or personal lives.
- **Orientation to learn**. Adult learners are more oriented to problem-centred activities than content-oriented activities.
- **Motivation to learn**. Adult learners have more intrinsic than external motivation.

Figure 2.2

Principles of Andragogy



Note. Adapted from *The adult learner: The definitive classic in adult education and human resource development,* by M. S. Knowles, E. F. Holton III and R. A. Swanson, 2015. Published by Routledge.

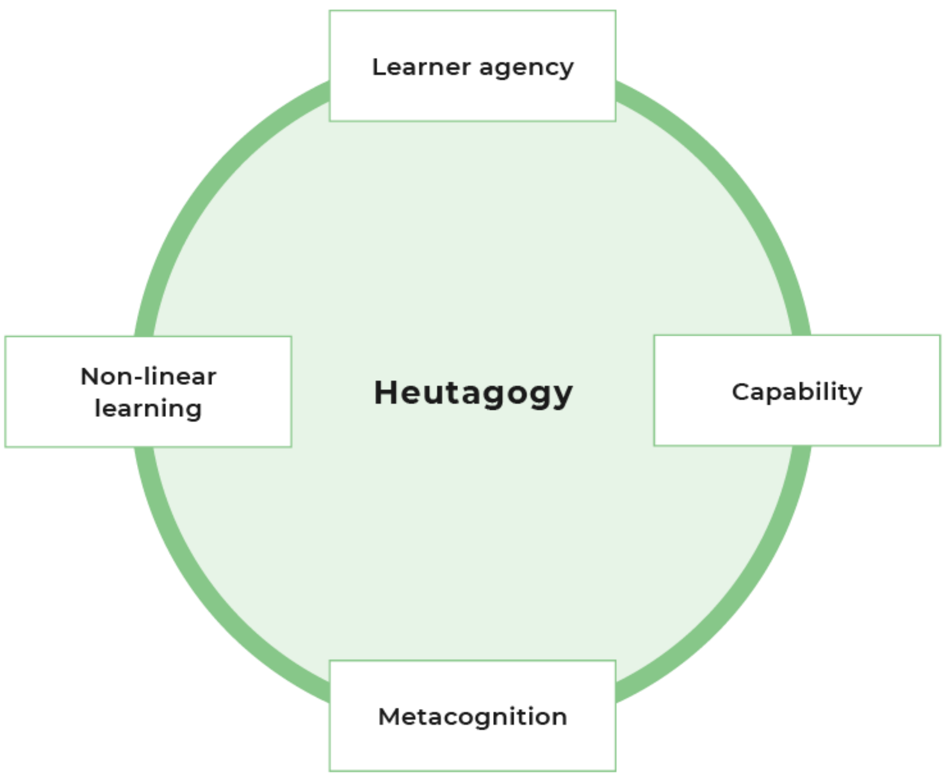
2.3.3 Heutagogy

Heutagogy is derived from the Greek root heureskein (heuristic), a teaching method that allows learners to discover themselves (Parslow, 2010). Heutagogy is a self-determined learning process where the learner determines what and how the learning should occur (Hase, 2011; Kenyon & Hase, 2001; Parslow, 2010). Heutagogy was developed as an extension of andragogy, where the learners perform immense work to fill their knowledge gaps through discovery and reflection (Parslow, 2010). The key principles of heutagogy are (Hase & Blaschke, 2019; see also Figure 2.3):

- **Learner agency**. The learner is the agent or the educator of their own learning.
- **Capability**. Self-efficacy makes the learner confident in dealing with new and unfamiliar situations.
- **Metacognition**. The learner uses a thinking process to self-reflect on the ways (what and how) they acquire new knowledge.
- **Non-linear learning**. The learners' experiences influence their divergent and unpredictable learning.

Figure 2.3

Principles of Heutagogy



Note. For more information, see Hase and Blaschke (2019).

2.3.4 Pedagogy-Andragogy-Heutagogy Continuum

The PAH continuum notion was developed by Luckin et al. (2010). The PAH continuum is a progression of learning and teaching activities from pedagogy to andragogy towards heutagogy (Agonács et al., 2020; Blaschke, 2016; Cochrane, 2014). Researchers debate whether PAH follows a continuum or non-PAH continuum perspective (Blaschke, 2016; Hase, 2016; Jones et al., 2019). In the PAH continuum, the learners' capabilities can be encouraged from the pedagogy level (passive recipients) to the andragogy level (active participants) towards the heutagogy level (decision makers), as shown in Table 2.1.

Table 2.1

Content has been removed due to copyright restrictions

Note. Adapted from "The impact of andragogy on learning satisfaction of graduate students", by C. E. Ekoto and P. Gaikwad, 2015, *American Journal of Educational Research*, *3*(11), 1378–1386.

In pedagogy, the educator controls the learning process by giving a defined curriculum to the learners, and learners have very limited autonomy. Andragogy differs from pedagogy as a learner-centred model; the learners are active participants, with the decision making and ownership of learning outcomes shared between the learners and educators. In andragogy, the learner will try to attain autonomy with some competency building. In heutagogy, the learner has more control over the learning process; they are proactive with a focus on immediate career goals, and self-driven with more autonomy. Heutagogy differs from andragogy as an evidence-based approach to learning that is grounded in neuroscience (Agonács & Matos, 2019). Heutagogy is considered an extension of andragogy, and andragogy an extension of pedagogy, as shown in Figure 2.4.

Figure 2.4

Progression From Pedagogy to Andragogy Towards Heutagogy

Content has been removed
due to copyright restrictions

Note. Adapted from "Heutagogy and lifelong learning: A review of heutagogical practice and self-determined learning", journal article by L. M. Blaschke, 2012. *The International Review of Research in Open and Distributed Learning*, *13*(1), 56–71.

2.4 Research Gap in Using Academagogy

To obtain an idea of the state-of-the-art research work focused on academagogy, the databases Google Scholar, ERIC, ProQuest and Informit were searched from October 2019 to May 2020. The search criteria were based on the motive for academagogy, its proof of concept and its sub-models (andragogy and heutagogy). Academagogy had fewer implementations compared to its sub-models. One reason may be that academagogy is a niche term introduced recently (in 2008) and has not been rigorously researched. An example of the search results for the general terms "Academagogy", "Andragogy" and "Heutagogy" in Google Scholar and ERIC is provided below (Table 2.2). In this example, an online-only criteria was used to screen these results, which excluded proposals, theoretical works, non-English papers, review articles and applications in face-to-face learning. The Google Scholar search results for general and online-only applications of academagogy, with respect to andragogy and heutagogy, are shown in Figure 2.5.

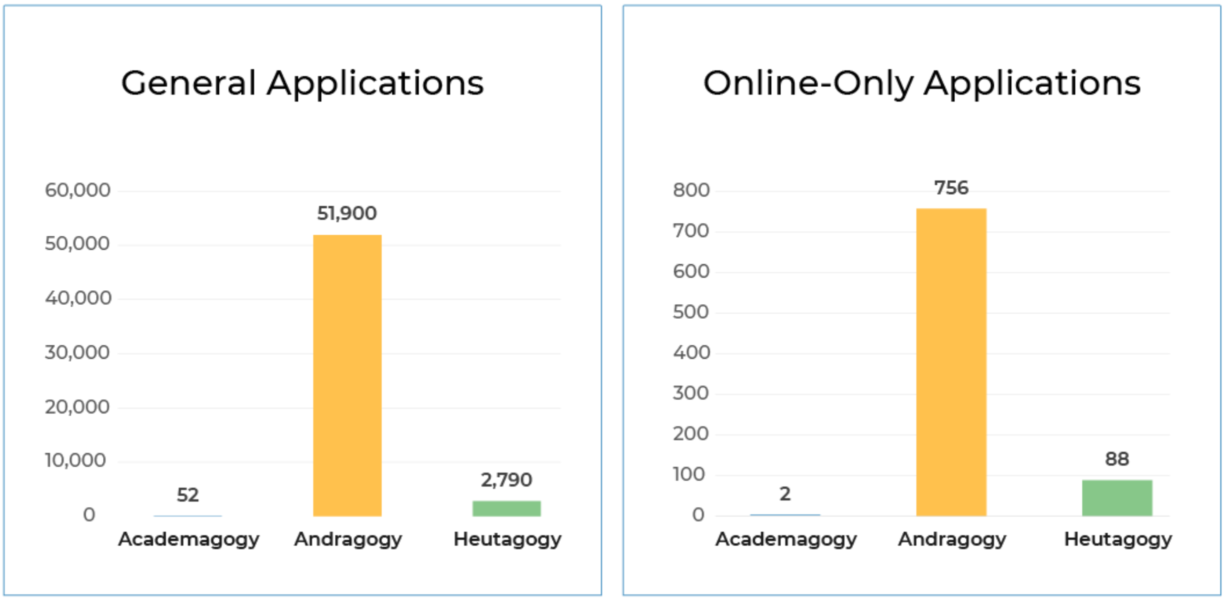
Table 2.2

Search Results from Google Scholar and ERIC

Search term	Google Scholar		ERIC	
	Before screening	After screening	Before screening	After screening
Academagogy	52	2	1	0
Andragogy	51,900	756	1,119	157
Heutagogy	2,790	88	33	12

Figure 2.5

Search Results for General and Online-Only Applications of Academagogy, Andragogy and Heutagogy

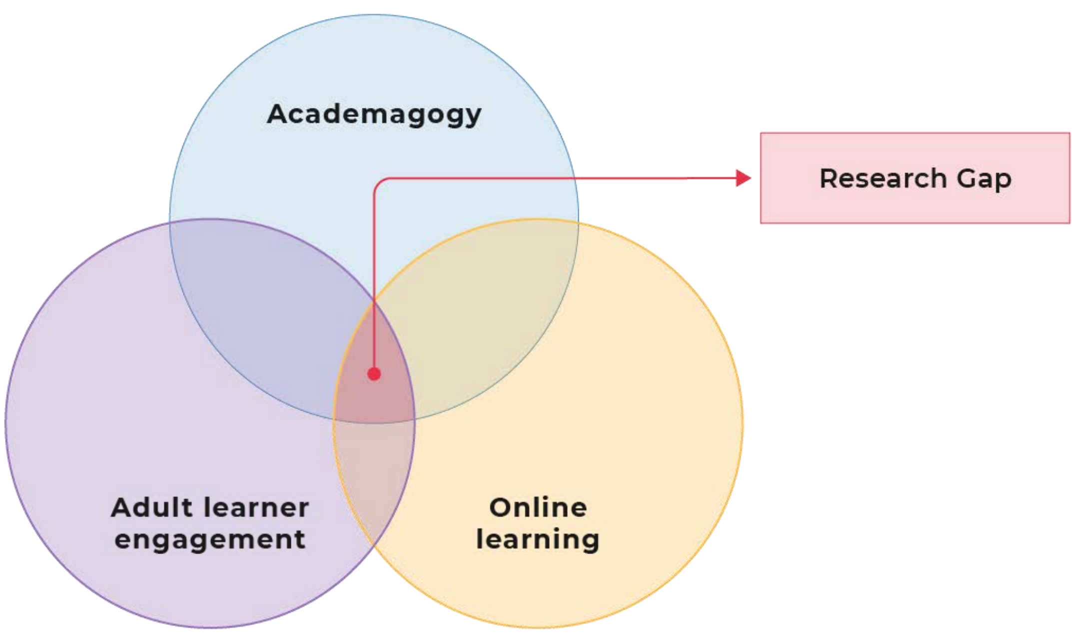


The above data clearly show that research literature on the academagogy model of teaching and learning was limited compared to its sub-models (andragogy and heutagogy) in both general and online-only learning applications. Furthermore, with literature (e.g., Hase, 2016; Holmes & Abington-Cooper, 2000) indicating the active theoretical existence of pedagogy (nearly 1,000 years), andragogy (nearly 180 years) and heutagogy (20 years), academagogy as a combination of the PAH models can be predicted to have a significant effect on learning outcomes. However, these search results indicate a research gap in the practical evidence for academagogy theory.

The relation between academagogy and online adult learner engagement is an unexplored area. Recent literature has shown an increased research interest in online learning and adult learner engagement (Babb et al., 2021; Doherty & Doherty, 2018; Henrie et al., 2015; Kara et al., 2019). Various interventions, such as gamification, ITS and LA, were applied to improve online learner engagement (Azevedo et al., 2022; Hamari et al., 2016; Tempelaar et al., 2019). In particular, the interventions based on educator–learner collaboration were found to have a positive impact on the higher education learning process (Hattie, 2015). Interaction between an educator and the learner is highly recommended, especially in online learning (Hattie, 2015; Ní Shé et al., 2019; Stone, 2017). This interaction necessitates the requirement of a learner-centred approach, such as academagogy, to facilitate the adult learners' online learning process and enhance their engagement. As the impact of academagogy on online adult learner engagement was unexplored (see the research gap in Figure 2.6), the effect of personalisation based on this model was focused on this research.

Figure 2.6

Research Gap in Studying the Effect of Academagogy on Adult Online Learner Engagement



2.5 State of the Art Applications

This section describes the applications of academagogy in face-to-face and online learning contexts. Also, the models related to academagogy are explained.

2.5.1 In Face-to-Face Learning

Literature concerning the applications of academagogy in traditional face-to-face classroom settings has shown an increase in the self-confidence of the learners and improved teaching experience for educators (Winter et al., 2009; McAuliffe & Winter, 2014b; Kennedy, 2018). The first case study on implementing academagogy showed a remarkable reduction in failure rates and positive comments from learners (Winter et al., 2009). Another study revealed that academagogy enabled learners to achieve higher grades compared to grades achieved by earlier teaching processes (McAuliffe & Winter, 2014b). In addition, research on a business management program framed by academagogy theory found that the program was appealing to educators by 90%, and learners had an 85% acceptance rate (Kennedy, 2018). Though the application of academagogy seems advantageous, it is limited by the heavy workload of educators (Kennedy, 2018; Winter et al., 2009).

The academagogical framework fits well for academic and corporate sectors due to the underlying concept of social constructivism (Murthy, 2011; Murthy et al., 2012; Murthy & Pattanayak, 2019). The academagogical framework aims to promote joint ownership of outcomes between learners and facilitators, by encouraging communication with teamwork and providing the millennial need for social connectivity on a 24/7 basis (Murthy et al., 2012). However, there is limited evidence to validate the academagogy framework, which highlights the need for further research.

2.5.2 In Online Learning

In online learning contexts, meagre evidence of academagogy was identified in the literature, except for the works by McAuliffe and Winter (2013, 2014a). The authors used a new form of e-tutorial with the Blackboard LMS for synchronous and asynchronous communication (McAuliffe & Winter, 2014a). The use of this e-tutorial showed the learners' development of cognitive knowledge and confidence as independent thinkers. Further, the e-tutorial challenged learners to "step up to the plate" in their learning, but they identified the work as intense and time consuming (McAuliffe & Winter, 2014a, p.7). The study also showed a majority of the online undergraduate learners felt more conscientious and took responsibility for their learning (McAuliffe & Winter, 2013). However, more research studies are required to understand why learners felt more conscientious with this academagogy approach.

2.6 Motivation for Using Academagogy

Academagogy substantiates the learning and teaching activities of adult learners since it is not simply a "pick and mix" of pedagogy or andragogy or heutagogy; rather, it is a "meshed model" which needs to be changed based on the cohort of learners and their learning experiences (Winter et al., 2009, p. 993, 997). The potential benefits and challenges of academagogy are discussed below.

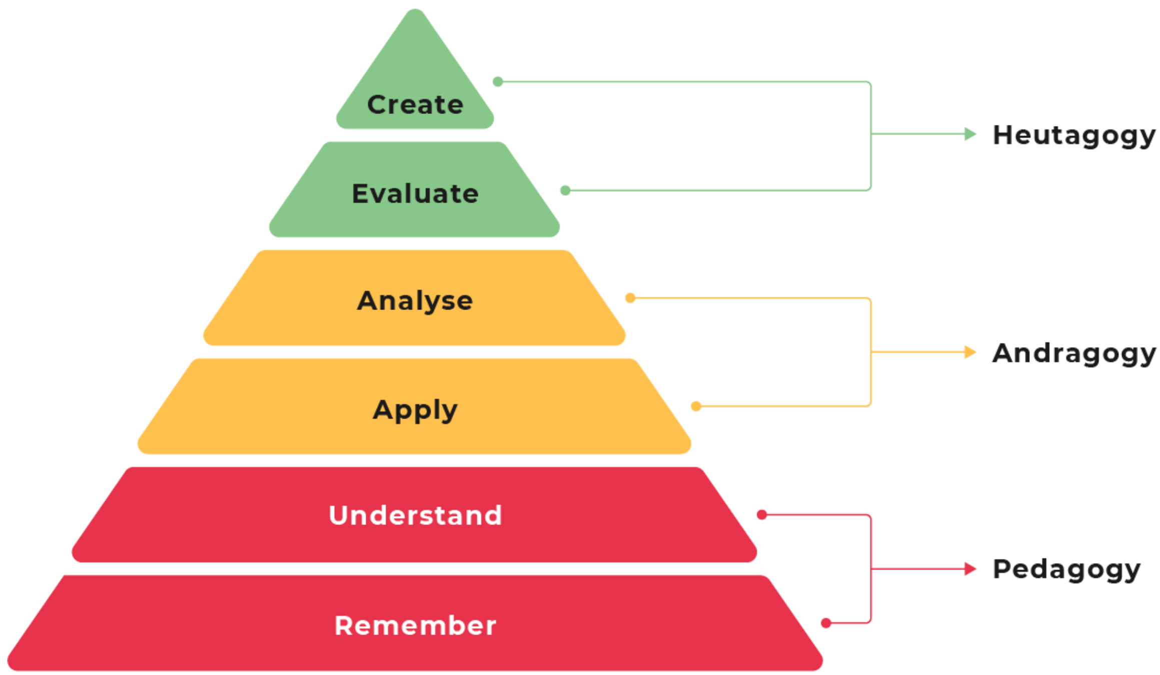
2.6.1 Potential Benefits

Academagogy develops 21st-century employment skills for learners. The primary working skills required for the 21st-century industry include self-directed learning, communication, collaboration, self-tuning to use new Information and Communication Technology (ICT) tools and readiness to learn in online environments (Bagustari & Santoso, 2019). The social constructivism concept of the academagogy framework may enable online learners to understand the learning context and apply the skills while working in the digital world. To obtain these skills, other researchers have also recommended a shift in the PAH continuum using learning and teaching activities (Agonács et al., 2020; Bagustari & Santoso, 2019; Jones et al., 2014).

Academagogy helps learners reach higher levels of Bloom's taxonomy. Figure 2.7 represents the PAH alignment with Bloom's taxonomy levels. The application of academagogy in an online subject aims to shift learners towards heutagogy by imparting the learning skills identified in Bloom's levels as the subject progresses (Addanki et al., 2020). Initially, parts of pedagogy are used to develop learners' basic cognitive skills, such as understanding and remembering. Secondly, parts of andragogy are selected to encourage the learner's metacognitive skills, such as applying and analysing the material. Finally, parts of heutagogy are chosen to enable the epistemic thinking capabilities of learners, such as critically evaluating and creating new knowledge from the learning material (Halupa, 2017).

Figure 2.7

Loose Alignment of Pedagogy-Andragogy-Heutagogy With Bloom's Levels



Note. Adapted from *Academagogy for enhancing adult online learner engagement in higher education*, by K. Addanki, J. Holdsworth, D. Hardy and T. Myers, 2020, AIS SIGED International Conference on Information Systems Education and Research. Association for Information Systems, United States of America.

Academagogy supports an educator in developing the scholarship of teaching and learning. Theories such as andragogy and heutagogy demand that educators learn how to provide learners with a positive social environment using electronic media (Cercone, 2008). Also, based on academagogy, previous researchers were able to teach metacognitive skills to learners by engaging and critically analysing the issues surrounding theory and practice (McAuliffe et al., 2015). Hence academagogy applications may be expected to enhance both teaching and learning activities.

Research on the academagogy model contributes to adult education literature. Adult learning theories such as andragogy and heutagogy were previously developed for traditional classroom environments. The availability of ubiquitous ICT tools provides the opportunity to implement mechanism to effectively use these adult learning theories in online learning contexts (Chametzky, 2014). This research study sets this context well, thereby contributing to the literature on adult education.

Generally, the pedagogy model is used by anyone aged one to 100 years (Halupa, 2017). Andragogy is primarily developed depending on the notion that adults learn differently from school children. However, there are situations where andragogy may be used with children (Holmes & Abington-Cooper, 2000). In the same way, there is evidence that heutagogy has also been used to nurture a happy learning environment in an Australian school (Blaschke, 2016). Further, heutagogy has been seen as an efficient teaching model for encouraging self-learning capabilities in undergraduate and postgraduate studies (Blaschke, 2016; Hase & Blaschke, 2019). Thus, academagogy could be used to teach learners ranging from primary school to undergraduate and doctoral students.

2.6.2 Challenges

As previously mentioned, the execution of academagogy is time consuming, as it requires the educator to tailor content for the learners' needs, which may change for each cohort (McAuliffe & Winter, 2014b; Murthy & Pattanayak, 2019). Extra support and planning are the primary requirements for academagogy (McAuliffe & Winter, 2014b; Murthy et al., 2012). Researchers have previously recommended that the framework be applied to smaller classes where meaningful interactions and mentoring by educators are possible (Murthy et al., 2012). The AI and LA that are currently used for personalisation in LMSs could help educators manage their workload for planning and address scalability issues in the application of academagogy (more details in Chapter 5).

Researchers have highlighted that it would be hard for some educators to apply academagogy in their teaching practices (Murthy et al., 2012; Pembridge & Paretti, 2010). If the educators stick to the sage-on-the-stage notion, activities such as planning based on the learners' previous experiences and current learning skills may be complex for the educators. Also, there might be challenges for educators from certain generations (e.g., baby boomers, generation X etc.) if they are required to present learning content relevant to different generations (e.g., millennials, neo-millennials, Nintendo generation etc.; see Malliarakis, 2018; McAuliffe & Winter, 2014b). Since the educators' primary responsibility is the success of the learner, they must be prepared to facilitate present- and future-generation learners with various ICT tools (Cretchley, 2009). University management should encourage both educators and learners to use academagogy to optimise the learning process (Barcelona, 2009; Hattie, 2015; Jones et al., 2019; Murthy et al., 2012).

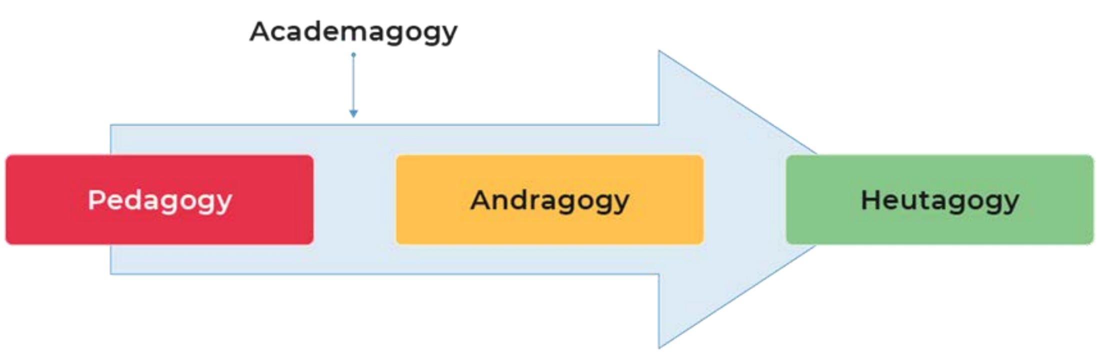
Information is scarce regarding the theory and practice of academagogy (Addanki et al., 2020). Though various books and applied research work on andragogy and heutagogy are present, there is less awareness among educators and administrators regarding the existence of various models like academagogy, andragogy and heutagogy (Akyıldız, 2019; Pembridge & Paretti, 2010). Even if the educators do not know the names of the models, they are familiar with them through the self-determination, lifelong learning, capabilities, double-loop learning and self-reflection concepts that are behind andragogy, heutagogy and academagogy models.

2.7 Using Academagogy Theory to Guide the Personalisation Process

The personalisation process, guided by academagogy in an LMS, uses the PAH continuum as a reference to identify the position and encourage the shift in learners' abilities along the PAH continuum, as shown in Figure 2.8. Learners at the pedagogy level may not have control over the learning materials (Luckin et al., 2011). Since the educator has full responsibility for the learning materials and how to deliver these materials (McAuliffe et al., 2008), this research assumed the pedagogy level as a starting point in personalising the learning experience for all learners. The role of andragogy in helping to personalise the learning experience is to allow learners' collaboration with their educator. This collaboration focuses on what and how learners can reach their learning goals (see Section 2.3.4 for an active role of learners at the andragogy level). As heutagogy enables learners to work on their goals, thus making them self-determined learners, the role of heutagogy is to help learners personalise their learning experience by allowing critical self-evaluation of their learning process.

Figure 2.8

Pedagogy-Andragogy-Heutagogy (PAH) Continuum as the Theoretical Framework



Note. Adapted from Academagogy for enhancing adult online learner engagement in higher education, by K. Addanki, J. Holdsworth, D. Hardy and T. Myers, 2020, AIS SIGED International Conference on Information Systems Education and Research. Association for Information Systems, United States of America.

The value of academagogy is its ability to assist the educator in observing the needs of individual learners and facilitating learners as they explore the learning materials. Moreover, personalisation through academagogy enables adult learners' personalised learning experiences, which can improve their engagement, consequently reducing attrition rates. Hence, this research focuses on academagogy following the PAH continuum as a framework for personalisation in an LMS.

2.7.1 Academagogy Design Principles

As specified in Table 1.1, the goal of the research was to improve adult learners' engagement by personalising their experiences in an LMS using academagogy. Learner engagement is a complex concept requiring an in-depth or longitudinal study of the learners' experiences (Muir et al., 2019). The DBR methodology was selected to study the impact of innovation (using academagogy for personalisation in an LMS) to improve adult online learner engagement. DBR allows a researcher to study innovation in a real-world learning context and communicate reusable knowledge through DPs (Reeves et al., 2005).

Design Principles (DPs) are the guidelines that contain theoretical insights into a phenomenon or an intervention (Pool & Laubscher, 2016). DPs provide insights with comprehensive documentation of methods, results and the context in which the innovative intervention is studied (Herrington et al., 2007). The DPs also guide other researchers to determine which insights from a research study could be relevant to their specific research (Herrington et al., 2007). Researchers have formulated academagogy DPs to improve learner engagement in higher education (Jones et al., 2019; Murthy et al., 2012; Murthy & Pattanayak, 2019). Jones et al. (2019) defined academagogy process knowledge with the DPs listed below:

- Ask learners how they would like to learn.

- Appreciate the diversity of the cohort.
- Understand that all the learners will not become self-directed at the same pace.
- Develop prompts to ensure educators know learners' movement between leading and supporting.
- Work with learners to identify different resource requirements to support their learning.
- Work with learners to identify areas of individual responsibility required to support their learning.
- Ensure learners fully understand the educator's role and what is expected from learners for them to become self-directed learners.

Murthy and Pattanayak (2019) applied academagogy DPs (Murthy et al., 2012) when training new recruits in a corporate setting, and showed that they influenced the participants' behavioural skills positively. However, the DPs were not implemented in a formal educational setting and were not rigorously studied. This research study's approach to an academagogical framework for designing a subject at the tertiary level is shown in Figure 2.9 and described below.

Figure 2.9

Academagogical Framework

Content has been removed due to copyright restrictions

Note. Adapted from "Pedagogical foundations for effective competency building in the hydrographic and cartographic sectors", by S. Murthy, R. Furness and D Wardle, 2012. Also adapted from "Implementing the principles of academagogy for effective learning facilitation in corporate organizations: A case study", by S. Murthy and B. Pattanayak, 2019, *Development and Learning in Organizations*, *34*(4).

1. Identify subject objectives with measurable outcomes with educators (subject matter experts) and learning designers.
2. Transform the subject objectives into specific learning outcomes.
3. Map learning outcomes with appropriate learning methodologies such as andragogy and heutagogy.
4. Use participatory learning to encourage learners' and educators' ownership of subject management by setting an appropriate schedule.
5. Deliver the subject with progress tracking; progress must be discussed among the educator, learners and the learning designer to make any changes in the subject if required.
6. Engage in overall reflection to continuously improve the subject content and consider delivery by incorporating new technology.

Although researchers have suggested DPs for the application of academagogy, there is limited evidence regarding the impact of academagogy on learner engagement. Academagogy DPs are further explored and discussed in Chapter 7.

2.8 Chapter Summary

This chapter has provided the relevant literature and necessary details to investigate the research question: How can we enhance the capabilities of an LMS to help educators personalise adult online learner experience using academagogy? Current LMSs are limited in supporting educators' personalisation of learning experiences according to individual adult online learner needs (Bajaj & Sharma, 2018; Demir et al., 2021). Previous studies have shown different technologies such as LA, BD, ML, AI and ITSs to help educators with personalisation in LMSs. However, there is a knowledge gap in the conceptual understanding of integrating different technologies with the teaching practices in an LMS, leading to complexities in implementing personalisation by educators (Mikić et al., 2022).

This chapter reviewed the knowledge gap and introduced the concept of academagogy to help educators implement personalisation in LMSs. In addition, this chapter also uncovered a research gap in the application of academagogy for personalisation in online learning environments. To bridge these knowledge gaps, novel longitudinal research is required to explore user experiences (of educators and adult online learners) with the application in an LMS. The DBR methodology was adopted to understand implications of this new application, as the methodology provides a theoretical grounding with empirical evidence in a real-world context, thus informing local and global practices (Anderson & Shattuck, 2012). Chapter 3 will include the details of the methodology used to address the research question, aim and objectives.

Chapter 3. Research Methodology

This chapter provides the overall methodology used to achieve the research aim and objectives presented in Chapter 1. DBR is discussed as the primary methodology for addressing the research question, aim and objectives in this thesis. The research plan and methods for participant recruitment, data collection and data analysis are presented.

3.1 Chapter Overview

This chapter presents the research methodology and related methods. Section 3.2 reiterates the research question and aim. Section 3.3 discusses the research paradigm that guided the actions of the researcher. Section 3.4 describes the research methodology and the phases involved in conducting the research. Section 3.5 details the participant recruitment method and selection criteria. Section 3.6 outlines the data collection methods and provides a justification for their choice. Section 3.7 explains the data analysis methods. Section 3.8 gives an overview of the research timeline, and finally, Section 3.9 provides a summary of the chapter.

3.2 Research Question and Aim

Chapter 1 introduced the problem of high attrition rates for adult online learners in higher education due to low engagement attributed to traditional teaching practices in LMSs. Previous studies have shown that personalisation of online learning experiences may reduce the attrition of adult learners (Shearer et al., 2020; Stone, 2017). Though personalisation plays an important role in engaging learners, its implementation was deemed complex for educators due to limited theoretical guidance in the use of various technologies such as LA and AI in LMSs (Bartolomé et al., 2018; Mikić et al., 2022). The literature review described in Chapter 2 highlighted the potential of academagogy theory to guide the personalisation process in an LMS. Based on the knowledge gaps identified in Chapter 2 (see Section 2.4), the research question and aim are presented below:

Research question: How can we enhance the capabilities of an LMS to help educators personalise adult online learner experience using academagogy?

Research aim: Improving personalised interaction between educators and adult online learners in LMSs using academagogy as a foundation.

3.3 Research Paradigm

The research paradigm refers to philosophical thinking or the basic set of beliefs that guide the actions of a researcher. This paradigm also defines the 'worldview' of the researcher, which describes the researcher's way of thinking and making meaning of real-world complexities (Kaushik & Walsh, 2019). A research paradigm provides the conceptual lens for the researcher to examine the methodological aspects of the research project, such as research methods to collect and analyse the data (Kivunja & Kuyini, 2017). There are four types of research paradigms:

1. The positivist paradigm is quantitative in nature; the research is conducted in controlled environments, and the results could be replicated (De Villiers, 2012).
2. Interpretivism is qualitative in nature; the researcher interprets the research carried out in natural settings. Though the results are not replicable in this type of research, evidence is drawn from multiple data sources; hence, the observations are triangulated by various types of data sets (De Villiers, 2012).
3. Critical/transformative research uses mixed methods with a research agenda to reform inequalities such as gender, race, ethnicity and disability experienced by participants in their social life (Creswell, 2014).

4. Pragmatic research uses mixed methods (both quantitative and qualitative methods) to understand the data, and uses one method to verify findings from another method, which supports the trustworthiness of the researcher's interpretations (Pool & Laubscher, 2016).

A pragmatic research paradigm was chosen to understand the research question and achieve the research aim and objectives. The pragmatic paradigm provides benefits from both empirical precision (offered by the positivist nature of quantitative thinking) and descriptive precision (offered by the interpretivist nature of qualitative thinking), instead of drawing incomplete decisions from selecting a single paradigm (Onwuegbuzie & Leech, 2005). This research was not focused on driving any transformation of social or political injustice to the participants; hence, the critical/transformative paradigm was discounted.

Pragmatism focuses on practical knowledge by combining the actual participants' behaviours, beliefs behind those behaviours and consequences of those behaviours (Kivunja & Kuyini, 2017). The focus of this research was to gain practical knowledge with the stakeholders (educators and adult online learners) while applying personalisation, supported by academagogy theory, in a real-world LMS setting. Therefore, this paradigm suited the research focus.

Pragmatism prioritises 'what works' in research, allowing the researcher to address the questions being investigated without concern for the quantitative or qualitative nature of the questions (Kivunja & Kuyini, 2017). In pragmatism, researchers are free to choose the best research methods, techniques and procedures to meet their purpose (Creswell, 2014). The DBR methodology was chosen following the pragmatic approach to study the effectiveness of the intervention in a real-world learning situation (i.e., personalisation of adult online learner experiences using academagogy in an LMS).

3.4 Rationale for Selecting the Design-Based Research Methodology

DBR investigates how and why an educational innovation works locally, thus assisting the formation of theoretical guidelines for global applications (Anderson & Shattuck, 2012). The guidelines are not designed to create theories that function with the same results in all contexts (Anderson & Shattuck, 2012). Instead, the guidelines reflect the conditions in which they operate (Anderson & Shattuck, 2012; Barab & Squire, 2004).

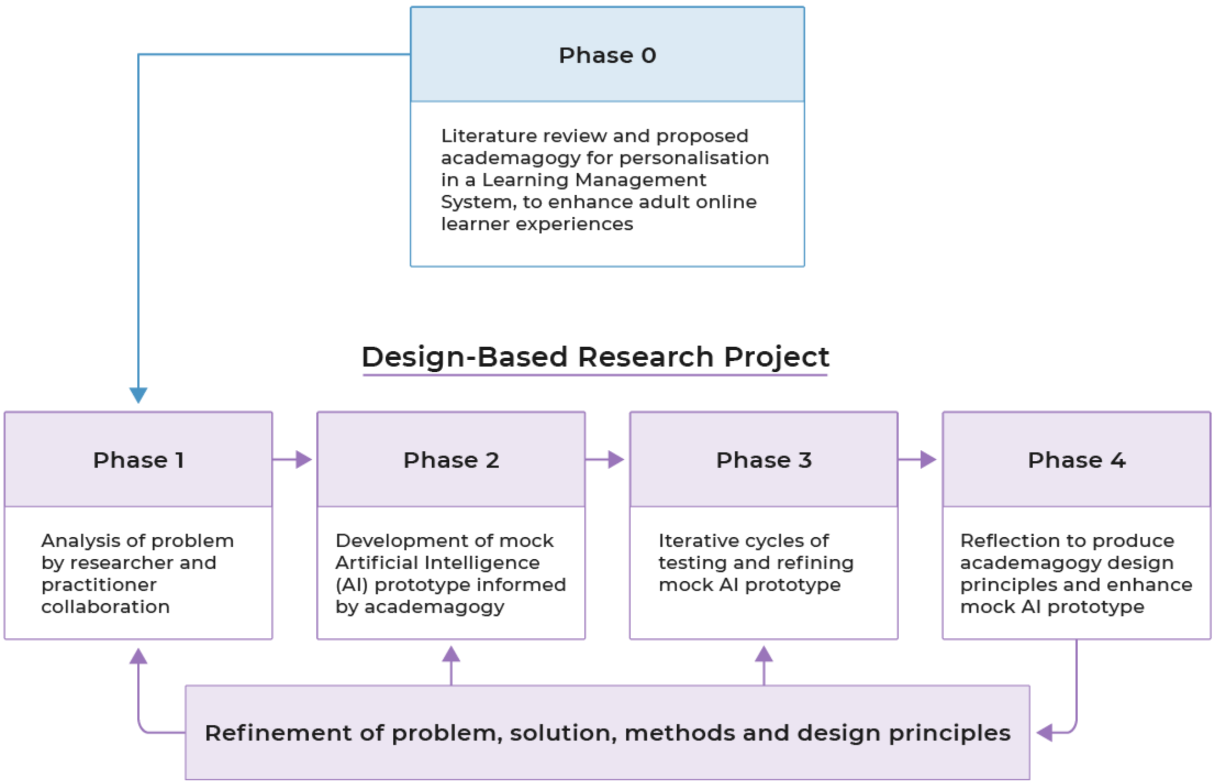
DBR has its origin in design research or development research; it uses the pragmatic tradition of American educational philosophy discussed by eminent philosophers such as John Dewey, William James and Charles Sanders Peirce (Anderson & Shattuck, 2012; Kaushik & Walsh, 2019). DBR is defined as a paradigm with the goal of using technology to solve problems and to design learning environments in complex, real-world settings (De Villiers, 2012). DBR is increasingly used as a research model for studies on the development of e-learning materials and technology-enhanced learning environments (Anderson & Shattuck, 2012). Grounded in the use of theoretical and empirical evidence to highlight the knowledge and solutions uncovered during the research (Barab & Squire, 2004), DBR provides an authentic arena for designing and testing interventions through consecutive cycles of design, enactment and analysis (Parmaxi & Zaphiris, 2020). DBR provides a structure for the qualitative and quantitative methods used in the study and supports rigour in analysis and reporting (Anderson & Shattuck, 2012).

Action Research (AR) is another methodology that provides understanding of an intervention's impact (e.g., technology or innovative teaching model) in a social setting, such as an educational context. AR "is about undertaking action and studying that action as it takes place" (Coghlan & Shani, 2005, p. 533). In general, AR is carried out by an educator to study and improve their own profession (Zeni, 1998). AR is occasionally carried out by outsiders (e.g., a researcher investigating an educator's practice) to investigate and improve the educator's practice (Zeni, 1998). Both AR and DBR share many epistemological and ontological underpinnings, often leading to researchers' confusion when choosing between the two methodologies (Anderson & Shattuck, 2012). However, DBR encourages collaborative partnerships between researchers and practitioners who form a design team, which is limited in AR (Anderson & Shattuck, 2012; Reeves et al., 2005; Wang & Hannafin, 2005).

The DBR methodology was chosen instead of AR so this research could benefit from collaboration with an experienced educator. The educator's expertise and learners' experiences contributed further understanding to address the research goal of personalisation using the academagogy framework in an LMS. The collaborative partnership led to the development of theory and guidelines for future researchers (see Chapter 6). This research involved a DBR study with five phases, as shown in Figure 3.1, which was adapted from Herrington et al. (2007; see also Figure 1.1). The research activities carried out in each phase are described in Table 3.1.

Figure 3.1

The Multi-Phased, Design-Based Research Project



Note. Adapted from *A preliminary study using academagogy to uncover the problems that block adult online learner engagement*, by K. Addanki, J. Holdsworth, D. Hardy and T. Myers, 2022, 24th Australasian Computing Education Conference, Association for Computing Machinery, United States of America.

Table 3.1

Research Activities Mapped to the Design-Based Research Phases

Phase	Objective	Research activity
Phase 0	Literature review	An extensive literature review was conducted identifying a research gap in using the learner-centred teaching model academagogy for personalising adult learner experiences in online learning at universities
Phase 1	Analysis of problem	Using the lens of academagogy theory, the ethnographic pilot study was carried out at an Australian university to observe the experiences of an adult learner cohort enrolled in a subject in the blended-learning mode
Phase 2	Development of solution	The extended study was organised to develop a mock Artificial Intelligence prototype to help educators in implementing academagogy theory for personalising the experiences of adult learners
Phase 3	Iterative cycles of testing and refining the solution	The extended study was used to test and refine the mock Artificial Intelligence prototype with another cohort of adult learners taking the same blended-learning subject
Phase 4	Reflection	The data from the pilot and extended studies were compared to produce Design Principles for personalising adult online learning experiences using academagogy

3.4.1 Phase 0—Literature Review

The initial phase of the DBR project involved a preliminary literature review for the identification of problems and existing solutions. The review involved an exploration of the research problem: The high attrition rate for adult learners in tertiary education, and especially adult learners' engagement with current LMSs for online learning (see Section 1.3). To understand the use of personalisation for enhancing adult learner engagement in higher education, a thorough literature review was conducted (Chapter 2).

3.4.2 Phase 1—Analysis of Problem

Phase 1 of the DBR project refers to the analysis of real-world problems by researchers and practitioners in collaboration. In this phase, Research Objective 1 was applied to: Identify and analyse educators' challenges and obstacles when personalising learning for adult students in an LMS using academagogy.

A pilot study was conducted in a real-world context using an ethnographic approach, to further understand the local context. Ethnography includes the researcher's participation in the field to understand what people are doing and how people are experiencing what they are doing (Dourish, 2014). In this study, a cohort of adult learners taking a subject in blended learning mode at James Cook University (JCU) using the Blackboard LMS was observed. The educator and learners were observed to understand their experiences through the lens of academagogy. A full documentation of the learners' and the educator's experiences are detailed in Chapter 4. These experiences revealed the adult online learners' problems could be potentially addressed by personalising their experiences using the academagogy framework with the LA (Addanki et al., 2022). However, the analysis of data gathered through this pilot study revealed the aforementioned scalability issues in terms of time and the extra workload for educators (see Section 2.6.2). These scalability issues were addressed in Phase 2.

3.4.3 Phase 2—Development of Prototype Solution

Phase 2 of the DBR project relates to designing and developing a prototype solution using existing DPs and technological innovations. Rooted in existing academagogy DPs (see Section 2.7.1) and current technologies such as LA and SA, a prototype solution was explored to help educators' personalisation in LMSs. Phase 2 was conducted to achieve Research Objective 2: Outline and describe the principles for applying academagogy to facilitate personalisation in an LMS.

Based on the scalability issues identified in Phase 1, the potential of AI in automating the process of personalisation based on academagogy was explored as a technology-based solution.

The increase of AI systems using LA and SA in higher education from 2020 to 2022 was promising, as these systems analyse larger volumes of learner data with less time and more accuracy to aid educators (Kaliisa & Dolonen, 2022; Zawacki-Richter et al., 2019). AI systems are limited because they lack users' involvement during the design process (Chichekian & Benteux, 2022; Prieto-Alvarez et al., 2018). In addition, poorly designed AI systems can lead to user frustration and abandonment of the system (Maulsby et al., 1993). Further, developing AI systems requires a vast amount of time, money and human resources. Wizard of Oz (WOz) is a practical approach for designing intelligent systems. WOz avoids the extensive resources used for systems that do not meet user needs by testing ideas early in the development process before building a fully functioning system (Sheline & MacLellan, 2018). Hence, before investing resources into the development of an AI system that meets user expectations, WOz, a low-fidelity prototyping method, was used to design the mock AI prototype.

The WOz method is an experimental technique used to develop a Human-Centred Design (HCD) prototype for AI systems (Maulsby et al., 1993; Porcheron et al., 2021). In a WOz experiment, a researcher rapidly tests a hypothetical AI system with real users by manually simulating the system's capabilities (Sheline & MacLellan, 2018). A human (i.e., wizard or researcher) simulates the system's intelligence and interacts with the users through a real or mock computer interface (Maulsby et al., 1993). The WOz method is a lightweight prototyping activity that ascertains additional information from users before developing a functional prototype that solves the targeting issue (Dow et al., 2005). The mock AI prototype was designed using the WOz method, which is detailed in Chapter 5.

3.4.4 Phase 3—Testing and Refining Prototype Solution

Phase 3 of the DBR project includes iterative cycles of testing and refining the prototype solution. Phase 3 was carried out to meet Research Objective 3: Provide preliminary insights about the combined impact of academagogy, LA and SA on the engagement of adult online learners.

In this research project, the mock AI prototype that was designed as a prototype solution in Phase 2 was iteratively tested and refined using an extended study. The aim of the mock AI prototype was to help an educator personalise the experiences of adult learners using academagogy in an LMS. The mock AI prototype was progressively tested and refined in three iterations that applied user-centred design methods. Since educators are the major stakeholders of this research (see Section 1.7.1), the mock AI prototype was refined using a co-design method with the educator involved in Phase 1. *Co-design* is a user-centred design method where the end user of the system is involved as a collaborator in the design process (Cavignaux-Bros & Cristol, 2020). Adult learners are also the stakeholders of the research; therefore, adult learners participating in the extended study were interviewed to gather their user experiences with the mock AI prototype. The details of Phase 3 are further described in Chapter 5.

3.4.5 Phase 4—Reflection

Phase 4 of the DBR project reflects the research results, which may advance theory and real-world applications. This phase aimed to achieve Research Objective 4: Provide User Experience (UX) design concepts for educators and learners focusing on personalisation in an LMS using academagogy.

In general, a DBR project results in two main types of outputs: scientific and practical (Herrington et al., 2007). The scientific (or theoretical) output refers to the evidence-based heuristic DPs that can inform future development and implementation. The practical output refers to artefacts such as software or professional development programs, designed with the aim of using technology to solve teaching, learning and performance problems. This study's design concepts (outputs) are:

- The DPs based on the research evidence are documented as theoretical output in Chapter 7.
- The artefact designed in this research was the mock AI prototype. More details of the prototype are discussed in Chapter 5.

3.5 Participants

This research focuses on the learning experiences of adult learners; hence, a purposive sampling technique and a voluntary participation criterion were used to recruit participants aged over 25 years. In a purposive sampling technique, the researcher selects participants who are most likely able to offer information that can be used to develop an answer to the research question (Marshall, 1996; Saldaña, 2016).

3.5.1 Recruitment Strategy

The pilot study in Phase 1 and the extended study in Phases 2 and 3 (see Table 3.1), involved recruiting participants from the adult learner group at JCU, Australia. JCU's Human Ethics Committee approved recruitment of the learners for the pilot and extended studies with approval number "H8321" (Appendix A). Learners enrolled in an Information Technology (IT) subject, named "Advanced Mobile Technologies" (a master's level subject), were approached for recruitment. This subject had a mix of international learners and domestic learners with diverse educational and cultural backgrounds. The diversity of the learners from this subject was optimal for studying the personalisation research question. The subject was also considered ideal for bridging the gap between academagogy theory and practice for personalisation since previous learners had reported difficulty with the hands-on learning of Java-based programming.

The pilot study was carried out in the first semester, from February to July 2021. Before the semester started, all learners enrolled in the subject were emailed a research advertisement by the JCU College of Science and Engineering (CSE) administration staff, sent on behalf of the researcher. The advertisement email informed the learners of the research project details, thus ensuring no adverse consequences for non-participation. Interested learners sent an email to the researcher indicating their voluntary participation. A consent form was then emailed to the interested learners. Six participants were recruited based on the criteria of being 25 years or older and interested in improving their general self-learning skills and knowledge about the subject (programming, research and presentation skills of Mobile Technologies).

The extended study was carried out in Phases 2 and 3 of the DBR project from July 2021 to July 2022. The educator who taught the subject in the pilot study was recruited for the extended study. In Phase 3 (from February to July 2022), learner participants were recruited based on the same recruitment criteria as the pilot study. However, only two participants volunteered for the study. Due to Australia's national and international border closures in response to the COVID-19 pandemic, there were very low enrolments in the subject for the year 2022. Therefore, to maintain the participant sample size requirements for this research, the learners enrolled in another subject, "Mobile Technologies" (an undergraduate version of the "Advanced Mobile Technologies" subject), were recruited. From this bachelor-level subject, seven participants indicated their interest. Thus, a total of nine learners participated in the extended study.

Though there may be general differences between bachelor and master-level learners which is highlighted as a limitation in this thesis (refer to Section 8.4.1), there were no significant differences identified between bachelor and master-level learners in the extended study. Both the bachelor and master-level learners were facilitated by the same educator at the same time using the same blended learning mode, with the only exception being one extra assessment activity done by master-level learners. Further, the use of the same recruitment criteria as the pilot study justified the participant sample in the extended study.

3.6 Data Collection Methods

The primary aim of this research was to personalise interaction between educators and adult online learners in LMSs using academagogy as a foundation. Therefore, different types of learner data were collected for the nuanced understanding of the application of personalisation based on academagogy in an LMS. Data such as learners' self-reflections and LA were collected over the 13-week semester. This data collection was followed by a scale called Online Student Engagement (OSE), semi-structured interviews and the collection of learners' grades at the end of the semester. Another data collection method, the technical icebreaker, was added in the extended study for identifying initial learner skills and implementing academagogy for personalisation based on learner needs.

3.6.1 Self-Reflections

Self-reflection is an act of active learning, where learners reflect on their personal experiences, feelings, actions and responses, and then interpret their reflections to learn from them (Getliffe, 1996). Reflections are increasingly used in higher education to encourage learners' self-regulated learning (Wallin & Adawi, 2017). Self-reflection can afford positive learning outcomes, such as goal setting and proactive use of learning strategies (De Lin et al., 2021).

The learners' needs played a major role in the personalisation process. Learner needs can be identified by the formative assessment of self-reflection (De Lin et al., 2021), which could help the educator adapt their instruction for the learners. In the pilot and the extended studies, learners wrote a self-reflection text (100 to 200 words in length) at the end of each practical session during the semester as a regular, weekly assessment piece for the subject. In this research, self-reflections written by the participants were collected every week, and the content of these reflections was used to gain a deeper understanding of the learners' needs so that the educator could tailor the instruction for applying academagogy.

3.6.2 Learning Analytics

The LA process involves measuring, collecting, analysing and reporting learners' data for the purpose of understanding and optimising their learning and the environment in which the learning occurs (Siemens, 2013). LA is a multi-disciplinary field that draws theories and methods from education, psychology, statistics, computer science, data science, neuroscience and social and learning sciences (Joksimovic et al., 2019). LA is predominantly used in online learning environments to personalise the learning experiences of learners, with an ability to provide timely assessment and feedback to individual learners at a large scale (Jones & Rienties, 2021).

LA can be used as a tool or methodology to collect the digital actions of learners in online learning. For example, whenever a learner opens an LMS, his or her actions are recorded as digital traces, such as the number of logins, time spent in the LMS and different web pages visited. The digital traces collected via the LA tool in an LMS provide a rich data source to identify learners at risk (Joksimovic et al., 2019). As the research project was to improve adult learners' engagement in online learning, where the learners are geographically separated from the researcher, the choice of LA was optimal to monitor the indirect learning behaviours (actions) of the participants. In this research, LA data such as the number of times an LMS was accessed, time spent on the LMS and the number of submissions the participants made within the LMS, were collected.

3.6.3 Online Student Engagement Scale

Measuring learner engagement in online learning is vital because the learners often feel isolated and disconnected due to geographic separation from educators and peers (Dixson, 2015). The OSE is a 5-point Likert scale used as a self-reporting instrument to collect participants' intellectual efforts, skills, performances and emotional components of learning. In an online learning environment, the learner may informally learn by discussing content with peers and educators outside the LMS; therefore, this informal learning is not observed by an LA tool. The OSE scale was included in this research to cover the broader spectrum of learner engagement.

3.6.4 Semi-Structured Interviews

Interviews are used to gather in-depth data about participants' experiences, views and beliefs regarding a specific research question or phenomenon (Ryan et al., 2009). The interviewer conducts semi-structured interviews using open-ended questions and explores spontaneous issues raised by the interviewee (Ryan et al., 2009). This flexible approach, with less-structured questions and follow up with additional details, was ideal for this research, and semi-structured interviews were conducted in both 2021 and 2022. The interviews were only conducted online using the Zoom platform due to the prevalence of COVID-19 in 2021 and 2022, as a measure to maintain social distancing for the health and well-being of participants.

3.6.5 Grades

Learners' performance in the form of grades or percentages at the end of the study period provides a quick evaluation of an intervention. Learner grades are the primary data collected in an educational setting, which are used to check the usability of a technology or teaching intervention (Denny et al., 2021; El Said & Mandl, 2021; McAuliffe & Winter, 2013, 2014b). Hence, learner grades such as grades for individual learning activities and final grades were collected in both the pilot and extended studies.

3.6.6 Technical Icebreaker

An 'icebreaker' is an activity used to collect the experiences of participants at the beginning of a study. An icebreaker activity may contain closed or open-ended questions regarding the previous experiences of the learners. Icebreakers have also been suggested to improve the learner's onboarding experience in online learning environments (Shearer et al., 2020). In this research, a technical icebreaker was conducted in 2022 as a self-reflection activity (refer Appendix G). The technical icebreaker consisted of open-ended questions about learners' previous programming (technical) experiences related to the subject, and general questions related to learners' motivation to enrol in the IT subjects and in the extended study. This item was administered as a brief survey posted on the LMS. The responses to the technical icebreaker were analysed to give insights to the educator for personalisation process (refer to Figure 5.4).

3.7 Data Analysis

A mixed methods data analysis approach was used to complement the different types of data collection methods in this research. Mixed methods provide a complete understanding of the research problems by comparing or explaining different perspectives drawn from quantitative and qualitative data (Creswell, 2014). A DBR project involves mixed methods to analyse participant data through triangulation, thereby providing rigour to the study. Hence, the research results were derived from mixed analysis using thematic analysis, content analysis, SA and LA methods.

3.7.1 Thematic Analysis

Thematic analysis is defined as a method for identifying, analysing and reporting patterns from the participant data (Braun & Clarke, 2006). This analysis has the advantage of organising data in a structured way and describing data in rich detail (Braun & Clarke, 2006). Thematic analysis involves the coding of data, where a researcher generates a short word or phrase to represent a portion of language-based (textual) or visual data (Braun & Clarke, 2006; Saldaña, 2016). Two cycles of coding approaches were used in this research: inductive and deductive. Inductive coding is a bottom-up approach defined as the process of openly coding the data without fitting it into pre-existing analytical perceptions of the researcher (Braun & Clarke, 2012). During the first cycle, the following inductive coding methods (Saldaña, 2016) were used:

- **In vivo coding**. Researchers use words or short phrases from the participant's own language as the codes.
- **Emotion coding**. Researchers label the emotions recalled, experienced or inferred by the participants.
- **Descriptive coding**. Researchers often assign a label for the data or a basic topic from a passage.
- **Process coding**. Researchers use gerunds ("ing" forms) exclusively to label observed and conceptual actions in the data.

In the second cycle of coding, the deductive approach was used. Deductive coding is a top-down approach defined as the process of closely mapping the pre-existing concepts, codes or ideas of the researcher to the raw data of the participant (Braun & Clarke, 2012). During the second cycle of coding, the following deductive coding methods were used:

- **Axial coding**. This method describes a code's property (characteristic or attribute) and dimensions (the location of a property along a continuum or range) and explores how the code and subcodes relate to each other (Saldaña, 2016).
- **Longitudinal coding**. This method codes the identity, change and development of individual participants over a period of time (Saldaña, 2016).

NVivo (version 12), a Computer Aided Qualitative Data Analysis Software was used to thematically analyse qualitative data (self-reflections and interviews). NVivo advantages data management and easy recall of the data at any time (Maher et al., 2018). In this research, NVivo was also used to perform a content analysis of the qualitative data and quickly generate visualisations of the data from a quantitative (numbers) perspective. Content analysis is defined as a method to analyse written, verbal or visual communication messages (Cole, 1988).

3.7.2 Sentiment Analysis

The SA method, also known as opinion mining or emotion analysis, uses NLP and ML techniques to analyse authors' opinions, sentiments, evaluations, attitudes and emotions in a piece of text (Hutto & Gilbert, 2014). SA provides a viable solution to analyse large volumes of learner-generated data, such as self-reflections, journals, blog posts, end-of-subject learner feedback and discussion forums. In online learning environments, analysis of the learner data is especially helpful for determining the overall sentiment of the class, and analysing individual learner data provides personalised interventions (Schubert et al., 2018). Tools such as Valence Aware Dictionary and sEntiment Reasoner (VADER), Afinn, IBM Tone Analyzer and Linguistic Inquiry and Word Count (LIWC) have been extensively used in higher education (Nielsen, 2011; Ott & Liesaputra, 2022; Slater et al., 2016).

The VADER SA tool was used in this research because it quickly analyses textual data ranging from a word to an essay in a fraction of a second (Hutto & Gilbert, 2014). This tool uses an input of text and outputs in the form of percentages for positive, negative and neutral emotions (Newman & Joyner, 2018). Positive emotions refer to opinion words like good, wonderful and amazing (Liu, 2012). Negative emotions may imply opinion words such as bad, poor and terrible (Liu, 2012), and neutral emotions imply the absence (neither nor) of positive or negative opinions (Liu, 2012). Mixed emotions refer to the presence of both positive and negative opinions in the same text. VADER works on Python-based ML algorithms that analyse the input text with a human-curated, gold-standard SA library of words (Hutto & Gilbert, 2014). This tool was used to analyse learner self-reflections (see Chapter 5). Though NVivo can be used to automatically analyse the sentiments from the textual data, VADER was used in this research as it widely used tool in higher education (Newman & Joyner, 2018).

3.7.3 Learning Analytics

LA was used as a data collection method (as mentioned in Section 3.6.2) and was also used as a method to analyse participants' actions and interactions within the LMS. LA provides a scalable option to analyse large volumes of learner-generated data in online learning environments (Joksimovic et al., 2019). The statistical analysis from the LA also helps identify the hidden patterns for learner engagement and retention (Fan et al., 2021). These patterns can aid in designing early interventions in the form of personalised support to help learners at risk.

The collected LA data, the number of times an LMS was accessed, time spent on the LMS and the number of submissions the participants made within the LMS were analysed to identify learning patterns.

3.8 Research Timeline

This research was completed in 18 months. The pilot study involved ethnographic observation of participants for six months while exploring details of the personalisation process in an LMS using an academagogy framework. Based on details of the pilot study, an extended study was conducted for 12 months over two phases (Phases 2 and 3) of the DBR project, as shown in Table 3.2. The first six months of the extended study involved co-designing a mock AI prototype using the WOz method to help educators personalise adult online learner experiences. The following six months of the extended study comprised the testing and refinement of the mock AI prototype with participants.

Table 3.2

Overview of the Research Timeline

Study	Timeline	Participants	Research activities	Data collection	Data analysis
Pilot Study in Phase1	February 2021 to July 2021	Six adult learners and one educator	Ethnographic observation of participants	Learners: semi-structured interview, self-reflections, grades, Online Student Engagement (OSE) scale and Learning Analytics at the end of the semester	Thematic and content analysis (interview transcripts, self-reflections and grades)
Extended Study in Phase 2	July 2021 to February 2022	One educator	Co-designing (understanding and prototyping) the mock Artificial Intelligence prototype with the educator	Educator: semi-structured interview at the beginning of the semester	Thematic analysis of the interview transcript
Extended Study in Phase 3	February 2022 to July 2022	Nine adult learners and one educator	Co-designing (testing and refining) the mock Artificial Intelligence prototype with the educator and learners	Learners: • technical icebreaker and OSE scale at the beginning of the semester • semi-structured interview in the middle of the semester • semi-structured interview, OSE scale and grades at the end of the semester • self-reflections and Learning Analytics collected every week during the semester. Educator: • Semi-structured interviews at the beginning, middle and end of the semester	Thematic and content analysis (Technical icebreaker, interview transcripts, self-reflections and grades) Sentiment Analysis on learner self-reflections (Valence Aware Dictionary and sEntiment Reasoner tool) Learning Analytics

3.9 Chapter Summary

The DBR methodology was chosen to explore how the capabilities of an LMS could be enhanced to help educators personalise adult online learner experiences using academagogy (see Figure 3.1). Since DBR aims to understand the possibility of technology to solve an educational problem (see Section 1.3), the choice of this methodology aided in understanding the technologies LMS, LA, SA and AI for personalisation. These technologies were systematically used in this research to personalise adult online learner experiences based on an academagogy framework. The pilot and extended studies were designed to continue the previous studies of personalising online learner experiences in the higher education context (Bartolomé et al., 2018; Cardenas et al., 2022; McLoughlin & Lee, 2010; Mikić et al., 2022; Walkington & Bernacki, 2020). The implications for using LA, SA and the mock AI prototype, which was guided by academagogy theory in this research, will potentially aid future research on personalising adult learner experiences in an LMS.

The next chapter provides a detailed explanation of the pilot study, where a cohort of adult learners was observed to find how to personalise their learning experiences in an LMS using academagogy theory.

Chapter 4. Pilot Study

This chapter describes an ethnographic pilot study of adult learners' and an educator's learning experiences, to explore ways of applying academagogy to enhance the capabilities of an LMS for personalisation. Results from the study showed that academagogy could potentially be a framework to personalise adult learner experiences. However, the study identified workload and extra time commitments as some of the challenges for an educator to apply academagogy.

4.1 Chapter Overview

The pilot study is related to DBR Phase 1, analysis of the problem, which is described in Chapter 3. The main objective of this pilot study was to observe the experiences of an educator personalising adult online learner experiences in an LMS. Section 4.2 describes participant recruitment for the pilot study. Section 4.3 provides a glimpse of the methods used to collect data for the pilot study. Section 4.4 explains data analysis procedures. Section 4.5 details the results of the pilot study. Section 4.6 highlights insights from the study and finally, Section 4.7 summarises the chapter.

4.2 Participant Recruitment

The research design of this pilot study involved the ethnographic observation of participants using qualitative and quantitative approaches to maximise the opportunity for a complete understanding of the learning setting. Ethnography is defined as the study of "social interactions, behaviours, and perceptions that occur within groups, teams, organisations, and communities" (Reeves et al., 2008, p. 512). Researchers in ethnographic studies participate in the context of the study to not simply gather the participants' data but also to understand what participants are doing and how they are experiencing their doings (Dourish, 2014).

Six participants were recruited using the recruitment strategy mentioned in Section 3.5.1. All participants in this pilot study were international learners at the master's level (fifth year) and aged 24 years and above. The educational background and work experience of the six participants are shown in Table 4.1. Participants provided written consent to share their learning experiences. The code names S1, S2, S3, S4, S5 and S6 were given to the six participants to ensure their anonymity in this research.

Table 4.1

Pilot Study Participant Information

Participant	Gender	Education background	Work experience
S1	M	Electronics and communication engineering	No work experience and had a gap of two years before enrolling in the master's degree
S2	M	Business administration	Ten years of work experience as a manager
S3	M	Computer science	Worked in the networking field
S4	M	Computer science	Worked in the Information Technology field for one and a half years
S5	F	Computer science	Worked as a web application developer for two years
S6	M	Electronics and communication engineering	Worked as an automation testing engineer

Note. Adapted from *A preliminary study using academagogy to uncover the problems that block adult online learner engagement*, by K. Addanki, J. Holdsworth, D. Hardy and T. Myers, 2022, 24th Australasian Computing Education Conference, Association for Computing Machinery, United States of America.

The teaching format used for this subject was blended learning, which included lectures and practicals. The lectures were delivered through online synchronous sessions and asynchronous recorded lecturettes. The practicals were conducted as face-to-face learning sessions in a computer lab. During each practical, learners worked with hands-on coding activities to develop mobile applications that were facilitated by a tutor (another teaching staff member, not the subject educator).

4.3 Data Collection

Data were collected through the learners' self-reflections and LA over the 13-week semester. These data collection methods were followed by a survey, a semi-structured interview and collection of each learner's grades at the end of the semester, as described in Section 3.6 and summarised below:

- **Self-reflections**. As a weekly subject assessment piece, learners wrote a self-reflection text (100 to 200 words long) at the end of each practical session. There were nine practicals in this subject. In total, 54 self-reflection texts were collected from the six participants. These self-reflections provided lived and in-depth experiences of learners as they worked on each practical.
- **LA**. Participant LA data were collected from the university's LMS. User interaction data, such as the number of times the subject was accessed, the number of interactions, time spent and the number of submissions the participant made within the subject site during the semester, were collected.
- **OSE scale**. At the end of the semester, participants were given the OSE. OSE is a 5-point Likert scale instrument used to collect participants' intellectual efforts, skills, performances and emotional components of learning (Dixson, 2015).
- **Semi-structured interviews**. At the end of the semester, participants were interviewed using online Zoom meetings. Participants consented to being recorded during the meetings. The audio recordings were then anonymised and transcribed into text

documents. These interviews provided additional data regarding the overall experience of learners in the subject.

- **Grades**. At the end of the semester, participants' grades for assessment activities were collected. The subject included the following assessment activities.
  - Assessment 1 was a mobile application development activity (creating and deploying a utility-based mobile application adhering to guidelines of the Android mobile platform).
  - Assessment 2 was a mobile application development activity (creating and deploying an education-based mobile application adhering to guidelines of the Android mobile platform).
  - Assessment 3 was a code review presentation activity (evaluating and discussing the technical aspects of mobile computing).
  - Assessment 4 was a comparative analysis report writing (exploring and reflecting on an academic research field involving mobile technology).

4.4 Data Analysis

A reflexive thematic analysis method was used to examine data from the self-reflections and interview transcripts. Reflexive thematic analysis is a traditional qualitative method used to identify, analyse and report important research data references (themes, categories and codes) based on the researcher's subjective skills (Braun & Clarke, 2020; Saldaña, 2016). The data were analysed through the subjective lens of identifying learner problem areas, emotions and evidence of learner position on the PAH continuum (see Section 2.3.4). The choice of lens was based on the research aims to improve personalised interactions between educators and adult online learners in an LMS using academagogy as a foundation.

Identifying adult learners' problem areas and addressing them immediately through personalised feedback from the educator enhances learning outcomes (Kara et al., 2019). Emotions influence adult learner interactions with educators in an online learning environment (Hewson, 2018), making emotions an essential research focus. Identification of a learner's position on the PAH continuum was inferred by analysing the data against the characteristics of a learner positioned at pedagogy, andragogy and heutagogy levels, which was extracted from previous studies (Blaschke & Marin, 2020; Luckin et al., 2011; also see Sections 2.3 and 2.7). This is outlined in Table 4.2 and described further below.

Table 4.2

Differences Among Learner Characteristics at Pedagogy, Andragogy and Heutagogy Levels

Characteristics	Pedagogy	Andragogy	Heutagogy
Dependence	Dependent	Independent	Interdependent
Cognition Level	Cognitive	Metacognitive	Epistemic
Motivation	External	Internal	Self-efficacy

Note. For more information, see Luckin et al. (2011).

At the pedagogy level, a learner is dependent on the educator to determine what, how, where and when to learn (Winter et al., 2008). The learner thinks cognitively by performing tasks such as computing, memorising, reading, perceiving and acquiring knowledge (Kitchener, 1983; Luckin et al., 2011). The learner's motivation is external, meaning the learner's study purpose is either for higher grades or to progress to the next level academically.

At the andragogy level, a learner tries to be independent by identifying their learning needs with or without the educator's help (Knowles, 1980). The learner thinks metacognitively by formulating learning goals, identifying learning resources and using strategies to attain learning goals set by the educator (Blaschke & Marin, 2020). The learner is a problem solver and intrinsically motivated by their self-esteem while learning.

A learner at the heutagogy level moves beyond acquiring skills and knowledge to adopting a more holistic approach (Blaschke & Marin, 2020). The learner becomes interdependent on particular resources to reach their goals (Nah, 1999). They develop self-efficacy (a sense of achievement) by using epistemic skills such as exploring, experimenting or creating (Blaschke & Marin, 2020). The learner, as a problem finder, is capable of defending the strategy they choose to solve a problem and can show the merits and demerits of the strategy (Kitchener, 1983).

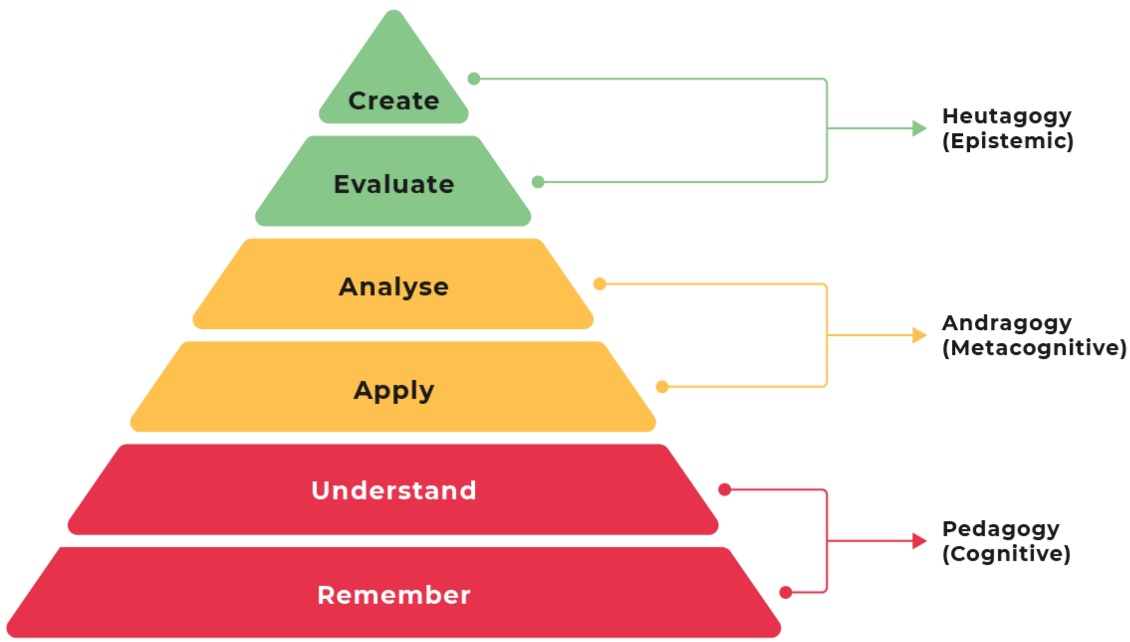
4.4.1 Pedagogy-Andragogy-Heutagogy Algorithm

As the primary concept of academagogy is to shift the abilities of learners from pedagogy to andragogy towards heutagogy (Winter et al., 2009), an algorithm was created to identify the steps for an educator to encourage learner abilities on the PAH continuum. The PAH continuum can potentially be used as a reference for educators to identify the level of learner agency, and for devising teaching strategies for personalisation supporting individual learners (Canning, 2010; Hase & Blaschke, 2019; Narayan et al., 2019). Canning (2010, p. 63) suggested that "acknowledging past learner experiences, reflecting on their impact and being aware of how they may influence future learning" can help educators design teaching strategies to encourage learner's agency toward heutagogy on the PAH continuum.

The PAH algorithm was developed to apply the longitudinal coding technique of thematic analysis (see Section 3.7.1). This algorithm lists the steps necessary to analyse a text and identify: (1) what level the learner is currently at in the PAH continuum and (2) if they are moving forwards or shifting backwards on the PAH continuum. The process of determining the learner's PAH level was developed by mapping their cognitive behaviours based on PAH literature (Table 4.2) with the action verbs of Bloom's taxonomy (cognitive domain). This concept was illustrated as a loose alignment between PAH levels and Bloom's taxonomy (see Section 2.6.1 and Figure 4.1).

Figure 4.1

Mapping the Pedagogy-Andragogy-Heutagogy Cognitive Differences With the Action Verbs of Bloom's Taxonomy (Cognitive Domain)



Note. Adapted from *Academagogy for enhancing adult online learner engagement in higher education*, by K. Addanki, J. Holdsworth, D. Hardy and T. Myers, 2020, AIS SIGED International Conference on Information Systems Education and Research. Association for Information Systems, United States of America. For more information, see Murthy et al. (2012).

The analysis of a learner's self-reflection text to find the learner's position on the PAH continuum is as follows:

- If the text shows action verbs related to the pedagogy level (e.g., remember and understand), then the learner was assumed to be at a pedagogy level (the same process is used to determine andragogy and heutagogy levels).
- If the text reveals action verbs related to two levels (i.e., pedagogy and andragogy levels or andragogy and heutagogy), then the following three aspects were considered together
    - **Aspect 1**. Changes in cognitive skills
    - **Aspect 2**. Changes in problem-solving skills
    - **Aspect 3**. Changes in emotions.

Aspect 1: Changes in cognitive skills can be a trigger indicating a learner is either progressing or shifting backwards on the continuum, as shown in Table 4.3.

Table 4.3

Differences in Pedagogy, Andragogy and Heutagogy With Respect to Cognitive Skills

Level on the Pedagogy-Andragogy-Heutagogy continuum	Cognitive skill	Example of actions derived from participant data
Pedagogy	Cognitive	Understanding, memorising
Andragogy	Metacognitive	Applying, problem-solving and analysing
Heutagogy	Epistemic	Experimenting, lateral thinking, critical thinking, problem finding and solving

Aspect 2: Changes in problem-solving skills can also be a trigger indicating a learner is either progressing or shifting backwards on the PAH continuum, as shown in Table 4.4.

Table 4.4

Differences in Pedagogy, Andragogy and Heutagogy With Respect to Problem-Solving Skills

Level on the Pedagogy-Andragogy-Heutagogy continuum	Problem-solving skill	Exemplar problem-solving skill derived from participant data
Pedagogy	Dependent	Learner needs educator's help to solve problems and passively receives the knowledge
Andragogy	Independent	Learner can solve problem with or without the help of the educator and is actively involved in the learning process
Heutagogy	Interdependent	Learner can solve problem by using some strategies, is able to demonstrate the merits and demerits of those strategies and is proactively involved in the learning process

Aspect 3: Finally, changes in emotions can be a trigger indicating a learner is either progressing or shifting backwards on the PAH continuum, as shown in Table 4.5.

Table 4.5

Differences in Pedagogy, Andragogy and Heutagogy With Respect to Emotions

Level on the Pedagogy-Andragogy-Heutagogy continuum	Example of emotions derived from participant data
Pedagogy	Mixed: mostly negative and sometimes positive
Andragogy	Mixed: mostly positive and sometimes negative
Heutagogy	Highly positive

The combination of these three aspects together indicated a trigger in the form of an increase in confidence or increase in negative emotions:

- If the trigger was an increase in confidence, then the learner was considered as progressing towards the next level on the PAH continuum.

- If the trigger was an increase in negative emotions, then the learner was considered as shifting back on the PAH continuum.

4.4.2 Content Analysis

Content analysis is a research method used to analyse written, verbal or visual communication messages (Cole, 1988). To maintain rigour and internal validity while analysing the textual data (self-reflections and interview transcripts), NVivo (Section 3.7.1) was used. The textual data were analysed using NVivo following the thematic analysis method. In the first coding cycle, the data were coded using open coding methods, emotion coding and in vivo coding inspired by the grounded theory approach (Saldaña, 2016).

During the transition from the first to the second cycle of coding, eclectic coding (Saldaña, 2016) was used as a purposeful combination of emotion coding, in vivo coding, process coding and descriptive coding (see Section 3.7.1). The eclectic coding resulted in a total of 95 primary codes. A second cycle of coding, axial coding, was used to identify main categories from the primary codes. This second cycle resulted in five main categories, as shown in Table 4.6.

Table 4.6

Major Categories Derived From the Content Analysis of Participant Self-Reflections and Interviews

Major categories	Description	Number of references
Pedagogy-Andragogy-Heutagogy	Any piece of text that shows evidence of pedagogy, andragogy or heutagogy characteristics	190
Emotions	Learner emotions or feelings while learning the subject	181
Problems	Any problems faced by learners	125
Takeaways	Key observations from the data or suggestions provided by the learners that could be useful in the subsequent offering of the subject	55
Learning environment	Anything related to learner resources that effected learning	36

4.5 Pilot Study Results

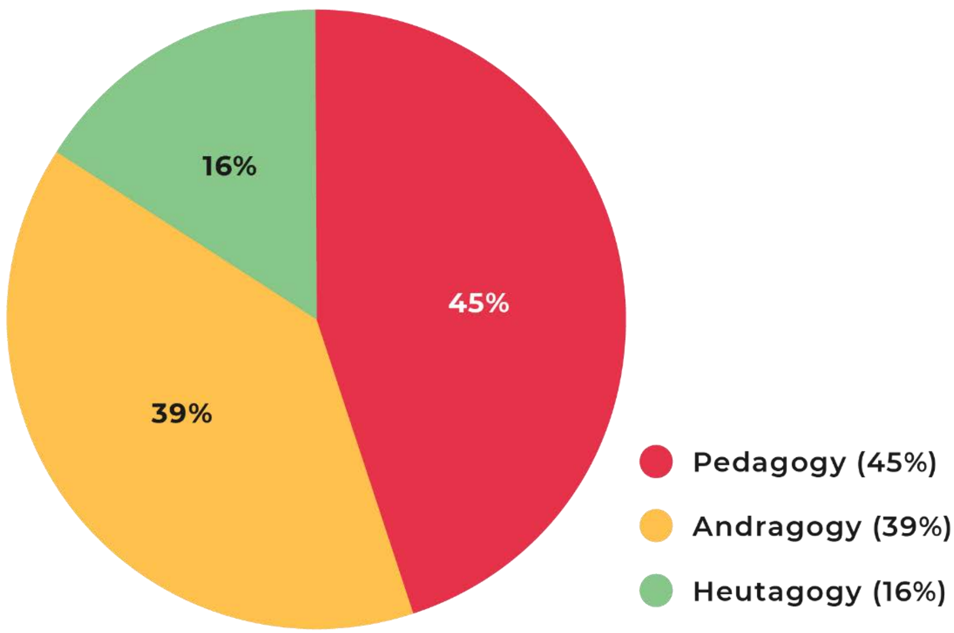
This section discusses findings from the thematic and cohort analyses. Findings were based on the results of mixed method analysis of participant data. The thematic analysis revealed the representing themes from three major categories (1) the learners' orientation towards Pedagogy, Andragogy and Heutagogy, (2) learner emotions while participating in the subject and (3) learner problems encountered in the subject. The following sections discuss these themes.

4.5.1 Learners' Orientation on the Pedagogy-Andragogy-Heutagogy Continuum

The PAH category from Table 4.6 was used to examine data with an in-depth mixed methods approach. By using the matrix coding technique in NVivo, the references of the PAH category were quantified. Out of a total of 190 references for the PAH category, the learners indicated (a) pedagogy characteristics by 86 references (45%), andragogy characteristics by 74 references (39%) and (c) heutagogy characteristics by 30 references (16%). The findings show that, in general, learners' characteristics were more orientated at the pedagogy and andragogy levels, followed by heutagogy, at the end of the semester, which is shown in Figure 4.2.

Figure 4.2

Learners' Orientation on the Pedagogy-Andragogy-Heutagogy Continuum

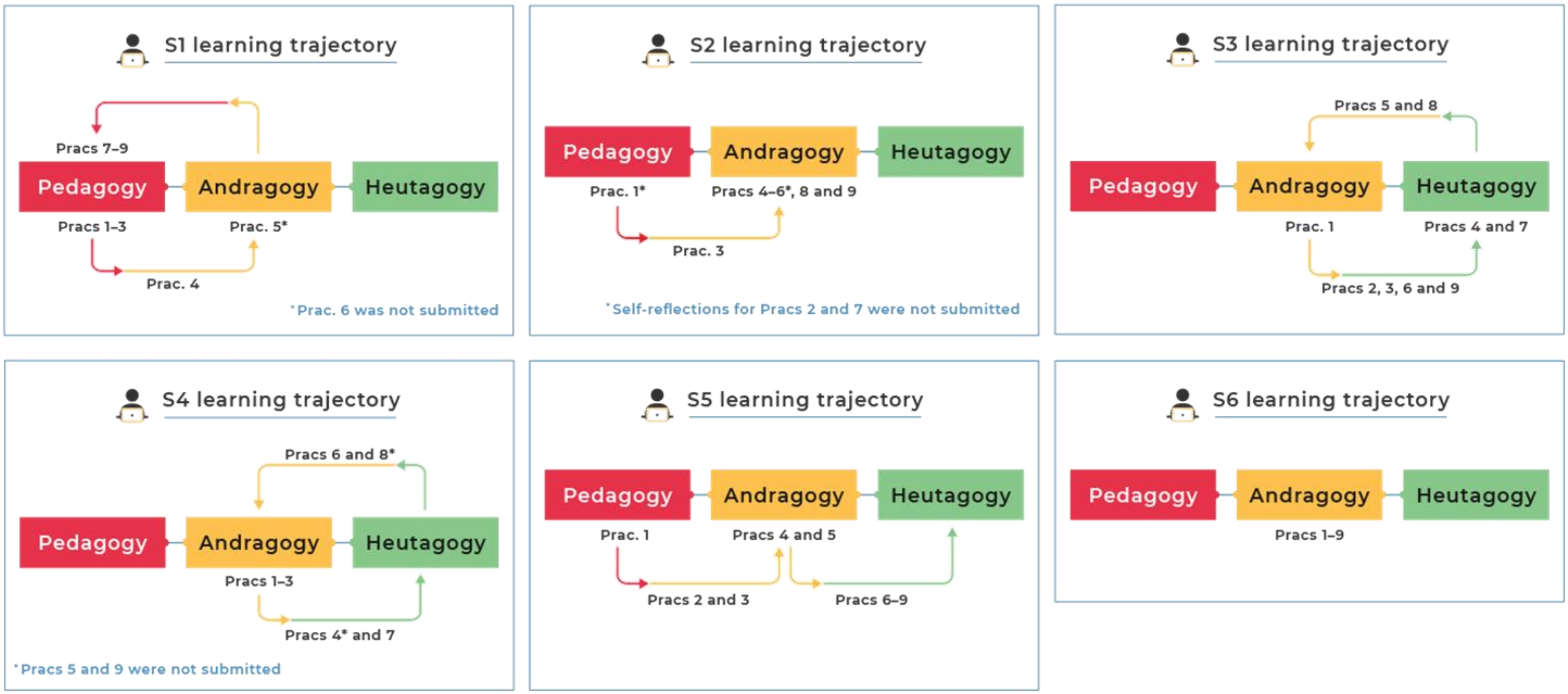


Note. Adapted from *A preliminary study using academagogy to uncover the problems that block adult online learner engagement*, by K. Addanki, J. Holdsworth, D. Hardy and T. Myers, 2022, 24th Australasian Computing Education Conference, Association for Computing Machinery, United States of America.

A longitudinal coding method was used to analyse the self-reflections and gather details of the factors affecting individual learner engagement over the semester. Longitudinal coding is a second-cycle qualitative analysis method used to closely review the data across time and explore participants' reported experiences (Saldaña, 2016). The longitudinal coding of participant self-reflections, from nine practicals over 12 weeks, revealed a trajectory along the PAH continuum with many learners progressing but few learners regressing on the PAH continuum when they encountered problems. Learners' progression or regression on the PAH continuum are visualised as a cyclic process called learning trajectories, as summarised in Figure 4.3 and detailed in Figures 4.4 to 4.9.

Figure 4.3

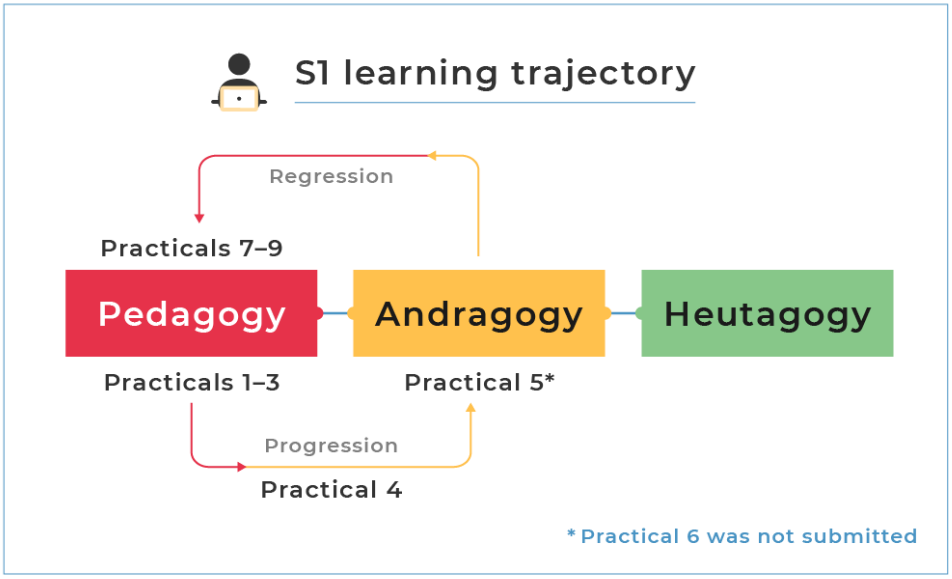
Learners' Position on the Pedagogy-Andragogy-Heutagogy Continuum



Note. Learning trajectories for all six participants (S1–S6) show forward (progression) and backward (regression) movement along the PAH continuum across nine practicals (abbreviated as Prac. or Pracs). Adapted from *A preliminary study using academagogy to uncover the problems that block adult online learner engagement*, by K. Addanki, J. Holdsworth, D. Hardy and T. Myers, 2022, 24th Australasian Computing Education Conference, Association for Computing Machinery, United States of America.

Figure 4.4

S1's Learning Trajectory



4.5.1.1 S1 Learning Trajectory. In the initial weeks of the semester (until Practical 3), learner S1 was not confident enough to work independently and was dependent on the educator because of problems with understanding the practical. The learner appeared to be at the pedagogy level:

> I have a hard time connecting the dots, since there are several parts of coding and parsing it into one piece. (S1, Practical 1 Self-reflection)

In the middle weeks (for Practicals 4 and 5), learner S1 tried to solve problems independently and gained confidence, which indicated their slow progression towards andragogy by Practical 4. By Practical 5, the learner was able to apply the concepts learned in the previous weeks and solve their problem, which showed they were at the andragogy level:

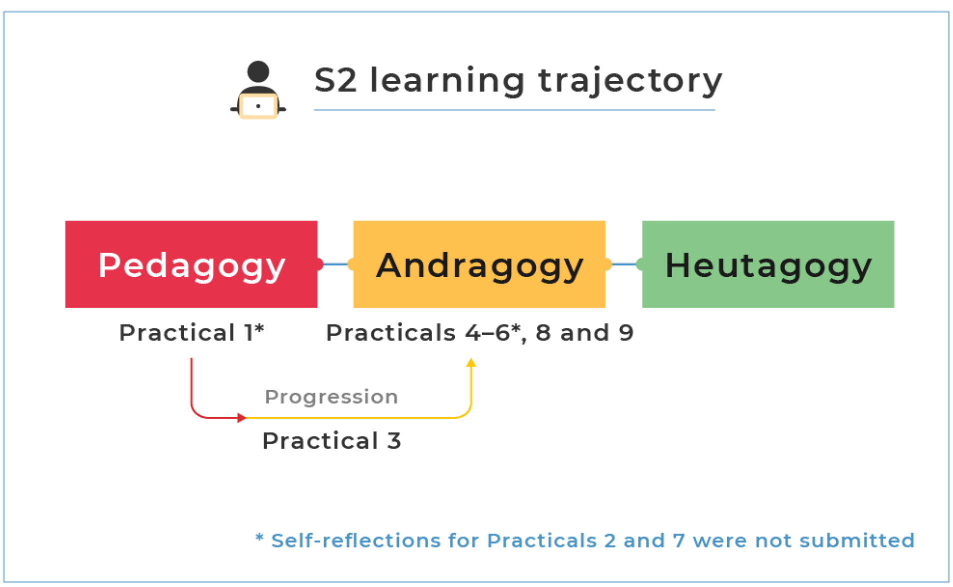
> First thing [I] figured out how to link two activities, which was the problem from my last practical. (S1, Practical 4 Self-reflection)

For Practical 6, learner S1 did not submit the practical due to personal reasons. In the final weeks (Practicals 7, 8 and 9), though the learner understood, the learner had difficulties applying the concepts of more technical tasks, such as interlinking Java and XML fragments and using Application Programming Interfaces (APIs). For these reasons, the learner shifted back to a pedagogy level:

> This prac. was the most difficult so far, the first few tasks of the first part was easy. And then the fragments made it tough to figure out what was going on … Since there are more fragments there is more to work in XML and more to interlink in Java, which makes it difficult to follow. (S1, Practical 8 Self-reflection)

Figure 4.5

S2's Learning Trajectory



4.5.1.2 S2 Learning Trajectory. For the initial week (Practical 1), learner S2 felt overwhelmed when working with Android Studio and had some problems with understanding Java programming, which indicated that the learner was at the pedagogy level:

> The first look and feel of Android Studio GUI was very overwhelming and confusing … hard to understand especially the interconnectivity of these files. Java for sure can be very daunting. (S2, Practical 1 Self-reflection)

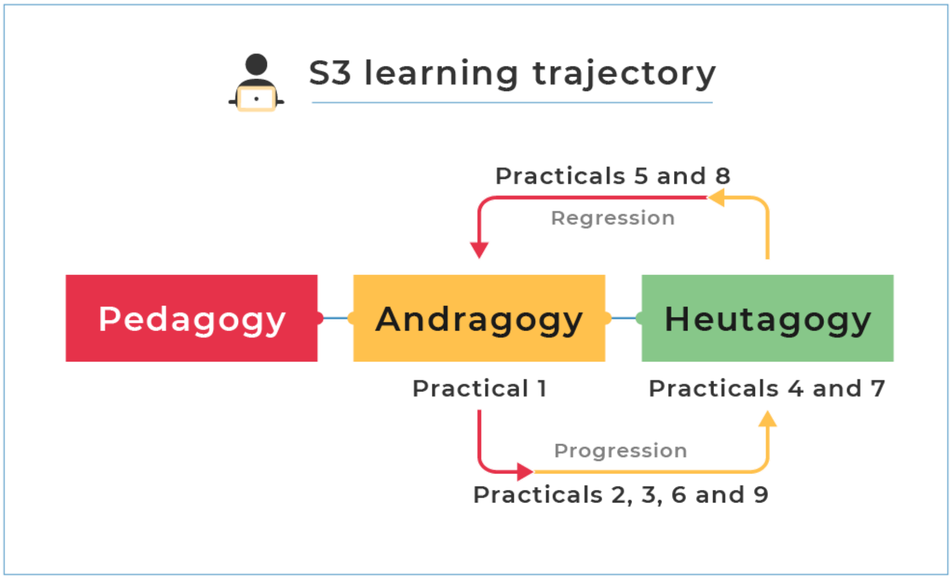
Later in the semester (Practicals 3, 4, 5, 6, 8 and 9), the learner started gaining confidence by working on problems with or without the help of the educator (independent). Additionally, learner S2 always seemed to be an active participant, which clearly showed progression towards andragogy. Though the learner had problems with certain tasks in Practical 4, they were able to work out the remaining tasks (occasional problems), thus sustaining progress at the andragogy level:

> I feel more confident about my ability to follow through my code with respect to the practical document. (S2, Practical 3 Self-reflection)

> Obviously feel way more confident in terms of Java files, layout and XML. Now the redlines started to decrease to a large extent. (S2, Practical 4 Self-reflection)

Figure 4.6

S3's Learning Trajectory



4.5.1.3 S3 Learning Trajectory. In the initial weeks (Practicals 1 and 2) learner S3 was able to remember Java programming concepts from a previous course and exhibited interest by actively participating in the learning process. Occasionally, the learner had some problems but was able to solve them almost on their own, and eventually gained confidence. Right from the beginning of the semester, learner S3 was motivated to use the concepts learned in the practicals to create their final app, which indicated that the learner was at the andragogy level and tending towards heutagogy:

> I had a bit of memories popping back to my head and understood what was happening in the code. (S3, Practical 1 Self-reflection)

> Although we were explained [taught] with an easier method to use the design section for most of the practical, I would like to focus on how the coding for the

> same [difficult method along with the easier method] and learn to code the complete thing as well. (S3, Practical 2 Self-reflection)

During the middle weeks (Practicals 3, 4, 5, 6, 7 and 8), learner S3 had problems in the practicals but tried to be independent. Further, the learner realised the importance of using strategies such as being patient and early preparation, indicating that they were moving back and forth between andragogy and heutagogy:

> Trying to be patient with errors like … it's definitely a learning experience and a checklist not to repeat the same mistakes. This week's practical made me realise the importance of being prepared in advance and to attend the practical for a better optimisation of time. (S3, Practical 5 Self-reflection)

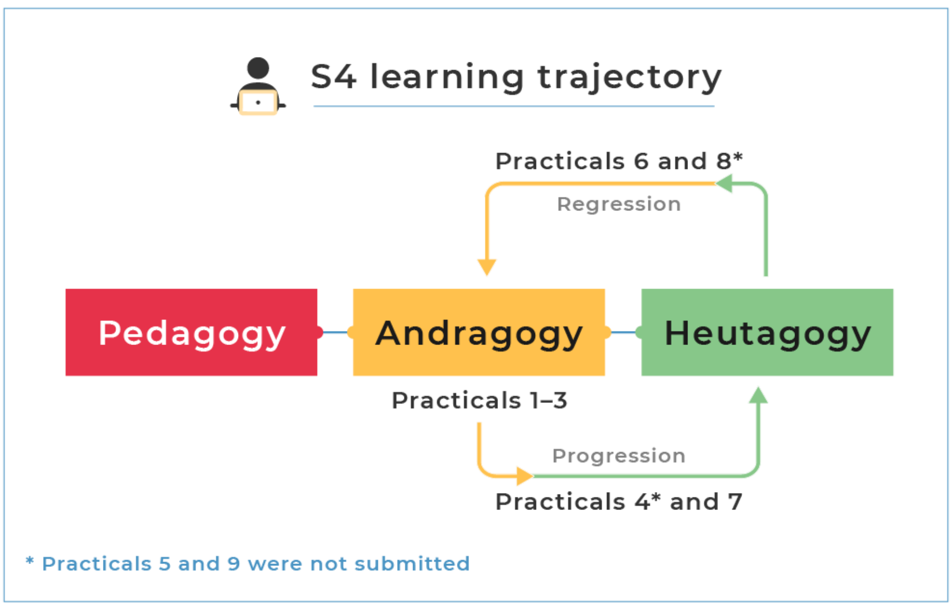
> Felt good and a bit relaxed to work on something small and easy for a change. There were almost zero errors on this practical I would say. The whole practical was completed well within time. And had a couple of minutes of help others with their app. The methods used were quite understandable and pretty straightforward. I realised the class had a bit of difficulty in finding the gravity sensor, and it was running at ease on my system. I suggested the others use API level above 19 and it quite worked fine. (S3, Practical 7 Self-reflection)

For the last practical, learner S3 tried to become interdependent by selecting resources to build the final app from the learning material provided by the educator in the LMS and also searching in the internet. Further, the learner became proactive by experimenting, which clearly showed that they were at the heutagogy level by the end of the semester:

> This was the first and only application where I actually tried installing on a phone and running it, since I use iOS [iPhone operating system] I did not have the option to try and experiment. Later borrowed my housemate's phone and tried it for the educational app since it wasn't running on the emulator. The errors were not complex and … video recording helped through with majority of it. The difference in feeling when we get to completely work on our own application is amazing. (S3, Practical 9 Self-reflection)

Figure 4.7

S4's Learning Trajectory



4.5.1.4 S4 Learning Trajectory. During the initial weeks (Practicals 1, 2 and 3), learner S4 tried to be independent by working on their own before the practical class, and they were able to recollect previous Java-coding memories. Though the learner had occasional problems, they were able to solve them, thus indicating their position at the andragogy level:

> Started working on this practical prior to the practical class to see where I stand. This practical was [a] little challenging, different from the Prac. 1, but it was fun working on this prac. … which refreshes my Java coding that I learned in my bachelors. (S4, Practical 2 Self-reflection)

By the middle of the semester (Practical 4), learner S4 had problems but was able to find the correct reason for the problems and solve them, thus making progress towards heutagogy.

> This was a fun app to build and work on, I can feel the learning curve increasing each week. The practical was more interactive and certain sections gave hints to use for the educational app, which is due for submission next month. (S4, Practical 4 Self-reflection)

For Practical 6, learner S4 seemed to shift back from the heutagogy level, potentially because of problems and not submitting Practical 5. However, the learner was able to work on those problems, thus indicating their position at an andragogy level:

> The practical was fun to play around with sounds, in the beginning the sounds weren't playing enough from one button, but then later try to fix the code one worked without error. (S4, Practical 6 Self-reflection)

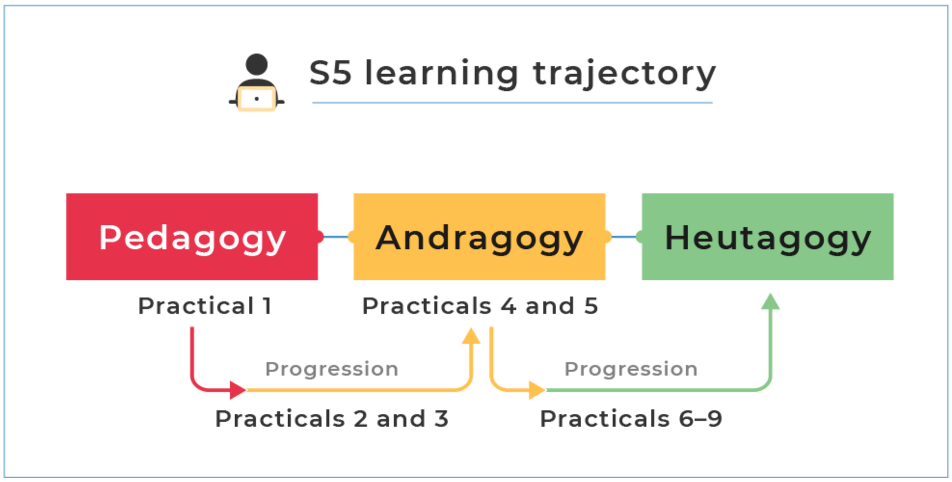
The learner enjoyed working on Practical 7 and started picking up concepts that could be useful in building their application for the future assignment (educational application), showing lateral thinking and progression towards the heutagogy level:

> The practical was fun to play around with different motions. This is a helpful source to build the application for the educational game. (S4, Practical 7 Self-reflection)

Learner S4 had some difficulties in Practical 8, for which they reflected that work was pending. The learner also did not submit Practical 9, thus indicating their regression to andragogy.

Figure 4.8

S5's Learning Trajectory



4.5.1.5 S5 Learning Trajectory. In the initial week of the subject (Practical 1), learner S5 felt stressed and was not confident in their Android Studio and Java abilities. The learner had difficulties in understanding practicals and sought the educator's help (dependent) to understand the practical, thus indicating that they were at the pedagogy level:

> Since I had no previous experience in Java programming, the practical was difficult to understand. I would also discuss about any doubts that I come across with my instructor. (S5, Practical 1 Self-reflection)

In the middle of the semester (Practicals 2 and 3), learner S5 felt less stressed because there was less coding. Although S5 still struggled to debug the code, the learner started gaining confidence with their work, with the help of the educator, thus tending towards the andragogy level:

> I could see that I could handle some small errors myself and keep up with the instructor during the practical session. (S5, Practical 2 Self-reflection)

In the later weeks (Practicals 4 and 5), learner S5 felt confident enough to complete some parts of the practical on their own and gained confidence by solving problems, which suggests that the learner was still at the andragogy level:

> I can read the warnings and figure out what is causing them and since the platform provides us [with] option[s] to fix them, I can easily tackle them. (S5, Practical 4 Self-reflection)

In the final weeks (Practicals 6, 7, 8 and 9), learner S5 found learning complex ideas challenging but interesting. Though the learner had some issues, they were able to solve them (problem solver) and planned to excel using various resources (instructor and online tutorials), indicating that the learner was trying to be interdependent and was progressing towards heutagogy:

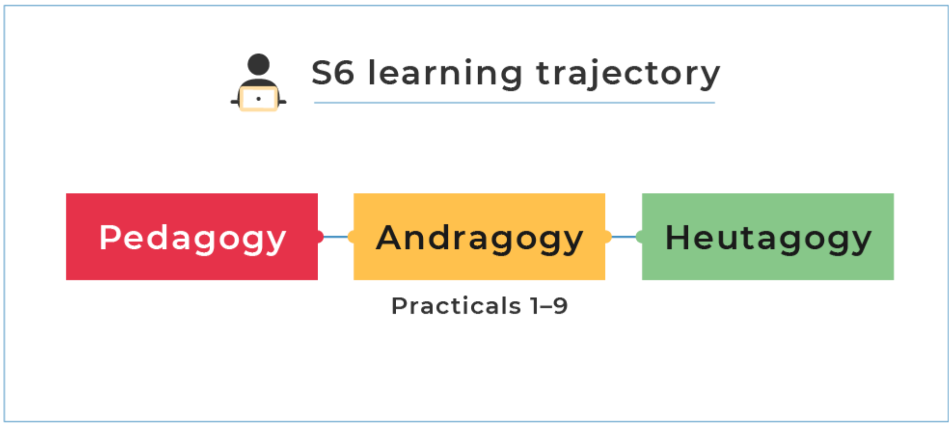
> Learning all the complex ideas and logic to pass data around the activity classes and XML elements seem tough but very interesting. (S5, Practical 6 Self-reflection)

> My plan is to use these concepts in final assessment for the educational game app. I would go through reference books to grab more concepts and reach out to the instructors whenever in doubt. Also, solving some complex problems from online

> tutorials can be the way for me to strengthen my Android programming skill[s]. (S5, Practical 9 Self-reflection)

Figure 4.9

S6's Learning Trajectory



4.5.1.6 S6 Learning Trajectory. In all practicals, learner S6 was able to understand and apply the concepts given in the reference examples. Though the learner struggled with programming errors, they were able to understand and became more aware of what should be taken care of to obtain the desired output. However, learner S6 did not try to experiment or create new applications on their own, thus indicating that they were at the andragogy level:

> After giving the Java code with XML language [it] made it clear to visualise to basically get the code to be running without any errors highlighting with red font. Finally, to get the UI to work efficiently as expected. (S6, Practical 3 Self-reflection)

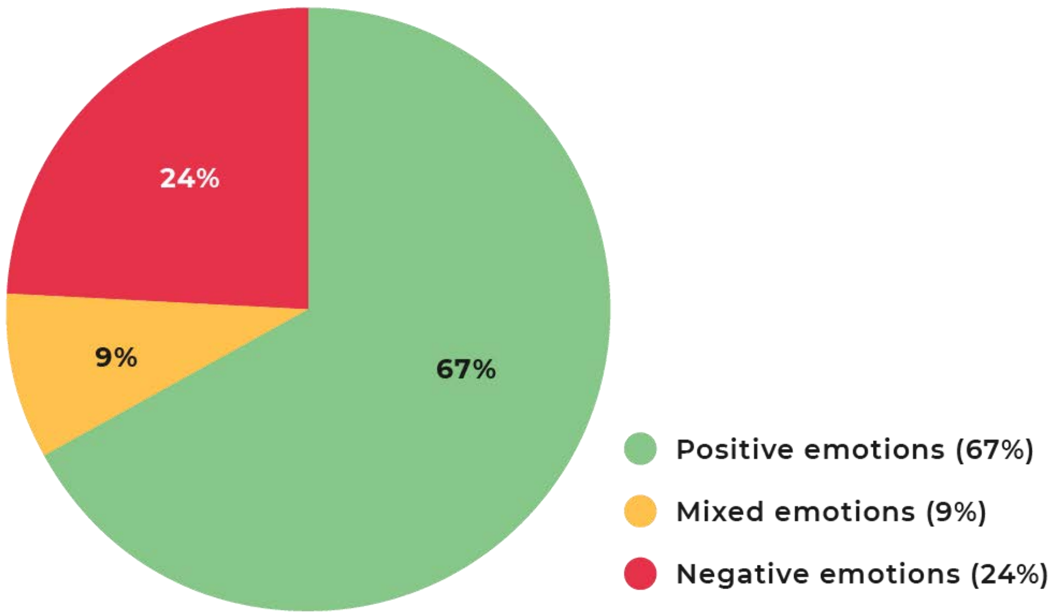
Learner S6 had written similar content for the self-reflection activity after every practical, which made it difficult to determine any progression/regression on the PAH continuum. This finding is outlined more deeply in Section 4.5.3.

4.5.2 Learner Emotions

The emotions category from Table 4.6 was also examined using the mixed methods approach. A matrix coding technique in NVivo software was used to quantify the references related to the emotions category. From a total of 181 references for the emotions category, learners reflected (a) positive emotions with 122 references (67%), (b) negative emotions with 43 references (24 %) and (c) mixed emotions (both positive and negative feelings) with 16 references (9%). The observation indicated that learners generally had a positive learning experience. Many participants reflected positive emotions (in self-reflections and interviews) followed by negative emotions, and mixed emotions had the lowest percentage of references (see Figure 4.10). The visualisation in Figure 4.10 reflects the combined qualitative and quantitative data analyses.

Figure 4.10

Learner Emotions



Note. Adapted from *A preliminary study using academagogy to uncover the problems that block adult online learner engagement*, by K. Addanki, J. Holdsworth, D. Hardy and T. Myers, 2022, 24th Australasian Computing Education Conference, Association for Computing Machinery, United States of America.

4.5.3 Learner Problems

Close examination of the problems category in Table 4.6 (Section 4.4.2) uncovered the following experiences from the learners. In the practicals, most learners had problems with Practical 6 (creating an application to use APIs for efficient mobile UI design patterns). Further investigation was needed to determine which aspects of using APIs were confusing to the learner. Half the learners had difficulty with Practicals 8 and 9 based on the concept fragments (using a Java class to modularise parts of an application).

For mobile application development, learners had trouble using SQLite (an API used for linking the application to access databases) and social integration (using APIs for integrating the application to a social network like Twitter). In addition, some learners used their progressive knowledge from practicals, while others used their metacognitive skills to build their applications:

> I used all the practicals to build up my final application. (S1, Interview)

> For me the challenging was SQLite, because we had to implement that method in final assignment … I had to use resources from outside, to see how this works. (S4, Interview)

> The difference in feeling when we get to completely work on our own application is amazing. When I started the subject, I had a slight feeling if it will be too much and if I can handle this, to my surprise we started from the basics and went up the ladder, and I must say I completely enjoyed every bit of it. This would just be the beginning of something, now that I have the confidence that an idea can be implemented into an application. (S3, Interview)

For the code review presentation, almost all the learners recommended allotting more time than usual (6 minutes) for presenting the technical aspects of the applications they built. In comparative analysis report writing, it seemed that most learners failed in time management for this activity. Also, learners suggested having a report writing workshop follow up either in the form of a discussion forum or self-reflections:

> Because there was no follow up. Even I was a little too casual and I didn't focus much on it, and I was looking into the other subjects, I was not planning much on

comparative analysis, because I knew I had time for it till the end, there was sufficient time to complete it. (S3, Interview)

In general, learners had problems with writing self-reflections. For example, some learners repeated the same text when writing their self-reflections for different practicals (18 instances when all six participants repeated their self-reflections, with seven of these instances relevant to only one participant). This behaviour was possibly caused by the learners' reluctance to reflect, or a poor understanding of writing self-reflection as a part of their self-learning. Also, some learners did not submit their reflections. Based on these findings, the educator planned to reiterate the importance of quality self-reflections to the learners in the next iteration of the subject.

4.5.4 Cohort Analysis

The cohort analysis of the learner data was performed not only from the quantitative perspective but also the mixed methods perspective. Cohort analysis is a quantitative research method that compares a group of individuals with some common characteristics (Glenn, 2005). The participants' data were compared from multiple data sets (self-reflections, LA, OSE scale, semi-structured interviews and grades) to identify patterns among the data sets. Though the participants' number is small, a large volume of data (from multiple data sets) was collected and analysed over a longitudinal study of 13 weeks. The study revealed a pattern that the more self-directed learner (e.g., learner S3, see Figure 4.3) was more often positioned at the heutagogy level while engaged with the practicals, and they obtained a higher grade for practical participation.

Practical participation is an assessment activity that relates to learners' demonstration of practical skills. The participants' PAH positioning seemed to relate to their practical participation grades, highlighted in bold as shown in Table 4.7. However, the final grades on the subject do not relate to the PAH positions given for practicals. For example, learner S3 was at the heutagogy level by the end of the last practical but achieved the second-highest final grade. Further, learner S5, who was at an andragogy level and nearing the heutagogy level by the end of the last practical, obtained the highest final grade. Learner S5 did not perform better than learner S3 in practical activities. However, S5 outperformed learner S3 in other activities (mobile app development, code review presentations and research report writing). Hence, PAH levels analysed from self-reflections did not always indicate success or the highest marks in the final grades. PAH levels were only determined for practicals, which contributed to 30% of the final grades.

Table 4.7

Comparing Participant Pedagogy-Andragogy-Heutagogy Levels With Their Assessment Grades

Assessment	S5	S3	S2	S1	S4	S6
Mobile application development (30%)	21	20	16	22	18	16
Code review presentation (10%)	8	6	8	5	6	7
Research report writing (30%)	24	17	23	23	15	14
Practical participation (30%)	**26**	**28**	**23**	**18**	**21**	**23**
Pedagogy (P), Andragogy (A) and Heutagogy (H) positioning						
	Towards H	**H**	**A**	**P**	**A**	**A**
Total grade (100%)	79	71	70	68	60	60

Note. Rows formatted in bold indicate signs of relationship. Adapted from *A preliminary study using academagogy to uncover the problems that block adult online learner engagement*, by K. Addanki, J. Holdsworth, D. Hardy and T. Myers, 2022, 24th Australasian Computing Education Conference, Association for Computing Machinery, United States of America.

4.6 Insights From the Design-Based Research Phase—Problem Analysis

The aim of this pilot study was to analyse the problems that educators might encounter when personalising adult online learners' experiences in an LMS through the lens of the academagogy framework. The use of learner trajectories on the PAH continuum to design personalised support for better engagement of adult online learners is explained in this section. Also, the need for more robust methods such as AI systems to leverage the application of academagogy is discussed below.

4.6.1 Pedagogy-Andragogy-Heutagogy Learning Trajectories

Mapping the PAH learning trajectories helped identify the learners at the pedagogy and andragogy levels, and the specific reasons for learners' levels. For example, in Practical 8, learner S1 was at the pedagogy level. The learner understood the idea of fragments (modularisation) in the practical however, they had a problem in applying the concept:

> Creating the fragments looks more complicated than I thought and consumed more time. But as we see it seems essential for the project to function efficiently. But still haven't figured out the right way to do it yet. (S1, Practical 8 Self-reflection)

The learner had the same problem but it intensified in the following practical and the related final assessment (mobile app development):

> This prac. was the most difficult so far . . . then the fragments made it tough to figure out what was going on. (S1, Practical 9 Self-reflection)

> I didn't use fragments in my last application development because I couldn't figure it out. (S1, Interview)

In this scenario, if the educator had been notified about learner S1's problem before starting Practical 9, the educator could have helped them with appropriate support (like providing a live demonstration). The educator's facilitation could have reduced the learner's stress in Practical 9 and the final assessment. Thus, an early notification may help educators become more quickly aware of learner problems and specific reasons, thereby assisting their provision of appropriate support to encourage the learners' progress towards the next level in the PAH continuum. These notifications may therefore help reduce the communication barriers between the educators and the adult learners in an online learning environment facilitated using an LMS.

4.6.2 Scalability Issue

Thorough analysis of learner data found that learners progressed along the PAH continuum towards andragogy and heutagogy, with some exceptions when learners regressed after encountering problems. Examining these exceptions provided further details on the learner's problem. If an online educator is made aware of these details, they may more quickly provide personalised support to improve the learners' engagement. However, the process of analysing learner data to apply academagogy for personalisation seemed overloaded. Previous researchers have also posited that the academagogy implementation involved extra work and time commitments from educators (McAuliffe & Winter, 2014b; Murthy & Pattanayak, 2019). Moreover, the analysis of learner data in the online learning environment is a complex task for personalisation (Clarizia et al., 2018). Clearly, there is a need for an AI system, such as an SA tool, to analyse the learner data and simplify the academagogy application in an online learning environment. Rigorous analysis of the learner data using an AI system may reduce educators' workloads to uncover adult learner problems in an online subject.

4.7 Chapter Summary

This chapter provided a detailed explanation of the ethnographic pilot study to observe the problems faced by educators and adult online learners in an LMS. The main purpose of this study was to explore ways of applying an academagogy framework for personalisation to improve adult learner engagement. The highlights of this study were:

- The PAH learning trajectories derived from academagogy theory could help to identify that a learner is having problems that could block adult online learner engagement.
- Analysing learner data using academagogy for PAH learning trajectories implied scalability issues in terms of time and workload for an educator facilitating online classes.

The next chapter will detail an extended study, involving a mock prototype of an AI system that was designed using the WOz method.

Chapter 5. Extended Study

This chapter illustrates an extended study for enhancing the capabilities of an LMS, to help educators personalise adult online learner experiences using academagogy. The pilot study in Chapter 4 identified scalability issues such as the extra workload and time required for an educator to apply academagogy. This chapter presents the design and refinement of a mock AI prototype to automate this application and addresses the limitations discussed in Chapter 4. The testing of this prototype showed a potential reduction in workload from an educator's perspective, and increased cognitive skills for self-learning, as indicated by adult learners' described experiences.

5.1 Chapter Overview

Chapter 5 discusses the extended study as a part of DBR Phases 2–3, the development of a solution and iterative cycles of testing and refining the prototype solution, which are described in Chapter 3. Section 5.2 explains the development of the mock AI prototype using the WOz method. Section 5.3 describes the testing and refinement of the mock AI prototype. Section 5.4 discusses the study results and Section 5.5 highlights the insights and implications. Finally, Section 5.6 summarises the chapter.

5.2 Development of Prototype Solution

The application of academagogy for personalisation involved observing adult online learners' experiences in the LMS and making appropriate decisions promptly in a real-world context. Observing learner experiences for personalisation in real-time is a complex process for an educator facilitating larger online classes (Mikić et al., 2022; Walkington & Bernacki, 2020).

Also, based on learners' experiences, behaviours and emotions, tailoring the teaching process using academagogy increased the complexity for the educator (Addanki et al., 2022).

As discussed in Section 1.4.2, academagogy is a learner-centred teaching model that allows an educator to select appropriate teaching models from pedagogy, andragogy and heutagogy (Winter et al., 2008). Pedagogy is an educator-centred teaching model where a learner is dependent on the educator to determine what, how, where and when to learn (Winter et al., 2008). Andragogy is a learner-centred teaching model where a learner tries to be independent by identifying their learning needs and actively collaborating with the educator (Blaschke, 2016). Heutagogy is a learner-driven model where the learner goes beyond simply acquiring skills to fill in knowledge gaps (Blaschke & Marin, 2020). Luckin et al. (2011) described the PAH continuum as a framework for developing learner cognitive skills to metacognition, and epistemic, as learners progress from pedagogy to andragogy towards heutagogy.

The PAH continuum was used as a framework for personalisation using academagogy in the pilot study (see Chapter 4). The pilot study showed that learner trajectories on the PAH continuum could be potentially used for personalisation based on academagogy. However, the pilot study revealed limitations, such as workload and time requirements, as scalability issues for applying the personalisation model. Consequently, a mock AI prototype was designed based on the WOz method to automate the academagogy application in an LMS.

WOz is a Human-Computer Interaction (HCI) method used to design AI systems at a lower cost (Browne, 2019). The wizard (researcher) uses this technique method to simulate an AI prototype ranging from a lightweight system to an apparently fully functional system (Salber & Coutaz, 1993). The wizard simulates the AI system's intelligence and interacts with the users through a real or mock computer interface (Browne, 2019). The mock AI prototype was aimed at automatically synthesising the learner data and notifying the educator to personalise the adult learners' experiences in an LMS based on academagogy.

The mock AI prototype was designed using Human-Centered Design (HCD) methods. HCD is a design approach that views people as central in the development of AI systems or services to advance peoples' capabilities for their well-being (Auernhammer, 2020). HCD highlights the involvement of stakeholders in the design process by considering peoples' needs, emotions, behaviours and perspectives in the development process (Auernhammer, 2020). The co-design method, which is a HCD approach, was used in developing the mock AI prototype. Since educators are the targeted end users of the mock AI prototype (see Chapter 4), an educator was involved as a co-designer for developing the mock AI prototype.

Co-design is a collaborative design process involving learners, educators, researchers, designers and developers (Prieto-Alvarez et al., 2018). As a part of co-designing the mock AI prototype, two activities were carried out in Phase 2; namely, understanding educator requirements and prototyping, as shown in Table 5.1. To understand and prototype the mock AI prototype, an educator was recruited from JCU (see Section 3.5). In a purposive sampling technique, a researcher selects the most productive sample to answer the research questions (Marshall, 1996). The research activities, which involved understanding educator requirements and prototyping, were carried out from July 2021 to February 2022.

Table 5.1

Activities in Phase 2

Phase	Objective	Timeline	Activities	Participant
Phase 2	Develop solution	July 2021 to February 2022	Co-design (understand, prototype)	Educator

5.2.1 Understanding Educators' Requirements

A semi-structured interview was conducted to ask the educator about their experiences with facilitating adult learners in an LMS using an academagogy framework (see Appendix D for interview questions). The interview transcript was transcribed and analysed using thematic analysis methods (see Section 3.7.1). In vivo, emotional and descriptive coding methods were used to identify primary themes from the interview transcript. The primary themes were further analysed using the axial coding method, which resulted in four major themes. These major themes were presented by using an empathy map (see Table 5.2). An empathy map is a visual tool to organise information from users or participants that gives a clear visual representation of user perspectives, such as needs, thoughts, feelings and desires, with respect to the system that is to be designed (Tschimmel, 2012).

The empathy map created from the educator's interview transcript included four major themes:

1. **Says**. This theme included the key verbal expressions of the educator.
2. **Thinks**. This theme contained the educator's thoughts about teaching experience and learner characteristics in the subject.
3. **Does**. This theme included educator's actions for providing support to the learners while teaching the subject.
4. **Feels**. This theme contained the educator's emotions for providing support to the learners.

Table 5.2

Empathy Map Derived From Interviewing the Educator

Says	Thinks
1. wanted to know about learners' programming skills in Java 2. wanted to pick up learner issues (inability to use emulator, logcat, debugging) as soon as possible 3. wanted "a way to access information effectively" (to see problem solving skills [new learnings in strong programmers] and learner troubles from self-reflection) 4. said that emulator was troubling learners 5. found Master's Information Technology (MIT) learners were more isolated than undergraduates 6. said that Learning Analytics were "not insightful enough information" 7. suggested that learners "make better use of our ability to help you" 8. said that "we [academics] have to learn to be just in time."	1. The learners had Java programming background benefits. 2. There were two groups of learners: Strong programmers (built sophisticated utility and educational app using Application Programming Interfaces not taught in class, able to solve emulator problem and adept at debugging) and weak programmers (used only practical knowledge to build utility and educational app, struggled with emulator and not able to understand logcat-interactive debugger). 3. MIT learners would know about the activeness of the lecturer in slack/discord. 4. This subject had dependency (if learners did not understand concepts in earlier practicals, it might affect their experience with later practicals and applications they need to build). 5. Learner issues were not passed onto lecturer from tutors.
Does	**Feels**
1. introduced self-reflections per practical in 2021 2. made short interim videos to encourage learners' development as a "cohort moving through the semester" 3. introduced logcat interactive debugger to help weak programmers 4. spent time on introverted learners' codes and tried to reach out to them if they had any problems.	1. worried: to balance the assignments meant being flexible to both learner groups (active and passive learners) 2. confused: about why some learners did not understand the importance of Logcat 3. disappointed: about how some learners left it too late with problems and reached out the day before an assignment 4. overloaded: by consistently checking learners' self-reflections and returning to the necessary tasks 5. isolated: from MIT learners due to blended learning 6. not satisfied: with the MIT learners' interactions, particularly with technical report writing activity 7. happy: with some learners who were developing sophisticated apps (e.g., calculating distance from moon) 8. interested: in some learners who were making money by developing apps/taking up work as a career 9. inspired: to solve learner problems as soon as possible.

5.2.2 Prototyping the Mock Artificial Intelligence System

The information from the empathy map shows that the educator was passionate about giving personalised support to the learners just in time. However, educators need assistance to analyse learner data in a larger online class using an LMS (Kaliisa & Dolonen, 2022; Schubert et al., 2018). The results of the pilot study also implied the heavy workload for educators when analysing learner self-reflections through the academagogy lens and providing personalised support in an LMS (Section 4.6.2). Thus, to help educators, the mock AI prototype was developed to simulate the potential solution using the WOz method.

WOz simulation allows design concepts, content and partially completed applications to be tested on users without the need to first create a completely working system (Dow et al., 2005). The WOz method offers practical ways to explore design and interaction ideas by helping to refine them before committing to more intensive development efforts (Browne, 2019). The mock AI prototype had two basic capabilities:

1. **Automatically analyse learner data**. The mock AI prototype automatically analyses the learner's self-reflection using the PAH algorithm based on thematic analysis (see Section 4.4.1) to identify the position of a learner on the PAH continuum.
2. **Send information to the educator in the form of a report**. The mock AI prototype sends the analysed information to the educator in the form of a report named the WOz weekly report and the WOz cumulative report, as shown in Figures 5.1 and 5.2 respectively.

Figure 5.1

Sample of the Wizard of Oz Weekly Report

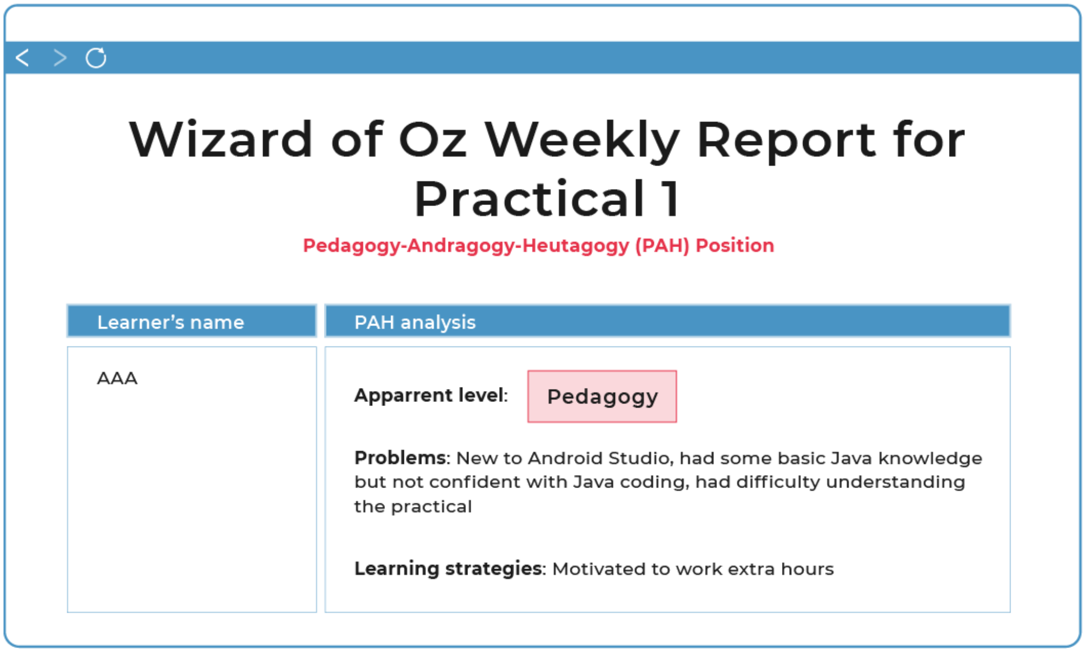
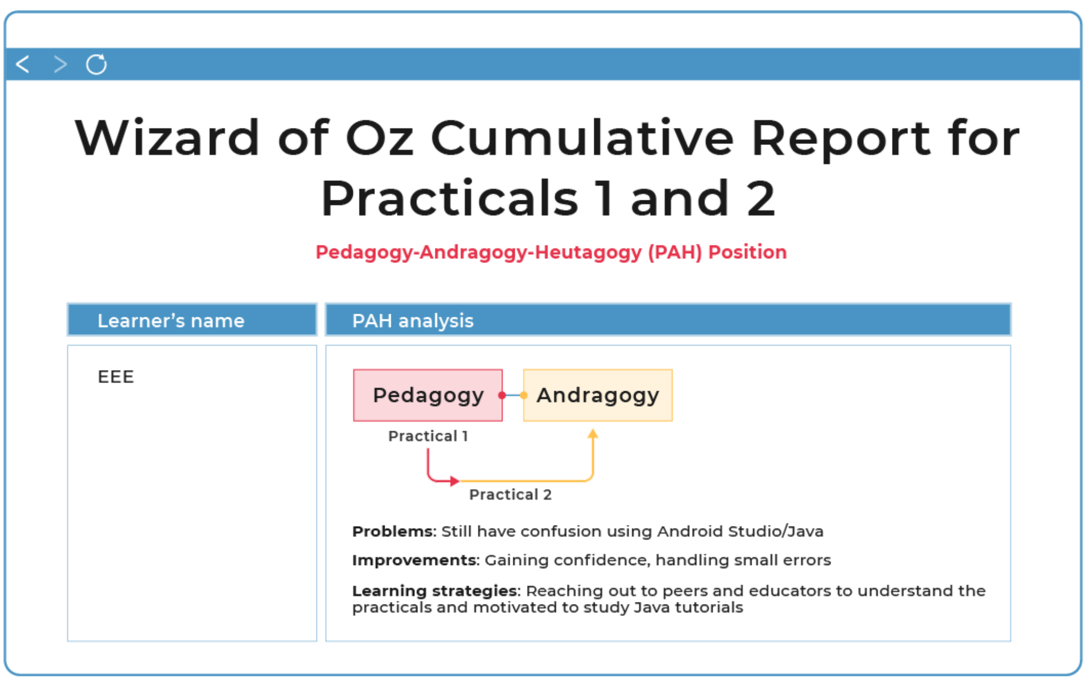


Figure 5.2

Sample of the Wizard of Oz Cumulative Report



For instance, the WOz weekly report contained information extracted from a self-reflection, such as the visualisation of the apparent level of a learner on the PAH continuum, the learner's problems and learning strategies for a particular week (see Figure 5.1). The WOz cumulative report also consisted of learner progress information in the form of visualisation (learner's position change on the PAH continuum), the learner's problems and how strategies used for the learning activities had progressed so far in a semester (see Figure 5.2).

5.3 Test and Refine the Prototype Solution

Phase 3 involved testing the WOz prototype from February 2022 to July 2022, with the activities shown in Table 5.3. The educator who participated in Phase 2 of the project continued their involvement during Phase 3: testing and refining the mock AI prototype solution. Along with the educators, the other stakeholders in the DBR project were adult learners. Hence, adult learners were recruited to test and refine the WOz prototype and also to identify their requirements.

Table 5.3

Activities in Phase 3

Phase	Objective	Timeline	Activities	Participants
Phase 3	Test and refine the solution	February 2022 to July 2022	User requirement gathering and co-design	Adult learners and educator

5.3.1 Participant Recruitment

Nine adult learners and an educator were recruited from JCU using a purposive sampling technique under ethics approval (Appendix A). These learners were part of the cohort enrolled in the "Advanced Mobile Technologies" and "Mobile Computing" IT subjects, which were offered at the university over 13 weeks during the February 2022 to July 2022 semester (see Section

3.5). The diversity of the learner participants in the extended study is presented in Table 5.4. The code names P1, P2, P3, P4, P5, P6, P7, P8 and P9 were given to the nine learners to ensure their anonymity in this research.

Table 5.4

Extended Study Participants Information

Participant	Gender	Previous education	Job/family responsibilities	Employment workload
P1	M	Secondary	Full-time work in the retail industry and study	40 hrs/week
P2	M	Secondary	No work, only study	0 hrs/week
P3	M	Secondary	Part-time tutoring and study	2 hrs/week
P4	M	Secondary	No work, only study	0 hrs/week
P5	F	Tertiary, Medicine	Part-time work, study and family responsibilities (primary carer)	12 hrs/week
P6	M	Tertiary, Science	Part-time work in the hospitality industry	20 hrs/week
P7	M	Tertiary, Vocational	Full-time work as a technical support officer in the telecommunications industry for the last two years, and study	30 hrs/week
P8	M	Tertiary, Science	No work	0 hrs/week
P9	F	Tertiary, Medicine	Ten years in business process outsourcing and Information Technology industry, currently working full-time	40 hrs/week

The learners were recruited based on the criteria of their voluntary interest in improving general self-learning skills, and knowledge about the subject (programming, research and presentation skills for Mobile Technologies). All the participants were aged 24 years and above. The information sheet and the consent forms used for recruiting the learner participants are presented in Appendix E and Appendix F, respectively.

In this extended study, only one participant (P3) was 24 years old during the case study. Although P3 was below 25 years old, which was mentioned as a defining characteristic of adult learners (see Section 1.2.2), P3 was allowed to participate in the study based on different factors. The voluntary interest of the participant, the characteristic of working part-time while studying (see Table 5.4), and also the debate about defining the age of adult learners in the literature were considered (Tilley, 2014). Some studies define adult learners as adult learners above 22 years (Kahu et al., 2013; Kara et al., 2019), while other studies consider the age as 24 years and above (Shapiro et al., 2018), and different studies define adult learners as above 25 years (Bowden & Merritt, 1995; Cercone, 2008; Moore & Shemberger, 2019; Morris et al., 2019). Since there is no consistency over the defining age of the adult learners in the literature, hence P3' age was given less importance in this study.

5.3.2 Data Collection

Data were collected from participants using the technical icebreaker activity, self-reflections, LA, OSE scale, semi-structured interviews and the participants' grades. Also, the educator's experiences were collected using semi-structured interviews. These data collection methods are described in Section 3.6 and summarised below:

- **Technical icebreaker**. A reflection activity that consisted of open-ended questions about learners' previous programming experiences related to the subject, and general questions related to learners' motivation to enrol in the subject. This item was administered as a brief survey posted on the LMS (see Appendix G for technical icebreaker questions).
- **Self-reflections**. At the end of each practical session during the semester, as a regular, weekly assessment piece for the subject, learners wrote a self-reflection text (100 to 200 words long). There were nine practicals in both subjects. In total, 65 self-reflection texts

were collected from the nine learner participants. These self-reflections provided lived and in-depth experiences of learners while working on each practical.

- **Learning Analytics**. Participant LA data were collected from the university's LMS. Learners' interaction data, such as the number of interactions the participants made within the subject site during the semester, were collected.
- **OSE scale**. At the end of the semester, participants were given the OSE scale. OSE is a Likert scale instrument used to collect participants' intellectual efforts, skills, performances and emotional components of learning (Dixson, 2015).
- **Semi-structured interviews**. Midway and at the end of the semester, the participants were interviewed via the online Zoom meeting platform. Also, the educator was interviewed at the beginning, middle and end of the semester. All learner participants and the educator consented to being recorded, and the audio recordings of their interviews were anonymised and transcribed into text documents. These interview transcripts provided additional data regarding the overall experiences of the learners and the educator.
- **Grades**. At the end of the semester, participants' grades for assessment activities were collected. The subject included the following assessment activities.
    - Assessment 1 was a mobile application development activity (creating and deploying a utility-based mobile application adhering to guidelines of the Android mobile platform).
    - Assessment 2 was a mobile application development activity (creating and deploying an education-based mobile application adhering to guidelines of the Android mobile platform).

- Assessment 3 was a code review presentation activity (evaluating and discussing the technical aspects of mobile computing).

5.3.3 Data Analysis

The technical icebreaker answers, learner self-reflections and interview transcripts were analysed using reflexive thematic analysis (see Section 4.4). In this study, data were analysed through the lens of academagogy. NVivo was used to manage the data storage, thus enabling quick access to the vital data.

VADER was used for instantaneous SA on learner self-reflections (see Section 3.7.2). VADER is a simple rule-based SA tool that takes an input of text of various lengths from words, sentences, paragraphs, essays and novels and gives the output as positive, negative and neutral percentages of emotions (Hutto & Gilbert, 2014). VADER has been increasingly used to detect learners' emotions in higher education and online learning (Hixson, 2020).

5.3.4 Testing Procedure

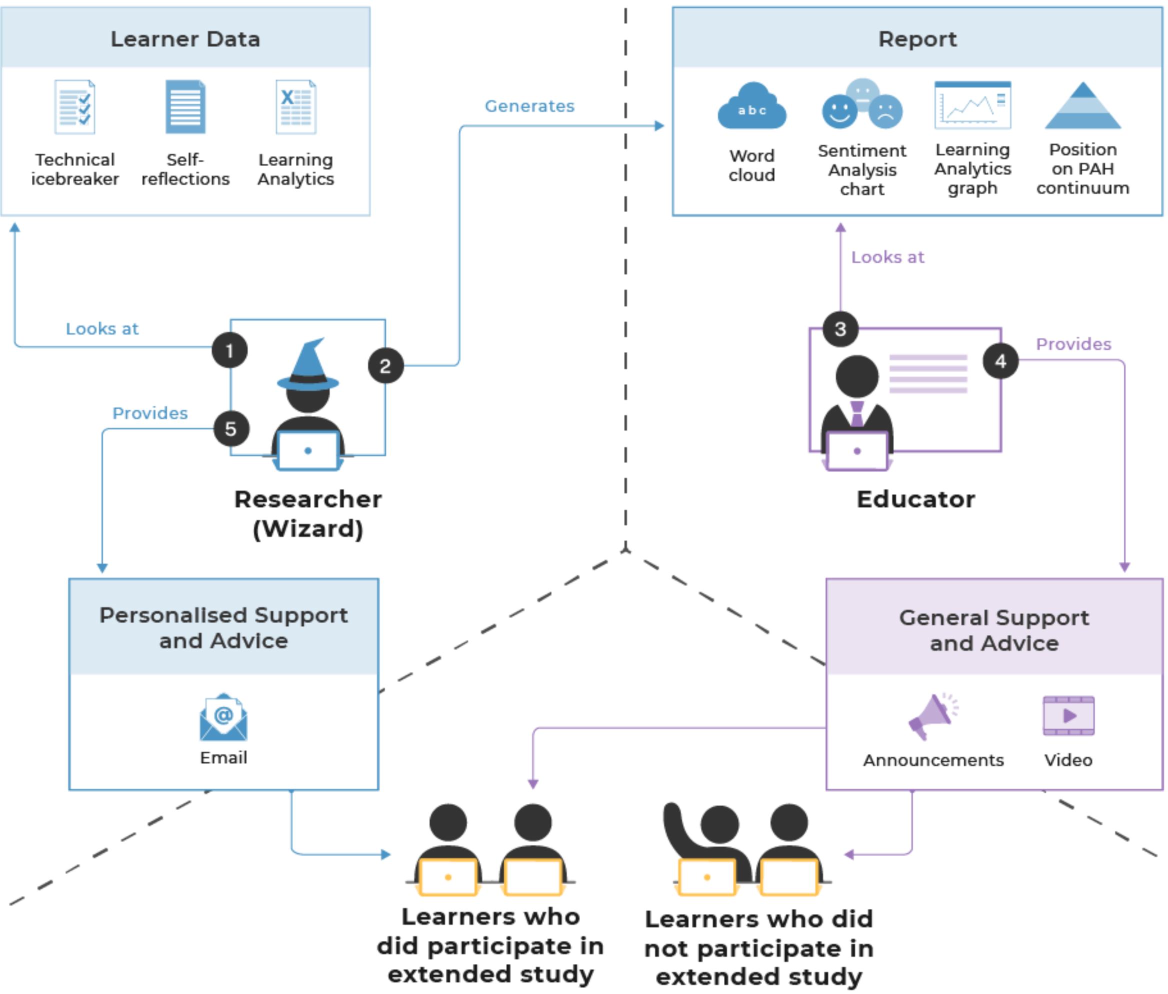
The mock AI prototype described in Section 5.2 was adapted from aspects of personalisation models and inspired by the WOz method (Kokku et al., 2018). The mock AI prototype was tested using a sequence of personalised communications in the extended study, as depicted in Figure 5.3 and below:

1. **The wizard (aka researcher) looks at and analyses learner data**. In the extended study, the wizard collected the learner data from the technical icebreaker, LA and self-reflections from the LMS. Also, the wizard analysed the learner data using thematic analysis and SA.

2. **The wizard generates the report for the educator**. In the study, the wizard generated a portable document format (PDF) report consisting of four sections as shown in Figure 5.3, and sent the report to the educator using email.
3. **The educator looks at the report**. The educator in this study used the report to create general support for learners.
4. **The educator provides general support and advice to all the learners**. The educator in this study uploaded the general support in the form of an announcement (text message) and a video into the LMS for all the learners in the subject.
5. **The wizard sends personalised support to the participants from the educator**. The wizard tailored the general support and emailed it to the individual participants.

Figure 5.3

Personalisation Process Diagram



The mock AI prototype was used during two stages in the extended study for personalising learner experiences; namely, diagnosis and continuous tracking, as explained in Table 5.5.

Table 5.5

Using the Wizard of Oz System in Two Stages for Personalisation

Stage	Timeframe	Data collection	Data visualisation
Diagnosis	Weeks 1 and 2	Technical ice breaker	Word clouds
Continuous tracking	Weeks 3 to 13	Learning Analytics Learner self-reflections	Learning Analytics graph Sentiment Analysis chart Thematic analysis showing the position on the Pedagogy-Andragogy-Heutagogy continuum

5.3.4.1 Stage 1: Diagnosing Learners' Needs. A diagnosis of learners' needs is essential to provide a clear sense of the learners' initial skills for personalisation (Shearer et al., 2020). Learners' needs can be diagnosed with an icebreaker activity including questions that interest learners. For example, queries include the skills and knowledge from previous subjects they can incorporate into their current subject, what they aim to learn by the end of the subject and their strengths and weaknesses (Shearer et al., 2020). Hence, a technical icebreaker was given to the learners in Week 1 of the semester as a learning activity (see Appendix G).

The participants submitted responses to the technical icebreaker activity into the LMS in Week 3. For example, in response to the question, "What do you hope to learn from this subject?" a participant provided responses such as "develop applications", "understanding fundamentals of mobile computing" and "learn more about XML and Java programming." Another participant (learner P5) wanted to gain understanding of mobile applications and create an application to use for extracurricular purposes:

> I hope to gain a better understanding of how mobile apps are made as well as gain practise in using OOP [Object-Orientated Programming]. In addition, it will be cool to be able to create a mobile app for myself. (P5, Icebreaker response)

The responses to each of the eight questions were analysed using thematic analysis in Week 4. During Week 5, the mock AI prototype reported the summary from the technical icebreaker responses to the educator in the form of word clouds, for quick understanding of learners' strengths, weaknesses and their motivation to enrol in the subject (see Figure 5.4). Using the report, the educator adjusted instruction based on the cohort's needs. The educator released the technical icebreaker results into the LMS as an announcement (textual message) and a short video. The announcement and the video contained the educator explaining the technical icebreaker results.

Figure 5.4

Sample of Word Cloud Summarising the Learners' End Goals

Note. The learners' end goals for learning the subject were to create mobile applications in the Android platform and improve their confidence in using Java programming skills.

5.3.4.2 Stage 2: Continuous Tracking. Continuous tracking of learners' experiences is another important aspect of providing timely and personalised support (Shearer et al., 2020). The mock AI prototype collected this form of learner data every week from Weeks 3 to 13 and sent the information to the educator in the form of WOz reports. The mock AI prototype tracked learners' experiences by analysing learner data in three dimensions: behavioural, emotional and cognitive. These data were analysed every week from Weeks 3 to 13.

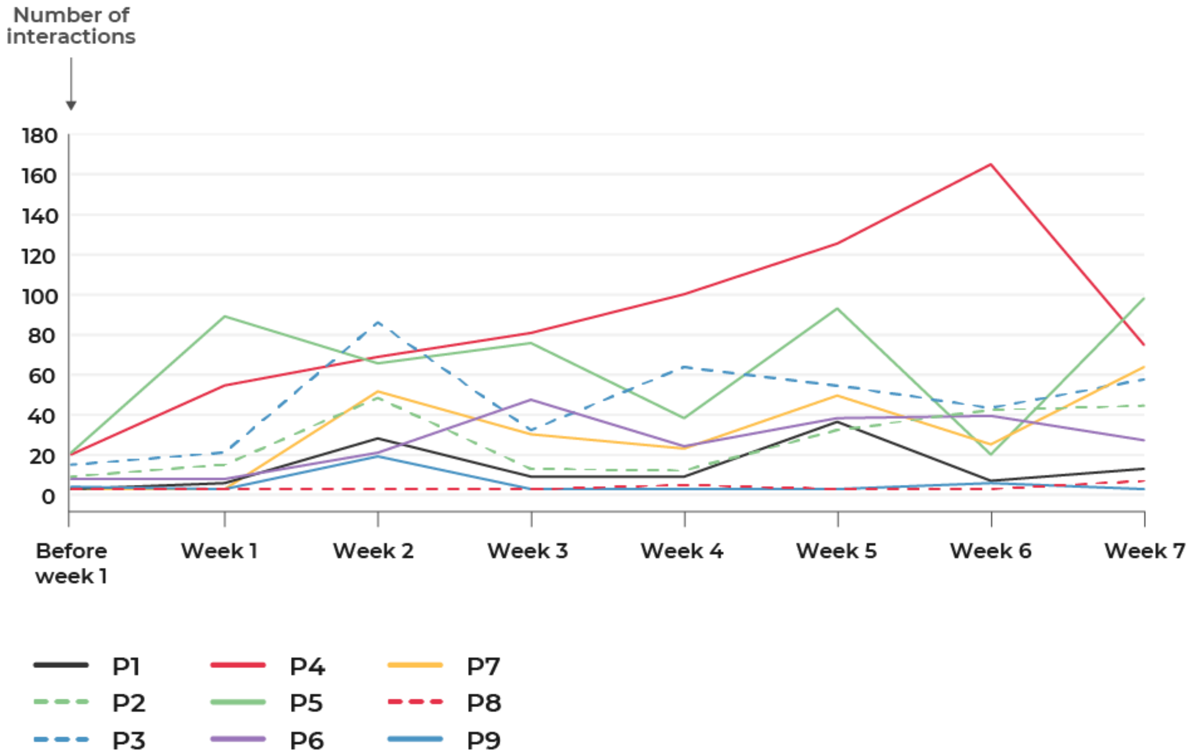
LA data were used to determine the behavioural dimension, such as the number of interactions the participants made in the LMS. The mock AI prototype sent a graph of the weekly interactions of individual participants, as shown in Figure 5.5.

The VADER tool (Hutto & Gilbert, 2014) was used to determine the emotional dimension of learners' self-reflections to check how learners felt emotionally. A chart of the average negative, neutral and positive emotion percentages of all the participants was provided by the mock AI prototype, as displayed in Figure 5.6.

A reflexive thematic analysis of the self-reflections was also used to determine each learner's cognitive dimension and identify their position on the PAH continuum. The mock AI prototype presented each participant with their position on the PAH continuum, as shown in Figure 5.7.

Figure 5.5

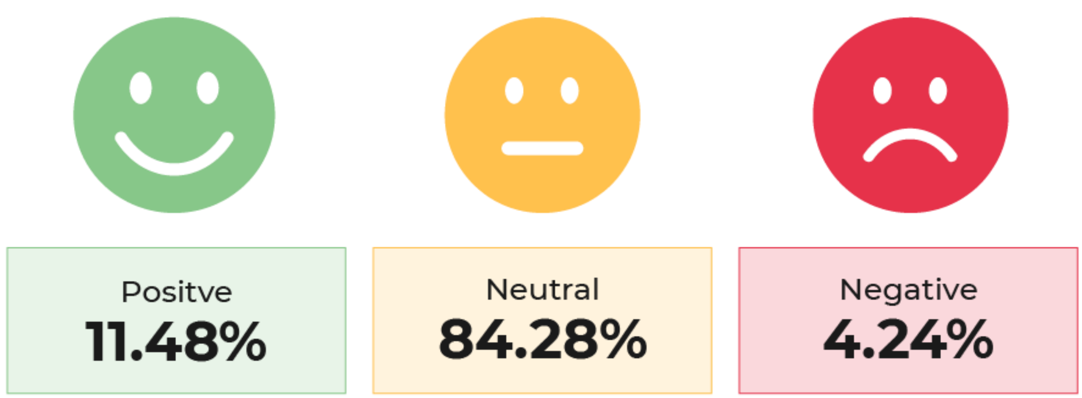
Individual Participants' Weekly Interactions in the Learning Management System



Note. Weekly interactions for up to Week 7 are included.

Figure 5.6

Sample of Sentiment Analysis Chart for All Participants in Week 7



Note. Sample is derived from the Valence Aware Dictionary and sEntiment Reasoner (VADER).

Figure 5.7

Sample of Pedagogy-Andragogy-Heutagogy Position of Learner P4 in Week 7 Using Reflexive Thematic Analysis

P4	**Apparent level**: **Heutagogy** **Problems:** did not mentioned **Strengths:** gaining confidence, internal motivation to learn different methods, making connections to real-world mobile applications **Future Learning strategies**: engage with peers, watch lecture videos and review slides

5.3.5 Refining Procedure

The mock AI prototype was refined in three iterations with the activities shown in Table 5.6 below.

5.3.5.1 Iteration 1. This iteration was conducted during Weeks 1 to 4. In this iteration, the mock AI system that was prototyped in Phase 2 (see Section 5.2.2) was used with the two basic capabilities: (1) analyse the learner self-reflections and (2) send the WOz reports (both the weekly and cumulative reports) to the educator. Due to challenges, such as late submissions and learners' missing self-reflections, finding learners' positions on the PAH analysis was complex. Hence, LA and SA graphs derived from participant data were added to the WOz reports, to provide a more clarified understanding of participants' interactions with the LMS, as shown in Figure 5.8.

The educator was interviewed at the end of Iteration 1 to explore their experiences with using the mock AI prototype. The educator suggested the mock AI prototype should support the progress of individual learners as the semester proceeded, and it could be used for creating one-to-one level personalised support.

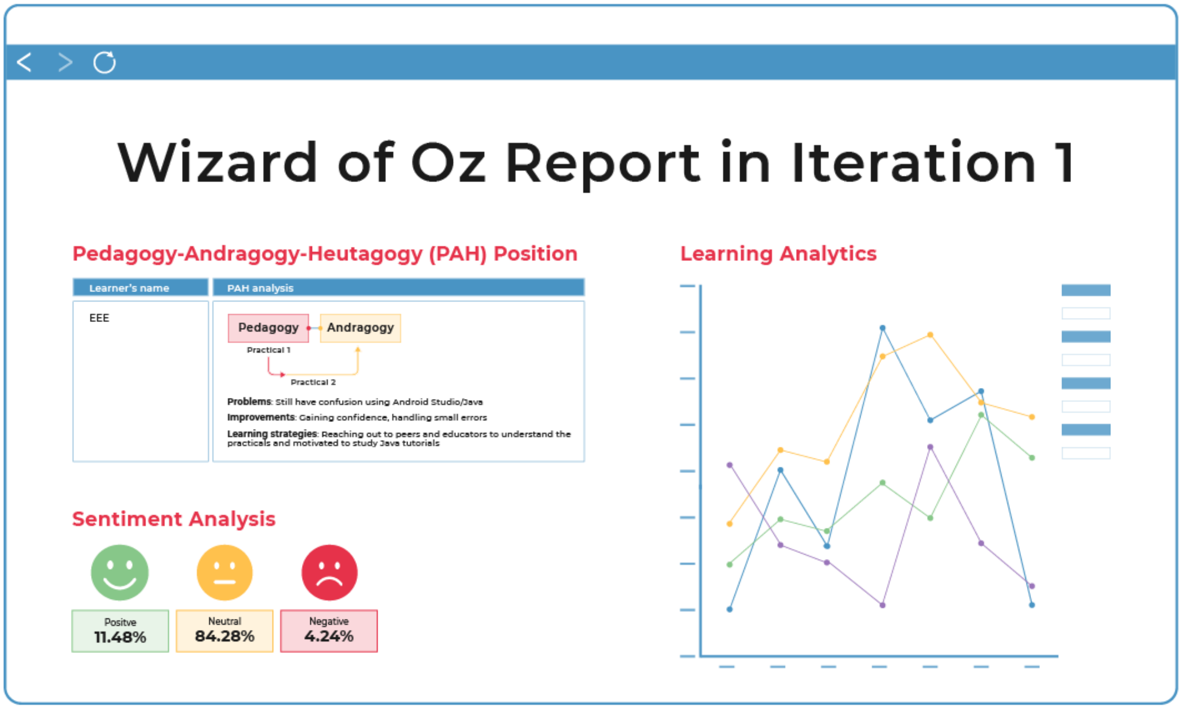
Table 5.6

Mock Artificial Intelligence Prototype Refinement in Three Iterations

Iteration details	Iteration 1	Iteration 2	Iteration 3
Timeline	Weeks 1, 2, 3 and 4	Weeks 5, 6, 7 and 8	Weeks 9, 10, 11 and 12
Participant activities	Work on practicals 1, 2 and 3	Work on practicals 4, 5 and 6	Work on practicals 7, 8 and 9
Educator activities	Subject Participation Review 1	Subject Participation Review 2	Subject Participation Review final
Researcher activities	Mini interview with the educator	Mini interview with the educator Interview with participants in the middle of the semester	Mini interview with the educator Interview with participants at the end of the semester
Wizard of Oz (WOz) system functionalities	1. Analysed learner self-reflections and Learning Analytics 2. Sent WOz reports to the educator	1. Analysed learner self-reflections and Learning Analytics 2. Sent WOz reports to educator 3. Maintained history of learners' progress	1. Analysed learner self-reflections and Learning Analytics 2. Sent WOz reports to the educator 3. Maintained history of learners' progress 4. Sent personalised support to the research participants

Figure 5.8

Adding Learning Analytics and Sentiment Analysis to the Wizard of Oz Reports in Iteration 1



5.3.5.2 Iteration 2. This iteration was conducted during Weeks 5 to 8. During this iteration, the third capability, maintaining a history of the learner's progress, was added to the mock AI prototype. The history of learners' progress was used to identify the learners who were progressing and those who were falling behind as the semester progressed. For example, an Excel spreadsheet showing the history of learners' progress is shown in Figure 5.9. The information in the history report was used to create personalised support for the learners at the individual level. Based on the WOz weekly, WOz cumulative and WOz history reports, the educator created personalised support to benefit all learners in the class.

Figure 5.9

Sample of Wizard of Oz History Report in Excel

Iteration 2 uncovered an ethical challenge for giving personalised support to the individual participants. This ethical challenge could lead to possible coercion due to the power imbalance between the educator and the research participants (National Health and Medical Research Council et al., 2007). Hence, a new capability was ideated so the mock AI prototype could send individual personalised messages to all the participants via institutional emails, thereby serving participants at a one-to-one level.

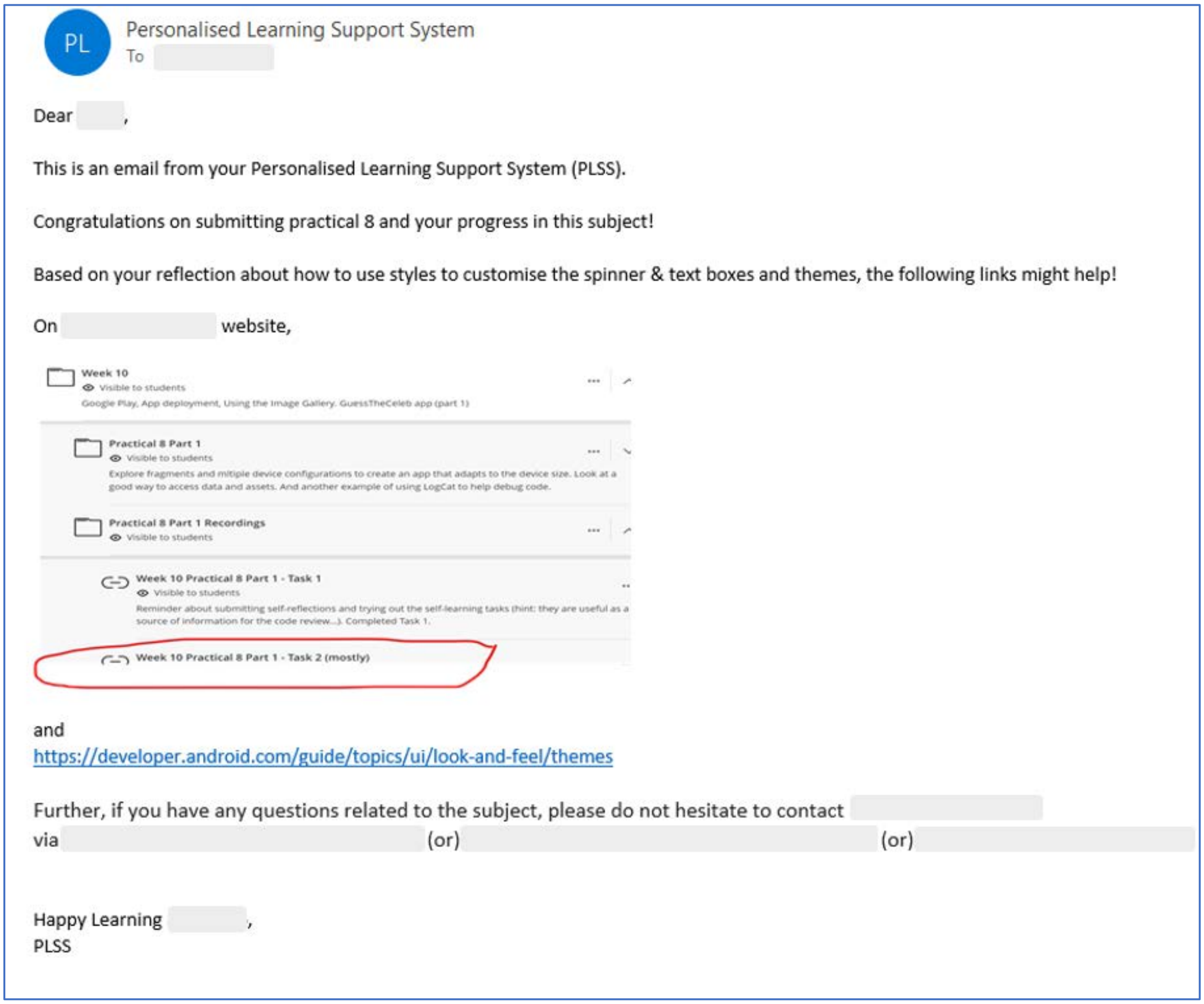
Subject Participant Review (SPR) videos and announcements the educator recorded and uploaded to the LMS functioned as one-to-many communications. As the purpose of the study was to provide individualised personalisation for each learner, a capability was designed to provide targeted support to each participant via email in compliance with ethics conditions.

Research participants were interviewed in this iteration to explore their opinions on obtaining personalised support from the mock AI prototype that was based on their self-reflections. All the participants confirmed receiving emails from the system.

5.3.5.3 Iteration 3. The final iteration was carried out during Weeks 9 to 12. Along with the three capabilities described in the first two iterations, the new capability to send personalised support to the participants was added to the mock AI prototype. The mock AI prototype used an email alias (Personalised Learning Support System) to send support to the research participants. For example, learner P3 mentioned a subject-related problem in their self-reflection after Practical 8: "understanding styles to customise spinner and text boxes and working with themes." Based on the reflection, the mock AI prototype sent personalised support with appropriate resources to address the learner's problem (See Figure 5.10).

Figure 5.10

Sample of Email Sent by the Mock Artificial Intelligence Prototype to a Participant



PL Personalised Learning Support System
To

Dear ,

This is an email from your Personalised Learning Support System (PLSS).

Congratulations on submitting practical 8 and your progress in this subject!

Based on your reflection about how to use styles to customise the spinner & text boxes and themes, the following links might help!

On website,

Week 10
Visible to students
Google Play, App deployment, Using the Image Gallery. GuessTheCeleb app (part 1)

Practical 8 Part 1
Visible to students
Explore fragments and mitiple device configurations to create an app that adapts to the device size. Look at a good way to access data and assets. And another example of using LogCat to help debug code.

Practical 8 Part 1 Recordings
Visible to students

Week 10 Practical 8 Part 1 - Task 1
Visible to students
Reminder about submitting self-reflections and trying out the self-learning tasks (hint: they are useful as a source of information for the code review...). Completed Task 1.

Week 10 Practical 8 Part 1 - Task 2 (mostly)

and
https://developer.android.com/guide/topics/ui/look-and-feel/themes

Further, if you have any questions related to the subject, please do not hesitate to contact
via (or) (or)

Happy Learning ,
PLSS

The interactions between the mock AI prototype and the learners are described in Table 5.7. During Weeks 9, 10, 11, 12 and 13, the mock AI prototype sent personalised messages to the research participants (see Figure 5.10). Based on the support, some participants reacted by submitting the learning activities or replying to the mock AI prototype. For example, learners P2, P4, P5 and P7 submitted their practical work, and learner P4 replied to the mock AI prototype in Week 9.

Table 5.7

Interaction Between the Mock Artificial Intelligence Prototype and the Participants

Week in the semester	Round of messages sent to all learners	Purpose of the message	Learners who acted based on the message	Learners who replied to the message
Week 9	1st	Practical 6 feedback	P2, P4, P5 and P7	P4
Week 10	2nd	Practical 7 feedback	P7	
Week 11	3rd	Practical 8 feedback	P5	
Week 12	4th	Practical 9 feedback and Assessment 2 feedback	P4	P7
Week 13	5th	Assessment 3 feedback	P2, P3 and P5	P7

At the end of Iteration 3, the educator and the learners were interviewed regarding their experiences using the mock AI prototype. The interview transcripts were analysed using thematic analysis (see Section 3.7.1). Themes that emerged from the interview transcripts provided additional functional requirements for designing a UI for a LAD in the future. The additional requirements suggested by the participants include:

1. A reminder pop-up message showing the due date for assignments, lecture timings and any new information added by the educator into the LMS (learner P7).
2. Encouragement messages to foster learners' motivation and confidence (learners P2, P5 and P7).
3. Peer analytics that show a visualisation of other learners' performance to motivate and connect to peers (learner P3).
4. Customised preferences to receive personalised messages. For example, some participants preferred institutional emails (learner P7), and some participants preferred

other communication channels such as mobile phones, Discord and Slack (learners P2, P4 and P5).

Additional requirements suggested by the educator include the following:

1. Along with the individual learner position on the PAH, present an aggregated view showing the position of the entire class on the PAH continuum.
2. Provide a customisable filter to separately view a group of learner performances, such as all external learners grouped together.
3. Present separate tabs for SA, LA and PAH analysis, so each tab can be self-explanatory with legends.

5.4 Extended Study Results

The main goal of the extended study was to develop, test and refine a mock AI prototype to enhance the capabilities of an LMS and thus enhance educators' personalisation. The purpose of personalisation in this research was to improve adult learner engagement in online learning environments**.** Learner engagement is a multi-dimensional, complex construct that needs an in-depth and longitudinal study of learners to understand the construct (Muir et al., 2019). Therefore, learner engagement was studied longitudinally over the 13-week semester. Learner engagement is predominantly measured in three dimensions; namely, behavioural, emotional and cognitive dimensions (Fredricks & McColskey, 2012). Thematic analysis and SA methods were used to observe participants' engagement over the semester along the three dimensions. The findings were based on the mixed methods analysis.

5.4.1 Behavioural Engagement

The weekly tracking of LA data provided the number of LMS interactions participants made over the semester. The number of interactions was averaged, revealing two groups of learners: active and passive, as shown in Table 5.8. The average number of interactions made by the passive group of learners was low compared to the average number of interactions made by the active group of learners.

Table 5.8

Average Number of Interactions Made by Active and Passive Participant Groups Every Week With Final Grade

Participants	Average number of interactions per week	Final grades (out of 100%)
	Passive learners	
P1	12	1.4%
P6	16	10%
P9	6	29%
	Active learners	
P2	30	80%
P3	40	78%
P4	81	72%
P5	63	78%
P7	38	77%

5.4.2 Emotional Engagement

Learners' emotions or feelings are essential to their academic achievement (Henrie et al., 2015). Learner emotions help educators understand how the entire class, and the individual, are learning while providing personalised interventions during the subject rather than at the end of the semester (Clarizia et al., 2018; Schubert et al., 2018). Tracking learner emotions using VADER revealed that learners felt more positive than negative emotions throughout the semester, as shown in Figure 5.11.

From the VADER analysis, neutral emotions seemed to dominate compared to positive and negative emotions (see Figure 5.11), which hindered in-depth observation of learner emotions. Hence, the individual participants' self-reflections were further analysed using NVivo. The emotional coding method (see Section 3.7.1) was used to code any emotions written by the participants in their self-reflection text. The percentages of emotional words (positive, negative and neutral) reflected by individual participants over the semester are presented in Figure 5.12. These findings do not show a significant difference between the participants in the passive group of learners P1, P6 and P9, and the participants in the active group of learners P2, P3, P4, P5 and P7.

Figure 5.11

Percentages of Negative, Positive and Neutral Emotions Reflected by all Participants Over the Semester

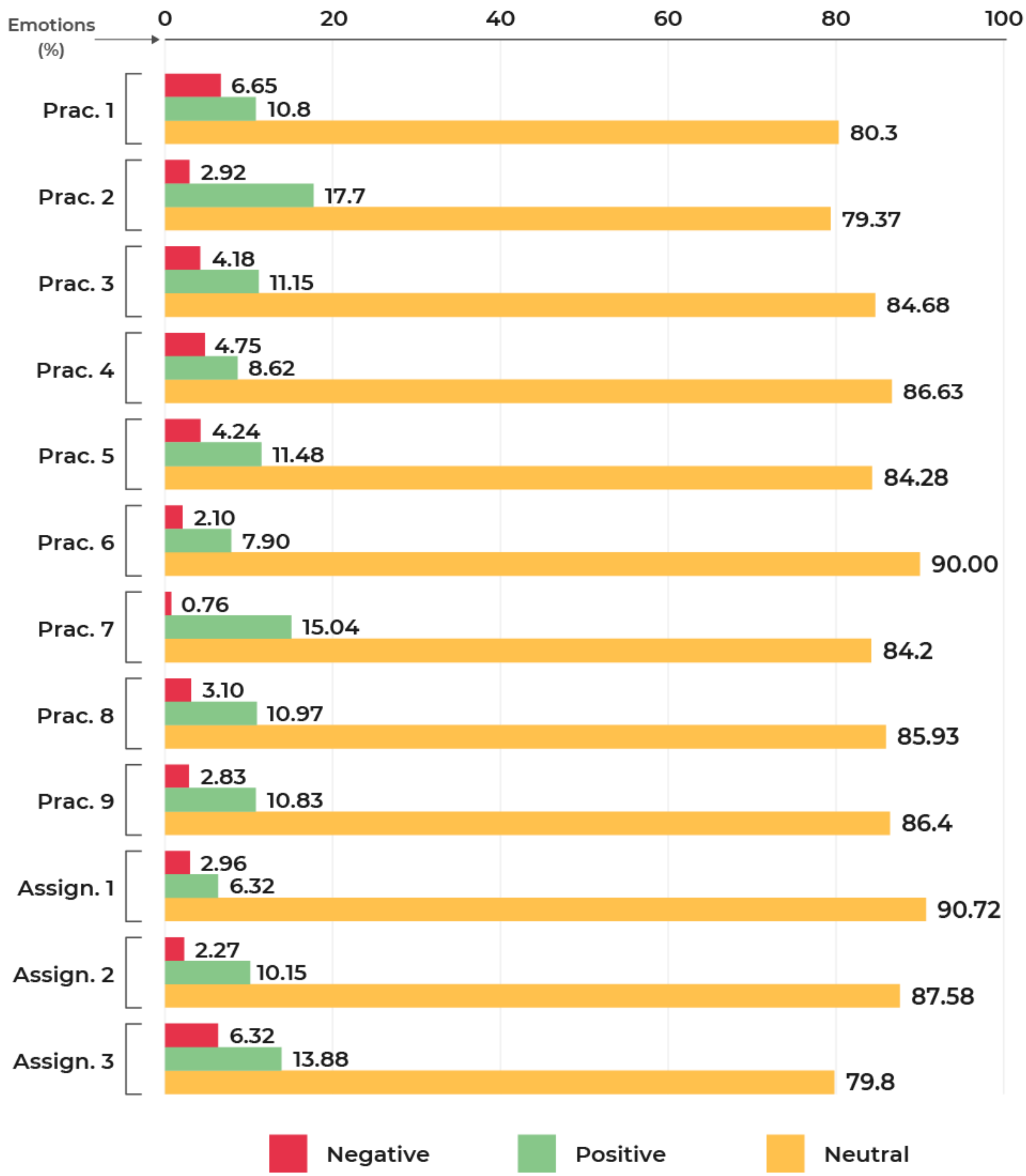
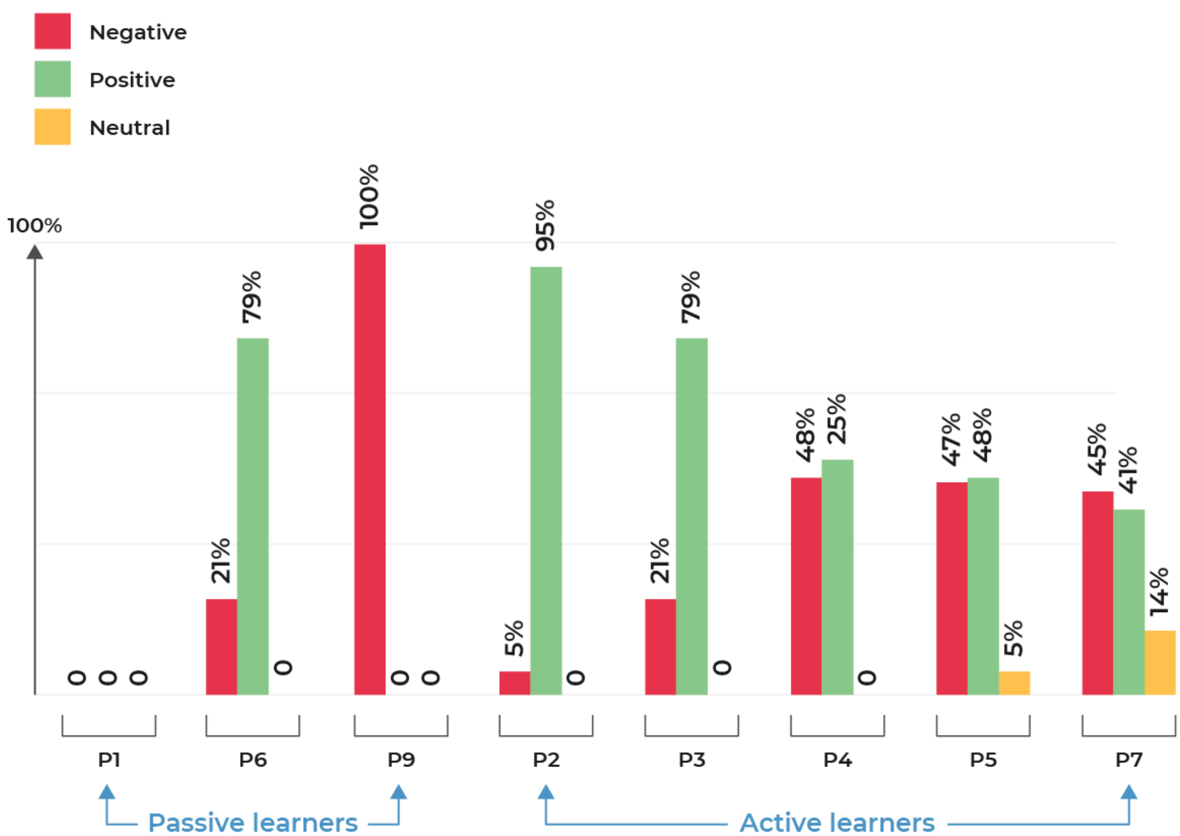


Figure 5.12

Percentages of Negative, Positive and Neutral Emotions Reflected by Individual Participants Over the Semester

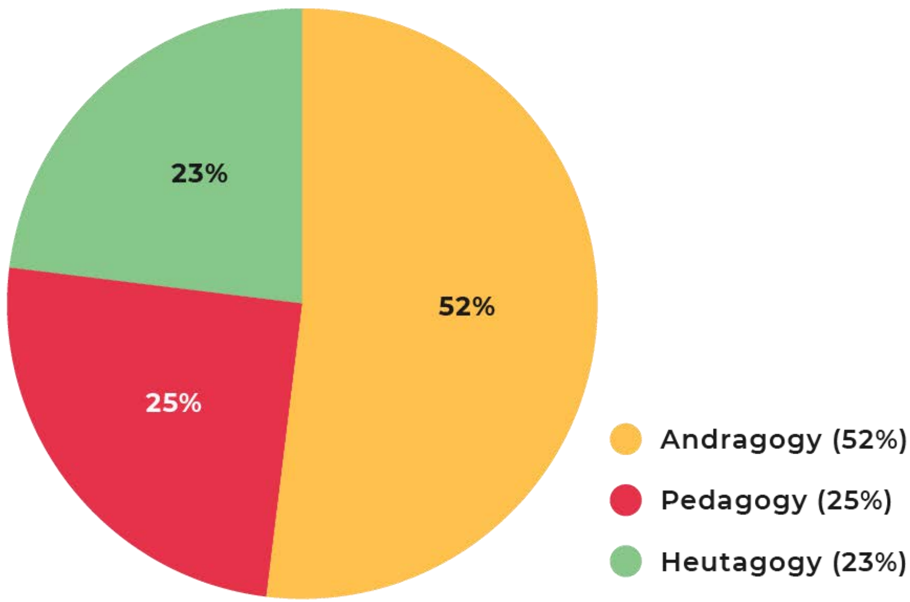


5.4.3 Cognitive Engagement

Based on the academagogical framework proposed by Murthy et al. (2012), learners' cognitive learning outcomes were assessed using Bloom's taxonomy cognitive levels. Learner self-reflections were coded using reflexive thematic analysis to identify the action verbs related to different cognitive levels in Bloom's taxonomy (see Section 4.4.1). The identified references for the action verbs were mapped to pedagogy, andragogy and heutagogy according to the differences in their characteristics, as suggested by Luckin et al. (2011). The mapped references of pedagogy, andragogy and heutagogy were analysed using the matrix coding technique in NVivo. Of the total 187 references for the code PAH, the learners reflected 47 references (25%) for pedagogy, 98 references (52 %) for andragogy and 42 references (23%) for heutagogy (see Figure 5.13). The analysis indicated that learners were oriented more towards andragogy in general.

Figure 5.13

Learners' Orientation Toward Pedagogy, Andragogy and Heutagogy

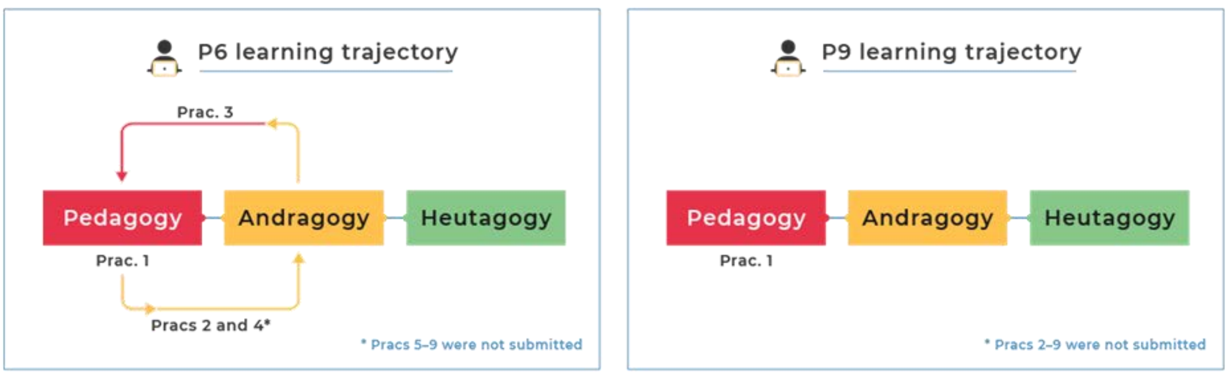


The PAH algorithm was used to identify the learning trajectories of individual learners over the semester (see Sections 4.4.1 and 4.5.1). The learning trajectories also showed the differences between passive and active groups of learners in their transitions along the PAH continuum.

In the passive group, learners P1, P6 and P9 had minimal participation, which was tracked in their learning trajectories over the semester (Figure 5.14). Learner P1's learning trajectory was not tracked since they did not submit any self-reflections, thus indicating the learner's passiveness. Though learners P6 and P9 submitted some learning activities and related self-reflections, the patterns were irregular, indicating their passiveness. This also was observed in their respective learning trajectories, where the learners mostly remained at the pedagogy level, though occasionally they transitioned to the andragogy level.

Figure 5.14

Learning Trajectories of the Passive Group of Participants

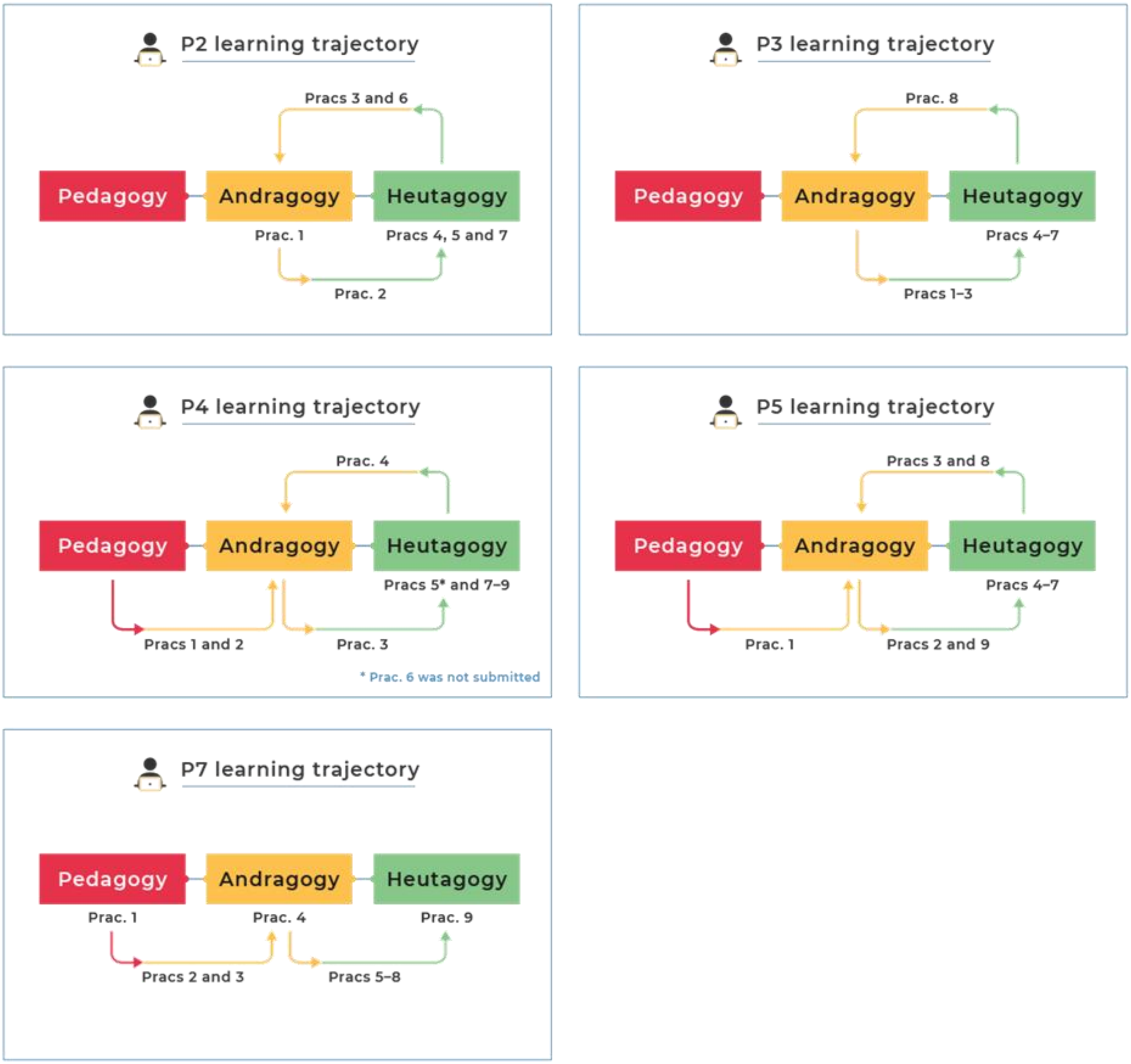


Note. P1's learning trajectory was not tracked as the participant did not submit any self-reflections. Practical names are abbreviated (Prac. or Pracs).

For the active group, learners P2, P3, P4, P5 and P7 transitioned more between andragogy and heutagogy levels, indicating their active participation in the learning process (Figure 5.15). Learners P2 and P3 shifted back and forth between andragogy and heutagogy. Though learners P4, P5 and P7 were at the pedagogy level for the initial practical, with some problems in executing Java programming for mobile application development, they were able to improve their logical understanding and application of the concepts for later practicals over the semester. This improvement might have led to the transitioning of learners P4, P5 and P7 from pedagogy to andragogy towards heutagogy.

Figure 5.15

Learning Trajectories of the Active Group of Participants



Note. Practical names are abbreviated (Prac. or Pracs).

5.4.4 Learners' Perceptions

Participants were interviewed twice during the semester about their experiences with the mock AI prototype. Analysis of learner interviews revealed that all participants felt the educator was interactive**.** Especially in the external (fully online learning) mode, participants felt more connected to the educator with a sense of class belonging based on the SPRs uploaded by the educator using the WOz reports:

> To be honest, it, I think it I think it's really good, because a lot of the time when I've done subjects in the past, when you're watching the recordings, it seems like it doesn't feel like you're being interacted with, it feels like you're watching a tutorial on YouTube that's been there for years, probably not today and yeah it feels like no one's really actually teaching you almost whereas when, as these videos popping up and it's like, "Hey guys check this out", it feels like you're actually being interacted with by real person yep who's actually trying to help you (P3, Interview)

> In the external sense, where you're not obligated to go in, or anything like that, still having contact. Even if it is that one-way contact where they chuck an announcement up, it still feels as though you know they care. Yeah. And that you're a part of this subject. (P7, Interview)

Further, the regular and timely personalised feedback made learners feel that the educator was keeping track of their learning journey. Also, participants felt that they were being cared for:

> But for some learners that are lagging behind or you know they miss a practical or two or even three. It definitely helps to have that email there was like this, some resources, you can maybe look through. (P1, Interview)

> If nobody is there, it's so easy to sort of go. I'll do it tomorrow I'll do it tomorrow, whereas if there's something keeping pushing you and saying hang on … you haven't done this. Then I said, "Okay", I get it done. (P5, Interview)

When the learners were asked whether they received any messages from the mock AI prototype, all participants confirmed receiving messages. Some participants elaborated that they felt more engaged with the personal emails from the mock AI prototype as well as the educator's support in the form of SPRs.

5.4.5 Educator's Experience

The educator was interviewed three times during the semester, at the end of each iteration in the testing and refining phase of the mock AI prototype. Earlier, the educator found it challenging to understand the LA reports and take any appropriate action since the reports were mainly quantitative and did not give a clear understanding of how to support individual learners. The educator expressed feeling a reduced cognitive load due to regular insights from the mock AI prototype, which was based on LA and the qualitative analysis of learner self-reflections:

> Other reports that we get they're not summarising things; it's not something that I could just look at momentarily [and] make a decision. I have to spend time I don't have a huge amount of time to do anything.

Analysis of the transcripts showed that the educator also felt connected to the learners. The educator used insights from the WOz reports to provide a snapshot of the entire class's progress through SPRs. The SPRs contained messages addressing all the learners, including passive and active learners. Passive learners were encouraged to use the resource links important to working on assignments, and to contact the educator directly in case of any extra time or support needed. The educator also encouraged active learners with appreciation messages:

> Mainly for me, being able to say, "Hey if you haven't handed your work and I'm still happy to mark up, but you need to get things under control and whatever reason, either send me a message [or] talk to me."
> It's interesting so that's what I mean about encouragement so it's not just mitigating problems it's also encouraging development.

The educator was able to see the behaviour of learners as if the learners were present before the educator, which made the educator feel the learners virtually:

> So the data that [the] mock AI prototype is collecting and giving information in the Woz report such as how many interaction[s] that students are making in the subject, how much interaction each learner is giving in terms of when they're submitting and what not. That's really useful. In addition, having a clear idea about particular things that they're having trouble with is useful. I can immediately say that something needs to be done to help the learners. Absolutely, I feel like the class is just in time.

Previously, the educator provided personalised support to the learners with communication channels other than the LMS, such as Discord and Slack, but the educator felt the communication was unorganised. The educator was under constant pressure to check those communication channels for any random question at a random time from any learner, which increased the cognitive load for the educator. The regular insights from the system made the educator aware of the learner's problems, emotions and learning strategies so that the educator was able to provide appropriate support at regular intervals. This process was coordinated, which increased the confidence of the educator. Based on insights from the mock AI prototype, the educator felt increased confidence to facilitate the personalised support at ease; this was because the educator's instruction was organised compared to their own instruction from previous years:

> I'd already been doing a fair bit of sort of reaching out to students but that was ad hoc it wasn't as coordinated, as it is now. I felt that I wasn't getting as many ad-hoc requests from people as a result of having pre-emptive and intervention based [on subject] participation reviews … now that it's more coordinated.

5.5 Insights From Design-Based Research Phases—Developing, Testing and Refining Prototype Solution

This section discusses the general potential of personalisation using academagogy to improve adult learner engagement in online learning environments. Specifically, the section explains how the mock AI prototype increased an educator's awareness of learner experiences to decrease the complexity of implementing personalisation in an LMS. Moreover, the increased awareness facilitated social presence, which is a vital element for the success of adult online learning.

5.5.1 Potential of the Mock Artificial Intelligence Prototype

The study presented results from the development, testing and refining of the mock AI prototype, which indicated positive outcomes regarding the emotional and cognitive dimensions of engagement. The emotional engagement pattern, where the participant group felt positive compared to negative emotions (see Section 5.4.2), is linked to higher academic performance (Riegel & Evans, 2021). The cognitive engagement pattern revealed that learners were oriented more towards andragogy by the semester's end, thus showing increased self-directed learning (see Section 5.4.3). This result also showed a positive outcome for the study since researchers have suggested shifting learner characteristics from pedagogy towards andragogy and heutagogy to design successfully personalised blended-learning support (Cochrane et al., 2021). Moreover, the educator's experience with the mock AI prototype also indicated a reduction in workload when finding and analysing the adult learners' problems to provide personalised support in an LMS.

The mock AI prototype can potentially be developed into a UI as a LAD with all the functional requirements gathered during the three iterations (see Section 5.3.5). A LAD is a UI of an LMS that shows a graphical representation of LMS data (Park et al., 2022; Verbert et al., 2013). Current LADs have design-related issues, such as a lack of actionability and theoretical guidance, which makes it challenging for educators to understand the visualisations and plan for appropriate teaching strategies (Kaliisa & Dolonen, 2022; Verbert et al., 2020). The mock AI prototype addressed these issues using a co-design method involving the educator, adult learners and the theoretical guidance of academagogy (see Sections 5.2 and 5.3).

5.5.2 Increase in Awareness of Learner Experiences

Educators face challenges in understanding individual learners' experiences since they do not meet the learners face-to-face in online learning environments (Clarizia et al., 2018). LA data are prominently used to observe online learner interactions with the LMS for personalisation. In this study, the interpretation of LA data, such as the number of learner interactions with the LMS, indicated the limitations of only using LA for designing personalised support.

The interpretation of interactions made by the active group of participants compared with their final grades was complex (see Table 5.8). For example, learners P3, P4, P5 and P7 made

40, 81, 63 and 38 interactions respectively per week and obtained 78%, 72%, 78% and 77% respectively as the final grades, while learner P2, who made lowest number of interactions 30 per week, obtained the highest grade as 80%. Hence, the number of learners' interactions in the LMS may not reflect their final performance. This finding indicates an incomplete understanding of learner performance if only LA data are used to design appropriate support for the learners. The finding also aligns with the notion that understanding different types of interactions with learning performance is challenging when designing personalised support (Joksimovic et al., 2019). Thus, for personalisation, LA data need to be complemented with other data, such as learner emotions (Suero Montero & Suhonen, 2014).

The unique combination of LA, SA and academagogy theory was used as a model for personalisation by the mock AI prototype. This system increased awareness of learner experiences by providing actionable insights from the analysis along the three dimensions. The weekly insight from the behavioural dimension helped the educator to quickly analyse how many times each learner was interacting with the LMS, and identify at-risk learners. This finding assisted the educator, who could prioritise and check on the at-risk learners. The emotional dimension revealed the learners' average positive, neutral or negative emotions for a particular week's learning content. This information helped the educator identify the hardest and easiest concepts linked to learners' negative and positive emotions for the week. Insights from the cognitive dimension also clarified the type of support learners needed, such as the re-explanation of a hard concept, or demonstration of an example to clarify concept application. Therefore, the educator's increased awareness of how learners were learning behaviourally, emotionally and cognitively provided an opportunity for the educator to more easily use the LMS to personalise the learner's experience at both the cohort and individual level.

5.5.3 Social Presence is Vital for Personalising Learner Experiences in Online Learning Environments

The CoI model identifies three essential elements for optimal online learning experiences: cognitive, social and educator presence (Garrison et al., 1999). Cognitive presence is related to the knowledge construction of the online learner and educator community (Garrison et al., 1999). Social presence in online learning is defined as the ability of community members (learners and educators) to project their characteristics into the community and present themselves as real people to other members. The educator's presence involves their design and facilitation of learning experiences.

Personalisation literature has highlighted the lack of educators' presence for learners in online learning environments (Bartolomé et al., 2018). However, this is one aspect of what is required for personalisation. Another aspect is that educators need learners' social presence for personalisation to improve their educators' presence. As mentioned in Section 5.5.2, educators face challenges with understanding individual learners' needs in an online learning environment, since the educators do not meet the learners directly to improve the presence of an educator. The increased awareness of learners' experiences (interactions, emotions, problems, achievements and learning strategies) using the personalisation model in this extended study, helped the educator design and facilitate personalised support, thus enhancing the educator's presence. For example, from the educator's perspective, the educator felt a heightened awareness of understanding learners' progress based on the insights given by the mock AI prototype (see Section 5.4.5).

The facilitation of personalised support not only resulted in the *educator's* increased presence but also the *learners'* increased social presence (see Section 5.4.4). This increase in social presence might have resulted in positive outcomes for cognitive engagement patterns (i.e., transition to andragogy as specified in Section 5.4.3), which aligns with the CoI model (Garrison et al., 1999). The extended study confirms the importance of the educator's social presence for the learner and the learner's social presence for the educator in online learning. This finding is consistent with previous studies on personalisation and social presence for designing better online learning environments (Clarizia et al., 2018; Holstein et al., 2019; Singh et al., 2022).

5.6 Chapter Summary

This chapter described an extended study where a mock AI prototype was developed, tested and refined to help educators personalise adult online learner experiences using an LMS based on academagogy theory. The mock AI prototype was designed using the WOz experimental technique, and the results from using the mock AI prototype show that:

- The mock AI prototype could potentially enhance the capabilities of an LMS to help educators personalise adult online learner experiences, thus improving learners' emotional and cognitive engagement.
- The mock AI prototype possibly increases educators' awareness of learner experiences, resulting in the simplification of personalising adult learner experiences in an LMS.
- The social presence of educators and learners is vital for a successful personalisation process in online learning environments.

The next chapter will discuss the reflections from the entire research, which was Phase 4 of the DBR project.

Chapter 6. Comparative Analysis

This chapter presents new findings generated by comparing learners' data from the pilot study in Chapter 4 and the extended study in Chapter 5. The comparison provides insights into the use of academagogy theory for personalising adult learner experiences in an LMS. The comparison also reveals patterns, such as improvement in the behavioural, emotional and cognitive engagement of the learners, with mixed results in terms of learners' final grades.

6.1 Chapter Overview

Chapter 6 explains the comparative research findings from the learners' data gathered through the DBR phases. This chapter compares the similarities and dissimilarities between DBR Phase 1, and DBR Phases 2 and 3. Phase 1 involved the pilot study that was conducted in 2021 (Chapter 4). The extended study, associated with Phases 2 and 3, was conducted in 2022 (Chapter 5). Section 6.2 describes the process of obtaining findings from the comparative analysis. Section 6.3 provides the contrast of the learners' behavioural engagement. Section 6.4 highlights the relative emotional engagement pattern of the learners. Section 6.5 explores the cognitive engagement findings across the learners from the two DBR phases. Section 6.6 compares the learner performance in terms of their grades at the end of the semester. Section 6.7 highlights the interrelated problems faced by adult online learners, and finally, Section 6.8 provides a summary of the chapter.

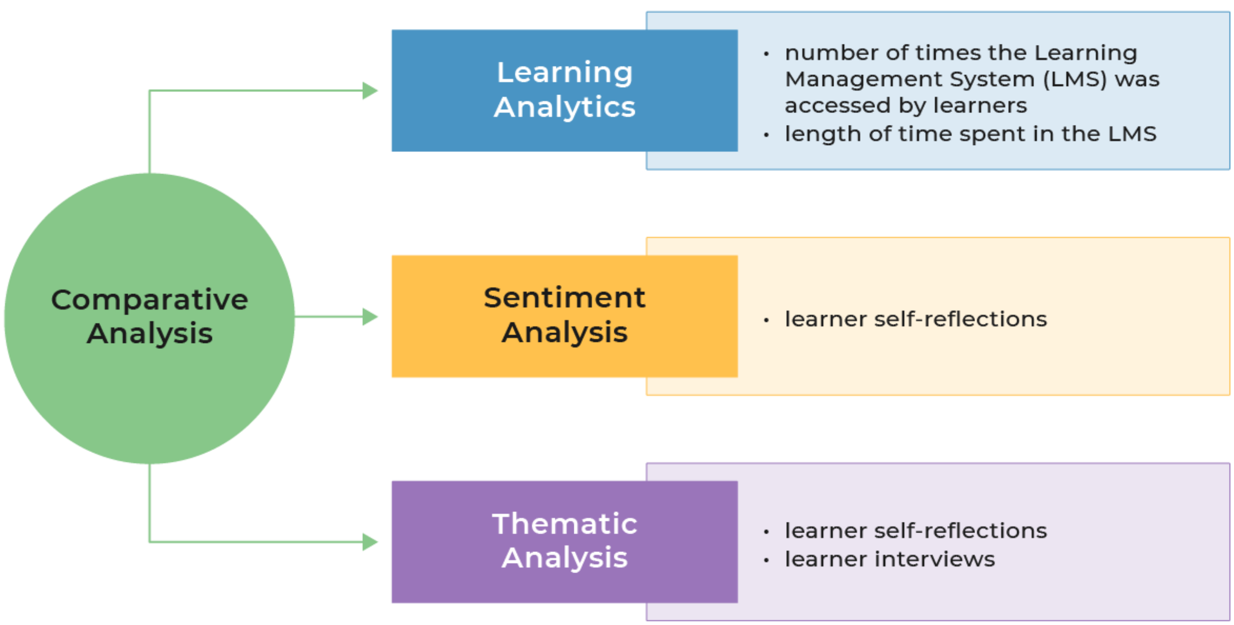
6.2 Comparative Analysis Findings

Comparative analysis is the method of comparing two or more items with the intent to discover new ideas about them. In DBR, a comparative analysis is utilised to generate new findings by comparing the data from different phases (Wang & Hannafin, 2005). The comparative analysis provides an in-depth evaluation of the research context, leading to evidence-based recommendations for theory and practice (Van den Akker et al., 2006).

A comparative analysis of the learners' data was conducted to identify preliminary results about the use of academagogy, LA and SA for personalisation on adult online learner engagement, thus addressing Research Objective 3 (see Table 1.1). The findings were obtained by comparing the learner data: LA, learner self-reflections, learner interviews and learner grades, as shown in Figure 6.1.

Figure 6.1

Deriving Research Results From Comparative Analysis of Learning Analytics, Sentiment Analysis and Thematic Analysis



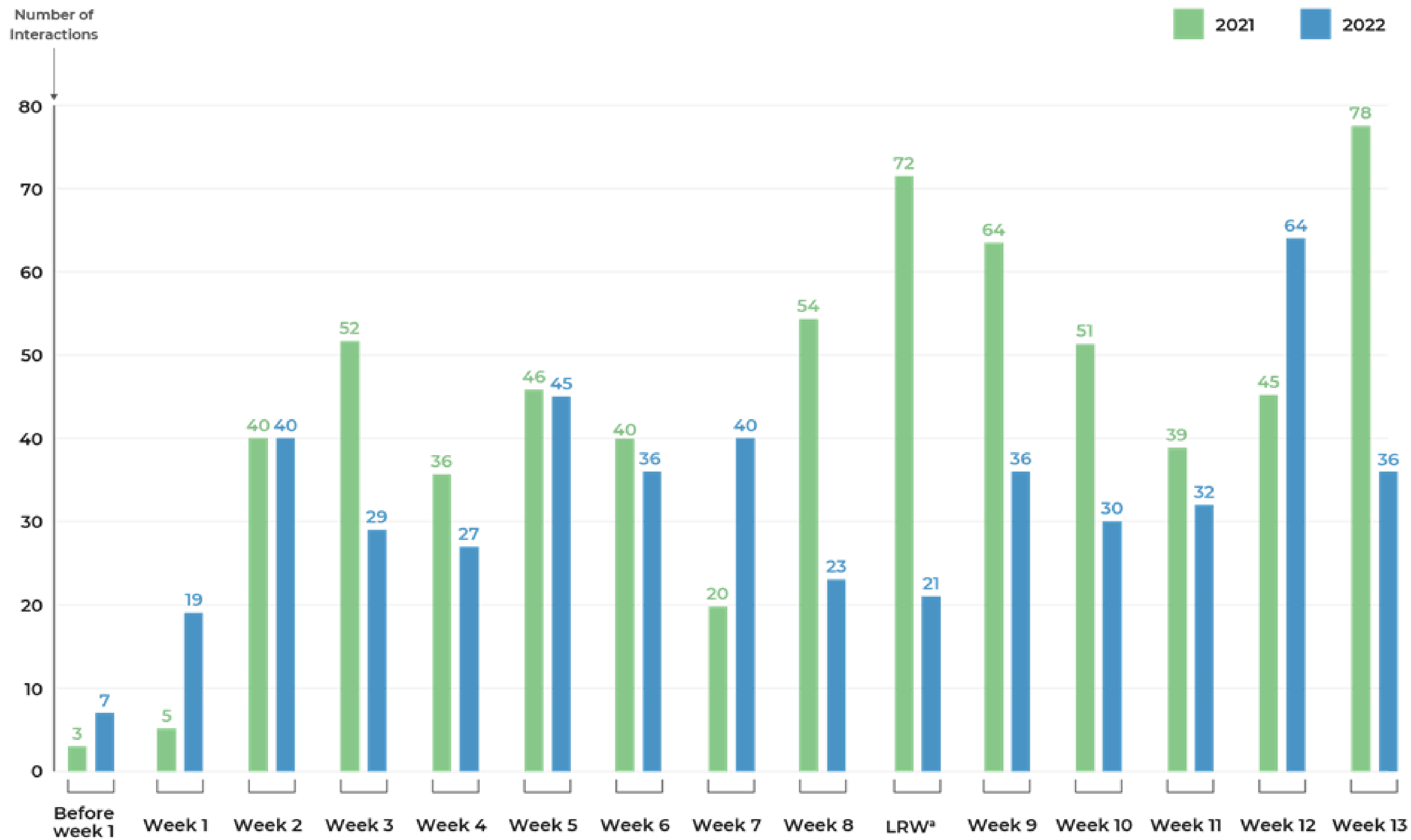
6.3 Improvement in Behavioural Engagement of Learners

The analysis of the LA data showed improvement in the behavioural engagement of learners. From the behavioural engagement pattern, it was observed that the 2022 cohort interacted more with the LMS at the beginning of the semester, whereas the 2021 cohort started making interactions starting from Week 1. This pattern indicated that the 2022 cohort started actively participating in the learning process very early in the semester (Figure 6.2).

In addition, the 2022 cohort spent 65 minutes on the LMS before Week 1, which is 21 times more than the three minutes spent by the 2021 cohort before Week 1, as shown in Figure 6.3. This observation also indicated the early engagement of the 2022 participants with the LMS. Thus, the behavioural engagement patterns of the 2022 cohort indicated a positive outcome for the study, as previous studies have shown early engagement with the LMS is a predictor of good learning performance (Denny et al., 2021; Koprinska et al., 2015). Additional analysis about the differences in behavioural engagement pattern is discussed in the next chapter (see Section 7.3.1).

Figure 6.2

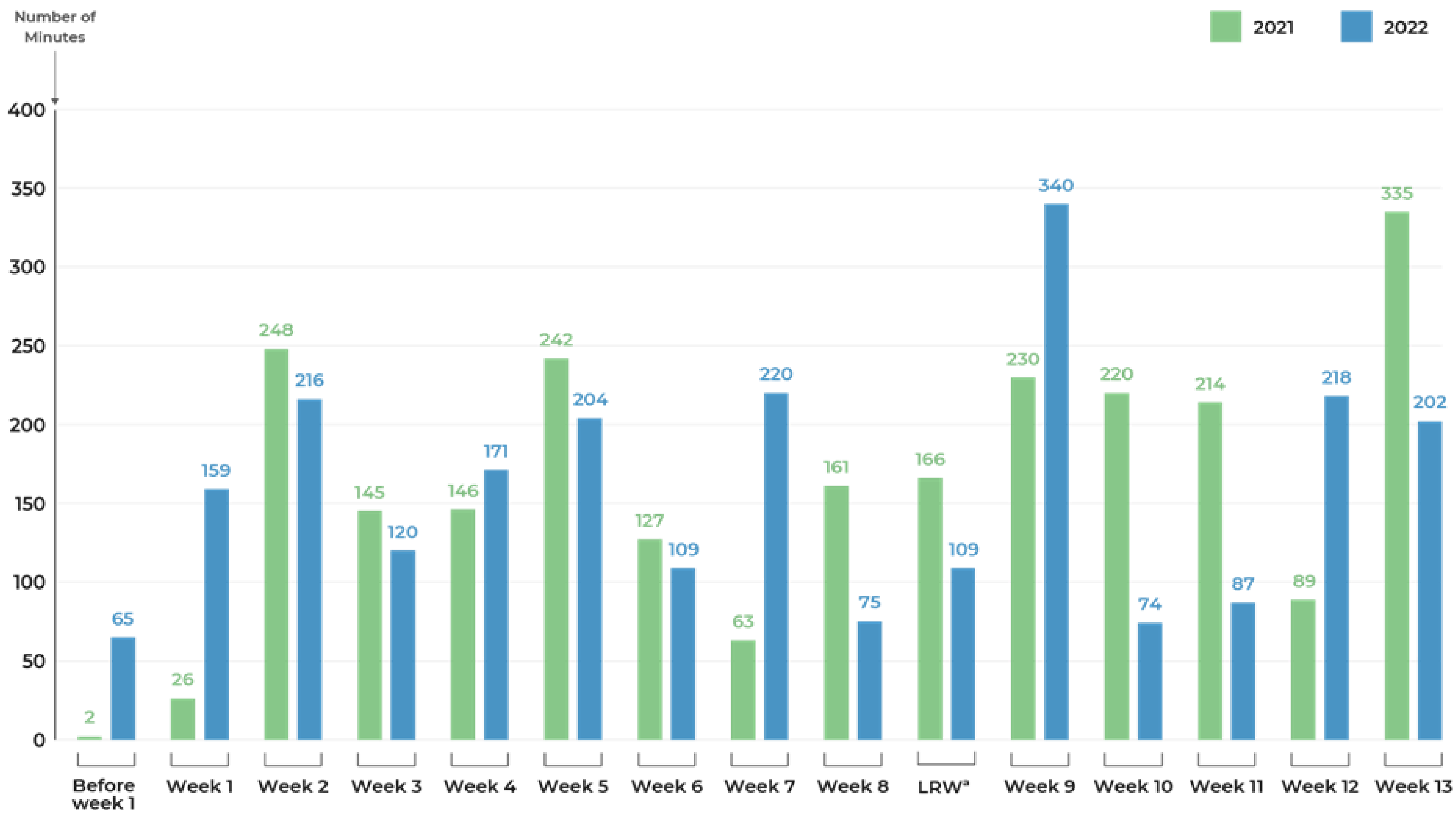
Comparing the Number of Interactions Per Week Made by the Participant Groups in 2021 and 2022



[a] LRW = Lecture Recess Week

Figure 6.3

Comparing Time Spent by the Participating Groups in 2021 and 2022 Cohorts



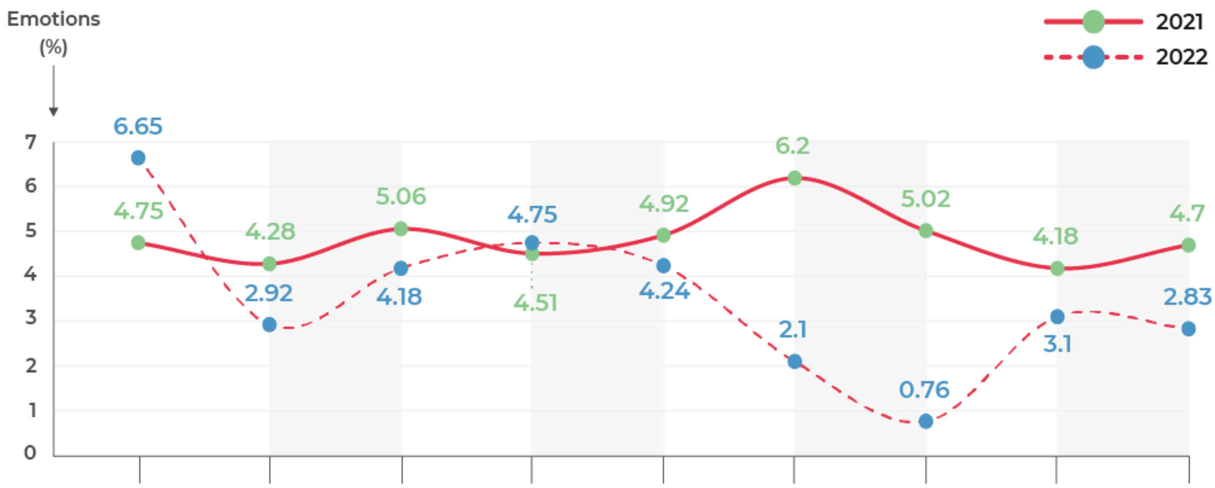
[a] LRW = Lecture Recess Week

6.4 Improvement in Emotional Engagement of Learners

The emotional engagement pattern indicated a positive outcome in general. Learners' emotions or feelings are essential to academic achievement (Henrie et al., 2015). Tracking learner emotions using VADER in this research revealed that learners in the 2022 cohort felt less negative than the 2021 cohort throughout the semester, as shown in Figure 6.4. Also, the 2022 cohort felt more positive than the 2021 cohort (see Figure 6.5). The emotional engagement pattern indicating when the learners felt more positive than negative is linked to high academic performance (Pekrun et al., 2011). Further analysis of the differences in emotional engagement pattern between the two cohorts is discussed in the next chapter (see Section 7.3.2). Encouraging positive emotions and reducing negative emotions is recommended since online learner engagement is influenced by emotions (Riegel & Evans, 2021; Suero Montero & Suhonen, 2014). However, the neutral emotions revealed a mixed pattern as shown in Figure 6.6. This observation might be due to the limitations of the VADER tool (Hixson, 2020), which is explained in Section 8.4.2.

Figure 6.4

Comparing the Negative Emotions Reflected by Participant Groups in 2021 and 2022



Note. Practical names are abbreviated (Prac. 1 to Prac. 9)

Figure 6.5

Comparing the Positive Emotions Reflected by Participant Groups in 2021 and 2022

Note. Practical names are abbreviated (Prac. 1 to Prac. 9)

Figure 6.6

Comparing the Neutral Emotions Reflected by Participant Groups in 2021 and 2022

Note. Practical names are abbreviated (Prac. 1 to Prac. 9)

6.5 Improvement in Cognitive Engagement of Learners

Learners' cognitive engagement was analysed from the reflexive thematic analysis of self-reflections and interview transcripts (see Section 4.4). The comparison of pedagogy, andragogy and heutagogy references from both cohorts showed that the 2022 participant group made a greater number of references for andragogy compared to the 2021 participant group. In total, 45%, 37% and 18% of the 2021 cohort's references were related to pedagogy, andragogy and heutagogy, respectively (see Figure 6.7), whereas 25%, 52% and 23% of the 2022 cohort's references were related to pedagogy, andragogy and heutagogy, respectively (see Figure 6.8). This observation showed that the 2021 cohort felt dependent on the educator, while the 2022 cohort felt independent and interested in working on their own. Detailed investigation about the differences in cognitive engagement pattern is presented in the next chapter (see Section 7.3.3).

Figure 6.7

Pedagogy-Andragogy-Heutagogy Orientation of the 2021 Cohort

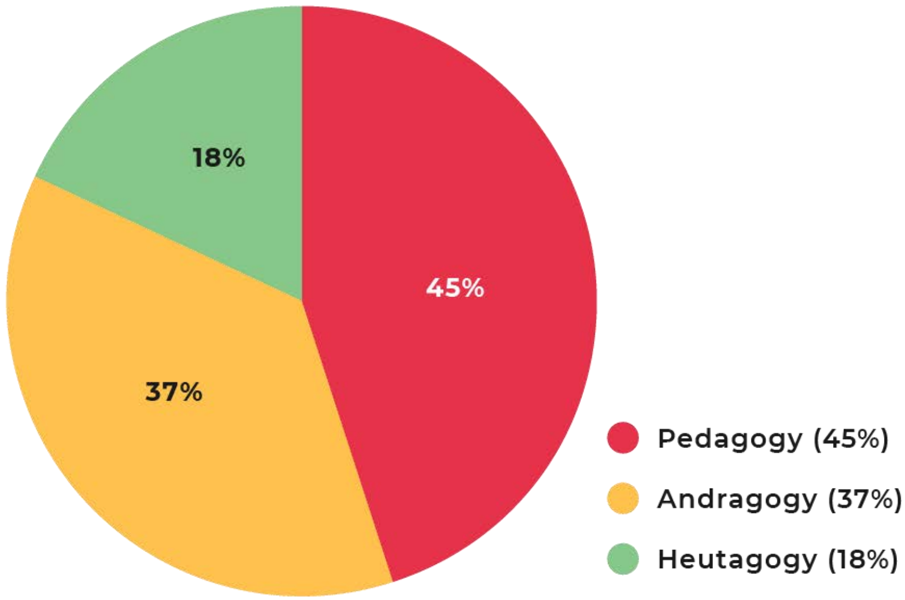
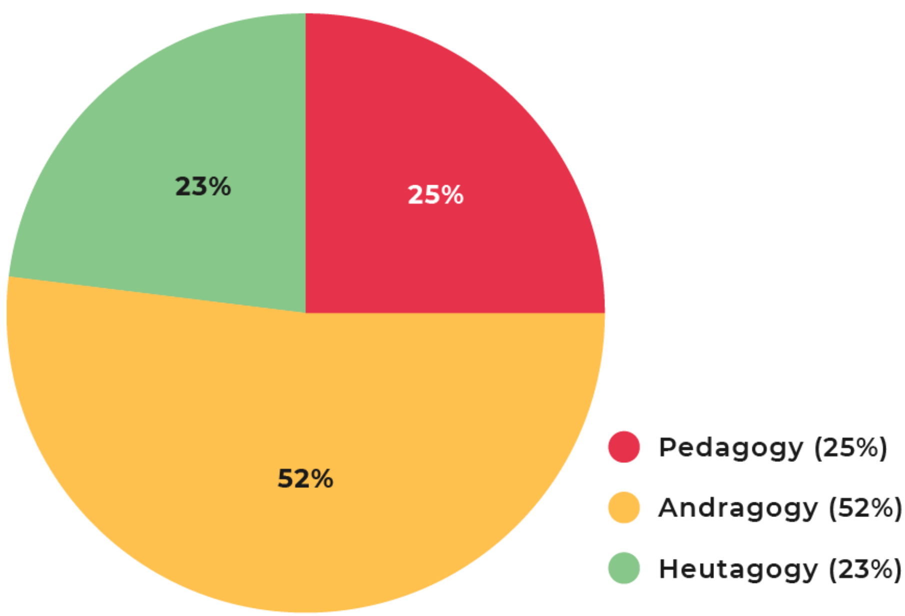


Figure 6.8

Pedagogy-Andragogy-Heutagogy Orientation of the 2022 Cohort



The cognitive engagement pattern inferred a positive outcome for the study since a previous study implied that shifting learner capabilities from pedagogy towards andragogy and heutagogy is essential to design successfully personalised blended learning support (Cochrane et al., 2021). The learner's cognitive skills could be further improved by future personalisation models that use technological affordances encouraging progression toward heutagogy on the PAH continuum (Narayan et al., 2019).

6.5.1 Temporal Pedagogy-Andragogy-Heutagogy Learning Trajectories

The observation of the 2021 and 2022 cohorts' PAH learning trajectories over the semester resulted in temporal insights. The PAH learning trajectories were derived from the PAH algorithm (see Section 4.4.1). The temporal PAH learning trajectories of both cohorts showed that the participants in the 2022 cohort consistently remained at the andragogy and heutagogy levels compared to the 2021 cohort, which mostly remained at the andragogy level for all practicals (as depicted in Table 6.1). This result infers that the 2022 cohort felt more self-directed in their learning compared to the 2021 cohort.

Table 6.1

Comparison of Temporal Pedagogy-Andragogy-Heutagogy Learning Trajectories of Participant Cohorts in 2021 and 2022

Practical number	2021 participant cohort trajectory	2022 participant cohort trajectory
1		

Practical number	2021 participant cohort trajectory	2022 participant cohort trajectory
2	Pedagogy → Andragogy	Pedagogy → Andragogy → Heutagogy
3	Pedagogy → Andragogy → Heutagogy	Pedagogy → Andragogy → Heutagogy
4	Pedagogy → Andragogy → Heutagogy	Pedagogy → Andragogy → Heutagogy
5	Andragogy → Heutagogy	Pedagogy → Andragogy → Heutagogy
6	Andragogy → Heutagogy	Andragogy → Heutagogy
7	Pedagogy → Andragogy → Heutagogy	Andragogy → Heutagogy

Practical number	2021 participant cohort trajectory	2022 participant cohort trajectory
8	Pedagogy → Andragogy → Heutagogy	Andragogy → Heutagogy
9	Pedagogy → Andragogy → Heutagogy	Andragogy → Heutagogy

Note. The size of boxes for pedagogy, andragogy and heutagogy in each cell of the participant group trajectories is indicative of the number of participants at that level on the Pedagogy-Andragogy-Heutagogy (PAH) continuum for that practical. Although the learning trajectories were derived from the PAH algorithm (Section 4.4.1), these boxes are not drawn to scale.

The participants in the 2021 cohort were mostly at pedagogy and andragogy levels for the first and second practicals. The majority of the participants were at an andragogy level from the third practical onwards until the sixth practical. However, after the seventh practical, some of the participants shifted back to the pedagogy level and by the last practical the majority were at the andragogy level.

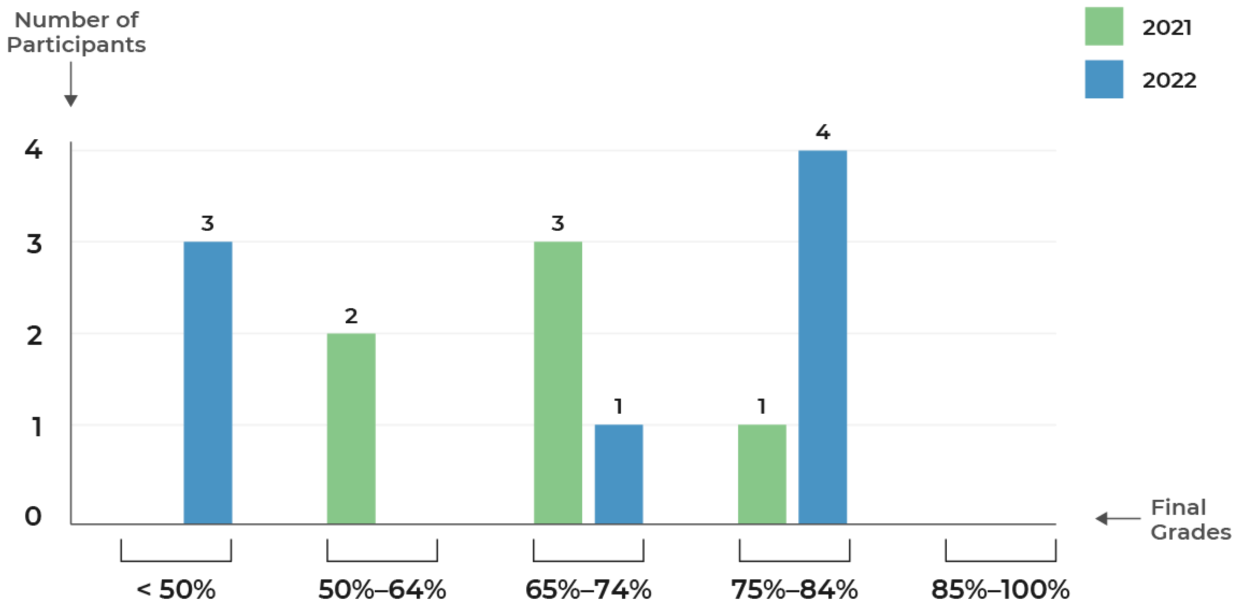
The participants in the 2022 cohort were mostly at the pedagogy level for the first practical. Later, the participants progressed to andragogy and heutagogy levels through Practicals 2 and 3, respectively. For the fourth practical, the majority of participants were at the andragogy level. From the fifth practical onwards to the eighth practical, most of the participants shifted to the heutagogy level. And for the final practical, participants remained at andragogy and heutagogy levels. These findings indicate that the participants in the 2022 cohort felt more self-regulated and showed more interest in independent learning than the 2021 cohort by the end of the semester. Thus, the participants in the 2022 cohort progressed to the heutagogy level by Practical 5 and mostly sustained that level for a longer time, which indicated that the participants in 2022 were more oriented towards self-learning compared to the participant group in 2021. This result also supports the improvement in cognitive engagement of learners' patterns shown in Figures 6.7 and 6.8 (above).

6.6 Mixed Result for Learner Performance

The spread of the distributed grades for the 2021 and 2022 participants revealed mixed results. Figure 6.9 shows that a greater number of participants in the 2022 cohort achieved higher grades compared to the participants in the 2021 cohort. For instance, in the 2022 cohort, four participants achieved grades between 75% to 84%, one obtained a grade between 65% to 74% and three participants obtained grades less than 50%. In the 2021 cohort, only one participant achieved grades between 75% to 84%, while three participants obtained grades between 65% to 74% and two participants' grades were between 50% to 64%. This observation indicated that even though the number of participants who achieved higher grades in 2022 was more compared to the 2021 cohort, there were some participants in the 2022 cohort who obtained grades less than 50% (any grade less than 50% was considered a fail in the subject). This observation implies a mixed result in terms of learners' performance, for the application of academagogy.

Figure 6.9

Distribution of Participant Grades in 2021 and 2022 Cohorts



The mixed result might have been caused by a delay in sending personal emails to participants using the mock AI prototype, as this occurred only during the last four weeks of the semester (refer to Section 5.3.5). The at-risk learners may be better facilitated if a dedicated support system or the mock AI prototype sent personal emails to learners from the first week of the semester.

6.7 Adult Online Learners Face Interrelated Problems

The analysis of learners' interview data from the two studies exposed three different types of problems, which are discussed in the following subsections.

6.7.1.1 Subject-Related Problems. These problems are related to the technical concepts in the subject, such as understanding and applying concepts. For example, some participants revealed that writing logic for developing mobile applications was challenging.

Subject-related problems may be due to a lack of pre-requisite knowledge or personal time-management issues that influence engagement with the learning resources.

> It requires some basic knowledge in Java to get started because what I experienced is that I came from ECE [Electronic and Communications Engineering] background not IT. So, I had very little knowledge in programming … that I had to learn Java so I took e-learning subject on Java and then came back to this subject that made a little bit easy. (S1, Interview)

6.7.1.2 Social Well-Being Problems. These problems are not related to the learning setting (subject-related problems) but influence learners' engagement. Some social-wellbeing problems included workplace problems, family responsibilities, illness and mental stress caused by COVID-19 infections. For example, learner P5 explained feeling exhausted and unable to concentrate on their studies for some weeks because they had a COVID-19 infection during the extended study. Also, learner P1 reported extra work shifts that conflicted with the learner's study.

> I felt like I did struggle, a bit with the practicals later in the semester just because I had issues outside of university but with workplace, they've been severely not considering my time for university put me on to being shifts works it's been, yeah it's stressful. (P1, Interview)

6.7.1.3 Adaptation to Online Learning. This problem relates to ease with the online learning process. The participants in the pilot study preferred face-to-face learning because they missed interacting with educators and peers, due to the mandatory shift to online or blended learning in response to COVID-19. Interestingly, most learners in the extended study posited that they were adapting to online learning:

> Face to face would be more fun will be more convenient. Because you have the lecture in front of you, and you can actually ask him questions. (S4, Interview)

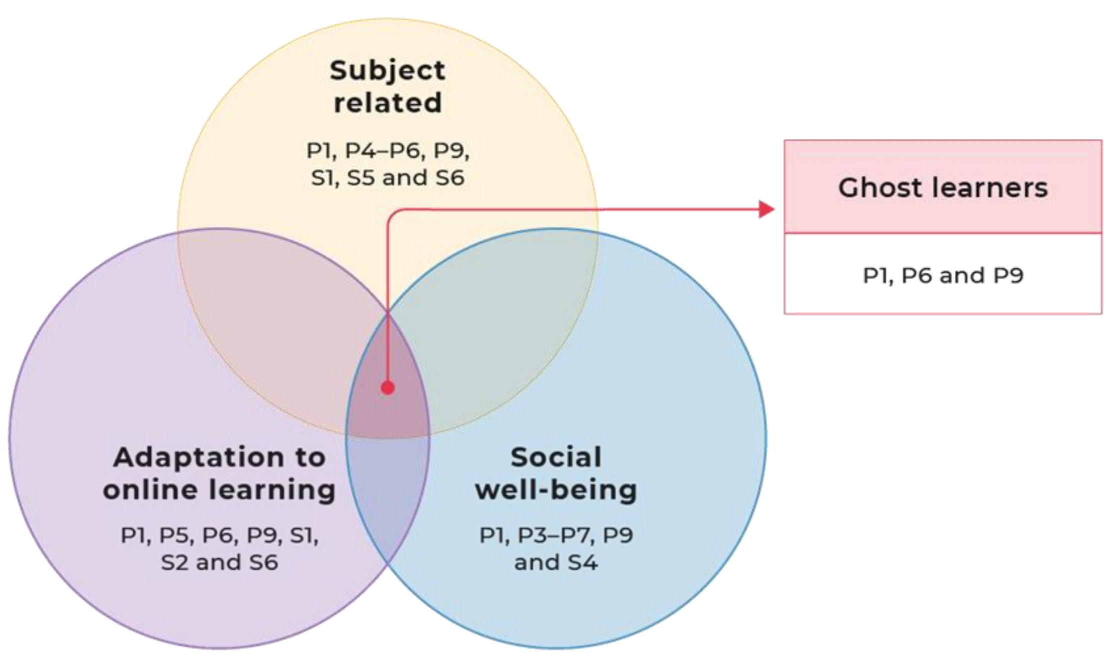
> I've personally been doing something online just because of my time yeah my limited time availability with work and everything well I'll finish a practical and have work. As soon as that practical finishes so I'll have to do the practical and then finish it early and then get ready for work and then go from there, so a lot of those practicals have to have been all done online um. But I still feel like I haven't suffered at all from that issue. (P1, Interview)

Also, the participants from both the pilot and extended study revealed time management as a common challenge. The time-management problem was identified as an aggregation of all three categories of problems. This observation was in parallel with a literature review highlighting that the challenges faced by adult online learners were interrelated (Kara et al., 2019). The learners who faced these problems, at the intersection of all three types of problems, tended to become ghost learners (i.e., more prone to fail in the subject), as shown in Figure 6.10.

Ghost learners are defined as learners who remain enrolled in the subject throughout the semester but never participate in the learning process (Linden et al., 2021). These learners had a very limited number of interactions in the LMS, which indicated that they were at risk of failing the subject (see Table 5.8, Section 5.4.1). For instance, learner P1 mentioned that they could not engage with the learning process because of work duties (working extra shifts due to the nonavailability of other staff), subject-related problems and dependence on their educator because of challenges with self-directedness in online learning. Another participant, learner P9, faced time-management problems because they were juggling family, job and study commitments. Learner P9 also expressed not being confident with Java programming. The combination of all problems together might have exacerbated learner P9's difficulty with learning the subject. Another participant, learner P6, faced problems such as time management with work responsibilities, health issues (asking educator for extensions on assessments) and subject-related problems due to a lack of experience in the technical concepts required for this subject. Further analysis of the ghost learner experiences is discussed in the next chapter (see Section 7.3.4).

Figure 6.10

Intersection of Problems Faced by the Participants



Note. Each circle in this Venn diagram represents a category of problems the participants experienced.

6.8 Chapter Summary

This chapter presented a comparison of the findings from Chapters 4 and 5. The comparison of the 2021 and 2022 participant cohorts revealed improvement in learners' behavioural, emotional and cognitive engagement patterns. These findings provide insight into the use of academagogy for personalising adult online learner experiences and enhancing their engagement in an LMS (see Chapter 7). Also, the comparison of learners' performance showed mixed results for their final grades, thus indicating a scope for further study.

Chapter 7. Discussion

This chapter presents the interpretation of findings from Chapters 4, 5 and 6. The findings were integrated and analysed to address the research objectives. Theoretical and practical implications of the research are highlighted in the chapter.

7.1 Chapter Overview

This chapter discusses the reflection from the entire research, which relates to Phase 4 of the DBR project as explained in Chapter 3. Section 7.2 revisits the research objectives and outlines the pilot and extended studies. Section 7.3 provides the insights and implications of the research. Section 7.4 explains the theoretical recommendations and Section 7.5 describes the practical recommendations. Finally, Section 7.6 summarises the chapter.

7.2 Revisiting the Research Objectives

The main aim of the research was to improve personalised interactions between adult online learners and educators in an LMS. Personalisation plays an important role in engaging adult learners and improving their retention in online learning (Cardenas et al., 2022; Shearer et al., 2020). Personalisation can be applied at three levels of interaction in an LMS (Mikić et al., 2022; see also Section 1.5). Adult online learners seemed to prefer interaction with the educator in an LMS compared to interaction with their peers or interaction with content (Lim et al., 2020; Martin & Bolliger, 2018; Moore, 1989). However, the existing LMSs are limited in supporting educators' personalised interactions with adult online learners (Cardenas et al., 2022; Dahlstrom et al., 2014). The personalisation process in an LMS has been deemed complex for educators due to difficulty in understanding learner experiences, choosing appropriate teaching strategies and dealing with scalability issues (Mikić et al., 2022).

Personalisation literature showed the use of technologies such as LA, BD, ML, SA, AI and ITSs to help educators reduce the workload involved in analysing learner data in LMSs (FitzGerald et al., 2018; Mikić et al., 2022). However, the literature posited limited theoretical understanding of integrating different technologies with teaching strategies for personalisation in LMSs (Bartolomé et al., 2018; Mikić et al., 2022; Walkington & Bernacki, 2020). This knowledge gap increases the complexity for educators in determining what technologies provide supportive interventions for adult online learners in LMSs (FitzGerald et al., 2018; McLoughlin & Lee, 2010; Zhang et al., 2022). Hence, academagogy theory was applied to guide the personalisation process in this research.

The primary aim of academagogy is to allow an academic to choose the appropriate teaching models, pedagogy, andragogy and heutagogy, based on adult learners' needs to personalise their experience (Winter et al., 2009). Pedagogy is an educator-centred teaching model where the learner is passive, and the educator is responsible for decision making in the learning process (Blaschke, 2016). Andragogy is a learner-centred teaching model where an educator allows the learners to collaborate in the learning process through active participation (Luckin et al., 2011). Heutagogy is a learner-driven teaching model where the learner is proactively involved with complete control over deciding what and how they want to learn (Blaschke, 2016). Previous studies have shown that academagogy has enhanced learner performance and improved both educators' and learners' experiences (McAuliffe & Winter, 2014a; Murthy & Pattanayak, 2019; Winter et al., 2009). However, the research is limited on the applications of academagogy, thus indicating a knowledge gap in understanding how academagogy can be applied and what effect academagogy can have on online learner engagement (Chapter 2). Based on these knowledge gaps, the research question and the objectives were formulated as follows:

- **Research question**. How can we enhance the capabilities of an LMS to help educators personalise adult online learner experience using academagogy?
- **Research Objective 1**. Identify and analyse educators' challenges and obstacles when personalising learning for adult students in an LMS using academagogy.
- **Research Objective 2**. Outline and describe the principles for applying academagogy to facilitate personalisation in an LMS.
- **Research Objective 3**. Provide preliminary insights about the combined impact of academagogy, LA and SA on the engagement of adult online learners.
- **Research Objective 4**. Provide UX design concepts for educators and learners focusing on personalisation in an LMS using academagogy.

The DBR methodology was selected to study the research question, as it provided a rigorous structural plan for studying the effect of innovation in technology-enhanced learning environments such as an LMS (Anderson & Shattuck, 2012). The DBR project involved two studies (see Chapter 3) with the following research findings.

7.2.1 Outline of Pilot Study Findings

Chapter 4 presented the pilot study, an ethnographic study of adult learners' and an educator's experiences in an LMS. The objective of the study was to identify and analyse an educator's challenges when personalising adult learner experiences in an LMS using academagogy (Research Objective 1). This study used the PAH continuum, based on academagogy, as the theoretical framework for personalisation. The key findings of this study were:

- The adult learners' trajectories on the PAH continuum could be potentially used for personalisation by identifying the nuances of learner problems that block their engagement in an online subject (Addanki et al., 2022).
- The analysis of learner data to determine PAH learning trajectories led to scalability issues in terms of an educator's time and workload.

7.2.2 Outline of Extended Study Findings

Chapter 5 reported an extended study, in which a mock prototype of an AI system was developed to address the scalability issues identified in the pilot study. The mock AI prototype was designed based on the WOz method, which is a HCI technique used to simulate AI system capabilities and test them before developing a functional system (Browne, 2019). The mock AI prototype was tested and refined with three iterations study. The results of this study were:

- The mock AI prototype showed the educator's increased awareness of online learner experiences, thus simplifying the process of personalisation.
- The mock AI prototype potentially aided the educator in enhancing learners' emotional and cognitive engagement.
- The social presence of educators and learners in an LMS could play a vital role in enhancing online learning experiences.

7.2.3 Overview of Comparative Analysis Findings

Chapter 6 described the comparative analysis findings of learner data from both the pilot and the extended studies. The purpose of the comparative analysis was to identify similarities and differences between the two studies based on the combined use of academagogy, LA and SA on the engagement of adult online learners (Research Objective 3). The findings showed that the use of academagogy, LA and SA for personalisation could improve adult online learner engagement in terms of behavioural, emotional and cognitive engagement patterns. The finding also indicated a mixed result on the learners' performance related to their final grades. In addition, the analysis posited that adult online learners face interrelated problems. Also, there is a limitation in comparing the differences of engagement patterns of the learners from the two studies at the time when assessments were due during the semester.

7.3 Insights from the Design-Based Research Phase—Reflection

The findings derived from the thematic analysis of the data (learner self-reflections, learner interviews and the educator's interviews) from the two studies informed the following research insights.

7.3.1 Onboarding Activities at the Start of the Study Period Increases Learners' Engagement

Onboarding activities like an icebreaker encourage adult learners to start interacting with the LMS early in the semester (see Figures 6.2 and 6.3). In the extended study, an icebreaker activity was given to the learners in Week 1, which included open-ended questions about learners' previous programming experiences related to the subject, and general questions related to learners' motivation to enrol in the subject. This self-reflection activity motivated the learners to think critically while evaluating their strengths and weaknesses:

> I thought it was good, and a good introduction to the reflection like reflecting on what I do know and what I don't know as well yeah. So, it also gave me an idea of what I needed to work on. (P7, Interview)

Some participants used these icebreaker activities to engage with their peers. For example, the educator uploaded the results of the technical icebreaker as an LMS announcement and a video in Week 5. Participants used these technical icebreaker results to self-evaluate their competencies by discussing them with their peers:

> According to the results, I had engaged with my fellow colleagues, just to discuss on where we are, how we can improve and yeah, it's been very helpful. (P4, Interview)

Based on their self-evaluation and peer engagement, the learners might have started interacting with various learning materials available in the LMS, which resulted in an increase of the 2022 cohort's LMS interactions at the beginning of the semester.

7.3.2 Personalised Feedback From Educator Influences Learners' Emotional Engagement

The emotional engagement result (see Section 6.4) indicated a pattern of more positive emotions and fewer negative emotions for the 2022 cohort compared to the 2021 cohort. This result might be due to the educator's increased interaction with learners in 2022, by providing personalised feedback in the form of SPRs (see Appendix H) and email messages based on the learners' self-reflections—all facilitated by the mock AI prototype (see Section 5.3.5). Though learners in the 2021 cohort submitted self-reflections, the educator provided general feedback, which was not personalised to the individual learners.

The learners in the 2022 cohort were emotionally engaged, as the participants felt an increase in comfort while sharing their feelings through self-reflections. For example, the participants in the 2022 cohort revealed positive emotions, such as “happy”, “good” and “less awkwardness” when sharing their experiences with the self-reflection activities:

> [It] made me feel less awkwardness. I realised that some people were a little bit ahead, some people were the same, and some people behind me so that made me feel good that I was in between. (P5, Interview)

> I think it was pretty good. Keep it up with the feedback on the weekly assignments as well that was really handy. Because you know there were, there were some things that I missed or could have done better and all that sort of stuff. (P7, Interview)

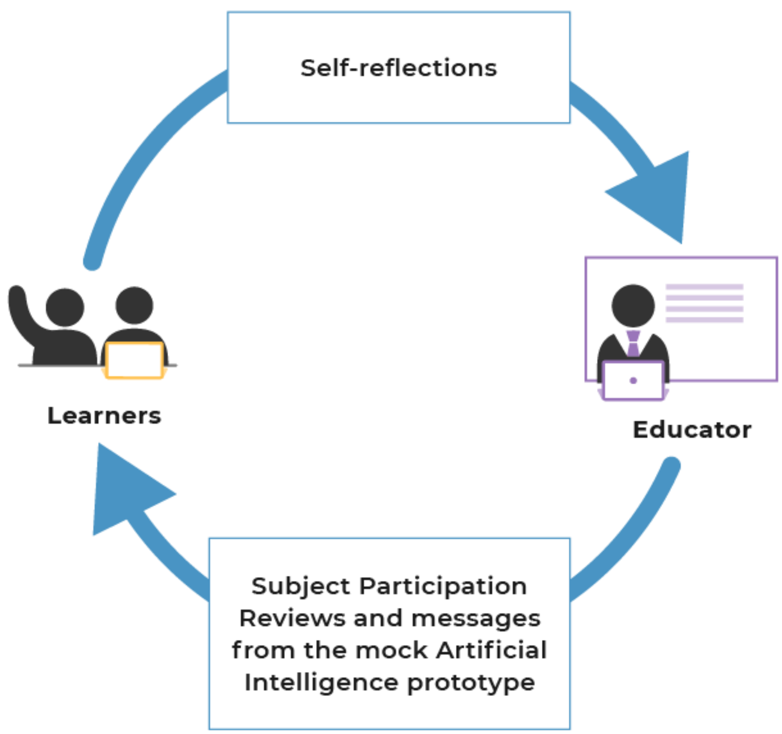
In addition, the participants in the 2022 cohort revealed positive learning experiences with the subject because learners felt there was “constant observation”, “tracking progress”, a “sense of belong[ing]”, “regular feedback” and “timely feedback.” This was due to the personalised feedback in the form of SPRs and personal email messages from the mock AI prototype.

7.3.3 Two-Way Feedback Between Educator and Learners Influences Learners’ Cognitive Abilities for Self-Learning

The cognitive engagement results indicated the 2022 cohort’s orientation on the PAH continuum, which showed a pattern of increased cognitive abilities for independent learning (see Section 6.5). The increase in these learners’ willingness for self-learning might be because of the feedback loop between the learners and the educator as shown in Figure 7.1. The feedback loop involved two-way communications from learners to the educator via self-reflections, and the educator's feedback to learners via SPRs and personal email messages at regular intervals in 2022.

Figure 7.1

Feedback Loop Between Educator and Learners



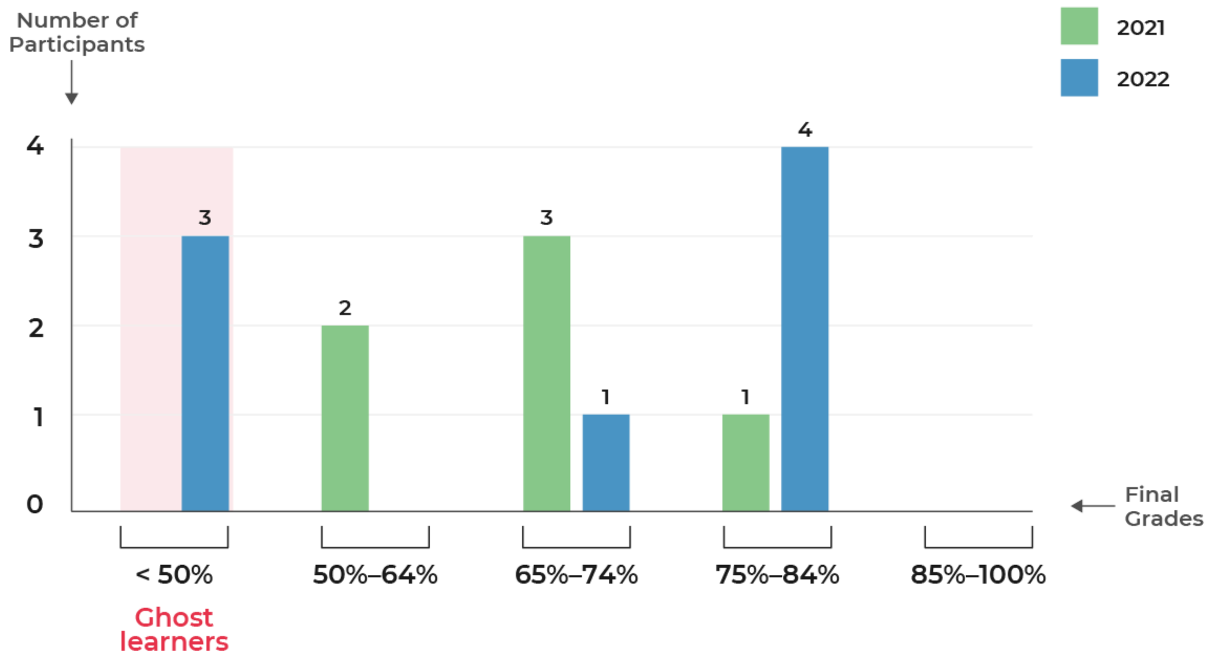
In addition, the utilisation of personalised feedback from the educator enhanced the learners' cognitive abilities. For example, the 2022 learners who actively participated in the learning process (see Figure 5.15, Section 5.4.3) by submitting their learning activities and utilising the personalised feedback were able to progress towards heutagogy on the PAH continuum. However, the learners who were passive (see Figure 5.14) with minimal participation mainly remained at the pedagogy level.

7.3.4 The Interrelated Problems Faced by Learners Could Influence Their Learning Abilities

The personalisation process based on academagogy presented a mixed result regarding learner performance (see Section 6.6), possibly because each adult learner's ability to learn was influenced by different types of problems. The mixed result for personalisation in the 2022 cohort may be due to the interrelated problems faced by ghost learners (Section 6.7). These ghost learners had miniscule participation in the learning process and tended to fail the subject (Linden et al., 2021). The ghost learners remained passive despite the personalised support as shown in Figures 5.14 and 7.2. This result shows that, for successful personalisation using academagogy, the learners should take responsibility for their self-regulated learning skills. The shared responsibility of the learning process between learners and educators is also identified in previous academagogy and online education literature (McAuliffe & Winter, 2014a; Stone & Springer, 2019).

Figure 7.2

Mixed Results for the Application of Academagogy with Ghost Learners



Note. One participant was missing from the 2022 cohort since the participant dropped enrolment from the subject during the extended study due to personal reasons.

7.3.5 Integrating Artificial Intelligence With Learning Management Systems Can Enhance Educators' and Learners' Experiences

The inclusion of AI tools to automatically analyse learner experiences and provide insights could enhance both learners' and educators' experiences. LMSs are adequate content repositories, but they are not capable of facilitating personalised learning experiences to address the diverse learning needs of adult learners (Bajaj & Sharma, 2018; Dahlstrom et al., 2014; Furini et al., 2022). Adult learners have felt isolated due to less interaction with educators in LMSs (Albinson, 2016; Kara et al., 2019). Moreover, educators have found it challenging to continuously monitor learner experiences and adapt teaching processes, as learners are not directly visible to educators in an LMS (Clarizia et al., 2018; Fan et al., 2021).

The design and the use of the mock AI prototype in the extended study revealed positive outcomes from both the learners' and the educator's perspectives. The educator reported an increased awareness of learner experiences and the reduced complexity of processes for personalising learner experiences (see Section 5.4.5). In addition, learners also felt an increased social presence of the educator, which alleviated their feelings of isolation while using the LMS (see Section 5.4.4). This insight aligns with other studies suggesting the necessity of AI integration into current LMSs for better teaching and learning experiences (Bagustari & Santoso, 2019; Furini et al., 2022; Iles, 2019).

7.4 Theory-Based Recommendations

The research findings show that the personalisation of adult learning experiences using an academagogy framework in an LMS improves adult learners' behavioural, emotional and cognitive engagement. These findings are based on the comparative analysis of learner data from the two studies (see Chapter 6). The contextual research findings and insights (see Section 7.3) have provided a theoretical understanding of the research to form DPs that personalise adult online learner experiences in an LMS using academagogy (Research Objective 2).

The DPs that are informed by theory in a DBR project can potentially assist future research in local and global educational contexts by providing reusable knowledge (Anderson & Shattuck, 2012; Herrington et al., 2007; Parmaxi & Zaphiris, 2020). DPs are not decontextualised principles or theories with equal effect in all contexts; instead, they reflect the conditions in which they operate (Anderson & Shattuck, 2012). DPs were developed for applying academagogy to facilitate personalisation in an LMS, as described in Table 7.1.

Table 7.1

The Development of Academagogy Design Principles for Personalisation in a Learning Management System

Development of Design Principles	Design-Based Research phases
Drafting	Phases 0, 1 and 2
Testing	Phase 3
Refining	Phase 4

7.4.1 Drafting Design Principles

DPs were drafted based on the previous academagogy literature. Researchers have proposed academagogy DPs to improve learners' engagement in higher education (Jones et al., 2019; Murthy et al., 2012). In addition, a case study revealed that academagogy DPs have encouraged ownership skills such as participants' design and delivery of a subject in a corporate context (Murthy & Pattanayak, 2019). However, researchers have recommended the validation of these principles with larger cohorts of learners in various contexts (Murthy et al., 2012; Murthy & Pattanayak, 2019). Moreover, academagogy DPs are yet not studied in an IT discipline. This knowledge gap was foundational for investigating the application of academagogy in online learning settings, which led to the creation of DBR Phases 0, 1 and 2. The prototype solution in Phase 2 was designed based on the following academagogy DPs that were drafted for personalisation:

- **DP1, diagnose the learning needs of individual learners**. The diverse learning needs of adult learners highlight the use of personalised teaching models rather than the traditional one-size-fits-all model. The diversity of adult learner needs is crucial for using academagogy (Jones et al., 2019; McAuliffe et al., 2008). Diagnosing each learner's needs is essential for personalisation as it portrays the learner's profile, such as learning styles, preferences and previous knowledge (Cardenas et al., 2022). An early diagnosis of learner's needs is necessary to address their expectations for improving engagement and retention (Stone, 2017). Activities such as online quizzes and icebreakers are used to diagnose learner needs (Ní Shé et al., 2019; Shearer et al., 2020).

- **DP2, afford pedagogical and technological support based on the learner's needs**. Based on the diagnosed learner needs, an appropriate choice of teaching models from pedagogy, andragogy and heutagogy could be used following the academagogical framework (Murthy, 2011; Murthy et al., 2012; Murthy & Pattanayak, 2019). Various technologies are suggested to encourage online engagement and interactivity, such as short videos and tools to provide synchronous and asynchronous activities (Stone, 2017).
- **DP3, give formative feedback to individual learners**. Feedback improves learner engagement (Denny et al., 2021). *Feedback* is defined as a process in which learners make sense of the comments about the quality of their work to develop their future performance (Lim et al., 2020). Establishing regular contact points with learners through formative feedback can support learner engagement (Moore & Shemberger, 2019; Murthy et al., 2012). Different methods of formative feedback may include weekly messages, timely responses, personal emails, phone calls or individual learner meetings (Moore & Shemberger, 2019).
- **DP4, provide just-in-time support using LA**. LA is predominantly used for providing timely personalised feedback for larger groups of learners (Joksimovic et al., 2019). The timely feedback encourages the learners to become more successful (Pistilli, 2017).

- **DP5, continuous improvement of the process**. Personalised learning requires that the teaching process be continuously adapted according to the learner's needs (Stones, 2017). This process involves continuously tracking the learner's progress and adjusting the teaching strategies based on the learners' requirements throughout the semester (McAuliffe & Winter, 2014a; Murthy & Pattanayak, 2019).

7.4.2 Testing Design Principles

The DPs drafted in Phase 2 were tested in Phase 3 by using the prototype solution (i.e., the mock AI prototype) in the extended study. The study was conducted for a 13-week semester, from February to July 2022, in two stages (see Section 5.3.4):

- Stage 1 focused on diagnosing the learner's needs. In this stage, DP1 from Phase 2 was implemented. Learner needs were diagnosed with the technical icebreaker activity (See Section 5.3.4.1).
- Stage 2 involved continuously tracking and personalising the learner experiences. In this stage, DP2, DP3, DP4 and DP5 were implemented in Phase 3. LA, SA and PAH analysis (thematic analysis of learner data based on academagogy) were used to monitor participant learning needs constantly. In addition, learners received personalised support based on their needs, in the form of LMS messages, LMS announcements and personal emails. Table 7.2 shows the mapping of the research activities carried out in Phase 3 to test the drafted DPs from Phase 2.

Table 7.2

Mapping of Design Principles With Research Activities in Phase 3

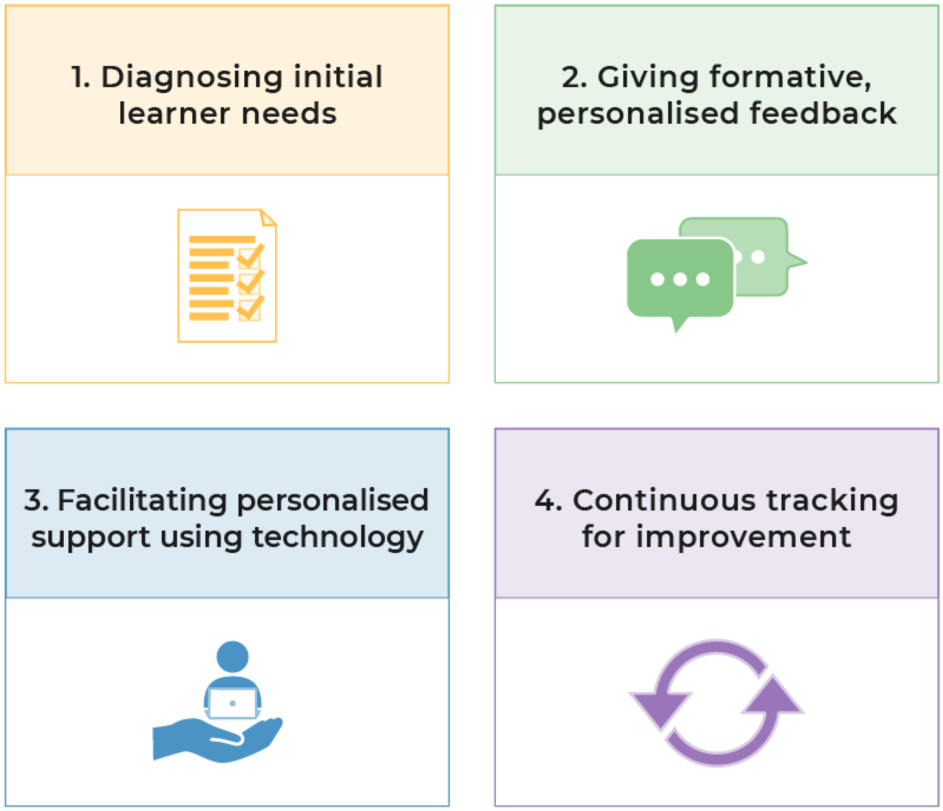
Research activities implemented in Phase 3	Drafted Design Principles (DPs) from Phase 2 (applied in Phase 3)
Stage 1: Diagnosis of initial learner needs (technical icebreaker)	DP1
Stage 2: Continuous tracking and personalising learner experiences 2a. Tracking (Learning Analytics, Sentiment Analysis and Pedagogy-Andragogy-Heutagogy analysis) 2b. Personalising (Learning Management System announcements, short videos and personal emails)	DP2, DP3, DP4, DP5

7.4.3 Refining Design Principles

The DPs were refined in Phase 4 based on the evidence from extended study results in Phase 3. Phase 4's reflection was carried out from July 2022 to December 2022. After testing the mock AI prototype based on DPs in Phase 3, the *DP*s for personalisation using academagogy were refined, as shown in Figure 7.3.

Figure 7.3

The Refined Academagogy Design Principles for Personalisation



The DPs were rigorously analysed and refined to achieve Research Objective 2. The refined DPs are presented in the following subsections.

7.4.3.1 *DP1*: Diagnosing Initial Learner Needs. A learner's needs change as time progresses. Hence, the original DP1 (diagnose the learning needs of individual learners) was specified as diagnosing initial learner needs. A technical icebreaker activity was given to the participants in Phase 3 in Week 2 to diagnose the initial skills of the learners, so that the educator could adapt the teaching process right from the beginning of the semester according to the cohort's needs.

The findings from participant interviews about the technical icebreaker at the end of the semester showed that participants felt encouraged. The participants thought that the technical icebreaker was an activity in which they could re-evaluate their skills for more personal learning, thus motivating them towards self-directed learning:

> It was a good to [do] the reflection like reflecting on what I do know. And what I don't know as well yeah. So, it also gave me an idea of what I needed to work on. (P7, Interview)

7.4.3.2 *DP2*: Giving Formative Personalised Feedback. The original DP2 (afford pedagogical and technological support based on the learner needs) and DP3 (give formative feedback to individual learners) were combined as *DP2*. For pedagogical support in *DP2*, the educator gave feedback to the learners at regular intervals in the SPR. This occurred three times during Weeks 5, 9 and 13 of the semester (see Table 5.6, Section 5.3.5). The SPRs contained textual messages describing the progress of the whole cohort (see Section 5.3.4.2). The educator simultaneously uploaded short video recordings describing the SPRs while giving synchronous and asynchronous support for the benefit of all learners. The SPRs might have helped the participants "keep on track", "know about the rest of the class" and be engaged by "gamification", which kept them motivated to learn.

7.4.3.3 *DP3*: Facilitating Personalised Support Using Technology. The original DP2 (afford pedagogical and technological support based on learner needs) and DP4 (just-in-time support using dispositional LA) were combined as *DP3*. In Phase 3, a mock AI prototype was designed to support educators in applying academagogy theory, thus addressing the scalability issue of learner data analysis raised in Phase 2. The mock AI prototype collected LA data and self-reflections from the participants (in the extended study) to automatically analyse the data and provide insights for the educator in the form of WOz reports. Based on these insights, the educator created personalised support.

Various technologies available in the LMS were used to deliver personalised support. The educator uploaded the personalised support into the LMS as announcements (SPRs) and short videos. Refer to Appendix H for an example of support given by the educator as an SPR in the form of an LMS announcement. Analysis of learner interviews revealed that all participants felt the educator was engaging. The online learners (learners who pursued the subject completely off campus) in particular felt more connected to the educator with a sense of belonging in the class:

> In the external sense, where you're not obligated to go in, or anything like that still having contact. Even if it is that one-way contact, where they chuck an announcement up, it still feels as though you know they care. Yeah. And that you're a part of this subject. (P7, Interview)

Also, the mock AI prototype delivered personalised support to the individual participants through their emails. Participants reflected different benefits by using words such as "avoids procrastination", "happy", "keeping an eye [on learning tasks]" and "motivation." These descriptions related to having the mock AI prototype send personal messages based on their learning needs:

> I did in my one of my self-reflections, I said that I would like to learn more about Android themes and then I got a message from the personalised learning support system and, "Here are some helpful links about what you've written about", and it

> sent me a link to documentation on that. So, I thought that was quite good. (P3, Interview)

7.4.3.4 *DP4*: Continuous Tracking for Improvement. The original DP5 (continuous improvement) was refined as *DP4*. Continuous improvement of the teaching and learning process was achieved by continuously adapting the teaching based on learner needs. Adapting teaching strategies requires constant monitoring of the learner's experiences (interactions, emotions and learning behaviours) for the optimal benefit of learners. Learner experiences were continuously tracked using LA, SA and PAH position visualisations, as shown in Figures 5.5, 5.6 and 5.7 (Section 5.3.4.1), respectively. This principle of continuous tracking helped the educator to change the instruction according to the individual learner's needs:

> So the data that [the] mock AI prototype is collecting and giving information in the Woz report such as how many interaction[s] that students are making in the subject, how much interaction each learner is giving in terms of when they're submitting and what not. That's really useful. In addition, having a clear idea about particular things that they're having trouble with is useful. I can immediately say that something needs to be done to help the learners. Absolutely, I feel like the class is just in time. (Educator, Interview)

7.5 Practical Recommendation

The practical recommendations in a DBR project refer to artefacts such as software for using technology to solve teaching, learning and performance problems (Herrington et al., 2007). The artefact designed in this research was the mock AI prototype, which was an early design method for developing functional software. The mock AI prototype could be potentially used to design LAD software.

A LAD is a UI that is used to visualise learning traces, such as online activities or website navigations in an LMS that are captured as log files (Verbert et al., 2013). LADs provide graphical representations of the current and historical state of a learner or a subject, for the benefit of individual learners or educators at the micro level, organisations (schools and universities) at the meso level and learning ecosystems at the macro level (Verbert et al., 2013). LADs have a wide range of applications, such as increasing awareness and self-reflection for learners and educators, improving engagement, enhancing interactions between learners and educators, identifying at-risk learners, predicting learning outcomes, facilitating teamwork and enabling social comparison.

Verbert et al. (2020) highlighted a lack of actionability and limited theoretical underpinning as the design-related issues of LADs. These issues make it hard for the end users (learners or educators) to understand the information provided by a LAD. Learners may need help in explaining how to enact the information given. From the educator's perspective, the challenge is linking LAD visualisations to appropriate teaching strategies. Thus, this research and other LAD studies suggest involving the end users in the design of LADs using HCD methods (Kaliisa & Dolonen, 2022; Khosravi et al., 2021).

The mock AI prototype developed in this research is an innovative contribution to technology-enhanced learning in higher education. The mock AI prototype was co-designed by involving stakeholders, such as an educator, and gathering user requirements from adult online learners. The use of the mock AI prototype in the extended study showed positive results both from the perspective of the educator and learners (see Section 5.4). Overall, the mock AI prototype provides practical recommendations and design concepts to benefit educators and learners by focusing on personalisation in an LMS using academagogy. This provision of design concepts consequently achieves the requirements of Research Objective 4.

7.5.1 Value of learner self-reflections

Learner self-reflections played a vital role in this research, deriving the valuable findings in the previous sections (see Sections 7.21 and 7.2.2). In this research, 54 self-reflections were collected during the pilot study, and 65 self-reflection texts were collected in the extended study. In sum, 119 self-reflections were collected, each ranging from 100 to 500 words, implying a maximum of 59500 words. Each word is rigorously analysed by the researcher using NVivo software for Thematic analysis and the VADER tool for Sentiment Analysis. This analysis is credible according to Natural Language Processing and Sentiment Analysis literature (Bai & Stede, 2022; Liu, 2012). Self-reflections were the key input to the PAH algorithm and the PAH learning trajectories, which are the novel contributions of the thesis.

As mentioned in Section 3.6.1, leaner self-reflections are rich data sources as they represent the learners' personal feelings, expressions, situational responses, and critical thinking. Self-reflections are widely collected data in higher and online education to understand the nuances of learner experience during their study period for providing just-in-time personalised support (Bai & Stede, 2022; Suero Montero & Suhonen, 2014). This research recommends encouraging learners to write self-reflections as a learning activity to benefit learners and educators (De Lin et al., 2021; Getliffe, 1996; Wallin & Adawi, 2017).

7.6 Chapter Summary

This chapter discussed the research findings addressing the research objectives. Firstly, Research Objective 1 was achieved through the pilot study, which identified and analysed the educator's challenges when personalising learning for adult online learners in an LMS. Secondly, the extended study findings revealed the UX design concepts for developing a mock AI prototype. The aim of this mock AI prototype was to help educators apply academagogy to facilitate personalisation in an LMS, thus achieving Research Objective 4. Thirdly, the comparative analysis findings provided preliminary insights into the combined use of academagogy, LA and SA on adult online learner engagement, addressing Research Objective 3. Finally, the theory-based recommendations addressed Research Objective 2 by identifying a set of DPs for applying academagogy and personalising adult online learner experiences in an LMS. The DPs are (1) diagnosing initial learner needs, (2) giving formative personalised feedback, (3) facilitating personalised support using technology and (4) continuous tracking for improvement. The next chapter provides a conclusion to the thesis by answering the main research question.

Chapter 8. Conclusion

This chapter summarises the research findings and explains the research contributions. Also, this chapter presents the research limitations and directions for future work. Finally, the chapter concludes the research presented in this thesis.

8.1 Chapter Overview

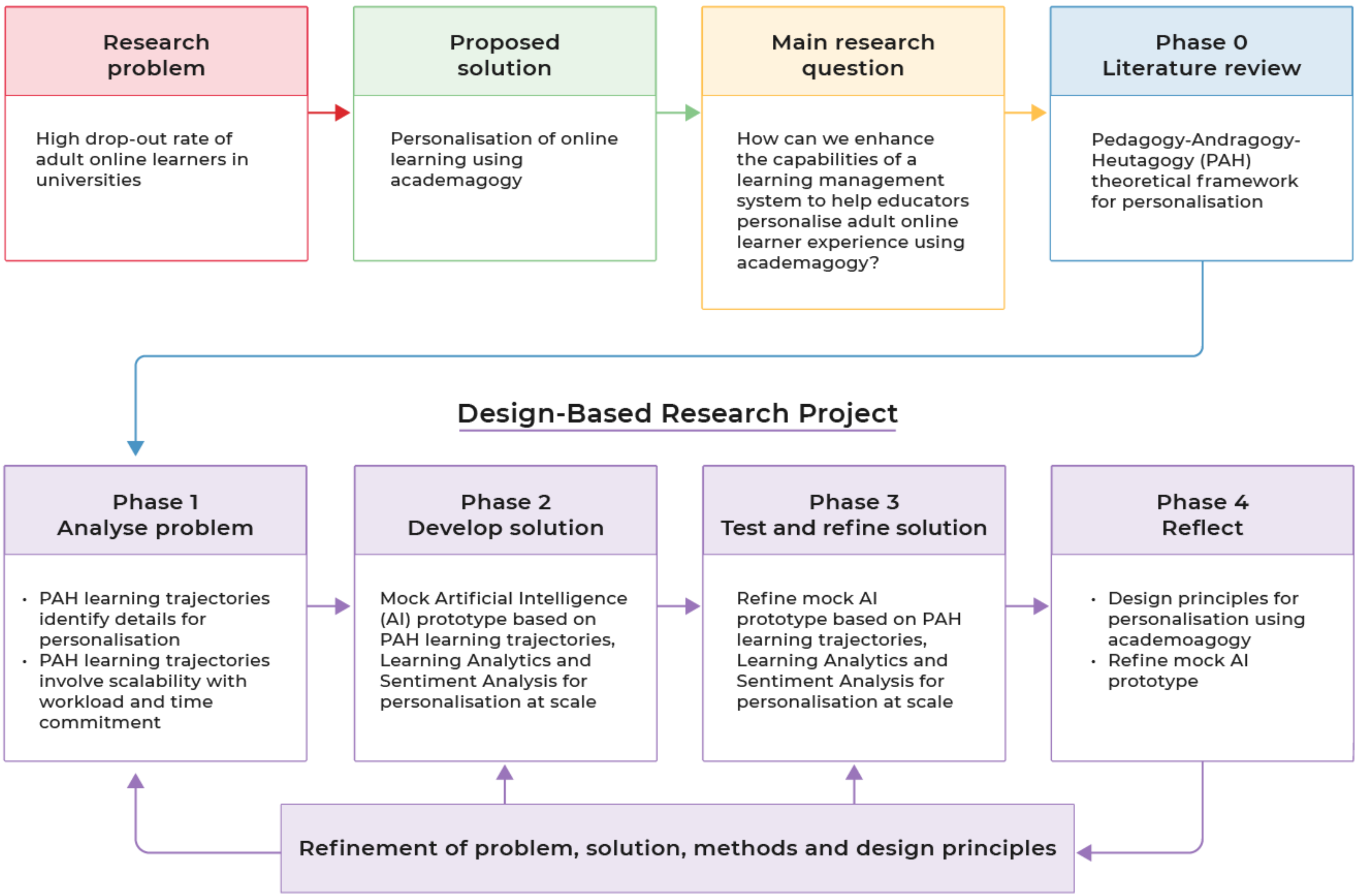
This chapter discusses the significance of the research findings and their practical implications. Section 8.2 revisits the research question and discusses the key research findings. Section 8.3 highlights the significance of the research contributions. Section 8.4 describes the limitations of the research. Section 8.5 provides future work directions and Section 8.6 presents concluding remarks.

8.2 Revisiting the Research Question

The high dropout rate of adult online learners in universities motivated the research in this thesis, as shown in Figure 8.1. A review of this high dropout rate showed various factors such as feelings of isolation, lack of interaction with educators and peers, work–life balance and challenges regarding the traditional one-size-fits-all teaching model for online learning (Kara et al., 2019). Indeed, research has found that the standard teaching model disengages adult learners in online learning environments (Bajaj & Sharma, 2018; Cercone, 2008; Ferreira & MacLean, 2017).

Figure 8.1

The Research Journey



Online learning studies have recommended the personalisation of online learning to enhance adult learner engagement and reduce high dropout rates (Mikić et al., 2022; Shearer et al., 2020; Sutton, 2021). Personalisation is defined as the learning process in which the pace of learning, content and instructional approaches are optimised according to the needs of each learner (Bray & McClaskey, 2013). Learners who have received personalised instruction have performed better than learners who received traditional instruction (Bloom, 1984). However, the implementation of personalisation was found to be a complex challenge due to the lack of proper integration of technological advancements with current teaching models (Bartolomé et al., 2018; Mikić et al., 2022).

Educators face challenges when determining operational methods for personalisation in an LMS. Studies using personalisation have suggested that a consistent theoretical grounding is necessary to guide educators' use of technologies in an LMS (Axelsen et al., 2020; Walkington & Bernacki, 2020). Therefore, this research used academagogy as the theoretical framework for guiding an educator's personalisation of adult online learner experiences in an LMS.

Academagogy allows an educator to select appropriate parts from the pedagogy, andragogy and heutagogy models to address the learners' educational needs and improve their learning outcomes (Winter et al., 2008). The academagogy model aims to shift learner capabilities from pedagogy (educator-dependent) to andragogy (learner-dependent) towards heutagogy (learner-driven; see Murthy & Pattanayak, 2019). However, the review of academagogy literature for enhancing adult online learner engagement showed a research gap (see Chapter 2), thus leading to the main research question: How can we enhance the capabilities of an LMS to help educators personalise adult online learner experience using academagogy?

The DBR methodology was selected to conduct the research (see Chapter 3). The DBR project contained five phases. The key research findings from each phase are presented in the next section.

8.2.1 Key Research Findings

- **Phase 0**. The literature review phase indicated that the PAH continuum can be used as a theoretical framework with academagogy for personalisation to improve adult learner engagement in online learning (Addanki et al., 2020).
- **Phase 1**. The problem analysis phase showed that the PAH learning trajectories based on the academagogy theoretical framework have the potential to identify details of the problems faced by adult learners in an LMS (Addanki et al., 2022). This phase also highlighted scalability issues for an educator applying academagogy in an LMS.
- **Phases 2 and 3**. The development, testing and refining of the prototype solution demonstrated how the mock AI prototype can reduce scalability issues related to applying academagogy for personalisation in an LMS.
- **Phase 4**. The reflection phase presented two main research outputs.
  - academagogy DPs for personalisation in an LMS (see Section 7.4)
  - a refined mock AI prototype (see Section 7.5).

Figure 8.1 (above) depicts the research journey that transitioned from identifying the broad research problem to the key research findings used to answer the main research question.

8.3 Research Contributions

This section describes the key contributions to the research fields, online learning and adult education. The research findings also contribute to personalisation theory and academagogy theory. Further, the findings support the real-world applications of academagogy in a higher education context.

8.3.1 Advancing Personalisation Literature

Personalisation is a recurring theme in the design of online learning environments for the engagement of adult learners (Mikić et al., 2022; Stone & Springer, 2019). However, the implementation of personalisation was deemed a complex challenge due to the lack of technological integration with current teaching models for designing operational methods in LMSs (Mikić et al., 2022; Walkington & Bernacki, 2020). Future efforts to implement the personalisation process therefore need clarification regarding who is doing the personalisation (either a computer or human), what is being personalised (either content or instruction or both), who the beneficiaries are (learners or educators), what tools are being used and how the tools are being used (Cardenas et al., 2022; FitzGerald et al., 2018). Literature has recommended a consistent theoretical framework to guide educators' use of different tools in LMSs for the personalisation process (Bartolomé et al., 2018). Also, to add value to the personalisation process, researchers have suggested a delicate balance between promoting learners' self-learning skills and educators' facilitation processes in online learning (McLoughlin & Lee, 2010). Hence, academagogy was considered to guide educators' facilitation of personalised learning experiences for adult online learners in an LMS.

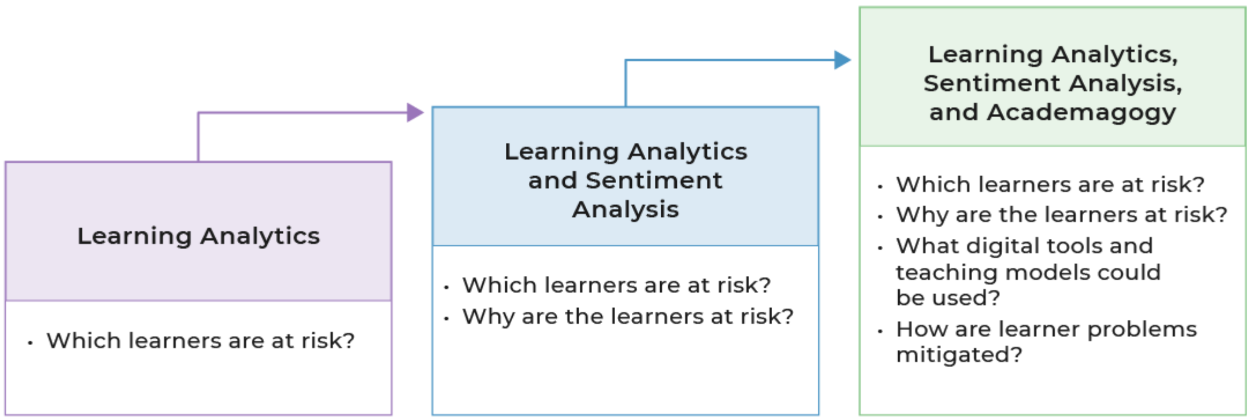
Appropriate technologies such as LA were used to reduce the complexity of applying academagogy to larger online classes. LA is defined as measuring, collecting, analysing and reporting learner data to optimise learning (Siemens, 2013). LA has vast applications in higher education, especially in identifying and supporting at-risk learners by designing personalised support (Axelsen et al., 2020). Previous LA studies have reported an incomplete view of learner experiences (Joksimovic et al., 2019; Silvola et al., 2021; Suero Montero & Suhonen, 2014). The quantitative data from LA, such as the number of logins, navigation patterns, clicks, reading habits and writing habits, are complex to interpret when designing operational methods for personalisation (Joksimovic et al., 2019; Suero Montero & Suhonen, 2014). Hence, researchers have suggested including qualitative data like learners' emotions to gain a more nuanced vision of individual learning patterns (Silvola et al., 2021; Suero Montero & Suhonen, 2014).

The SA of learner emotions can potentially complement LA for observing learner experiences. SA is an NLP technique that automatically detects the author's opinions in a piece of text (Hutto & Gilbert, 2014). SA is also an efficient way for an educator to track a single learner or an entire cohort of learners for personalising instruction in an LMS (Clarizia et al., 2018). Thus, SA was included to obtain a clarified picture of classroom experiences.

The integration of LA, SA and academagogy formed a novel personalisation model in this research. Figure 8.2 illustrates the theoretical framework integrating LA, SA and academagogy to personalise adult learners' experiences in an LMS. The unique combination of LA, SA and academagogy theory for the personalisation model presented in this research increased the educator's awareness of learner experiences by providing actionable insights (see Section 5.5.2). The educator's increased awareness of learners' behavioural, emotional and cognitive learning provided an opportunity for the educator to efficiently personalise the learners' experiences at the cohort and individual levels in the LMS (see Section 5.4.5). Therefore, the new personalisation model contributes promising personalisation applications for the benefit of learners and educators in higher education.

Figure 8.2

Theoretical Framework for the Novel Personalisation Model



8.3.2 Enhancing Capabilities of a Learning Management System to Support Personalisation

The mock AI prototype has potential to be developed as an innovative educator-facing LAD. A LAD is a UI that graphically visualises the learning traces from LMS activities such as blog posts and discussion forums (Verbert et al., 2013). Further, a LAD provides visualisation of web navigations captured in log files**,** including the frequency of learner visits, time spent by the learner and any submissions or downloads made by the learner (Verbert et al., 2020). The primary focus of LADs is to support decision making by providing visualisations about learners' data to the learners themselves at the micro level, to educators and administrators at the meso level and to society at the macro level (Verbert et al., 2020).

Literature has reported a lack of actionability and limited theory as design-related issues for developing LADs (Park et al., 2022; Verbert et al., 2020). These issues made it hard for the end users (learners and educators) to understand the information given by a LAD (Verbert et al., 2020). Learners may need further guidance regarding how to action this information. From an educator's perspective, the challenge is with linking the visualisation to appropriate teaching strategies (Verbert et al., 2020).

This lack of actionability is due to partial information indicating the learners' experiences, as the current LADs mostly use quantitative data such as LMS interactions depicted in Table 8.1. Traditional LADs collect LMS interactions such as online material access, frequency of learner visits and length of time within the learning environment (Suero Montero & Suhonen, 2014). Earlier LADs have had a prominent feature in identifying learners at risk (Khosravi et al., 2021). To date, current LADs use multimodal data from multiple sources such as LMS interaction traces, and emotional information of the learners from various sources such as audio, video, self-reports and sensor data such as eye-tracking (Ez-zaouia & Lavoué, 2017). This multimodal data provides both quantitative and qualitative data collection and analysis for a better understanding of learner experiences in online learning environments.

Table 8.1

Capabilities of Learning Analytics Dashboards

Variable	Traditional Learning Analytics Dashboards (LADs)	Current LADs	Future LADs
Collects	Quantitative data	Multimodal data	Multimodal data
Reports	Incomplete visualisations of learner experiences	In-depth visualisations of learner experiences	Enhanced visualisations of learner experiences with actionable insights based on theoretical guidance
Use	Easily identifies at-risk student	Not only identifies at-risk student, but also identifies the reasons for why the student is at risk	Not only identifies at-risk student, but also identifies the reasons for why the student is at risk and what type of teaching strategies could be used to help at-risk students

Bridging learning theories to decide on instructional strategies can improve both learners' and educators' actionable intelligence (Khosravi et al., 2021; Park et al., 2022). From learners' perspectives, a LAD based on theoretical guidance can enhance self-regulated learning capabilities (Park et al., 2022). From educators' perspectives, the connection between theory and visualisation enables the adaption of instruction according to learner needs for personalised feedback (Khosravi et al., 2021). Further, researchers have suggested co-design methods involving the learners and the educators to address the limited actionability of LADs (van Leeuwen et al., 2021). The co-design methods encourage collaborative relationships among designers, educators and learners, which can address the actual needs, context and practices of the intended users (van Leeuwen et al., 2021).

The WOz method was used to co-design a mock AI prototype as an early-stage UI for helping educators personalise adult learner experiences in an LMS. The educator was involved in the co-design and testing of this prototype. The learners in both studies also participated in the development of the mock AI prototype for user requirement gathering (see Section 5.3 and Table 5.3). The mock AI prototype was refined in three iterations with the extended study (see Section 5.3.5). This extended study revealed findings, such as learners' improved engagement with more positive emotions and enhanced cognitive skills with learners becoming more self-directed. The learners experienced the social presence of the educator, which is an essential element for the success of online learning (Garrison et al., 1999). Moreover, the educator felt an increased awareness of learner experiences, thus simplifying the process of personalisation. Consequently, the educator had a lighter workload to provide personalised support at a scale using the mock AI prototype. Freeing up the educator's valuable time and resources can have implications for providing better support for the learner (Holstein et al., 2019; van Leeuwen et al., 2021). Thus, the mock AI prototype contributes to future technological and pedagogical advancements in LADs.

The key capability of the mock AI prototype was the summarisation of the class and individual learners' performance by analysing learner data such as self-reflections and LA data. In addition, the prototype's capability of notifying an educator, with highlights such as learning problems at a cohort level and individual learner level, helped the educator to create timely personalised support. Therefore, this research answered the main research question.

8.3.3 Extending Academagogy Theory

Academagogy theory has extended from differentiation learning to personalisation learning theory (see Section 2.2). Personalisation includes differentiated learning because the learning objectives, content, feedback, method of delivery and learning pace vary according to learners' specific interests (Bray & McClaskey, 2010). Academagogy is a differentiated learning theory where an educator can tailor the teaching process according to the needs of a cohort or group of learners (Winter et al., 2009).

This research aimed to improve personalised interactions between the educator and adult online learners in an LMS by using academagogy as a foundation. Based on the research aim, the novel personalisation model used LA, SA and PAH learning trajectories to identify individual learner needs in an LMS. The educator provided balanced support using insights from the novel personalisation model, to encourage more independent learners who can metacognitively monitor their learning progress and reflect on their learning. Findings from the DBR project indicated that learners felt more willing to work independently rather than solely dependent on the educator by the end of the study period (see Section 6.5). Thus, this research contributes to the extension of an academagogy teaching model at the cohort level, to support individual learners' development as self-determined learners.

The research also addressed a research gap regarding the applications of academagogy theory in online learning environments in higher education. This research is the first mixed methods study on using academagogy for personalisation in an LMS to improve adult online learner experiences. Researchers have studied academagogy in face-to-face and online learning contexts, and for training recruits in corporate settings (McAuliffe & Winter, 2013, 2014a; Murthy & Pattanayak, 2019; Winter et al., 2009). However, these studies lacked qualitative reasoning for the results obtained and also did not focus on IT learners. This longitudinal DBR project spanned 18 months while observing an educator and two cohorts of adult online learners (see Section 3.8). The insights from this project indicated that personalisation based on academagogy improves adult learner engagement in an LMS. This was achieved by explaining the three sub-constructs of learner engagement (behavioural, emotional and cognitive). Also, this project contributes to the literature by providing a qualitative study on the academagogy DPs for personalisation (see Figure 7.3 and Section 7.4.3), and a mock AI prototype (Chapter 5) addressing the bottlenecks for the practical application of academagogy. The final academagogy DPs are as follows:

- diagnosing initial learner needs
- giving formative personalised feedback
- facilitating personalised support using technology
- continuous tracking for improvement.

Moreover, determining the position of learners on the PAH continuum was identified as a novel assessment tool. This study contributed a process of identifying the maturity of cognitive engagement by deriving the learner's position on the PAH continuum, which is based on academagogy theory and Bloom's taxonomy. Previous researchers proposed identifying learner positions on the PAH continuum to measure learners' progress (Agonács & Matos, 2017). However, pre- and post-subject self-reporting instruments were used to measure learners' progress (Agonács et al., 2020). The novelty of this research is that the cognitive engagement patterns were derived by analysing learners' self-reflection texts each week and capturing temporal learners' progress on the PAH continuum in the form of PAH learner trajectories rather than checking learners' momentary progress from pre- and post-subject survey measurements. The analysis of the cognitive, emotional and behavioural engagement patterns guided the personalisation model, which resulted in the identified transition of learners from pedagogy towards andragogy in the extended study (see Chapter 5 results).

8.4 Limitations of the Research

Alongside the benefits, the research presented in this thesis had some limitations, providing directions for future work. This section describes the limitations and the steps needed to address the limitations in future research.

8.4.1 Comparison of Participant Groups

The comparison of the participants in the two studies to evaluate the personalisation model is limited. The participants in the 2021 pilot study were all master's learners (see Table 4.1). All the participants in this cohort were also international learners with a background in tertiary-level education. Some participants were working part-time during the study, but with no substantial workload. In comparison, the participants in the 2022 extended study were six learners at a bachelor's level and three learners at a master's level. The 2022 cohort was also a combination of domestic and international learners. This combination was due to the prevalence of domestic and international border closures caused by the COVID-19 pandemic in 2020 and 2021. In 2022, the master's subject had only three enrolments, and out of those three enrolled learners, only two learners volunteered for the research project. To maintain the participant sample size requirements for the project, participant recruitment was adjusted to include learners from the bachelor's version of the subject. The recruitment strategy was followed in compliance with ethics, by using an information sheet and consent forms. In summary, nine learners were recruited for the study in 2022. The diversity of the participants in the extended study is presented in Table 5.4 (see Section 5.3.1).

Although the participants varied in both studies, the same data collection and analysis methods were used in the comparative analysis (see Chapter 6). These real people were studied in natural settings by not only considering their individual characteristics, but also the context of the study (Herrington et al., 2007). The diversity of the real research participants studied in this research provided rigour through the triangulation of data within the pilot study (see Chapter 4) and the extended study (see Chapter 5) and across the studies (see Chapter 6) according to temporal, spatial and situational influences suggested by Marshall (1996). The diversity of participants in both studies justified the purpose of the research project: personalisation for enhancing adult learner engagement.

The comparison of participants' engagement with the personalisation model using an academagogy framework resulted in the following outcomes: (a) early engagement of the learners to the LMS, (b) positive emotions among the learners, (c) willingness of learners to work independently and (d) enhanced social presence in online learning. However, the comparison showed a mixed result on the final grades indicating the learner's performance, specifically with ghost learners (see Figure 7.2). This result was attributed to challenges faced by the ghost learners identified in this research, thus shedding light for future research. Moreover, there is limited analysis of the effect of participant background (i.e computer science) on the final grades using academagogy theory both in the pilot study and the extended study.

8.4.2 Applicability of the Valence Aware Dictionary and sEntiment Analysis Tool

Learner emotions were analysed using the VADER SA tool in this research (see Section 3.7.2). The VADER has primarily been used for business domain-related texts such as social media interactions, New York Times editorials, movie reviews and reviews of products like cameras, mobile phones and laptops (Hutto & Gilbert, 2014). Hence the emotion analysis provided by the VADER tool may not be accurate, as the research participants were university learners enrolled in a computer science subject, who might have used domain-dependent words related to computer science, not the domain that VADER was trained for. These domain-dependent words might have had different polarities (positive, negative and neutral) compared to the words VADER was trained to analyse (Hixson, 2020). For example, the word "fast" for a laptop business review, such as "this laptop's processing speed is fast", might have a positive sentiment; however, the word "fast" in a classroom review, such as "the teacher is fast and difficult to understand", has a negative sentiment. This study agrees with the perception that sentiment tools used for analysing learner emotions need to be retrained for the educational domain words (Beasley & Piegl, 2020; Hixson, 2020).

8.5 Future Work

In this research project, participants were observed through the lens of academagogy to identify learner needs for personalisation. Participants in the pilot study were not made aware of the PAH continuum. The cognitive engagement results in this study showed that a majority of the participants' orientation was towards pedagogy. In the extended study, participants were told they would receive personalised email support based on their reflections, LA data and grades during the recruitment process. Participants in the extended study were also not made aware of the PAH continuum. The cognitive engagement pattern of participants in the extended study revealed that they shifted from pedagogy towards andragogy on the PAH continuum. The engagement patterns of both cohorts indicate that the application of academagogy improves cognitive abilities for independent learning. In the future, it would be interesting to see participants' PAH orientation (especially ghost learners), when the participants are provided with information regarding andragogy (self-directed) learning and heutagogy (self-determined) learning before the start of the study (Winter et al., 2009). Participants' understanding of self-learning capabilities in the PAH continuum could show different research implications for academagogy theory.

Technical icebreaker was used for identifying the general previous skills of the participants in this research (see Section 5.3.4.1). In future, the answers to technical icebreaker activity could be analysed using PAH algorithm to identify the initial position of a learner on the PAH continuum. Also, this initial position identification could be used to devise a scoring or ranking system on the PAH continuum leading to gamification effect. The data collected in this research is available for future work and accessible at JCU Research Database on request.

While using the mock AI prototype, a thematic analysis method was also used to derive the PAH learning trajectories from learner self-reflections (see Section 3.7.1). In this study, a semi-automated method was used for thematic analysis, which included both manual and NVivo software. Automating the process of finding the learners' position on the PAH continuum could reduce the bias of manual analysis. The PAH analysis could be automated by using an NLP model such as Latent Dirichlet Allocation. This could be used to develop an ML model to first classify text into pedagogy, andragogy and heutagogy levels, then find a learner's position on the PAH continuum (Bai & Stede, 2022; Bakharia et al., 2016). Also, other components in the mock AI prototype were LA and SA. For the components LA and SA, tools such as Blackboard LA software and VADER could be used contextually, as described in this research (see Section 3.7). Thus, the entire data analysis process used for the personalisation model and designing the mock AI prototype could be automated for future applications such as smart LADs.

8.6 Concluding Remarks

Online learning is rapidly increasing in universities, potentially because of the digitalisation and globalisation of higher education. Adult learners continue to be the major group of learners pursuing online education at universities because of benefits such as reskilling, upskilling and lifelong learning. However, adult learners face challenges with the one-size-fits-all teaching model that uses LMSs to facilitate online learning at universities. Personalisation is recommended to improve the engagement of adult learners. Nevertheless, the personalisation process was regarded as complex because of the limited guidance on operational methods made available for educators.

In summary, this thesis presented a novel personalisation model based on academagogy theory to guide educators for personalisation in an LMS. This thesis also illustrated DPs for using the learner-centred teaching model, academagogy, for guiding the personalisation process. The application of the academagogy DPs for personalisation indicated an improvement of adult learners' engagement in the LMS. Moreover, a mock prototype of an AI system was designed to help educators apply academagogy DPs. This mock AI prototype can be further developed into an intelligent LAD serving learners, educators and university administrators in tertiary education. I believe the research presented in this thesis will contribute to promising personalisation applications benefiting educators and adult learners in tertiary education.

References

Addanki, K., Holdsworth, J., Hardy, D. & Myers, T. (2020, December 12–13). *Academagogy for enhancing adult online learner engagement in higher education* [Paper presentation]. AIS SIGED International Conference on Information Systems Education and Research 2020*,* Association for Information Systems, United States of America. https://aisel.aisnet.org/siged2020/26

Addanki, K., Holdsworth, J., Hardy, D. & Myers, T. (2022, February 14–18). *A preliminary study using academagogy to uncover the problems that block adult online learner engagement* [Paper presentation]. 24th Australasian Computing Education Conference, Association for Computing Machinery, United States of America. https://doi.org/https://doi.org/10.1145/3511861.3511872

Aeiad, E. & Meziane, F. (2018). An adaptable and personalised e-learning system applied to computer science programmes design. *Education and Information Technologies*, *24*(2), 1485–1509. https://doi.org/10.1007/s10639-018-9836-x

Agonács, N. & Matos, J. F. (2017, October 26–27). *Engagement driven massive and open online learning environment: A heutagogy-based MOOC (h-MOOC)* [Paper presentation]. European Conference on e-Learning, Porto, Portugal.

Agonács, N. & Matos, J. F. (2019). Heutagogy and self-determined learning: A review of the published literature on the application and implementation of the theory. *Open Learning: The Journal of Open, Distance and e-Learning*, *34*(3), 223–240. https://doi.org/10.1080/02680513.2018.1562329

Agonács, N., Matos, J. F., Bartalesi-Graf, D. & O'Steen, D. N. (2020). Are you ready? Self-determined learning readiness of language MOOC learners. *Education and Information Technologies*, *25*, 1161–1179. https://doi.org/10.1007/s10639-019-10017-1

Akyıldız, S. T. (2019). Do 21st century teachers know about heutagogy or do they still adhere to traditional pedagogy and andragogy? *International Journal of Progressive Education*, *15*(6), 151–169. https://doi.org/10.29329/ijpe.2019.215.10

Albinson, P. (2016, March 22). *Exploring student engagement and disengagement in university education, can vocational activities/practice-based learning help?* [Paper presentation]. The 21st Annual International Conference for Process Improvement, Research and Education (INSPIRE), Bournemouth, United Kingdom. http://eprints.bournemouth.ac.uk/23376/

Anderson, T. & Shattuck, J. (2012). Design-based research: A decade of progress in education research?. *Educational Researcher*, *41*(1), 16–25. https://doi.org/10.3102/0013189x11428813

Arnold, K. E. & Pistilli, M. D. (2012, April 29–May 2). *Course signals at Purdue: Using learning analytics to increase student success* [Paper presentation]. Second International Conference on Learning Analytics and Knowledge.

Auernhammer, J. (2020, August 11–14). *Human-centered AI: The role of human-centered design research in the development of AI* [Paper presentation]. Synergy - DRS International Conference 2020. https://doi.org/10.21606/drs.2020.282

Axelsen, M., Redmond, P., Heinrich, E. & Henderson, M. (2020). The evolving field of learning analytics research in higher education: From data analysis to theory generation, an agenda for future research. *Australasian Journal of Educational Technology*, *36*(2). https://doi.org/http://dx.doi.org/10.14742/ajet.6266

Azevedo, R., Bouchet, F., Duffy, M., Harley, J., Taub, M., Trevors, G., Cloude, E., Dever, D., Wiedbusch, M., Wortha, F. & Cerezo, R. (2022). Lessons learned and future directions of MetaTutor: Leveraging multichannel data to scaffold self-regulated learning with an intelligent tutoring system. *Frontiers in Psychology*, *13*, Article 813632. https://doi.org/10.3389/fpsyg.2022.813632

Azorín, C. (2020). Beyond COVID-19 supernova. Is another education coming? *Journal of Professional Capital and Community*, 5(3/4), 381–390. https://doi.org/10.1108/jpcc-05-2020-0019

Babb, S. J., Rufino, K. A. & Johnson, R. M. (2021). Assessing the effects of the COVID-19 pandemic on nontraditional students' mental health and well-being. *Adult Education Quarterly*, 72(2). https://doi.org/10.1177/07417136211027508

Bagustari, B. A. & Santoso, H. B. (2019). Adaptive user interface of learning management systems for education 4.0: A research perspective. *Journal of Physics*, (Conference Series).

Bai, X. & Stede, M. (2022). A survey of current machine learning approaches to student free-text evaluation for intelligent tutoring. *International Journal of Artificial Intelligence Education*, 1–39. https://doi.org/10.1007/s40593-022-00323-0

Bajaj, R. & Sharma, V. (2018). Smart education with artificial intelligence based determination of learning styles. *Procedia Computer Science* 132, 834–842. Elsevier. https://doi.org/https://doi.org/10.1016/j.procs.2018.05.095

Bakharia, A., Bruza, P., Watters, J., Narayan, B. & Sitbon, L. (2016, March 13–17). *Interactive topic modeling for aiding qualitative content analysis* [Paper presentation]. The 2016 ACM on Conference on Human Information Interaction and Retrieval, Association for Computing Machinery, United States of America.

Barab, S. & Squire, K. (2004). Design-based research: Putting a stake in the ground. *Journal of the Learning Sciences*, *13*(1), 1–14. https://doi.org/10.1207/s15327809jls1301_1

Barcelona, R. J. (2009). Pressing the online learning advantage: Commitment, content, and community. *The Journal of Continuing Higher Education*, *57*(3), 193–197. https://doi.org/10.1080/07377360903262218

Bartolomé, A., Castañeda, L. & Adell, J. (2018). Personalisation in educational technology: The absence of underlying pedagogies. *International Journal of Educational Technology in Higher Education*, *15*(1). https://doi.org/10.1186/s41239-018-0095-0

Bates, A. W. T. (2018). *Teaching in a digital age: Guidelines for designing teaching and learning*.

Beasley, Z. & Piegl, L. (2020). A domain-dependent lexicon to augment CAD peer review. *Computer-Aided Design and Applications*, *18*(1), 186–198. https://doi.org/10.14733/cadaps.2021.186-198

Bizami, N. A., Tasir, Z. & Kew, S. N. (2022). Innovative pedagogical principles and technological tools capabilities for immersive blended learning: A systematic literature review. *Education and Information Technologies*, 28, 1373–1425. https://doi.org/10.1007/s10639-022-11243-w

Blaschke, L. M. (2012). Heutagogy and lifelong learning: A review of heutagogical practice and self-determined learning. *The International Review of Research in Open and Distributed Learning*, *13*(1), 56–71.

Blaschke, L. M. (2016). *Strategies for implementing self-determined learning (heutagogy) within education: A comparison of three institutions (Australia, South Africa, and Israel)* [Master's thesis]. Carl von Ossietzky Universität.

Blaschke, L. M. & Marin, V. (2020). Applications of heutagogy in the educational use of e-portfolios. *Revista de Educación a Distancia (RED)*, *20*(64). https://doi.org/10.6018/red.407831

Bloom, B. S. (1984). The 2 sigma problem: The search for methods of group instruction as effective as one-to-one tutoring. *Educational Researcher, 13*(6), 4–16. https://doi.org/http://dx.doi.org/10.3102/0013189X013006004

Boeren, E., Roumell, E. A. & Roessger, K. M. (2020). COVID-19 and the future of adult education: An editorial. *Adult Education Quarterly*, *70*(3), 201–204. https://doi.org/10.1177/0741713620925029

Bowden, R. & Merritt, J., R. (1995). The adult learner challenge: Instructionally and administratively. *Education*, *115*(3), 426–433.

Braun, V. & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology*, *3*(2), 77–101. https://doi.org/10.1191/1478088706qp063oa

Braun, V. & Clarke, V. (2012). Thematic analysis. In H. Cooper, P. M. Camic, D. L. Long, A. T. Panter, D. Rindskopf & K. J. Sher (Eds.) *APA handbook of research methods in psychology, Vol 2: Research designs: Quantitative, qualitative, neuropsychological, and biological.* (pp. 5–71). American Psychological Association https://doi.org/10.1037/13620-004

Braun, V. & Clarke, V. (2020). One size fits all? What counts as quality practice in (reflexive) thematic analysis? *Qualitative Research in Psychology*, *18*(3), 328–352. https://doi.org/10.1080/14780887.2020.1769238

Bray, B. & McClaskey, K. (2010). Personalization vs differentiation vs individualization.

Bray, B. & McClaskey, K. (2013). A Step-by-Step Guide to Personalize learning. *Learning and Leading with technology, 40*(7), 12–19.

Browne, J. T. (2019, May). *Wizard of Oz prototyping for machine learning experiences* [Paper presentation]. The 2019 CHI Conference on Human Factors in Computing Systems.

Canning, N. (2010). Playing with heutagogy: exploring strategies to empower mature learners in higher education. *Journal of Further and Higher Education*, *34*(1), 59–71. https://doi.org/10.1080/03098770903477102

Cardenas, L. S. H., Castano, L., Guzman, C. C. & Alvarez, J. P. N. (2022). Personalised learning model for academic leveling and improvement in higher education. *Australasian Journal of Educational Technology*, *38*(2).

Caruth, G. D. (2014). Meeting the needs of older students in higher education. *Participatory Educational Research*, *1*(2). http://www.partedres.com

Cavignaux-Bros, D. & Cristol, D. (2020). Participatory design and co-design—the case of a MOOC on public innovation. In M. Schmidt, A. A. Tawfik, I. Jahnke & Y. Earnshaw (Eds.), *Learner and user experience research*. EdTech Books.

Cercone, K. (2008). Characteristics of aiult learners with implications for online learning design. *Association for the Advancement of Computing In Education Journal*, *16*(2), 137–159.

Chametzky, B. (2014). Andragogy and engagement in online learning: Tenets and solutions. *Creative Education*, *5*(10), 813–821. https://doi.org/10.4236/ce.2014.510095

Chichekian, T. & Benteux, B. (2022). The potential of learning with (and not from) artificial intelligence in education. *Frontiers in Artificial Intelligence, 5*, Article 903051. https://doi.org/10.3389/frai.2022.903051

Clarizia, F., Colace, F., De Santo, M., Lombardi, M., Pascale, F. & Pietrosanto, A. (2018, January). *E-learning and sentiment analysis: A case study* [Paper presentation]. The 6th International Conference on Information and Education Technology. https://doi.org/10.1145/3178158.3178181

Cochrane, T., Narayan, V., Aiello, S., Birt, J., Cowie, N., Cowling, M., Deneen, C., Goldacre, P., Mehrasa, A., Sinfield, D., Stretton, T. & Worthington, T. (2021, November 30). *Back to the Future Post Pandemic Socially Constructed Blended Synchronous Learning Vignettes from the Mobile Learning SIG* [Poster presentation]. ASCILITE 2021: 38th International Conference on Innovation, Practice and Research in the Use of Educational Technologies in Tertiary Education. https://doi.org/10.26188/17096882

Cochrane, T. D. (2014). Critical success factors for transforming pedagogy with mobile Web 2.0. *British Journal of Educational Technology, 45*(1), 65–82. https://doi.org/10.1111/j.1467-8535.2012.01384.x

Coghlan, D. & Shani, A. B. R. (2005). Roles, Politics, and Ethics in Action Research Design. *Systemic Practice and Action Research*, *18*(6), 533–546. https://doi.org/10.1007/s11213-005-9465-3

Colchester, K., Hagras, H., Alghazzawi, D. & Aldabbagh, G. (2017). A survey of artificial intelligence techniques employed for adaptive educational systems within e-learning platforms. *Journal of Artificial Intelligence and Soft Computing Research*, *7*(1), 47–64.

Cole, F. L. (1988). Content analysis: process and application. *Clinical nurse specialist*, *2*(1), 53–57.

Creswell, J. W. (2014). *Research design: Qualitative, quantitative, and mixed methods approaches* (4th ed.). SAGE Publications.

Cretchley, P. (2009). Are Australian universities promoting learning and teaching activity effectively? An assessment of the effects on science and engineering academics.

International Journal of Mathematical Education in Science and Technology, *40*(7), 865–875. https://doi.org/10.1080/00207390903199228

Csikszentmihalyi, M. (2000). *Beyond boredom and anxiety*. Jossey-bass.

Dabbagh, N. & Fake, H. (2017). College students' perceptions of personal learning environments through the lens of digital tools, processes and spaces. *Journal of New Approaches in Educational Research*, *6*(1), 28–36. https://doi.org/10.7821/naer.2017.1.215

Dahlstrom, E., Brooks, D. C. & Bichsel, J. (2014). *The current ecosystem of learning management systems in higher education: Student, faculty, and IT perspectives*. https://library.educause.edu/resources/2014/9/the-current-ecosystem-of-learning-management-systems-in-higher-education-student-faculty-and-it-perspectives

Daniel, J. S. (1997). Why universities need technology strategies. *Change: The Magazine of Higher Learning*, *29*(4), 10–17. https://doi.org/10.1080/00091389709602322

De Lin, O., Gottipati, S., Ling, L. S. & Shankararaman, V. (2021, October 13–16). *Mining informal & short student self-reflections for detecting challenging topics – a learning outcomes insight dashboard* [Paper presentation]. 2021 IEEE Frontiers in Education Conference (FIE), Lincoln, United States of America.

De Villiers, M. R. (2012). Models for interpretive information systems research, part 2. In M. Mora, O. Gelman, A. L. Steenkamp & M. Raisinghani (Eds.), *Research methodologies, innovations and philosophies in software systems engineering and information systems* (pp. 238–255). https://doi.org/10.4018/978-1-4666-0179-6.ch012 del Valle, R. & Duffy, T. M. (2007). Online learning: Learner characteristics and their approaches to managing learning. *Instructional Science*, *37*(2), 129–149. https://doi.org/10.1007/s11251-007-9039-0

Demir, F., Bruce-Kotey, C. & Alenezi, F. (2021). User experience matters: Does one size fit all? Evaluation of learning management systems. *Technology, Knowledge and Learning*, *27*(1), 49–67. https://doi.org/10.1007/s10758-021-09518-1

Denny, P., Whalley, J. & Leinonen, J. (2021, February 2–4). *Promoting early engagement with programming assignments using scheduled automated feedback* [Paper presentation]. 23rd Australasian Computing Education Conference, South Australia.

Dixson, M. D. (2015). Measuring student engagement in the online course: The Online Student Engagement Scale (OSE). *Online Learning*, *19*(4). https://eric.ed.gov/?id=EJ1079585

Doherty, K. & Doherty, G. (2018). Engagement in HCI: Conception, theory and measurement. *ACM Computing Survey*, *51*, Article 99. https://doi.org/10.1145/3234149

Dourish, P. (2014). Reading and Interpreting Ethnography. In J. S. Olson & W. A. Kellogg (Eds.), *Ways of knowing in HCI* (pp. 1–23). Springer.

Dow, S., MacIntyre, B., Lee, J., Oezbek, C., Bolter, J. D. & Gandy, M. (2005). Wizard of Oz support throughout an iterative design process. *IEEE Pervasive Computing*, *4*(4), 18–26.

Ekoto, C. E. & Gaikwad, P. (2015). The impact of andragogy on learning satisfaction of graduate students. *American Journal of Educational Research*, *3*(11), 1378–1386.

El Said, G. R. & Mandl, T. (2021). How did the COVID-19 pandemic affect higher education learning experience? An empirical investigation of learners' academic performance at a university in a developing country. *Advances in Human-Computer Interaction*, *2021*, 1–10. https://doi.org/10.1155/2021/6649524

Ez-zaouia, M. & Lavoué, E. (2017, March 13–17). *Emoda: A tutor oriented multimodal and contextual emotional dashboard* [Paper presentation]. 7th International Learning Analytics & Knowledge Conference, Vancouver, Canada.

Fan, S., Chen, L., Nair, M., Garg, S., Yeom, S., Kregor, G., Yang, Y. & Wang, Y. (2021). Revealing impact factors on student engagement: Learning analytics adoption in online and blended courses in higher education. *Education Sciences*, *11*(10). https://doi.org/10.3390/educsci11100608

Ferreira, D. & MacLean, G. (2017). Andragogy in the 21st century: Applying the assumptions of adult learning online. *Language Research Bulletin*, *32*.

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

Flynn, J. T. (2013). MOOCS: Disruptive innovation and the future of higher education. *Christian Education Journal*, *10*(1), 149–162.

Fredricks, J. A., Blumenfeld, P. C. & Paris, A. H. (2004). School engagement: Potential of the concept, state of the evidence. *Review of Educational Research*, *74*(1), 59–109.

Fredricks, J. A. & McColskey, W. (2012). The measurement of student engagement: A comparative analysis of various methods and student self-report instruments. In S. L. Christenson, A. L. Reschly & C. Wylie (Eds.), *Handbook of research on student engagement* (pp. 763–782). Springer. https://doi.org/10.1007/978-1-4614-2018-7_37

Furini, M., Gaggi, O., Mirri, S., Montangero, M., Pelle, E., Poggi, F. & Prandi, C. (2022). Digital twins and artificial intelligence. *Communications of the ACM*, *65*(4), 98–104. https://doi.org/10.1145/3478281

Garrison, D. R., Anderson, T. & Arche, W. (1999). Critical inquiry in a text-based environment: Computer conferencing in higher education. *The Internet and Higher Education*, *2(2–3)*, 87–105.

Garrison, D. R. & Kanuka, H. (2004). Blended learning: Uncovering its transformative potential in higher education. *The Internet and Higher Education*, *7*(2), 95–105. https://doi.org/10.1016/j.iheduc.2004.02.001

Getliffe, K. A. (1996). An examination of the use of reflection in the assessment of practice for undergraduate nursing students. *International Journal of Nursing Studies*, *33*(4), 361–374.

Glenn, N. D. (2005). *Cohort analysis* (Vol. 5). Sage.

Global Market Insights. (2022). *E-learning market size by technology (online e-learning, learning management system (LMS), mobile e-learning, rapid e-learning, virtual classroom), by provider (service, content), by application (academic [K-12, higher education, vocational training], corporate [SMBs, large enterprises], government),* *COVID-19 impact analysis, regional outlook, growth potential, competitive market share & forecast, 2022 – 2028*. Global Market Insights. https://www.gminsights.com/industry-analysis/elearning-market-size

Halupa, C. (2017). Reaching "creating" in Bloom's taxonomy: The merging of heutagogy and technology in online learning. In C. Zhou (Ed.), *Handbook of research on creative problem-solving skill development in higher education*. IGI Global.

Hamari, J., Shernoff, D. J., Rowe, E., Coller, B., Asbell-Clarke, J. & Edwards, T. (2016). Challenging games help students learn: An empirical study on engagement, flow and immersion in game-based learning. *Computers in Human Behavior*, *54*, 170–179. https://doi.org/10.1016/j.chb.2015.07.045

Hase, S. (2011). Learner defined curriculum: Heutagogy and action learning in vocational training. *Southern Institute of Technology Journal of Applied Research*.

Hase, S. (2016). Self-determined learning (heutagogy): Where have we come since 2000? *Southern Institute of Technology Journal of Applied Research*.

Hase, S. & Blaschke, L. M. (2019). Heutagogy and digital media networks. *Pacific Journal of Technology Enhanced Learning*, *1*(1), 1–14. https://doi.org/10.24135/pjtel.v1i1.1

Hattie, J. (2015). The applicability of visible learning to higher education. *Scholarship of Teaching and Learning in Psychology*, *1*(1), 79–91. https://doi.org/10.1037/stl0000021

Henrie, C. R., Halverson, L. R. & Graham, C. R. (2015). Measuring student engagement in technology-mediated learning: A review. *Computers & Education, 90*, 36–53. https://doi.org/10.1016/j.compedu.2015.09.005

Herrington, J., McKenney, S., Reeves, T. & Oliver, R. (2007). Design-based research and doctoral students: Guidelines for preparing a dissertation proposal. Association for the Advancement of Computing in Education.

Hewson, E. R. F. (2018). Students' emotional engagement, motivation and behaviour over the life of an online course: Reflections on two market research case studies. *Journal of Interactive Media in Education*, *2018*(1). https://doi.org/10.5334/jime.472

Hixson, T. (2020). Reactions vs. reality: Using sentiment analysis to measure university students' responses to learning ArcGIS. *Journal of Map & Geography Libraries*, *15*(2–3), 263–276. https://doi.org/10.1080/15420353.2020.1719266

Holmes, G. & Abington-Cooper, M. (2000). Pedagogy vs. andragogy: A false dichotomy? *The Journal of Technology Studies*, 26(2).

Holstein, K., McLaren, B. M. & Aleven, V. (2019). Co-designing a real-time classroom orchestration tool to support teacher–AI complementarity. *Journal of Learning Analytics*, *6*(2). https://doi.org/10.18608/jla.2019.62.3

Hutto, C. J. & Gilbert, E. (2014, June 1–4). *VADER: A parsimonious rule-based model for sentiment analysis of social media text* [Paper presentation]. 8th International AAAI Conference on Weblogs and Social Media, Michigan United States of America.

Iles, H. R. E. (2019). *Perceptions of tertiary educators and their students toward the integration of AI mentors to support learning* [Master's thesis, Eastern Institute of Technology].

Jaggars, S. S. & Xu, D. (2016). How do online course design features influence student performance? *Computers & Education*, *95*, 270–284. https://doi.org/10.1016/j.compedu.2016.01.014

Joksimovic, S., Kovanović, V. & Dawson, S. (2019). The journey of learning analytics. *HERDSA Review of Higher Education*, *6*.

Jones, C., Matlay, H., Penaluna, K. & Penaluna, A. (2014). Claiming the future of enterprise education. *Education + Training*, *56*(8/9), 764–775. https://doi.org/10.1108/et-06-2014-0065

Jones, C., Penaluna, K. & Penaluna, A. (2019). The promise of andragogy, heutagogy and academagogy to enterprise and entrepreneurship education pedagogy. *Education + Training*, *61*(9), 1170–1186. https://doi.org/10.1108/et-10-2018-0211

Jones, M. & Rienties, B. (2021). Designing learning success and avoiding learning failure through learning analytics: The case of policing in England and Wales. *Public Money & Management*, *42*(1), 32–39. https://doi.org/10.1080/09540962.2021.1979335

Kahu, E. R., Stephens, C., Leach, L. & Zepke, N. (2013). The engagement of mature distance students. *Higher Education Research & Development*, *32*(5), 791–804. https://doi.org/10.1080/07294360.2013.777036

Kaliisa, R. & Dolonen, J. A. (2022). CADA: a teacher-facing learning analytics dashboard to foster teachers' awareness of students' participation and discourse patterns in online discussions. *Technology, Knowledge and Learning*, *28*(3), 937–958. https://doi.org/10.1007/s10758-022-09598-7

Kandri, S. E. (2020). How COVID-19 is driving a long-overdue revolution in education. *World Economic Forum*. https://www.weforum.org/platforms/covid-action-platform/articles/how-covid-19-is-sparking-a-revolution-in-higher-education

Kara, M., Erdoğdu, F., Kokoç, M. & Cagiltay, K. (2019). Challenges faced by adult learners in online distance education: A literature review. *Open Praxis*, *11*(1). https://doi.org/10.5944/openpraxis.11.1.929

Kaushik, V. & Walsh, C. A. (2019). Pragmatism as a research paradigm and its implications for social work research. *Social Sciences*, *8*(9). https://doi.org/10.3390/socsci8090255

Kennedy, K. (2018). *Exploring entrepreneurship education using project based learning in business management program at a Canadian college*. [Doctoral thesis, University of Liverpool]. https://livrepository.liverpool.ac.uk/3020786/1/H00016493_Jan2018.pdf

Kenyon, C. & Hase, S. (2001, March 28–30). *Moving from andragogy to heutagogy in vocational education* [Paper presentation]. The Australian Vocational Education and Training Research Association (AVETRA) Conference, Australia.

Khosravi, H., Shabaninejad, S., Bakharia, A., Sadiq, S., Indulska, M. & Gašević, D. (2021). Intelligent learning analytics dashboards: Automated drill-down recommendations to support teacher data exploration. *Journal of Learning Analytics*, *8*(3), 133–154. https://doi.org/10.18608/jla.2021.7279

Kitchener, K. S. (1983). Cognition, metacognition, and epistemic cognition: A three-level model of cognitive processing. *Human Developmen*t, *26*(4), 222–232.

Kivunja, C. & Kuyini, A. B. (2017). Understanding and applying research paradigms in educational contexts. *International Journal of Higher Education*, *6*(5). https://doi.org/10.5430/ijhe.v6n5p26

Knowles, M. S. (1980). *The modern practise of adult education: From pedagogy to andragogy*. Cambridge.

Knowles, M. S., Holton III, E. F. & Swanson, R. A. (2015). *The adult learner: The definitive classic in adult education and human resource development*. Routledge.

Kokku, R., Sundararajan, S., Dey, P., Sindhgatta, R., Nitta, S. & Sengupta, B. (2018, April 15–20). *Augmenting classrooms with AI for personalized education* [Paper presentation]. 2018 IEEE international conference on acoustics, speech and signal processing (ICASSP), Calagary, Canada.

Koprinska, I., Joshua, S. & Kalina, Y. (2015). Students at risk: Detection and remediation. *Educational Data Mining*, 512–515.

Liao, L. F. (2006). A flow theory perspective on learner motivation and behavior in distance education. *Distance Education*, *27*(1), 45–62. https://doi.org/10.1080/01587910600653215

Lim, L. A., Dawson, S., Gašević, D., Joksimović, S., Fudge, A., Pardo, A. & Gentili, S. (2020). Students' sense-making of personalised feedback based on learning analytics. *Australasian Journal of Educational Technology*, *36*(6).

Linden, K., Ploeg, N. V. D. & Hicks, B. (2021, November 29–December 1). *Ghostbusters: Using learning analytics and early assessment design to identify and support ghost students* [Paper presentation]. Back to the Future–ASCILITE '21, Australia.

Liu, B. (2012). *Sentiment analysis and opinion mining*. Springer Nature.

Luckin, R., Clark, W., Garnett, F., Whitworth, A., Akass, J., Cook, J., Day, P., Ecclesfield, N., Hamilton, T. & Robertson, J. (2011). Learner-generated contexts: A framework to support the effective use of technology for learning. *Web 2.0-Based E-Learning*, 70–84. https://doi.org/10.4018/978-1-60566-294-7.ch004

Maher, C., Hadfield, M., Hutchings, M. & de Eyto, A. (2018). Ensuring rigor in qualitative data analysis. *International Journal of Qualitative Methods*, *17*(1). https://doi.org/10.1177/1609406918786362

Malliarakis, C., Tomos, F., Shabalina, O. & Mozelius, P. (2018, October). *Andragogy and E.M.O.T.I.O.N.: 7 key factors of successful serious games* [Paper presentation]. 12th European Conference on Games Based Learning, France.

Marshall, M. N. (1996). Sampling for qualitative research. *Family Practice*, *13*(6), 522–525.

Martin, F. & Bolliger, D. U. (2018). Engagement matters: Student perceptions on the importance of engagement strategies in the online learning environment. *Online Learning*, *22*(1). https://doi.org/10.24059/olj.v22i1.1092

Martin, F., Ritzhaupt, A., Kumar, S. & Budhrani, K. (2019). Award-winning faculty online teaching practices: Course design, assessment and evaluation, and facilitation. *The Internet and Higher Education*, *42*, 34–43. https://doi.org/10.1016/j.iheduc.2019.04.001

Matthews, D., Tan, L. & Edwards, D. (2017). *Development of an online engagement scale*. https://research.acer.edu.au/higher_education/56/

Maulsby, D., Greenberg, S. & Mander, R. (1993, April 24–29). Prototyping an intelligent agent through Wizard of Oz [Paper presentation]. INTERCHI93: Conference on Human Factors in Computing, Amsterdam, Netherlands.

McAuliffe, M., Hargreaves, D., Winter, A. & Chadwick, G. (2008). Does pedagogy still rule? *Australasian Journal of Engineering Education*, 15(1), 13–18.

McAuliffe, M., Martin, P., Cameron, L. & Hankinson, J. (2015). Embedding metacognitive skills in spatial design education. *International Journal of Innovation, Creativity and Change*, *2*(2).

McAuliffe, M. & Winter, A. (2013). Distance education and the application of academagogy: A case study. *International Journal of Innovation, Creativity and Change*, *1*(2).

McAuliffe, M. & Winter, A. (2014a, July 7–9). *Applying academagogy: the transference of an organised heuristic teaching approach to the digital realm* [Paper presentation]. 6th

International Conference on Education and New Learning Technologies. International Academy of Technology, Education and Development (IATED), Barcelona, Spain.

McAuliffe, M. & Winter, A. (2014b). Using academagogy to meet the needs of millennial learners: A comparative case study. *European Scientific Journal*.

McGill, T. J. & Klobas, J. E. (2009). A task–technology fit view of learning management system impact. *Computers & Education*, *52*(2), 496–508. https://doi.org/10.1016/j.compedu.2008.10.002

McLoughlin, C. & Lee, M. J. W. (2010). Personalised and self regulated learning in the Web 2.0 era: International exemplars of innovative pedagogy using social software. *Australasian Journal of Educational Technology*, *26*(1), 28–43.

Mikić, V., Ilić, M., Kopanja, L. & Vesin, B. (2022). Personalisation methods in e-learning-A literature review. *Computer Applications in Engineering Education*. https://doi.org/10.1002/cae.22566

Moore, J. L., Dickson-Deane, C. & Galyen, K. (2011). e-Learning, online learning, and distance learning environments: Are they the same? *The Internet and Higher Education*, *14*(2), 129–135. https://doi.org/10.1016/j.iheduc.2010.10.001

Moore, K. & Shemberger, M. (2019). Mass communication andragogy for teaching online adult learners. *Teaching Journalism & Mass Communication*, *9*(1).

Moore, M. G. (1989). Editorial: Three types of interaction. *American Journal of Distance Education*, *3*(2), 1–7. https://doi.org/10.1080/08923648909526659

Moore, M. G. (1991). Editorial: Distance education theory. *American Journal of Distance Education*, *5*(3), 1–6. https://doi.org/10.1080/08923649109526758

Morris, P. D., Cobb, C. M. & Higgs, M. A. S. (2019). High-impact practices and the adult online learner. *World Journal of Educational Research*, *6*(4). https://doi.org/10.22158/wjer.v6n4p463

Muir, T., Milthorpe, N., Stone, C., Dyment, J., Freeman, E. & Hopwood, B. (2019). Chronicling engagement: Students' experience of online learning over time. *Distance Education*, *40*(2), 262–277. https://doi.org/10.1080/01587919.2019.1600367

Murphy, M. P. A. (2020). COVID-19 and emergency eLearning: Consequences of the securitization of higher education for post-pandemic pedagogy. *Contemporary Security Policy*, *41*(3), 492–505. https://doi.org/10.1080/13523260.2020.1761749

Murray, M. C. & Perez, J. (2015). Informing and performing: A study comparing adaptive learning to traditional learning. *Informing Science: The International Journal of an Emerging Transdiscipline*, *11*, 111–125.

Murthy, S. (2011, July 14–16). *Academagogical framework for effective university education - promoting millennial centric learning in global knowledge society* [Paper presentation]. 2011 IEEE International Conference on Technology for Education, Chennai, India.

Murthy, S., Furness, R. & Wardle, D. (2012). Pedagogical foundations for effective competency building in the hydrographic and cartographic sectors.

Murthy, S. & Pattanayak, B. (2019). Implementing the principles of academagogy for effective learning facilitation in corporate organizations: A case study. *Development and Learning in Organizations*, 34(4). https://doi.org/10.1108/DLO-06-2019-0135

Nah, Y. (1999). Can a self-directed learner be independent, autonomous and interdependent?: Implications for practice. *Adult Learning*, *11*(1), 18–25.

Narayan, V., Herrington, J. & Cochrane, T. (2019). Design principles for heutagogical learning: Implementing student-determined learning with mobile and social media tools. *Australasian Journal of Educational Technology*, *35*(3).

National Health and Medical Research Council, Australian Research Council & Universities Australia. (2007). *National Statement on Ethical Conduct in Human Research 2007 (Updated 2018).* The National Health and Medical Research Council. Commonwealth of Australia, Canberra.

Newman, H. & Joyner, D. (2018, June 27–30). *Sentiment analysis of student evaluations of teaching* [Paper presentation]. International Conference on Artificial Intelligence in Education (AIED) 2018, London, United Kingdom. https://doi.org/10.1007/978-3-319-93846-2_45

Ní Shé, C., Farrell, O., Brunton, J., Costello, E., Donlon, E., Trevaskis, S. & Eccles, S. (2019). *Teaching online is different: Critical perspectives from the literature*. https://www.researchgate.net/publication/336879238

Nielsen, F. A. (2011). *A new ANEW: Evaluation of a word list for sentiment analysis in microblogs* [Paper presentation]. ESWC2011 Workshop on 'Making Sense of Microposts': Big things come in small packages, Crete, Greece.

Oliver, E. (2015). Alternative assessment to enhance theological education. *HTS Teologiese Studies / Theological Studies*, *71*(3). https://doi.org/10.4102/hts.v71i3.3002

Onwuegbuzie, A. J. & Leech, N. L. (2005). On becoming a pragmatic researcher: The importance of combining quantitative and qualitative research methodologies. *International Journal of Social Research Methodology*, *8*(5), 375–387. https://doi.org/10.1080/13645570500402447

Ott, C. & Liesaputra, V. (2022). Using affective learning analytics in industry-focused projects: Experiences and challenges. *Australasian Computing Education Conference*, 153–162. https://doi.org/10.1145/3511861.3511878

Park, E., Ifenthaler, D. & Clariana, R. B. (2022). Adaptive or adapted to: Sequence and reflexive thematic analysis to understand learners' self-regulated learning in an adaptive learning analytics dashboard. *British Journal of Educational Technology*. https://doi.org/10.1111/bjet.13287

Park, J. H. & Choi, H. J. (2009). Factors influencing adult learners' decision to drop out or persist in online learning. *Educational Technology & Society*, *12*(4), 207–217.

Parmaxi, A. & Zaphiris, P. (2020). Lessons learned from a design-based research implementation: a researcher's methodological account. *International Journal of*

Research & Method in Education, *43*(3), 257–270. https://doi.org/10.1080/1743727x.2019.1671327

Parslow, G. R. (2010, Mar). Commentary: Heutagogy, the practice of self-learning. *Biochemisty and Molecular Biology Education*, *38*(2), 121. https://doi.org/10.1002/bmb.20394

Pekrun, R., Goetz, T., Frenzel, A. C., Barchfeld, P. & Perry, R. P. (2011). Measuring emotions in students' learning and performance: The Achievement Emotions Questionnaire (AEQ). *Contemporary Educational Psychology*, *36*(1), 36–48. https://doi.org/10.1016/j.cedpsych.2010.10.002

Pembridge, J. J. & Paretti, M. (2010, June 7–9). *Andragogical practices in capstone design courses* [Paper presentation]. Capstone Design Conference, Boulder, Colorado.

Pistilli, M. D. (2017). Learner analytics and student success interventions. *New Directions for Higher Education*, *2017*(179), 43–52. https://doi.org/10.1002/he.20242

Pool, J. & Laubscher, D. (2016). Design-based research: Is this a suitable methodology for short-term projects? *Educational Media International*, *53*(1), 42–52. https://doi.org/10.1080/09523987.2016.1189246

Porcheron, M., Fischer, J. E. & Reeves, S. (2021). Pulling back the curtain on the Wizards of Oz. *Proceedings of the ACM on Human-Computer Interaction*, *4*(CSCW3), 1–22. https://doi.org/10.1145/3432942

Prieto-Alvarez, C. G., Martinez-Maldonado, R. & Anderson, T. D. (2018). Co-designing learning analytics tools with learners. In J. Lodge, J. Horvath & L. Corrin (Eds.), *Learning analytics in the classroom* (pp. 93–110). https://doi.org/10.4324/9781351113038-7

Raes, A. (2021). Exploring student and teacher experiences in hybrid learning environments: Does presence matter? *Postdigital Science and Education*, *4*(1), 138–159. https://doi.org/10.1007/s42438-021-00274-0

Rapanta, C., Botturi, L., Goodyear, P., Guàrdia, L. & Koole, M. (2020). Online university teaching during and after the Covid-19 crisis: Refocusing teacher presence and learning activity. *Postdigital Science and Education*. https://doi.org/10.1007/s42438-020-00155-y

Reeves, S., Kuper, A. & Hodges, B. D. (2008). Qualitative research methodologies: Ethnography. *BMJ: British Medical Journal*, *337*(7668), 512–514. https://doi.org/10.1136/bmj.a1020

Reeves, T. C., Herrington, J. & Oliver, R. (2005). Design research: A socially responsible approach to instructional technology research in higher education. *Journal of Computing in Higher Education*, *16*(2), 96–115.

Riegel, K. & Evans, T. (2021). Student achievement emotions: Examining the role of frequent online assessment. *Australasian Journal of Educational Technology, 37*(6), 75–87.

Robb, P. C. (2013). *How to engage a group of diverse adult learners in a way that also raises rigor and increases learning*. https://www.semanticscholar.org/paper/How-to-Engage-a-Group-of-Diverse-Adult-Learners-in-Robb/80a4b636e5c851c1f48940c175a98bc7d81fd38e

Ryan, F., Coughlan, M. & Cronin, P. (2009). Interviewing in qualitative research: The one-to-one interview. *International Journal of Therapy and Rehabilitation, 16*(6), 309–314.

Saldaña, J. (2016). The coding manual for qualitative researchers.

Schubert, M., Durruty, D. & Joyner, D. A. (2018). *Measuring learner tone and sentiment at scale via text analysis of forum posts* [Paper presentation]. 8th Edition of the International Workshop on Personalization Approaches in Learning Environments (PALE), London, United Kingdom.

Seaman, J. E., Allen, I. E. & Seaman, J. (2018). Grade increase: Tracking distance education in the United States. *Babson Survey Research Group*. http://www.onlinelearningsurvey.com/highered.html

Shapiro, D., Dundar, A., Huie, F., Wakhungu, P. K., Bhimdiwala, A. & Sean Eric Wilson, S. E. (2018). Completing college: A national view of student completion rates—fall 2012 cohort (Signature Report No. 16). *National Student Clearinghouse Research Center*. https://eric.ed.gov/?id=ED595341

Shearer, R. L., Aldemir, T., Hitchcock, J., Resig, J., Driver, J. & Kohler, M. (2020). What students want: A vision of a future online learning experience grounded in distance education theory. *American Journal of Distance Education*, *34*(1), 36–52. https://doi.org/10.1080/08923647.2019.1706019

Sheline, R. & MacLellan, C. J. (2018, December 2–8). *Investigating machine-learning interaction with Wizard-of-Oz experiments* [Paper presentation]. 32nd Conference on Neural Information Processing Systems (NeurIPS2018), Montreal, Canada.

Siemens, G. (2013). Learning analytics. *American Behavioral Scientist*, *57*(10), 1380–1400. https://doi.org/10.1177/0002764213498851

Silvola, A., Näykki, P., Kaveri, A. & Muukkonen, H. (2021). Expectations for supporting student engagement with learning analytics: An academic path perspective. *Computers & Education, 168*. https://doi.org/10.1016/j.compedu.2021.104192

Šimko, M., Barla, M. & Bieliková, M. (2010, September). *ALEF: A framework for adaptive web-based learning 2.0* [Paper presentation]. International Federation for Information Processing (IFP) Conference on Key Competencies in the Knowledge Society (KCKS), Brisbane, Australia.

Singh, J., Singh, L. & Matthees, B. (2022). Establishing social, cognitive, and teaching presence in online learning—a panacea in COVID-19 pandemic, post vaccine and post pandemic times. *Journal of Educational Technology Systems*. https://doi.org/10.1177/00472395221095169

Singh, V. & Thurman, A. (2019). How many ways can we define online learning? A systematic literature review of definitions of online learning (1988–2018). *American Journal of Distance Education*, *33*(4), 289–306. https://doi.org/10.1080/08923647.2019.1663082

Slater, S., Joksimović, S., Kovanovic, V., Baker, R. S. & Gasevic, D. (2016). Tools for educational data mining. *Journal of Educational and Behavioral Statistics*, *42*(1), 85–106. https://doi.org/10.3102/1076998616666808

Smith, B. M. (2019). *Adult learning principles used with nontraditional students in higher education to enhance learner satisfaction and retention* [Doctoral Thesis, Lindenwood University].

Stone, C. (2017). *Opportunity through online learning: improving student access, success and retention in online higher education.* The National Centre for Student Equity in Higher Education (NCSEHE), Curtin University. https://apo.org.au/node/94591

Stone, C. & Springer, M. (2019). Interactivity, connectedness and 'teacher-presence': Engaging and retaining students online. *Australian Journal of Adult Learning*, *59*(2).

Suero Montero, C. & Suhonen, J. (2014, November 20–23). Emotion analysis meets learning analytics – online learner profiling beyond numerical data [Paper presentation]. Koli Calling '14:14th Koli Calling International Conference on Computing Education Research, Koli, Finland.

Sutton, H. (2021). COVID-19 accelerates online learning trends, need for portable credentials. *Recruiting & Retaining Adult Learners*, *23*(5), 8–9.

Swan, K. (2005). A constructivist model for thinking about learning online. In J. R. Bourne & J. C. Moore (Eds.), *Elements of Quality Online Education: Engaging Communities:Vol. 6*. (pp. 13–31).

Tempelaar, D., Rienties, B. & Nguyen, Q. (2019, November 7–9). *Learning engagement, learning outcomes and learning gains: lessons from LA* [Paper presentation]. 16th International Conference on Cognition and Exploratory Learning in Digital Age, Cagliari, Italy.

Tilley, B. P. (2014). What makes a student non-traditional? A comparison of students over and under age 25 in online, accelerated psychology courses. *Psychology Learning & Teaching*, *13*(2), 95–106. https://doi.org/10.2304/plat.2014.13.2.95

Tschimmel, K. (2012, June 17–20). *Design thinking as an effective toolkit for innovation* [Paper presentation]. XXIII ISPIM Conference: Action for Innovation: Innovating from Experience, Barcelona, Spain.

Van den Akker, J., Gravemeijer, K., McKenney, S. & Nieveen, N. (Eds.). (2006). *Educational design research*. Routledge.

van Leeuwen, A., Teasley, S. D. & Wise, A. F. (2021). Teacher and student facing learning analytics. In C. Lang, G. Siemens, A. F. Wise, D. Gašević & A. Merceron (Eds.) *Handbook of learning analytics* (2nd ed.). SoLAR. https://doi.org/10.18608/hla22.013

Verbert, K., Duval, E., Klerkx, J., Govaerts, S. & Santos, J. L. (2013). Learning analytics dashboard applications. *American Behavioral Scientist*, *57*(10), 1500–1509. https://doi.org/10.1177/0002764213479363

Verbert, K., Ochoa, X., De Croon, R., Dourado, R. A. & De Laet, T. (2020, March 23–27). *Learning analytics dashboards* [Paper presentation]. 10th International Conference on Learning Analytics & Knowledge, Frankfurt, Germany.

Walkington, C. & Bernacki, M. L. (2020). Appraising research on personalized learning: Definitions, theoretical alignment, advancements, and future directions. *Journal of Research on Technology in Education*, *52*(3), 235–252. https://doi.org/10.1080/15391523.2020.1747757

Wallin, P. & Adawi, T. (2017). The reflective diary as a method for the formative assessment of self-regulated learning. *European Journal of Engineering Education*, *43*(4), 507–521. https://doi.org/10.1080/03043797.2017.1290585

Wang, F. & Hannafin, M. J. (2005). Design-based research and technology-enhanced learning environments. *Educational Technology Research and Development*, *53*(4), 5–23.

Winter, A., McAuliffe, M., Chadwick, G. & Hargreaves, D. (2009, December 6–9). *Implementing academagogy: The first case study* [Paper presentation]. 20th Annual Conference for the Australasian Association for Engineering Education.

Winter, A., McAuliffe, M., Hargreaves, D. & Chadwick, G. (2008). *The transition to academagogy* [Paper presentation]. Philosophy of Education Society of Australasia (PESA), Brisbane, Queensland.

Zawacki-Richter, O., Marín, V. I., Bond, M. & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education – where are the educators? *International Journal of Educational Technology in Higher Education*, *16*(1). https://doi.org/10.1186/s41239-019-0171-0

Zeni, J. (1998). A guide to ethical issues and action research [1]. *Educational Action Research*, *6*(1), 9–19. https://doi.org/10.1080/09650799800200053

Zhang, L., Basham, J. D. & Carter, R. A. (2022). Measuring personalized learning through the Lens of UDL: Development and content validation of a student self-report instrument. *Studies in Educational Evaluation*, *72*. https://doi.org/10.1016/j.stueduc.2021.101121

Appendix A

Ethics Approval for Research

This administrative form
has been removed

Appendix B

Information Sheet 2021—Pilot Study

JAMES COOK UNIVERSITY AUSTRALIA

INFORMATION SHEET – Learners of SP1 2021

PROJECT TITLE: **Enhancing adult learner engagement to online learning activities in higher education**

You are invited to take part in a research project about improving student engagement with personalised instruction in the subject CP5307. The project aims to improve the quality of online instruction. The study is being conducted by **Kranthi Addanki** and will contribute to her thesis as a part of Doctor of Philosophy (Information Technology) at James Cook University.

The criteria to participate in this study is that you are of age 25 years or above, and a having an interest in improving your general learning skills and the knowledge about the subject materials (programming skills, research skills, and presentation skills in the context of Mobile Technology).

If you agree to be involved in the study:

1. Your learning interaction data (such as learning analytics and mini self-reflections) in CP5307 will be monitored during the semester to plan for better learning outcomes
2. You will be given a survey at the end of the semester to check your overall experience with the subject which should take less than 10 minutes
3. You will be invited for an interviewed by Kranthi at the end of the semester. The interview will-
    - be used to collect your suggestions on how to improve online instruction in CP5307
    - be conducted via Zoom
    - should take less than 1 hour of your time
    - interview will be recorded which includes audio recording only.

Taking part in this study is completely voluntary and you can stop taking part in the study at any time without explanation or prejudice.

If you know of other students of CP5307 who are taking the subject in SP1 2021 and that might be interested in this study, please pass on this information sheet to them so they may contact Kranthi to volunteer for the study.

Your personal details will not be collected and so your data will be anonymous. Your participation and data will be confidential. The data from the study will be used in thesis and research publications. You will not be identified in any way in these publications.

There no risks identified in this study or project. However, if you feel any stress at any point, please contact JCU Student Equity and Wellbeing unit - studentwellbeing@jcu.edu.au or by phone using (07) 423 21150 (or ext. 21150) for Cairns campus or (07) 478 14711 (or ext. 14711) for Townsville campus.

If you have any questions about the study, please contact – **Kranthi Addanki** or **Dr Jason Holdsworth.**

Principal Investigator: Kranthi Addanki
College: College of Science and Engineering, James Cook University
Phone:
Email: kranthi.addanki@my.jcu.edu.au

Supervisor: Dr Jason Holdsworth
College: College of Science and Engineering, James Cook University
Phone:
Email: jason.holdsworth@jcu.edu.au

Appendix C

Consent Form 2021—Pilot Study

This administrative form
has been removed

Appendix D

Lecturer Interview Questions

1) How long have you been a lecturer, and how long teaching this subject? Did you develop it? How long since the subject has been revised?

2) Please give a description of your typical student. What are their strengths and weaknesses?

3) What aspects of your students' thinking would you like more information about?

4) What aspects of the subject do you think students have trouble with?

5) Could you please explain what information you want to know from the analysis of students' reflections from the following activities in the subject?

   a. practicals
   b. code reviews
   c. mobile applications (Utility App and Educational App)
   d. technical report

6) Could you suggest the preferred means of communicating the information?

7) How frequently do you want the information to be sent to you?

   a. practicals
   b. code reviews
   c. mobile applications (Utility App and Educational App)
   d. technical report (Workshops)

8) Please explain the form do you want the information? (question about the format of the report in the form of word document or pdf or excel sheet)

9) Please tell me about a situation (in the past) where it would have been helpful to have just-in-time information about how a student was doing?

10) Do you currently make use of any learning analytics data in teaching your subject? If so, what is it? If not, why not?

Appendix E

Information Sheet 2022—Extended Study

JAMES COOK UNIVERSITY
AUSTRALIA

INFORMATION SHEET – Learners of SP1 2022

PROJECT TITLE: **Enhancing adult learner engagement to online learning activities in higher education**

You are invited to take part in a research project about improving student engagement with personalised instruction in the subjects CP 5307/ CP 3406. The project aims to improve the quality of online instruction. The study is being conducted by **Kranthi Addanki** and will contribute to her thesis as a part of the Doctor of Philosophy (Information Technology) at James Cook University.

The criteria to participate in this study is that you are of age 25 years or above and have an interest in improving your learning skills and the knowledge about the subject materials (programming skills, research skills, and presentation skills in the context of Mobile Technology).

If you agree to be involved in the 12-week case study (Feb 2022- May 2022), then:

- You will be given a survey during the first week which may take less than 15 minutes. This survey will be used to identify whether you need any learning support
- Based on your learning needs, you will be provided with an opportunity for personalised learning support by your instructor
- Your learning interaction data (learning analytics, Discord/Slack discussions, mini self-reflections and grades) in this subject will be monitored for the purpose of providing better learning support
- Two interviews – one is during mid-semester and the other is at the end of the semester, you will be interviewed by Kranthi. These interviews will be used to get your opinion regarding the usefulness of personalised learning support given to you and may take up to 1hr time each. The interviews will be done online through Zoom and will be audio recorded
- During the final week, there will be a survey (will take less than10 minutes) to check your experience with the subject

Taking part in this study is completely voluntary, and you can stop taking part in the study at any time without explanation or prejudice.

If you know of other students who are taking CP 5307/CP 3406 and that might be interested in this study, please pass on this information sheet to them so they may contact Kranthi to volunteer for the study.

Your personal details will not be collected so your data will be anonymous. Your participation and data will be confidential. The data from the study will be used in thesis and research publications. You will not be identified in any way in these publications.

There no risks identified in this case study or project. However, if you feel any stress at any point, please contact JCU Student Equity and Wellbeing unit- studentwellbeing@jcu.edu.au or by phone using (07) 423 21150 (or ext. 21150) for Cairns campus or (07) 478 14711 (or ext. 14711) for Townsville campus.

If you have any questions about the study, please contact – **Kranthi Addanki** or **Dr Jason Holdsworth.**

Principal Investigator: Kranthi Addanki
College: College of Science and Engineering, James Cook University
Phone:
Email: kranthi.addanki@my.jcu.edu.au

Supervisor: Dr Jason Holdsworth
College: College of Science and Engineering, James Cook University
Phone:
Email: jason.holdsworth@jcu.edu.au

Appendix F

Consent Form 2022—Extended Study

This administrative form
has been removed

Appendix G

Technical Icebreaker Questions

Task 0 – Technical Icebreaker – 10mins

Please answer the follow question about yourself, add them as an entry into the "Self-reflections" Journal in LearnJCU:

1. List the names of all programming languages you have previous experience with and state how confident are working with each one on your own. (highly, moderately, or limited)
2. What kind of debugging techniques are you familiar with? How confident are you in using each debugging technique? (highly, moderately, or limited)
3. What kind of problem-solving techniques are you familiar with? How confident are you in using each problem-solving technique? (highly, moderately, or limited)
4. How important is code readability? (highly, moderately, or limited) Please explain the reason for your response on code readability.
5. What kind of Data structures and algorithms are you familiar with (e.g., stacks, queues, lists, sets, string processing, inheritance)? How confident are you applying each kind? (highly, moderately, or limited)
6. Provide a short description about a program that you created previously/recently.
7. Are you required to take this subject as a part of your degree?
8. What do you hope to learn from this subject?

Appendix H

Sample Subject Participation Review

(Subject Participation Review sample was taken from the subject LMS website with permission from the educator)

Subject Participation Issues:

- About **70%** of students submitted the 1st practical **and** its reflection on time (excellent!)
- About **74%** of students submitted the 2nd practical and most reflections on time.
- Overall, about **30%** of students are not participating enough with the content (e.g. didn't submit the self-reflections along with the prac. work for Practical 1 & 2, or didn't interact with the subject content regularly enough over the last month).
- Some students appear to be **EXT** students and **MIT** students.

Action Plan:

- Ensure that all students are aware that **50%** of the weekly participation marks are for completing **prac. exercises**, the other **50%** is for completing the weekly **self-reflections**!
- Students can submit **any** missing self-reflections for the previous few practicals **without penalty**—as long as they do this by the end of **Week 5**.
- Based on submitted self-reflections so far, please reach out to your lecturer for advice about
    - any ongoing Android/Emulator installation problem
    - lack of confidence about programming in Java, XML and using the features of Android Studio

    - any issues using layouts such as LinearLayout and TableLayout
- Please note that subject content and practicals are designed to help students with the Utility App and Education App.
- Any other problems—please just ask the educator via #cp3406 on Slack or CP3406/CP5307MobileTechChat via Discord.

Links to Check Out So Far:

- The "Java resources" folder contains useful support materials to improve your confidence with Java.
- To improve your confidence with Android (XML, layouts, the IDE) check out the following videos.
    - Week 1—advice about Android Studio
    - Week 1—inspiration/ideas for your Utility app
    - Week 2—how to use the journal system to enter your self-reflections
    - Week 2—how to use the emulator and here
    - Week 2—demo of unit testing here and continued here
    - Week 3—solution to QuickSum, talked about useful features in Android Studio and useful aspects of Java and discussed MVC
    - Week 3—example of using a 3rd party API
    - Week 3—advice about dealing with emulator issues
    - Week 4—what does "at-a-glance" mean and how do intents work?