Technology enabled categorisation of learners for improved support in experiential learning.

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Abstract

The purpose of this thesis is to examine which data captured by experiential learning technology can be used to understand more about students 'perspectives, mindsets and skills. The objective is to examine how technology-enabled real-time analysis of learner data can be used by learning facilitators and instructional designers to improve the practice of experiential learning in higher education institutions. The study adopts an anti-positivist perspective that acknowledges habit as a driver of deterministic behaviour and that deterministic behaviour can be examined using scientific methods. The data used in this research is retrospectively de-identified student learning data captured by an experiential learning technology which has been used to structure and support the facilitation of an experiential business project program.

The research findings outline the quantitative outcomes followed by an integrative qualitative discussion that explores how the findings could be used to inform the practice of experiential learning design and facilitation. Specifically the methodology outlines: the experiential business project program design, the classification of learning tasks into independent variable categories, and the results of student responses to three surveys. The three surveys being: the Revised Implicit Theories of Intelligence Survey**,** Revised Two Factor Study Process Questionnaire and a learning history survey and the manner in which these surveys were dummy coded into dependent variables, with a detailed description of how the regression analysis is conducted. The results section presents and examines the five regression models developed. The purpose of the examination is to explore the extent to which learner data from an experientially developed learning technology could be used to understand more about students 'perspectives, mindsets and skills.

The integrative discussion examines each of the three research questions explicitly. The discussion focused on research question one examines the nature of the learning tasks that have a significant relationship with one or more of the learning theory based dependent variables. It investigates whether there is an alignment between what is known about the nature of learners who exhibit or employ a particular mindset, approach to learning or learning history and the learning task categories use as independent variables in the five regression models presents in the results. The discussion focused on research question two examines what additional learning data could be captured to improve the predictive power of the five regression models. The discussion focused on research question three examines how displaying predictive insights, using learner data, alongside learning theory insights could be used by instructional designers and learning facilitators. The discussion explores how facilitators and learning designers could use the information to customise facilitator support, aid in the development of incentives that encourage learners to engage with learning content that they do not naturally lean towards and support the adaption of learning content to align better with a learner's motives.

This study further proposes an example of the benefits of integrating learning analytics and learning theory, how learning theory based analysis could enable more use of experiential learning within higher education institutions, enable experiential learning facilitators to provide more tailored support of students during experiential learning programs and how the results of the analysis could help students extract more of the benefits from the available learning out of experiential learning programs.

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Chapter 1 Introduction

Introduction

Higher education is at a significant transition point. On a macroeconomic level global demand and student mobility are increasing (OECD, 2017) resulting in inflated and internationalised classrooms (OECD, 2010). Simultaneously, higher education itself is making the transition from elite to mass education (Milliken, 2004) and attempting to respond to the pressure of the market to focus on more instrumental outcomes (Strohl, 2006) that tend to focus on work readiness (Bandaranaike & Willison, 2015) and 21st Century skills (World Economic Forum, 2016). 21st Century skills extend beyond foundational knowledge to competencies and character qualities including collaboration, creativity, leadership and adaptability (World Economic Forum, 2016) that literature suggests are best acquired through experience (Blackwell et. al, 2001; Proctor, 2011; Wilton, 2011; Nenzhelele, 2014) through the use of higher order thinking skills.

In my work as a learning facilitator, instructional designer and educational technologist, I have observed that when students are sent to complete their learning through the use of field experience on experiential learning programs like internships, service learning and co-ops, facilitators lose visual and verbal feedback loops that allow them to understand the nuance of each student's learning process, assess students' level of understanding and identify when students need support. As a result, a facilitator’s ability to tailor support based on feedback loops is inhibited. Employing an integrative educational technology has the potential to re-establish the feedback channel in an experiential learning program but what is not yet clear is whether the data captured and generated by these types of technologically based, experiential learning platforms could be used to display theoretically sound insights about students in order for facilitators to better understand their students' learning needs and provide more tailored support.

My Purpose & Motivation for this Research

Prior to my work as an experiential learning facilitator, designer and technologist I was a social innovator, investing much of my time coaching social entrepreneurs in Australia, the USA, China and Tanzania. In 2013 I was in Tanzania to launch a social entrepreneurs training program. A series of events including teaching friends how to add fractions with a stick in the dirt and a revelation about the complexity of the problems the social entrepreneurs I was working with were trying to solve made me acutely aware of the disparity between my access to education and the access of my Tanzanian peers and colleagues. This awareness led me to return to Australia to re-skill and acquire the knowledge and skills I need to be able to contribute to opening up access to quality learning in low resource economies. Upon completion of this research my goal is to return to my work as a social innovator with a focus on improving access to quality education on a global scale.

My Learning Facilitator Journey & Learning Philosophy

When I started teaching I had no theoretical foundation for understanding learning. As a result, my approach to teaching evolved through experience. In essence, I learned to teach utilising an emergent process that was similar to the experiential learning cycle (Kolb, 1984). I used the experiential learning cycle to examine my practice and how I could change it in order to improve my impact on students 'acquisition of concepts. While teaching leadership, teamwork and innovation, I came to realise that to learn these concepts required not only the ability to understand the theoretical concepts associated with them but to be able to apply them in daily life. The application of leadership, teamwork and innovation to daily life was twofold. Firstly, as a lens to examine current behaviour and determine whether altering behaviour would result in a better outcome. Secondly, as a diagnostic tool to help leader and manage others.

Retrospectively I became aware of theoretical concepts that helped explain what I was experiencing. I became aware of Bloom's Taxonomy of Educational Objectives, first introduced by Bloom et al. in 1956. Bloom's Taxonomy has three domains one of which is the cognitive domain. The cognitive domain is based on the notion that there are levels of complexity to learning a concept based on what a person can do with that piece of knowledge. For example, the ability to recall or restate a theoretical concept is more straightforward than analysing how the theoretical concept is impacting a real-life situation. Additionally, I came to know the concept of constructive alignment (Biggs & Tang, 2011) that further explained and added depth to what I was experiencing in my teaching.

After more than a decade using this experiential approach to learning and retrofitting theory as I became aware of it, I developed the capability to sense and intuit a learner's behaviour and intervene with additional perspective, insight and knowledge that helped unearth habitual behaviours that may need to be re-considered. When I started my doctoral thesis, I learned that I was using critical reflective practice (Brookfield, 1998; Schon, 1983) to develop my facilitation skills. Moreover, with this process of supporting students to bring a habit into conscious thought for re-consideration through experiential learning I was attempting to cultivate the same capability in my students. Enabling a learner to consider whether a process of un-learning, a conscious choice "to give up, abandon, or stop using knowledge, values or behaviours to acquire new ones," is required (Cegarra-Navarro & Wensley, 2018) was, in my view, developing their lifelong learning capability and metacognition.

As online education and the use of technology in higher education began to increase in Australia, I was challenged by the need to transfer my preferred learning and teaching methodology of experiential learning (Kolb, 1984) into the online learning paradigm. When using experiential learning methods to achieve learning goals, my role as a facilitator is to create an experience and react with support, insight and questions in response to how students are engaging with the experience.

Crawley, Fewell and Sugar (2009) identified that facilitators lose valuable affective cues when transitioning into online instruction. The affective cues I lost included facial expressions, body language and tone of voice. This loss inhibited my ability to assess student engagement and learning. At the time, learning management systems did not provide an alternative feedback loop to replace these affective cues (Coppola et al., 2001).

The loss of affective data points impacted my ability to tailor my support of students in the dynamic and immediate way I was used to. The technology was restricting my pedagogical choices. The learning management systems I had access to were optimised for pedagogical approaches that leaned towards teacher-centred learning (Gibson, 2001) and lower-order thinking skills on Bloom's Taxonomy (Anderson & Krathwohl, 2001). At the time, research into online learning focused on how teaching should be adapted to fit the available technology (Juan et al., 2011; Kebritchi et al., 2017) instead of exploring how technology could evolve to replace affective data points and support different pedagogical practices. This situation resulted in a frustrating move back to more traditional pedagogies before transitioning out of teaching into instructional design and instructional technology development. The goal of this transition was to contribute to building technology that supported experiential learning.

Instructional design lacks a widely accepted definition. Merrill, Drake, Lacy and Pratt claim that instruction is a science and instructional design is the use of the principles of this science that are founded on empirical evidence (1996). Alternatively, Reiser and Dempsey define it as a “systematic process that is employed to develop education and training programs in a consistent and reliable fashion” (2007, p.11; 2012, p.8). A third definition that is widely cited and accepted in literature is attributed to both George Siemens and Curtis Broderick: it claims instructional design as an art and a science that transitions a learner from a stage of not knowing to knowing. Both originating websites are no longer accessible, but the definition itself is widely cited in academic journals and textbooks. Despite the lack of an agreed definition, the common theme across the definitions implies the use of a structured process that facilitates a learner from not knowing to knowing.

My work in the fields of instructional design and instructional technology, “the systematic study of designing, developing and evaluating instructional programs, processes and products that must meet the criteria of internal consistency and effectiveness" (Seels & Richey, 1994, p. 127), over the last five years has informed my beliefs about the use of technology in learning and teaching. One of those beliefs is that learning programs where the design and technology are integrated enable the use of learning analytics, specifically, the use of real-time learning analytics to provide the data points facilitators need to sense and intuit the needs of their learners. This belief is supported by learning analytics research that suggests real-time learning analytics can provide useful insights that will help facilitators intervene in the learning process (Gasevic, et al., 2017; James et al., 2018). However, the current learning analytics research that clusters students into categories to personalise the learning experience lacks a connection to learning theory (Bannert et al., 2014; Kirschner, 2017; Kovanovic et al., 2015). Using these same learning analytics techniques with learning theories like learners 'mindset (Dweck, 2017), approaches to learning (Platow et al., 2013) and learning history (Kwak, 2016) could enrich the research and improve the impact of real-time learning analytics and the development of machine learning algorithms designed to transition these intervention processes into the predictive paradigm.

Aggregating Learning Analytics & Learning Theory

A review of the learning analytics literature indicates the potential for real-time learning analytics driven by machine learning algorithms to augment teaching and facilitation in technology-enabled learning environments (Hernandez-Lara et al., 2019; Alblawi & Alhamed, 2017). However, both the educational research and learning analytics research community indicate a need for learning analytics research that is underpinned by learning theory (Gasevic et al., 2017; Gašević et al., 2016; Lodge & Lewis, 2012; Rogers et al., 2016; Wise, 2014; Wise & Shaffer, 2015; Avella et al., 2016; Gasevic et al., 2014; Kirkwood & Price, 2013; Lodge &

Corrin, 2017; Lockyer et al., 2013; McArthur et al., 2005; Reimann, 2016). The potential gap is identified by researchers and practitioners from the learning (Reimann, 2016) and technology fields (Gašević et al., 2014; 2016; 2017). Lockyer, Heathcote & Dawson (2013) specifically highlight the need for aligning learning analytics with instructional design. The alternative to aggregating learning analytics and learning theory research is for the two research communities to continue to operate in parallel. This situation could result in the automation of learning analytics in instructional technology features that have no impact on learning (Tuomi, 2018) and teachers using instructional technology that restricts instead of optimises their pedagogical choices (Justus, 2017).

The call for learning analytics research to be underpinned by learning theory highlights an opportunity for research and exploration into how learning analytics, educational data mining and machine learning grounded in learning theory could improve educational practice. The literature suggests that aggregating learning analytics and learning theory can improve learning processes and learning design (Avella et al., 2016; James et al., 2020; Reimann, 2016), thus supporting the intention of this research to explore how learning analytics, educational data mining and machine learning, underpinned by learning theory, can be used to improve technology-enhanced experiential learning that utilises the experiential learning cycle.

Rationale for the study

The aim of this research project is to explore how learning theory combined with learning analytics analysis (LA) can be used to predict a learner's perspective, mindset and skills when participating in experiential learning programs for developing competencies and character qualities needed for the 21st Century (World Economic Forum, 2016). The first objective is to understand how data produced by a learner during an experiential learning program that is supported by an experiential learning management system (eLMS) could be used to gain insights about a learner's perspectives, mindsets and skills. The second objective to identify additional data that needs to be collected to automate the analysis or improve the predictive model. The knowledge produced through this research project could define predictive insights that enable educators to provide tailored support to students engaging in experiential learning.

Purpose

The primary purpose of the study is to inform the creation of instructional technology built to facilitate experiential learning programs designed to develop 21st Century Skills. A secondary purpose of the study is to inform the use of instructional technology in both the instructional design and facilitation of experiential learning programs designed to develop 21st Century Skills.

As businesses, governments and not for profit organisations place demands on higher education institutions to produce work-ready graduates higher education institutions are turning to experiential learning programs to meet these demands. However, instructional technology being used to facilitate experiential learning programs does not adequately support this pedagogical practice. A deeper understanding of how emerging technologies including machine learning, learning analytics and educational data mining could inform the practice of experiential learning for 21st Century Skill development. The study has the potential to make a contribution to current international discussion about the integration of learning analytics and learning theory and its impact on higher education teaching and learning. And, more specifically, to the practice of experiential learning designed to develop 21st Century Skills. The study is small scale but provides insight that could inform the development of artificial intelligent systems designed specifically to support the teaching and learning of experiential learning and 21st Century Skill development.

Thesis Structure

The thesis is organised as a narrative journey. Chapter 2 begins by reviewing literature about the nature of the Fourth Industrial Revolution, its challenges and its impact on learning. It then explores the emergence of 21st Century Skills and examines the conversations surrounding the role of higher education institutions in developing 21st Century Skills, looking specifically at the literature surrounding the use of experiential learning and emerging technologies in the development of 21st Century Skills. The chapter reviews the literature surrounding experiential learning theory, specifically homing in on Kolb's Experiential Learning Cycle, its use in the development of 21st Century Skills and how technology is currently perceived and being used in this practice. The chapter concludes with an examination of emerging technologies currently being used in higher education teaching and learning, and explicitly examines the consistently highlighted gap when it comes to the integration of learning analytics and learning theory research.

Chapter 3 explains the experiential business project program that provides the context and the data used to conduct this research. Chapter 4 highlights and justifies my methodological approach and presents my research questions, sampling choices and ethical considerations. Chapter 5 outlines and discusses the results of the research. The chapter first explains the instruments used to classify students into learning theory-based categories and presents the overall results. The results are laid out and discussed in the order in which the research was conducted in order to make the process explicit. The chapter concludes by presenting the results of the multiple regression analysis performed by combining user behaviour data engaging with the different categories of learning tasks and their self-assessment scores on the instruments.

Chapter 6 uses the results presented in Chapter 5 to explicitly address and discuss the three research questions. Finally, Chapter 7 presents the potential implications of the research on the integration of learning analytics and learning theory, on the use of experiential learning for 21st Century Skill development and perhaps most importantly my personal current and future practice.

Terminology

Throughout the study the term '21st Century Skills 'is used to explain the non-academic skills needed for work in the Fourth Industrial Revolution. These skills are often referred to as employability skills, human skills, soft skills and professional skills.

Chapter 2: Literature Review

Introduction

This study sits at the intersection of four rapidly developing fields of research in higher education. The purpose of the study is to aggregate the four fields into a socio-technical system and examine how the socio-technical system can impact learning and teaching. The four fields of research are the 4th Industrial Revolution (4thIR), 21st Century Skills development, experiential learning theory and emerging technology. This study holds the potential to generate insights that will contribute to the transformation of higher education learning and teaching so that it can meet the demands of the 4thIR.

This literature review will outline the nature of the 4thIR, the challenges it is presenting and how it is impacting the nature and role of higher education, narrowing in on the need for the development of 21st Century Skills. The literature on 21st Century Skill development will focus on the nature of 21st Century Skills, how higher education institutions are supporting their development with a specific focus on examining the literature surrounding the use of the experiential learning cycle. Then it will continue by examining how the emerging technologies of the 4thIR are used to support higher education learning and teaching that uses the experiential learning cycle for 21st Century Skill development. Finally, the literature review will provide an overview of educational data mining, learning analytics, machine learning, and how they are currently used in higher education learning and teaching. The review will examine the widely acknowledged gap in research that aggregates learning theory and emerging technology research. Moreover, it will identify how the proposed potential research could add to higher education learning and teaching as a whole and specifically the development of 21^{st} Century Skills needed for the 4^{th}IR.

The criteria used for sourcing literature to review was determined for each of the four fields of the literature review. Literature focused on the 4thIR included both academic literature and global economic, development and futures reports since 2013. The literature on 21^{st} Century Skills was limited to literature specifically referring to 21^{st} Century Skills and the World Economic Forum 21^{st} Century Skills framework since 2014, explicitly excluding employability skills and professional skills due to their short-term nature. The review of experiential learning theory and the experiential learning cycle reached further. Foundational research that led to the initial presentation of the cycle, its core developments and critiques are included alongside literature from the past five years focused on how experiential learning theory and explicitly the experiential learning cycle is used in higher education. Finally, the literature review of emerging technology focuses on learning analytics, educational data mining, and machine learning, a subset of artificial intelligence. The review discusses how each of these technologies is used in higher education learning and teaching. This literature review covers all research literature from the past five years, but due to the emergent and fast-paced status of this body of knowledge conference proceedings from the Society of Learning Analytics Research and Educational Data Mining conferences are also included, in order to cover the most recent developments.

Each section begins with an overview of the field of research and its value. The overview is followed by subsections that focus on how each field is linked to the three other fields. The 4thIR literature highlights the demand and needs for change in higher education learning and teaching. The 21st Century Skills literature presents 21st Century Skills as the skills needed for success in the 4thIR and overviews how the development of these skills is embedded in higher education, with a particular focus on experiential learning pedagogies. This review is followed by an overview of how technology is used to support the learning and teaching of 21st Century Skills in higher education. The experiential learning theory section explains the nature of the theory and the experiential learning cycle, how it is being used in higher education and specifically for the development of 21st Century Skills, finally narrowing in on how technology is used to support programs that use experiential learning theory and the experiential learning cycle in the development of 21st Century Skills. This section closes with a particular focus on how emerging technologies are used or in this case, the lack of emerging technologies used in the learning and teaching of 21st Century Skill development that uses experiential learning pedagogies.

The final section of the literature review describes the nature of learning analytics, educational data mining, machine learning, and how they are used in higher education. The literature review then focuses on their use to support experiential learning and 21st Century Skill development. The most pertinent point discussed is the pervasive call for research in these fields to include learning theory and specifically how this could impact 21st Century Skill development that uses experiential learning pedagogies.

The Historical Context for this Research

Higher education is at a significant transition point. On a macroeconomic level, global demand and student mobility are increasing (OECD, 2017). This demand and mobility are resulting in inflated and internationalised classrooms (OECD,2010). Simultaneously, higher education itself is making the transition from elite to mass education (Milliken, 2004) and attempting to respond to the market's pressure to focus on more instrumental outcomes (Strohl, 2006). These instrumental outcomes tend to focus on work readiness (Bandaranaike & Willison, 2015) and 21st-century skills (World Economic Forum, 2016) needed by the fourth industrial revolution workforce market. 21st Century skills extend beyond foundational knowledge and lower-order thinking skills to competencies and character qualities including collaboration, creativity, leadership and adaptability (World Economic Forum, 2016). Literature suggests that these competencies, character qualities and higher-order thinking skills are best acquired through experience and opportunities to practice (Blackwell et al., 2001; Proctor, 2011; Wilton, 2011; Nenzhelele, 2014).

In addition to higher education itself having a history of elitism (Milliken, 2004) and misogyny (Morley, 2011) that it is attempting to change, the transition to models of learning like cooperative education and internships has followed its historical trend. Although cooperative education and internships are proven to be beneficial and successful in preparing students for the workplace (Ambrose & Poklop, 2015), they have not been designed with all learners in mind. In response, governments, philanthropists and businesses are investing in research designed to broaden participation in alternative models of experiential learning. There is particular interest in models that are accessible for non-traditional students and students from underrepresented minority groups (Jona & Rosca, 2017; Santo et al., 2020).

Preliminary research (James et. al., 2018; James et. al., 2020; Joksimovic et. al. 2020) suggests that the integration of technology into cooperative education and internships could provide structure, facilitate communication and provide data to educators that empower them to inject support and additional learning content based on each students' needs. This introduction of technology, and explicitly emerging technology like learning analytics, into experiential learning programs, like capstone projects and virtual internships can:

- Maintain and in some cases, improve learning outcomes (Modestino, 2021).
- Make these opportunities more accessible for non-traditional and underrepresented students (James et al., 2020), if the technology, pedagogy and content development are integrated (Lockyer & Dawson, 2012).
- Be leveraged to understand an individual student's unique experience so that educator support can be equitable and intentional (Santo et al., 2020).

The integration of technology into existing models of learning higher education institutions are using to address the needs of the market in the fourth industrial revolution will continue to grow access to these opportunities for traditional students. Whereas, the use of technology to enable new models of experiential learning like remote capstone projects and virtual internships will open up access to these opportunities for all learners. This will provide higher education institutions with a pathway forward that will allow them to continue to break down their traditionally elitist and misogynistic attitudes and structures while also responding to the fourth industrial revolution's market needs. Resulting in a higher education system that is designed for and accessible for everyone.

The 4th Industrial Revolution

Characteristics of the 4th Industrial Revolution

The 4th IR presents an era of human and machine augmentation (Bonciu, 2017) that the World Economic Forum (WEF) poses as an "unprecedented challenge for the human future" (Flowers et al., 2018, p179). The current era's nature of "abrupt and radical change" in the way economic and social activities are now done and the speed, scope and impact of change on society identifies it as a new industrial revolution (Schwab, 2017, p. 11). This change in the way things are done is attributed to the emergence of the Internet of Things (IoT), big data, artificial intelligence and robotics (Bonciu, 2017; Djankov & Saliola, 2019; Philbeck & Davis, 2018; World Economic Forum, 2018). Philbeck and Davis highlight the ease by which these technologies are embedded into our physical environment and caution of their ability to influence our "physiological condition and cognitive faculties" (26, p.2).

On the macroeconomic level, Buckup (2017) highlights that industrial revolutions have the propensity to enable two opposing forces, economic benefit for all and concentration of wealth. Bonciu (2017, p.8) agrees with and extends this concern claiming a systemic pattern of the past three industrial revolutions being "diffusion of economic benefit" at the start and a "concentration of power" due to the "concentration of capital" towards the end. This concern is about the 4thIR and highlights that realisation of the opportunity for economic prosperity in the 4thIR depends on the ability of all stakeholders to instigate reform in human capital development (World Economic Forum, 2018 p. iii).

Another unique element of this industrial revolution is its pervasiveness and speed due to global connectivity (Bonciu, 2017). However, the pervasiveness does not correlate to equity, particularly when it comes to developing economies (Shvetsova & Kuzmina, 2018). Lambrechts and Sinha (2019) highlight South Africa's unique challenges that conflict with the decentralization that the 4thIR enables. Similarly, Mehta and Awasthi (2019, p. 10) claim that studies on technology change focus on industrialized economies and state that negative impacts in India will be more severe due to the Indian workforce being engaged primarily in "low-skilled and low-paid informal sectors".

4th Industrial Revolution and its Challenges

This 4thIR that is characterized by human-machine augmentation and rapid change is depicted in the literature as presenting two fundamental challenges. The first is a disparity in the number of positions available and number of people looking for work (Deloitte Insights, 2018; WEF, 2018; Whysall et al., 2019); the second is the different and rapidly changing knowledge and skills required when compared to the 3rd Industrial Revolution (Deloitte Insights, 2018; Djankov & Saliola, 2019; Kondakov, 2017; Shvetsova & Kuzmina, 2018).

The disparity in the number of positions available and the number of people looking for work will impact different industries at different times and different velocities. Traditional industries like manufacturing are already starting to see a paradigm where “the number of open jobs exceeds the number of people looking for work” (Deloitte Insights, 2018. p. 2) and the Deloitte Insights report goes on to qualify that this situation is impacting the ability of manufacturers to meet the supply needs of their customers. Whysall, Owtran and Brittain (2019, p.119) looked at the challenge from a human resource perspective, and highlight that in addition to the shortage of workers, organisations are impacted by an emerging trend of "poaching readymade talent"; yet challenge the fundamental assumption of this practice that the skills already exist in the system. Moreover, research highlights a talent attraction challenge, a shift in core competencies (Djankov & Saliola, 2019, p. 123) and “a distinct lack of work readiness amongst newly graduated employees.”

The shift in core competencies or skills required by workers in the 4thIR is the most prolific claim in the literature to date, yet there is a lack of studies that focus on the changing nature of the workforce (Djankov & Saliola, 2019; Ebhard et al. 2017; Kazancoglu & Ozkan-ozen, 2018; Van Wyk, 2016). Schwab (2017) and Djankov & Saliola (2019, p. 5) highlight the need for organisations and governments to transition their thinking and see "human capital investment as an asset rather than a liability,” a challenging proposition in the face of the above mentioned "poaching" trend. Despite the increased use of robots, artificial intelligence and machines in the 4thIR humans “will determine the overall production strategy, monitor the implementation of this strategy, and if need be, intervene in the cyber-physical production system” (Gorecky, 2014, in Pfeiffer, 2015, p. 7). Humans will no longer do the physical or mental work but facilitate the doing (Kazancoglu & Ozkan-ozen, 2018; Shvetsova & Kuzmina, 2018); a fundamentally different set of tasks and required skills (Ghislieri et al, 2018).

The shift in skills the job market is demanding has increased the amount of research focused on teaching and learning practice designed to develop competencies required in this new paradigm (Caratozzolo & Alvarez, 2018; Kazancoglu & Ozkan-ozen, 2018; Shvetsova & Kuzmina, 2018; Van Wyk, 2016). Skills originally called 'soft skills', now presented as professional skills or by the World Economic Forum as 21st Century Skills (WEF, 2016), are increasingly on employers 'preference list and subsequently being introduced into the curriculum. Caratozzolo and Alvarez (2018) highlight that the introduction into the classroom of 21st Century Skills, particularly creativity and critical thinking, tended to be done by infusing activities into the classroom or by the introduction of technology. About the use of technology in teaching these skills, they argue that it is a "structured mental process", not the technology itself, that produces learning. Perhaps more concerning for the higher education sector is the claim that higher education institutions cannot keep pace with the rate of change of the 4thIR (Shvetsova & Kuzmina, 2018) and the need to prepare students for roles that do not yet exist "using technology that is not invented to solve problems which, up till now, we did not face." (Ebhard et al. 2017, p.48).

4th Industrial Revolution and Learning

The exponential rate of change predicted in the 4thIR means that learning needs to be lifelong and that higher education models need to evolve based on that demand (Ostergaard & Nordlund, 2019). The line between work and learning is no longer well-defined, calling for innovation in the existing education system and new learning models (Régio et al., 2016). Lifelong learning is visualised in the WEF 21st Century Skills framework as a 'wraparound 'skill (WEF, 2017). Lifelong learning competencies include "self-management, learning to learn, initiative and entrepreneurship, information retrieval, and decision making" (Hursen, 2014 as cited in Régio et al., p. 25). This shift towards lifelong learning calls for not only the redesign of qualifications to meet skill needs (Venkatraman et al., 2018) but also an understanding that students can no longer learn all the knowledge they need in a four-year degree (Jeganathan et al., 2019).

An emergent theme of the 4thIR literature is a need for change in higher education (Ostergaard & Nordlund, 2019; Penprase, 2018; Schleicher, 2019): a change in the overall system to better align education with the workplace (Deloitte Global Business Coalition for Education, 2018, Jeganathan et al., 2019; Venkatraman et al., 2018); a change in career development and career education (Hirschi, 2017); a change in the priorities of governments (Djankov & Saliola, 2019); and a change in the way teaching and learning is done (Caratozzolo & Alvarez, 2018, Venkatraman et al., 2018). In reference to engineering, Jeganathan, Khanm Raju and Narayanasamy (2019, p.1) call for a "discipline-independent framework for curriculum". The suggestion of a general engineering curriculum at the undergraduate level is about engineers being able to engage with and create cyber-physical systems that a functionally-focused engineer would not have the capability to do. Perhaps this thinking on generalisation needs to extend beyond the walls of engineering education to the whole higher education institution.

Venkatraman, de Souza-Daw and Kaspi (2018) highlight the fault in the system between employers and higher education. Universities claim to prepare students for the future of work and employers claim that students lack employability skills. There is a call for employers to be more engaged in the higher education system from the design of curriculum through to assessment of students' skills (Ferrandez-Berrueco & Kekale, 2014; The Australian Industry Group, 2016; Universities UK, 2016; Venkatraman et al., 2018). Almeida and Simoes (2019) challenge the education system to adopt the technologies of the 4th Industrial Revolution in the classroom suggesting that past education paradigm shifts took place as the education system adopted the emerging technology of the current industrial revolution. The technologies of the 4^{th}IR enable more autonomy (Demartini & Benussi, 2017), personalisation and flexibility (Bartolome et al. 2018), suggesting that perhaps it is the technology of the 4^{th}IR that will enable a lifelong learning paradigm where the line between work and learning no longer exists.

21st Century Skills

A primary claim of the literature surrounding the 4th IR is the shift in the skills, abilities and character qualities humans need to participate in an era of human-technology integration successfully. This shift is a direct result of the transition from routine physical and cognitive work to non-routine work that requires critical thinking, decision-making and interpersonal skills (Perry, 2018; WEF, 2015). A body of literature has emerged focused on:

- the nature of these skills (Mohd Zaid et al., 2018; Niemi & Multisilta, 2016; Soffel, 2016; Tan, 2016; Wolff & Booth, 2016);
- who is responsible for cultivating them (Csapó & Molnár, 2017; Tasso et al., 2017; Yates, 2015);
- how they are best developed (Ahuna et al., 2014; Morgan, 2016; Snape, 2017; Tasso et al., 2017); and
- what role emerging technology can play in the process (Songkram et al. 2019; WEF, 2015).

The nature of 21st Century Skills

The literature surrounding exploration and articulation of the skills required for the 4th IR tend to call these skills, abilities and character qualities 21st Century Skills (Ganayem & Zidan, 2018; Mohd Zaid et al., 2018; Morgan, 2016; Niemi & Multisilta, 2016; Soffel, 2016; Songkram et al. 2019; Tan, 2016; WEF, 2015; Wolff & Booth, 2016). These skills are presented as lists broken down into domains (Kivunja, 2014; WEF, 2015) that group the skills not into functional areas but by how humans approach the external environment with the particular skill (Wolff &

Booth, 2016). There is a large body of literature focused on the development of 21st Century Skills but "since they involve social, psychological and emotional processes" the effective capturing and measurement of them is still problematic (Morgan, 2016, p.807). This problem is also identified by Breslow who claims a significant gap in understanding when it comes to how 21st Century Skills are learned (2015, p.420), suggesting a gap in the closed-loop instructional system (Wolff & Booth, 2016) when it comes to tracking outcomes and measurement of interventions.

A common theme emerging from the literature is the desire to develop frameworks that articulate and categorise a set of 21st Century Skills (Ganayem & Zidan, 2018; Germaine et al. 2016; Morgan, 2016; Snape, 2017; Songkram, 2017a; Songkram et al. 2019; Tasso et al., 2017; WEF, 2015; Wolff & Booth, 2016). Two of the most discussed are the World Economic Forum 21st Century Skills (WEF, 2015) and the P12 set of skills (P21 Partnership for 21st Century Learning, 2015). The WEF list breaks the skills into foundational literacies, that include the skills that are the traditional focus of education along with literacies in ICT, finance and culture; competencies needed to solve complex challenges; and character qualities that highlight behaviours or intents that are part of one's identity (WEF, 2015). In the WEF Framework, the list of 16 21st Century Skills is encircled by the 17th skill, lifelong learning.

The P21 skills list is similar to the WEF list, developed by a consortium including government, educational leaders and business leaders (National Education Association, n.d.). The emergence of these and other lists have enabled a common language and framework for global, national and institutional discussion and action around measurement (WEF, 2015; Wolff

& Booth, 2016) of both the skills themselves and interventions identified as holding the potential to develop them effectively.

The call for 21st Century Skills in the literature seems to stem from the workplace with employers and industry bodies publicly ranking the skills they are looking for in potential employees (Kyllonee, 2013; Perry, 2018; Roohr et al. 2019; The Boston Consulting Group. 2018). Boyles highlights that creativity, critical thinking and leadership are ranked highest by companies in the United States of America (2012). A global macro analysis identified an increasing "demand for non-routine analytical and interpersonal skills" across many industries (The Boston Consulting Group. 2018, p. 5). An employer survey in the UK found teamwork, positive attitude and adaptability to be the most sought-after skills (Kyllonee, 2013). In developing countries, the focus on these more complex skills has perhaps gone too far with international agencies suggesting a “de-emphasis of basic knowledge” to focus on “complex cognition”, forgetting the ‘stackable ’nature of learning and cognition (Abadzi, 2016, p.253). The terms used to describe these sought-after skills - complex cognition and higher-order thinking - suggests that although 70% of employers indicate the importance of critical thinking (AMA, 2012 as cited in Roohr et al. 2019), they should be considered a valuable addition, not a replacement for, basic cognitive skills.

21st Century Skills and Higher Education

The proliferation of industry and employer surveys highlighting the skills they require (Kyllonee, 2013; Perry, 2018; Roohr et al. 2019; The Boston Consulting Group. 2018) coupled with claims that university graduates are not prepared for work (Wolff & Booth, 2016) is presenting a fundamental challenge to the higher education sector. Wolff and Booth (2017) highlight multiple factors that could contribute to higher education graduates being unprepared including a disagreement between employers and higher education about whether the skills are sufficiently taught, mismatch in educational programs and employer needs and ultimately whether it is even the role of higher education institutions to create work-ready graduates.

The question about the role higher education should play in the 4thIR and 21st Century Skill development is common in the literature (Csapó & Molnár, 2017; Tasso et al., 2017; Yates, 2017). Wolff and Booth (2016, p. 52) note a tendency in academic literature to critically examine the claims of employers suggesting that this pressure to produce work-ready graduates lies in tension with the "greater public good mission that is the heart and soul of higher education." The crux of this debate and tension lies in whether the mission of higher education institutions should continue to take a longer term and holistic approach that prepares students for a life of meaning and service or should pivot to include and emphasize producing graduates that are immediately desirable to the employment market. Although this tension is worthy of the attention it receives, the inclusion of 21st Century Skill development in higher education transcends the debate. A character quality of persistence, the ability to engage in lifelong learning and effectively communicate are essential skills humans need irrespective of why higher education institutions choose to focus on them.

In contrast, employer-focused literature takes the position that the debate has already been decided, and higher education is responsible for developing the talent they need (Carnevale

& Hanson, 2015; Jacobs, 2014; Tasso et al., 2017). Employer-focused literature seems to come from a perspective where it is the role of higher education to develop 21st Century Skills and prepare graduates for work (Andrade, 2016; Chamorro-Premuzic & Frankiewicz, 2019; Hodgman, 2018; The Boston Consulting Group. 2018). As a result, the discussion has moved on to second-order claims that include a fundamental shift in the nature of higher education. In some reports, higher education institutions are blamed for students being unprepared for employment (Chamorro-Premuzic & Frankiewicz, 2019; Hodgman, 2018; The Boston Consulting Group. 2018). Moreover, industry reports highlight the need for "educational practices that involve students in active, effortful work – practices including collaborative problem solving, internships, research, senior projects, and community engagement" (Hart Research Associates, 2013, para 6 as cited in Andrade, 2016). These educational practices require active industry and higher education collaboration, suggesting that perhaps the industry's perspective that it is higher education's role to develop 21st Century Skills is premature and inaccurate. A large volume of the literature that identifies and examines learning and teaching practices used to develop 21st Century Skills that fit within the higher-order skills and complex cognition domains include work-integration (WACE, 2019), real-world problems (Songkram et al. 2019) and learning by doing (Frache et al., 2017).

On a global level, the United Nations General Assembly adopted the Sustainable Development Goals in 2015[1], as part of a refreshed global strategy focused on sustainability. Sustainable Development Goals Four and Eight focus on education and highlight a transition in the global conversation from formal education to lifelong learning (United Nations General

[1] For more information on the Sustainable Development Goals see https://sustainabledevelopment.un.org/

Assembly; 2015). In 2019 the key themes discussed at the World Economic Forum's annual meeting were training talent, developing talent and a call for new education and career models (Mphuthing, 2019). Finally, the World Association for Cooperative Education's 2019 charter focuses on increasing the volume of work-integrated learning experiences and developing a framework for the evaluation of work-integrated learning experiences as they increase in volume and popularity (WACE, 2019). It is evident that the global conversation of governments, the business community and higher education is focusing on 21st Century Skill development and higher education's role in that process, as opposed to higher education institutions being fully responsible.

21st Century Skills and Higher Education Learning & Teaching

As noted above, the literature and global conversation surrounding the role of higher education in 21st Century Skill development is increasing in volume. In parallel, there is an increase in the volume of literature examining the teaching and learning of 21st Century Skills in higher education institutions. A large volume of the literature focused on how higher education institutions are developing students '21st Century Skills examines how specific pedagogical practices are used to develop 21st Century Skills in general. Sabat et al. (2015) examine the value of Service Learning for 21st Century Skill development. Service learning is "a form of experiential learning that combines academic coursework with voluntary service in the community" (Deeley, 2010, p.2). The research found a non-significant difference in perception of 21st Century Skill development between the control group and the students offered the service-learning intervention. Limitations cited the low volume of participants being a cause of the non-significant findings (Sabat et al., 2015). Perry conducted a similar study to examine the value of film production for the development of 21st Century Skills (2018). Qualitative analysis of students 'post-intervention assessments found student perception of 21st Century Skill development to be positive. However, the study did not include any educator or industry perceptions and relied solely on the reflective writing of the students upon which to draw their conclusion. Project-based learning (Rabacal et al., 2018; Songkram et al. 2019), service learning (Sabat et al. 2015), filmmaking projects (Perry, 2018), a maker space (Sheffield et al., 2017), technology education (Snape, 2017), serious games (Romero et al., 2015) and game-based learning (Qian & Clark, 2016) are all highlighted and examined as pedagogies for the development of 21st Century Skills in higher education teaching and learning.

Another section of the literature focuses on broader pedagogical practices and a specific 21st Century Skill (Ahuna et al., 2014; Dieu et al., 2018; Egan et al., 2017; Khlaisang & Songkram, 2017b; Kivunja, 2014; Mohd Zahid et al., 2018; Qian & Clark, 2016; Romero et al., 2015). Dieu et al. (2018) look at experiential learning for the development of collaborative problem-solving (CPS). The analysis found a significant increase in CPS after the intervention with the research concluding that "doing experiential learning assignments help students to develop their CPS competency in a sustainable way" (p. 510). Despite the positive result, the immediacy of the post-intervention survey calls into question whether the experiment is a real test of sustained learning. Mohd Zahid et al. (2018) found that active learning, in the form of peer instruction, increases students 'conceptual knowledge of a topic. However, once again, a low sample size of twenty students calls into question the generalisability of the results.

It appears that a common limitation of research focused on the teaching and learning of 21st Century Skills is small and homogenous sample sizes (Mohd Zahid et al., 2018; Sabat et al. 2015) and the self-perception-based nature of data analysed (Dieu et al., 2018; Mohd Zahid et al., 2018). Perhaps these cited limitations highlight the need for combining learning theory research and learning analytics research, a common theme of learning analytics research discussed in more detail below (Avella et al., 2016; Gasevic et al., 2014; Kirkwood & Price, 2013; Lockyer et al., 2013; Lodge & Corrin, 2017; McArthur et al., 2005; Reimann, 2016)

The overarching theme of the literature surrounding 21st Century Skill development in higher education is ‘learning by doing ’also known as experiential learning (Council, 2018; Coy et al., 2017; Dieu et al., 2018; Fischer, 2018; Fry, 2017; Guerra, 2017; Lotti, 2015; Ornstein & Hunkins, 2012; Servant-Miklos, 2018; Sipes, 2017; Smith, 2017; The Boston Consulting Group, 2018; Tasso et al., 2017), with reflection (Dieu et al., 2018; Niemi & Multisilta, 2015), industry feedback (Kivunja, 2015; Songkram, 2017b) and peer feedback (Niemi & Multisilta, 2015; Wanner & Palmer, 2018) facilitating the identification and extraction of learning from experience. The literature surrounding 21st Century Skills acknowledges that experiential learning teaching practices are complex to deliver. This acknowledgement is often followed by a discussion about the potential emerging technologies to augment teaching and learning in order to help close the skill gap (Csapo & Molnar, 2017; Khlaisang & Songkram, 2017; Morgan, 2016; Songkram, 2017b; Songkram et al. 2019; WEF, 2015).

21st Century Skill development and the use of Technology

In most cases, research focused on 21st Century Skills in higher education institutions does not explicitly involve technology. However, discussion of the *potential* of technology in 21st Century Skill development is prevalent (Ganayem & Zidan, 2018; James et al., 2018; James et al. 2020; Songkram et al., 2019; The Boston Consulting Group, 2019). The World Government Summit Report highlights personalisation, opening up access to education in underserved communities and the development of higher-order thinking skills as three of the core benefits technology can bring to 21st Century Skill development (Boston Consulting Group, 2018). The World Economic Forum's report on the potential of technology for 21st Century Skill development found that technology is used to:

- support instruction in nations without well-trained teachers;
- open up access to education through scalability that results in cost reduction;
- understand students' learning and free teachers from operational tasks in order to focus on teaching (2015).

This potential is explored by James et al. (2020) who present a technology enabled Virtual Internship that integrates instructional design, the learning management system and real-time learning analytics to automate operational tasks and augment elements of instruction. This model supports the report's hypothesis that the potential of technology is "most effective if applied within an integrated instructional system" (p. 8) particularly when it comes to competency and character quality development.

Academic literature focused on the use of technology for 21st Century Skill development in higher education presents evidence-based theoretical models of what a virtual learning environment for skill development would need to include (Khlaisang & Songkram, 2019;

Songkram, 2017; Songkram, 2017a; Songkram et al., 2019). However, some authors make the qualification that learning will "occur only with an effective and good design of online learning" (Songkram, 2019, p.7). This qualification supports the notion that technology and instructional design should be more integrated in this practice (Boston Consulting Group, 2018; Hickman & Akdere, 2017; James et al. 2018; James et al., 2020; WEF 2015). This further supports the call for education technology-based research, like learning analytics, to better integrate learning theory into their educational technology practice (Avella et al., 2016; Gasevic et al., 2014; Kirkwood & Price, 2013; Lockyer et al, 2013; Lodge & Corrin, 2017; McArthur et al, 2005; Reimann, 2016).

Experiential Learning Theory

Introduction

Research and practice focused on 21st Century Skill development uses “learning by doing” or experiential learning theory and pedagogies at its core (Council, 2018; Coy et al., 2017; Dieu et al., 2018; Fischer, 2018; Fry, 2017; Guerra, 2017; Lotti, 2015; Ornstein & Hunkins, 2012; Servant-Miklos, 2018; Sipes, 2017; Smith, 2017; The Boston Consulting Group, 2018; Tasso et al., 2017). Experiential learning theory is founded on the following propositions: that learning

- is a process, is re-learning;
- requires resolution of conflict;
- is an adaption to the world;
- is transference between environment and individual and is a constructive process (Andersen et al., 2000; Kolb & Kolb, 2005a).

These propositions are shared by scholars including Dewey, Lewin and Piaget whose work and research are considered the foundation upon which experiential learning theory is built (Kolb, 1984, 2015; Kolb & Kolb, 2005a, 2017, 2018). Experiential learning theory defines learning as "the process whereby knowledge is created through the transformation of experience" (Kolb, 1984, p.41), a definition that has been accepted, acknowledged and reinforced in research and literature on experiential learning since it was first proposed (Andersen et al., 2000; Dishke et al., 2015; Mainemelis et al., 2002; Martinez et al., 2010; Ozar, 2015).

Over the years, the literature focused on experiential learning theory has extended to include practical models and frameworks that can be applied and examined in learning and teaching practice. These elements and models include the experiential learning cycle (Kolb, 1984) and nine learning styles and a framework for analysing the social system surrounding the learning environment (Kolb & Kolb, 2005a). Experiential learning, intermittently referred to as experiential education, is discussed as an umbrella term for service learning, global learning, work-integrated learning, adventure education, career education and many other pedagogical practices used in higher education (Ozar, 2015; Tiessen et al., 2018). Furthermore, and most pertinent for this research, the experiential learning cycle is used as the underlying framework for 21st Century Skill development (Sandlin et al, 2018; Tiessen et al, 2018).

The nature of the Experiential Learning Cycle

To learn by doing requires an immersive experience, a way of extracting information and a means of integrating the information with existing knowledge. This cyclical process is referred to as an experiential learning cycle (Botelho et al. 2015; Kolb & Kolb, 2005a; Kuk & Holst, 2018; Miller & Maellaro, 2016; Sandlin et al, 2018). Kolb's experiential learning cycle, a model that steps learners through four distinct cognitive processes, is the most widely-used and acknowledged cycle in the literature (Botelho et al. 2015; Kolb, 2015; Kolb & Kolb, 2017, 2018; Kuk & Holst, 2018; Leonard & Roberts, 2016; Miller & Maellaro, 2016; Sandlin et al., 2018; Wallace, 2019). The cycle is founded on Lewin, Dewey and Piaget's models of learning, all cyclical and all acknowledge learning as a process of transformation, not an outcome (Kolb, 1984).

The four learning modes of Kolb's experiential learning cycle are concrete experiential, reflective observation, abstract conceptualization and active experimentation. The cycle steps learners through "a process of constructing knowledge that involves a creative tension among the four learning modes" (Kolb & Kolb, 2005a, p.194). Kolb's research and the subsequent literature extend these learning modes into learning styles, suggesting learner preferences based on our biology, experience and present situation (Kolb & Kolb, 2005a).

Kolb's experiential learning cycle is critiqued by Javis, who challenges the model's ability to articulate the complex process of extracting learning from a social context (1987). This critique is followed by an attempt to propose a more complex model that Kuh and Holst (2018, p. 151) re-integrate with Kolb's Cycle, highlighting the core premise of both cycles as "reflection play[ing] a mediating role between experience and learning". Michaelson's feminist lens on experiential learning challenges a perceived mind-body split occurring within the experiential learning cycle. Michaelson (2015) questions the removal of the 'reflector 'from the social context. However, in the explanation and use of the experiential learning cycle in literature, there is no explicit articulation of reflective observation and abstract conceptualization requiring removal from the social context.

Jones and Bjelland add pre-reflection to Kolb's experiential learning cycle based on the premise that pre-reflection enables a higher degree of reflective observation within the cycle (2004). Sandlin, Price and Perez (2018, p.24) applied pre-reflecting finding that it "allowed students to be cognizant of the expectations" suggesting that perhaps the impact of pre-reflection is a clear articulation of learning objectives that can be achieved by other means as opposed to an essential addition to the cycle. Furthermore, Leonard and Roberts (2015) found that 'performance pressure' short-circuited the learner's journey through the experiential learning cycle impacting the learner's ability to aggregate the new knowledge into their existing knowledge. They are suggesting that perhaps the benefit of pre-reflection could be a result of the time and space allocated to the learning outcomes.

Instead of attempting to add to the cycle Miller & Maellaro (2016) combine Kolb's experiential learning cycle with the 5 Whys problem-solving tool that gives the learner a structured thinking process to help elicit more insight in the reflective observation mode. Providing a structured process to the reflective observation mode of the cycle appears to give learners with lower levels of reflective capability a pathway to generate more insights from the specific learning experience that could also help them develop a more advanced reflective capability.

Kolb's Experiential Learning Cycle is reinforced in the literature beyond educational theory. Linking neuroscience to experiential learning, Zull (2002; 2011) proposes that the learning cycle emerges from the biology of the brain, with each of the four learning modes engaging a different quadrant of the brain. Perhaps a more compelling argument for the widespread use of Kolb's experiential learning cycle is its dominance in both research and practice highlighted in experiential learning theory literature reviews from 2015 - 2018 (Kolb, 2015; Kolb & Kolb, 2017, 2018). The latest bi-annual bibliography of experiential learning research found an additional 219 references with valid contributions to the research and practice of experiential learning (Kolb & Kolb, 2019). A 1999 bibliography analysis of over one thousand references highlighted the pervasiveness of experiential learning research, with articles found as broadly as management, education, medicine and law (Kolb et al., 2001).

Experiential Learning Cycle and Higher Education

In higher education, experiential learning theory and the experiential learning cycle is used across a broad spectrum of faculties including engineering (Mills & Teagust, 2003; Widiastuti & Budiyanto, 2018), business (Dixon, 2014; Henderson, 2018; Leal-Rodrigues & Albort-Morant, 2019) and health (de Groot et al., 2018, Graber et al., 2017; Pangelinan et al. 2018). The research literature mimics this breadth as educators examining their practice and publishing insights. Widiastuti and Budiyanto (2018) present the use of the experiential learning cycle as a pedagogical basis for curriculum design in engineering education and highlight the need for a longer-term study to validate the perceived positive impact further. Dixon (2014) presents an MBA course based on experiential learning and the experiential learning cycle developed as a differentiator in the MBA course market. The market differentiator motivation of this study unearths a caution when it comes to the quality of experiential learning in the curriculum. Henderson (2018) highlights the labour intensity and complexity of course re-design in order to implement effective experiential learning. However, as research and literature continues to validate the positive impact of experiential learning (Henderson, 2018, Jackson, 2013, Tiessen et al., 2018), Jorgenson & Shults (2012), Qiubo et al. (2016), and Tiessen et al. (2018), all express increasing concern regarding the consumerist orientation of experiential learning that may not have a learning impact.

As the percentage of non-traditional students accessing higher education rises (National Center for Education Statistics, 2016) and institutions evolve to accommodate their learning needs, the use of experiential learning has expanded (Buglione, 2012; Burns & Danyluk, 2017). Petrovic-Dzerdz and Trepanier (2018) present a model of online experiential learning where students hunt for and gather information about learning goals online, share it with the class and ultimately co-design the curriculum with the teacher. Although there is an apparent use of the experiential learning cycle in the course design, the concrete experience element of the experiential learning cycle is research and analysis with the rest of the cycle focused on the course content, thus breaking the cycle. Beckem and Watkins investigate the use of immersive experiential learning simulations to move online students from lower-order processes of learning to higher-order processes of learning (Beckem & Watkins, 2012). These immersive simulations appear to stay more faithful to the experiential learning cycle and include natural assessment in the simulation but are costly and complex to develop. James and Humez (2020) present a 'virtual internship' model that leverages a technology-enabled pedagogy of structured feedback and reflection that steps learners through the experiential learning cycle. They suggest that the use of technology to drive pedagogical outcomes enables the scalability of the program while maintaining the efficacy of the learning. This hypothesis still needs to be examined, tested and validated, a process this thesis research can make a contribution to.

The use of the experiential learning cycle is as prevalent outside the classroom as it is inside the higher education classroom, particularly in global mobility programs (Tovar & Misischia, 2018) and career development (Maguire, 2018; Tiessen et al., 2018). When it comes to career development, experiential learning eases the transition from university to the workforce (Mate & Ryan, 2015), improves 21st Century Skills (Billet, 2011; Martin et al., 2011) and, from the student perspective, has a positive impact on career advancement (Tiessen, 2018). Maguire (2018) examined the use of experiential learning in the early stages of a degree and found that it significantly lifted students' confidence in their chosen field of study and subsequent career. Tiessen et al., (2018) examine the impact of experiential learning and career outcomes more holistically, finding that participating in experiential learning programs positively impacts career trajectory. Nevertheless, they point out the need to continue to optimize experiential learning programs and make them more accessible.

Experiential Learning Cycle and 21st Century Skills in Higher Education

The development of 21st Century Skills is a common theme in literature associated with the use of experiential learning and the experiential learning cycle in higher education (de Groot et al., 2018, Graber et al., 2017; Jackson, 2013; Pangelinan et al., 2018; Petrovic-Dzerdz & Trepanier, 2018; Sandlin et al., 2017; Tiessen et al., 2018; Widiastuti & Budiyanto, 2018). The prevalence in the literature aligns with practice, specifically, in the emergence of university-mandated experiential learning as a part of graduation requirements (Isaak et al., 2018; Laws et al., 2016). In some cases, these mandates are meeting resistance from faculty who already teach experiential learning courses that meet the mandated criteria. Issak et al. (2018. p.34) explain their resistance to their institutions mandate highlighting “choice as the *sine qua non* of experiential learning”.

Literature that includes the use of the experiential learning cycle for the development of 21st Century Skills in higher education is just as broad as literature about the use of the experiential learning cycle in general. The literature examines particular pedagogies like cooperative education (Flemming & Haigh, 2017), service learning (Henderson, 2018), simulations (Birt et al., 2018; Widiastuti & Budiyanto, 2018), team-based projects (Gundala, Singh & Cochran, 2018; Sandlin et al., 2017) and online learning (Petrovic-Dzerdz & Trepanier, 2018) that use the experiential learning cycle. Flemming and Haigh (2017) examine the perceptions of cooperative education, a prevalent form of experiential learning, stakeholders when it comes to its overall purpose. The study found that ‘employability ’was the agreed intended outcome of this form of experiential learning. However, the authors go on to caution against the short-sighted nature of this outcome proposing that cooperative education should be designed to develop 21st Century Skills that prepare graduates for a career in the 21st Century not just their first job.

Henderson (2018, p. 59) critically examines the use of service-learning in economics education. The study explicitly takes a more critical view of the use of the experiential learning cycle for the development of 21st Century Skills calling it an "opportunity cost" that takes "time away from economics instruction". The research goes on to examine the use of the experiential learning cycle and service-learning to facilitate the application of economics concepts to a real-life situation. Overall, the literature that includes the use of the experiential learning cycle in the development of 21st Century Skills focuses on a particular application of the cycle and not the experiential learning cycle itself.

Throughout the literature, there is a discussion about roadblocks and challenges when it comes to implementing experiential learning programs that focus on 21st Century Skill development. In Wurdinger and Allison's (2017, p.25) study, 97% of faculty respondents agreed that experiential learning programs developed 21st Century Skills but saw the class size and class duration as a contextual roadblock to implementing experiential learning. The study explicitly stated that if "universities are committed to high-quality pedagogy" they will have to evolve not only their curriculum and teaching but also the structures and environment surrounding it. Henderson (2018) identifies a third roadblock to the implementation of experiential learning for 21st Century Skill development is the cost of developing and implementing courses and goes on to present solutions to the cost of developing and implementing experiential courses that include larger class sizes and pooling industry recruitment resources with others in the institution.

Extending beyond the operational issues of implementing experiential learning programs, Wright et al. (2018) examine the 'shadow 'sides of the student experience. Access to technology, transportation to travel to learning sites and available time to invest are all cited as issues that could lead to an inequitable experience for students from low socio-economic areas and other non-traditional students who are juggling study, work and family commitments. Psychologically, the study highlights that the context of experiential learning experiences could "impose a burden on a vulnerable student's psychological well-being" (p.764). On a pedagogical level, there is a risk that students' learning does not align with the intended learning and learning goals (Hibbert et al, 2017; Kolb & Kolb, 2005).

These above-mentioned roadblocks and challenges create barriers when it comes to the implementation of programs that use the experiential learning cycle for 21st Century Skill development. However, emerging literature suggests that perhaps emerging technologies can play a role in minimizing and in some cases eliminating these challenges. James, Humez & Laufenberg (2020) present a technology-enabled 'virtual' internship that opens up access to experiential learning for non-traditional students. James et al. (2018) examine the use of learning analytics for providing better insight into the overall experience of students participating in experiential learning programs, suggesting that access to the data can enable facilitators to provide more effective support for students when they need it. These conceptual studies are starting to shape the role emerging technologies could play in enabling more experiential learning programs, designed to develop 21st Century Skills. This use of technology could result in more experiential learning embedded in higher education curricula and therefore make experiential learning more accessible to more students.

Experiential Learning and the use of Technology

There is a lack of research and literature about how technology is used in experiential learning within higher education institutions, specifically, on how emerging technologies like artificial intelligence, machine learning, educational data mining and learning analytics could be used to support experiential learning. The bulk of the literature that does include or highlight the use of technology in experiential learning relegates the technology to facilitating operational tasks (Beckem & Watkins, 2012; Pangelinan et al., 2018) or providing a communication channel (Widiastuti & Budiyanto, 2018). In most research, the technology is viewed as a fixed infrastructure that learning designers build 'on-top-of 'and facilitators use to push information back and forth (Beckem & Watkins, 2012; Pangelinan et al., 2018; Widiastuti & Budiyanto, 2018) as opposed to being a flexible and dynamic element of a socio-technical system that can play an integral role in the design and facilitation of learning (James et al, 2018; James et al., 2020)

An exception is the use of virtual reality (VR) and augmented reality (AR) in simulations that mimic the real-world in the physical and online classroom (Birt et al., 2018; Widiastuti & Budiyanto, 2018). Birt et al. (2018) examine the use of different mobile mixed-reality tools in medical simulations finding that students prefer the more immersive nature of virtual reality. Widiastuti and Budiyanto explore the use of simulations in mechanical engineering employing the experiential learning cycle as the underlying pedagogy (2018). Although there is the use of technology and the experiential learning cycle, the use of the technology is limited to enabling the 'concrete experience' and plays no role in facilitating the rest of the learning cycle.

The emerging technologies of the 4thIR hold much more currently underutilized potential (James et al., 2018). The USA Office of Educational Technology (2018) highlights emerging technologies 'potential to personalize the learning experience, organize learning around real-world challenges and break down the walls of the classroom enabling learning everywhere. In experiential learning specifically, Watson and Ogle (2013) highlight the benefits of smartphones and internet connectivity in enabling the transition of learning from the lab to the real-world. However, in their model, the teacher is still physically present where the learning is taking place. This model makes the use of the technology no different from that of simulations where the technology is enabling a real-life 'concrete experience 'and not enabling the rest of the learning cycle.

James, Humez and Laufenburg (2020) present a model of online experiential learning where instructional design is integrated with technology design enabling the teaching and facilitation to be augmented by machine learning and learning analytics. James et al. (2018) propose that this integration of the instructional design with the technology also enables the use of learning analytics to measure the impact of experiential learning programs and support data-driven course re-designs. Unlike the already-mentioned uses of technology in simulations and real-world learning, this model utilises the technology to support the entire experiential learning cycle. The technology provides insights to facilitators so that they can intervene with support when students are stuck in the cycle and provide feedback that may lead to deeper reflection and insight.

Emerging Technology

Introduction

Emerging trends in the use of advanced computing technologies include artificial intelligence (AI), machine learning (ML) and big data analytics (BDA). Artificial intelligence is a machine mimicking cognitive functions of the human brain. Over the years since its inception, it has been defined as "the exciting new effort to make computers think" (Haugeland, 1996 p.2) and "the study of how to make computers do things at which, at the moment, people are better" (Rich & Knight, 2009, p.3). Machine learning is research that "seeks to develop computer systems that automatically improve their performance through experience" (Mitchell et al. 1990) and expands upon the effort of make computers think through adding the ability of technology to acquire information that improves its ability to perform tasks without being explicitly programmed.

Artificial intelligence was conceptualised in the 20th century popular culture before researchers and philosophers began exploring the theoretical possibility. Turing (1950), proposed that if humans use both information and reason, technology could do the same. However, bringing this theoretical possibility into practical reality was inhibited by the processing power of computers, their structure and cost as well as the macroeconomic forces to drive the change. In the subsequent years these barriers and obstacles where overcome. Today, the development of artificial intelligence follows a cyclical process of saturating the existing storage and computational capacity of computers, then waiting for storage and computational capacity to expand to another magnitude of scale and repeat.

In education today, artificial intelligence, particularly machine learning, is being used to detect early student drop out rates (Dalipi et al., 2018; Kondo et al., 2017; Berens et al., 2018; Tai Chui et al. 2018); predict academic performance (Alkhasawneh & Hobson Hargraves, 2014; Alsuwaiket et al., 2019; Hernandez-Blanco et al., 2019; Sohail et al., 2018); and make recommendations to administrators about business decisions (Baskota & Ng, 2018; Ipina et al., 2016; Samin & Azim, 2019). When comparing the nature and use of machine learning in education to that of educational data mining and learning analytics, Sciarrone (2018) finds that its primary use and differentiator is the prediction of future behaviour. Ciolacu et al. (2018, p. 23) claim that "artificial intelligence is the new electricity," meaning that artificial intelligence is an underlying capability and infrastructure that enables or *powers* other things — suggesting that machine learning could be considered an enabler of educational data mining and learning analytics. The prevalence of machine learning algorithms being used in educational data mining and learning analytics research (Al-Shabandar et al. 2018; Hernandez-Blanco et al. 2019; Ifenthaler, 2017; Mimis et al. 2018; Wongwatkit & Prommool, 2018; Zhang & Qin, 2018) reinforces this notion. Hernandez-Blanco et al. (2018) take this reinforcement one step further by collating and examining the use of deep learning (a machine learning technique) in educational data mining, finding that it is an emergent field that is increasing in prevalence.

The increase in prevalence and transformational potential of artificial intelligence, machine learning and big data in education is being met with caution. Williamson (2017) reminds us that code is not objective and to consider the bias and world view of technicians and the commercial interests of the corporations who own the technologies. And, despite the above mentioned positive benefits for both teachers and students the reliance on technologies and technology companies that have an underlying commercial interest is contributing to a shift in the balance of power in the educational system (Buchanan & McPherson, 2019).

Big data is “the information asset characterized by such a high volume, velocity and variety to require specific technology and analytical methods for its transformation into value” (De Mauro et al., 2016, p. 122). In literature, the emergence of big data is discussed for the positive *and negative* potential impacts on society and individuals. Boyd and Crawford (2011) highlight the need to critically examine the concept of Big Data, and related assumptions and biases. They specifically challenge the claim of objectivity, assert that bigger is not always better and highlight the need to understand the forces and systems driving the development of systems and processes that leverage big data.

The use of BDA in education and specifically in higher education has emerged in two communities of practice, educational data mining and learning analytics. Linan and Perez (2015) define the two practices through a comparison based on use, approach, origin and method. For example, they claim that educational data mining is reductive, automated discovery emerging from educational software development that leverages human judgement. This claim is in contrast to learning analytics which aims to leverage human judgement, empowers instructors and students, is holistic and originates from web-intelligent curricula (Bronniman et al., 2018; Clow, 2013; Long et al., 2011). Essentially they state that education data mining is machine first and learning analytics is human first. Literature from both research communities reinforces and refutes this perspective. Some of the literature places learning analytics as a sub-section of educational data mining (Aldowah et al., 2019), whereas other authors reinforce the separation suggesting that educational data mining "tends to focus more on the technical challenges than the pedagogical challenges" (p 687) and learning analytics "on the pedagogical questions" (Clow, 2013, p. 687).

The Nature of Emerging Technology in Higher Education

Artificial Intelligence and Machine Learning in Higher Education

Artificial intelligence is "computing systems that are able to engage in human-like processes such as learning, adapting, synthesizing, self-correction and use of data for complex processing tasks" (Popenici & Kerr, 2017, p. 2). Ciolacu et al. (2018) break artificial intelligence in education into five areas: machine learning, natural language processing, computer vision and hearing, responding and decision-making. They highlight that the main ways machine learning is used in education to date are to self-customise learning, mine data, detect plagiarism and, of most interest to this research project, to develop cognitive technologies. Balica (2018), taking a macro-economic and metaphysical perspective of the current state of machine learning, the distribution of machine learning talent and the perceived benefit of machine learning to global education, found that out of a 3200 respondent sample 71% believe the likelihood artificial intelligence will aid global education is very high (41%) or high (24%).

The foundational driver of machine learning is an algorithm, a set of processes followed in a problem-solving calculation, that adjusts itself in order to increase its accuracy. Machine learning research is broken down further based on the task an algorithm is developed to do. For example, Naïve Bayes Classifier is used to classify objects. Hayati et al. (2018) use Naïve Bayes

Classifier to assess a learner's cognitive presence. Sivakumar and Reddy use Naïve Bayes Classifier to determine the sentiment of learners' writing (2017). Breaking down machine learning in education research based on purpose, there are two prominent groups: prediction of performance (Alkhasawneh & Hargraves, 2014; Cui et al., 2019; Pang et al., 2017; Sandu & Gide, 2018; Sohail et al., 2018; Xu et al., 2019) and prediction of dropouts (Aulck et al., 2016; Dalipi et al., 2018; Kondo et al., 2017; Berens et al., 2018; Tai Chui et al. 2018;) with multiple outliers doing more exploratory work.

When it comes to students dropping out of university, Berens et al. (2018, p. 20) are using administrative data to predict drop-out with an early detection system and after four semesters working with an institution can 'train' the algorithm to improve its predictions from 79% to 90% accuracy. Their work intends to predict dropout and "optimize (prevent or speed up) student attrition through diagnosis and intervention" in order to avoid unnecessary cost for students and prevent wasting public funds. Used ethically, an early detection system holds significant value when it comes to student success in higher education. However, an early detection system itself is morally neutral and could be used by institutions to deny entry or force dropout if students are predicted to drop out. Moreover, as the detection system *learns,* it can learn a bias or error that is difficult to detect resulting in the algorithm producing false positives and institutions being responsible for decision bias that could significantly impact an individual's future (Bostrom & Yudkowsky, 2014).

Narrowing in on the learning and teaching environment, researchers are examining the use of machine learning algorithms to identify students who "require extra attention" (Dambic et al., 2016, p. 1) and to predict academic motivation based on their use of learning management systems and engagement with learning content (Babic, 2017). Babic (2017) compared artificial neural networks, classification trees and support vector machines ’performance on categorizing students on Vallerand et al.'s (1992, p. 455) Academic Motivation Scale. The researcher asserts that all three methods "gained acceptable results" with neural networks outperforming the other methods. However, the neural network only had a 77% classification accuracy. It accurately predicted below-average motivation but dropped to 65% accuracy with its positive motivation predictions. This drop in accuracy suggests that there is a group of students with low motivation exhibiting indicators of positive motivation without actually being positively motivated. The researcher concludes by highlighting the potential value for academic teachers but does not mention the need for teachers to understand the ‘false positive ’errors that could result in some students with low motivation being missed and therefore being overlooked when it comes to executing interventions.

Although the use of machine learning in education holds lots of future potential when it comes to predicting performance and dropout there are limitations in the body of research itself when it comes to identifying the implications for practice. A significant portion of the research presents results with minimal discussion about the benefits and challenges when it comes to implementation (Aulck et al., 2016; Kondo et al., 2017; Pang et al., 2017; Santur et al., 2016; Sohail et al., 2018; Soobramoney & Singh, 2019). The lack of discussion about machine learning implementation suggests that perhaps machine learning and the use of specific machine learning algorithms is best positioned as a research method that enables education data mining and learning analytics. This notion reinforces Ciolacu et al.’s (2018) suggestion that artificial intelligence is the underlying electricity that enables educational data mining and learning analytics research and practice.

Educational Data Mining in Higher Education

According to Linan and Perez (2015, p. 100) educational data mining "adapts statistical, machine-learning and data-mining methods to study educational data." Zhang and Qin (2018) offer a more abstract definition and purpose of solving educational problems using data mining that is similar to Siemen and Baker's (2012) definition at the second Learning Analytics and Knowledge Conference that is cited widely in the subsequent literature (Baker & Inventado, 2014; Blaikie & Priest, 2019; Romero & Ventura, 2012; Siemens, 2013). Although there is no agreed definition such as there is for learning analytics, there appears to be a common understanding amongst researchers and practitioners.

Educational data mining practice is iterative (Linan & Perez, 2015), with researchers and practitioners testing, evaluating, adjusting practice and testing again. The educational data mining analysis process is similar to most research analysis processes with data preparation, data mining, analysis and evaluation phases. However, in many cases, the data is from existing educational data sets as opposed to being purposefully collected and therefore requires more data cleaning in the preparation phase (Zhang & Qin, 2018). As educational data mining practice has grown, the research community has attempted to sub-divide the practice down in different ways.

Aldowah, Al-Samarraie and Fauzy's (2019) recent review identified four sub-sections: learning analytics, predictive analysis, behavioural analytics and visualisation. They suggest that educational data mining is the underlying infrastructure or processes that are used for multiple purposes. Linan and Perez (2015) organise the existing research based on how educational data mining is being used. Some of the uses, like predicting student performance (Ba Saleh, 2017; Mimis et al., 2019; Rojanavasu, 2019) and predicting dropout (Simon et al., 2019; Sukhbaatar et al., 2018; Tasim et al., 2019) are utilized more like business analytics to predict and plan for institutional performance. Other uses, like adaption of content based on predictive models (Appalla et al., 2017; Jugo et al., 2016; Wongwatkit & Prommool, 2018) and student grouping and profiling (Kurdi et al., 2018; Linan & Perez, 2015; Nuankaew et al., 2019), are utilized for learning and teaching. There are several other attempts at classifying the educational data mining literature (Bakhshinategh et al., 2017; Manjarres, Moreno Sandoval & Salinas Suarez, 2018; Regis Lyra Bezerra da Silva et al., 2019; Thakrar, Jadeja & Vadher, 2018) suggesting that the field has hit adolescence and is trying to define itself.

Overall, there are three main types of literature available in the educational data mining body of knowledge:

- research that attempts to classify and define the overall practice of educational data mining (Aldowah et al., 2019; Bakhshinategh et al., 2017; Manjarres, Moreno Sandoval & Salinas Suarez, 2018; Regis Lyra Bezerra da Silva et al., 2019; Thakrar, Jadeja & Vadher, 2018);
- research focused on evaluation or comparison of different educational data mining methods (Abdar, Zomorodi-Moghadam & Zhou, 2018; Rambola et al., 2018; Ramos et al., 2016); and

- research that uses educational data mining as a research method to generate insights (Appalla et al., 2017; Ashraf et al., 2018; Jugo et al., 2016; Simon et al. 2019; Wongwatkit & Prommool, 2018).

There is also a lack of research that combines data-mining techniques with educational theory. Kurdi, Al-Khafagi and Elzein (2018) attempt to understand students' behaviour using data-mining techniques but fail to leverage existing educational theory such as learning orientation (Elliot & McGregor, 2001), growth mindset (Dweck & Yeager, 2019) or approaches to learning (Asikainen & Gijbels, 2017) as a lens, relying solely on random clustering to generate meaning. Nuankaew et al. (2019) utilise educational data mining to explore student perceptions regarding self-regulated learning but do not find a correlation between learning style and behaviour. They intend to collect more data in the future in order to overcome the perception-based bias of students, but it will still be self-perception-based.

Learning Analytics in Higher Education

Unlike educational data mining research, learning analytics researchers have defined their research as "the measurement, collection, analysis and reporting of data about learners and their contexts, for the purposes of understanding and optimizing learning and the environments in which it occurs" (Long et al., 2011, p. iii). This definition is widely acknowledged and supported within the literature (Clow, 2013; Gasevic et al., 2015; Gasevic et al., 2017; Kim & Moon, 2018; Long & Siemens, 2011). The definition frames the purpose of learning analytics to be the improvement of learning and teaching (Clow, 2013) in contrast to educational data mining that appears to focus on educational business decision-making and *customer* (student) retention.

Despite the difference in purpose, the iterative processes and research methods used in learning analytics research are similar to educational data mining (Clow, 2013). The primary distinction between the two is the requirement that learning analytics research asks "clear pedagogical questions" (Bronniman et al., 2018, p.354). Learning analytics research uses a wide variety of methods for generating insight and understanding learning and the learning environment, but the overall approach tends to follow a process of select, capture, aggregate, report, predict, use, refine and share (Jeong, 2016; Kim & Moon, 2018; Lias & Elias, 2011).

The literature on the use of learning analytics in higher education is split into two areas: how to capture data in useful ways and how data and insights can be used in the practice of learning and teaching (McKee, 2017). The latter is less prevalent (Ferguson et al., 2014; Lockyer et al., 2013; McKee, 2017; West et al., 2016; Wise, 2014; Wise et al., 2016) perhaps due to the notion that learning analytics research builds on educational theory (Gasevic et al., 2017). This notion may be why there is such a prevalent call for a deeper connection between learning analytics, learning theory and learning science (Avella et al., 2016; Gasevic et. al., 2014; Gašević et al., 2016; Gasevic et al., 2017; Kirkwood & Price, 2013; Lockyer et al., 2013; Lodge & Corrin, 2017; Lodge & Lewis, 2012; McArthur et al., 2005; Reimann, 2016; Rogers et al., 2016; Wise, 2014; Wise & Shaffer, 2015). The integration of learning analytics and learning theory holds significant benefits to students, including the optimization of learning pathways, personalized interventions and scaffolding (Bronnimann et al., 2018). It can also be used to provide a more holistic view of the learner so that the teacher can use the information to intervene in the learning process (Hernandez-Lara et al., 2019; Alblawi & Alhamed, 2017).

The core ethical concerns surrounding the use of big data in processes like learning analytics lies in the use of personal data (Drachsler & Greller, 2016; Hoel & Chen; 2019; Ifenthaler & Schumacher, 2016; Polonetsky & Tene, 2013; Rubel & Jones, 2016; Slade et al., 2019; Young, 2015). Knight et al., (2016) conducted a research study to understand the perspectives of instructors and students when it comes to learning analytics. The research found that students expressed concerns about what elements of their data faculty should have access to suggesting the option of either opting in or out (p. 222); a sentiment mirrored by instructors when it came to individual student data, preferring overall insights based on the cohort data to avoid bias (p.229).

The concern about data privacy is mirrored if not elevated in the literature when it comes to using student data for learning analytics research (Cormack 2016a; Cormack 2016b; Datatilsynet, 2013; Hoel & Chen; 2018; Hoel & Chen; 2019; Zeide 2017). This concern is particularly pertinent when personal data is being used by parties outside the learner/teacher relationship for the training of algorithms and development of predictive models. The conversation about data privacy in this context centred around legitimate interest; whether the action is for public benefit. In learning analytics and machine learning within an education paradigm, education technology companies and higher education institutions would argue that the algorithms and predictive models developed serve the public interest. GDPR and other data privacy law raises a caveat to legitimate interest with the impact and risk for the individual's data being processed (Cormack, 2016a). One of the ways the impact and risk to individuals is being minimised is through data de-identification and the development of risk matrixes and processes to test for re-identification (Khalil & Ebner, 2016).

The literature highlights notable limitations when it comes to the use of learning analytics in teaching and learning (Bronnimann et al., 2018; Davis et al. 2017; Wise et al. 2016). Bronnimann et al. (2018) found that academics are still apprehensive about learning analytics and have the propensity to think in terms of small data, thus limiting the potential impact learning analytics could have when augmenting the teacher/student relationship. Davies et al. (2016, p. 1) found a limitation when it came to learning designers if their approach to design focused only on "content and control" at the surface and failed to consider the deeper layers like data-management. This sentiment is reinforced by Behrens and DiCerbo (2014) and Wise et al. (2016) who suggest designers should design with data capture and use in mind as opposed to settling for whatever happens to be collected. On the institution level and perhaps even the macroeconomic level, there is a lack of available resources when it comes to physical and human resources with the necessary skills (Bronniman et al., 2018).

Despite the ethical concerns and current challenges of learning analytics research, the literature highlights a vast array of potential particularly when it comes to how learning analytics are used in the practice of teaching and learning (Wise et al., 2016). Three areas of future potential in the use of learning analytics in teaching and learning that are relevant to this research are the use of personality factors to better understand learners; the increasing prevalence of learning analytics in classes utilizing active learning pedagogies; and real-time measurement of motivation. Alblawi and Alhamed (2019, p.128) examined the use of natural language processing (NLP) for improving student performance predictions and found that "taking sentiment into account alongside other personality factors produced more accurate results". They are suggesting that personality factors impact learning and, therefore, should be considered when supporting a student through a learning experience.

Hernandez-Lara et al. (2019), use NLP to better understand the interactions of learners in a simulation game where learning happens through social construction (Kent, et al., 2016). The study examined and classified the social interactions in order to understand the different types of interactions and whether there was a correlation between specific interactions and outcomes. The study shows the potential for the use of learning analytics in courses that use active learning pedagogies and requires learning analytics to extend beyond content consumption and log data analysis. The preliminary identification of links between particular social interactions and performance suggests that learning analytics can be used by educators to examine students' acquisition and use of concepts 'in-progress' as opposed to evaluating a summative assessment. This notion is reinforced by Knight et al. (2014), who frame the way teachers use learning analytics as their pedagogical choice and suggest that constructivist learning analytics focus on learning progress, not outcome. Wise et al. (2016), take the use of learning analytics in active learning one step further, suggesting student use of learning analytics to support the metacognitive function of self-regulation required in active learning.

Gasevic et al. (2017), attempt to understand the real-time motivation level of students in a learning experience by combining emergent study strategies based on trace data and self-report results based on a well-known instrument for identifying learning motive and learning strategy based on Biggs' (1987) approaches to learning. The research found correlations between four emergent study strategies and the four categories of the self-report instrument, suggesting that perhaps trace data can be used to identify motivation in real-time and be used by instructors to "derive specific recommendations for their students" (Gasevic et al., 2017, p. 123).

Emerging Technology in Higher Education Experiential Learning and 21st Century Skill Development

Although the literature focused on emerging technologies in classes that utilize active learning pedagogies is increasing, there is limited focus on the use of emerging technologies in courses that use experiential learning pedagogy to develop 21st Century Skills. A conceptual paper at the 2018 Australian Cooperative Education Network conference suggested the potential use of learning analytics to the community of educators focused on this practice but did not present any research findings (James et al. 2018). James, Humez & Laufenburg (2020) present a 'virtual 'internship model that is designed for data management, overcoming Davies et al.'s. (2016) highlighted limitation when it comes to the design of learning. However, the research project is yet to present any explicit research findings.

The only literature found on the use of machine learning, educational data mining or learning analytics with either experiential learning or 21st Century Skill development focused on the use of games for measuring persistence in elementary school students (DiCerbo, 2014). However, Wise et al. (2016) present a process model of self-regulation informed by learning analytics analysis that is markedly similar to Kolb's experiential learning cycle (Kolb, 1984) without making the connection to the existing educational theory: a specific example of the acknowledged and highly cited 'gap' in learning analytics research (Avella et al., 2016; Gasevic et al., 2014; Kirkwood & Price, 2013; Lockyer et al., 2013; Lodge & Corrin, 2017; McArthur et al., 2005; Reimann, 2016).

Conclusion

This review of literature on the 4th Industrial Revolution, 21st Century Skills, the experiential learning cycle and emerging technologies within the context of higher education covers a broad base of literature. The objective of this broad-reaching review was to present a conceptual hypothesis for the need for this research project and perhaps the development of a new research field. The broad base of the literature makes it difficult to identify any explicit main agreements and disagreements of the literature overall. However, it does highlight the lack of connectivity between these four bodies of research and the potential their integration holds. The overarching commonality from the four bodies of literature is that higher education needs to not only incrementally innovate but transform itself in order to continue to add value in the 4th Industrial Revolution.

From my perspective, the literature determines that successful contribution to work in the 4thIR requires not only domain knowledge but lifelong development of 21st Century Skills. The literature highlights that using experiential learning and the experiential learning cycle to develop 21st Century Skills holds potential, but research examining this is limited in volume and scope. The notion that a revolution's emerging technologies hold the keys to solving the problems it creates suggests that perhaps artificial intelligence and big data analytics, if used with caution, could be utilized to enable more use of experiential learning pedagogies for the development of 21st Century Skills. The next chapter offers an illustration of an experiential learning program and technology platform that integrates learning theory and learning analytics in the design of the technology, the instructional design of the experiential learning program and the facilitation of the experiential learning program.

Chapter 3: Learning Context

Introduction

This study will be conducted using de-identified and retrospective data from an experiential learning program. Firstly, this chapter will outline the experiential learning program, its context, program structure and assessment items. This will also include a detailed explanation of two reflection exercises and a demographic survey that results in the choice of learning instruments and theory used and examined in the study. Secondly, this chapter will discuss the nature of the three learning theories and how they can contribute to how students engage in learning.

Experiential Learning Program

Practera is an experiential learning technology start-up that provides experiential learning services and technology to higher education institutions. Practera's experiential business project program (hereafter referred to as EBP) offers university students, studying in Australia, the opportunity to do a three-week real-world business analyst project for an industry client. Students participating in the EBP are a mix of domestic and international students, undergraduate and postgraduate students studying in multiple faculties from over ten different universities. The majority of international students participating in the program are from the Asia and Pacific regions, particularly China and India. The majority of student participants are from engineering, technology and business faculties.

During the EBP students work in teams of four or five to deliver a real project to an industry client. Practera's learning facilitation team recruits industry clients. Each industry client brings a real project to their team of students and is required to provide feedback and support to their team as they deliver the project. The industry clients are a mix of small businesses, technology start-ups, large corporations, not for profit organisations and government departments. The types of real-world projects student teams work on include social media analysis, competitor analysis and product comparisons.

The EBP is designed to develop students 21st Century Skills (WEF, 2015) and is delivered using Practera's experiential learning management system (eLMS). Before the start of the EBP students are allocated to a team, assigned a client and project, then enrolled on the eLMS. The eLMS is facilitating the learning of theoretical learning content and capturing the results of learning that takes place as students complete their industry client's project. The eLMS contains all the learning content, facilitates all submissions of work to and feedback from industry clients and other team members. The eLMS steps each team through all the learning content and tasks required to complete their client's project. Practera's facilitation team uses a learning analytics dashboard to monitor team progress, team cohesion, and client engagement, and to offer support through gamification-based incentives and tailored facilitator interventions.

The EBP acts as the catalyst for students to develop their teamwork skills, communication skills, critical thinking skills and business analysis skills. The learning outcomes of the program are:

- Generate, manage and execute a business project using agile project management methodology;
- Apply theoretical concepts and skills in a real work environment;

- Apply reflection techniques to identify key learning points;
- Engage relevant stakeholders to seek feedback and apply insights to a business project.

Program Structure

The EBP is delivered over three weeks and is highly structured. The structure enables scalability and drives learning outcomes for students and project outcomes for the clients. Figure 1 outlines the structure of the EBP, including when student teams focus on different activities related to their client's project and when they are required to submit project tasks to their client for feedback.

Figure 1

The EBP - Structure and Learning Content

Week	Topic	Content Overview	Deliverables
0	Welcome	Students invited to enrol on Practera, complete Practera familiarisation and attend orientation workshop	Self Assessment + Skill Development Plan
1	Project Plan	Students create a project plan and submit it to their client for feedback	Project Plan
2	Project Execution	Students complete the client project and create a draft project report to submit to the client for feedback.	Draft Project Report Self & Peer Assessment # 1 Skill Development Plan Revision
3	Project Presentation	Students use feedback to finalise the project report and plan their presentation.	Project Presentation + Project Report Self & Peer Assessment # 2

Client Project Submissions

Throughout the EBP, student teams submit items related to their client's project for feedback. Additionally, student’s complete reflection exercises, self-assessments and peer-assessments on collaboration skills. Figure 2 provides a brief overview of the project deliverables and assessment items and their relevance to the learning outcomes.

Figure 2

The EBP - Assessable Items

Deliverable	Description	Learning Outcomes	Format / min. requirement	Primary Feedback	Recommended weight
Project Plan	A Project Plan that re-states the project brief, provides an overview of the project plan and schedules all relevant meetings	1,4	500 words	Industry Client	20%
Draft Project Report	A Draft Project Report outlining key findings for the project conducted.	1,4	500 words each	Industry Client	10%
Project Report & Presentation	Generate written report and presentation that provides an overview of the project. This submission includes all project documents, code, formulas etc.	1,2,4	10 min Presentation, 10 min Q&A + Project Report or Project Documentation	Industry Client	40%
Teamwork Skill Development	Completion of 2 skill development plan, 3 self-reviews on teamwork skills and 2 peer reviews of teamwork skills	3	2 x 500 words	Team Members	30%

Reflection Exercises

Throughout the EBP students have the opportunity to complete reflection exercises designed to help students examine their overall approach to the industry project they are completing. These reflection exercises were designed into the EBP to:

1. Facilitate the development of students' metacognition
2. Provide a structured reflection process that explicitly stepped the students through the experiential learning cycle in order to extract learning that extended beyond the application of their technical skills.

In these two reflection exercises, the students complete a self-assessment instrument and provide instructions that help them reflect on the results of the instrument and how the insights gained from the survey could help them understand their past behaviour and plan their future behaviour. The two instruments used for these reflection exercises are:

1. Revised Two Factor Study Process Questionnaire (Appendix 1)
2. Revised Implicit Theories of Intelligence Survey (Appendix 1)

Demographic Data Survey

Prior to starting the EBP students are asked to complete a demographic data survey. The original intention was to gain practical information about the learner that helped provide insights that enabled the program facilitators to match the student with an appropriate team and an appropriate industry client. Three of the questions on the demographic survey ask about the students learning history. After facilitating the EBP multiple times it appeared that students with different learning histories were experiencing different types of challenges engaging in the EBP. As a result, the information from the learning history survey began to be used to identify students that the facilitators needed to proactively support in order to ensure they have a successful first engagement with their industry client.

Learning Theories

The concept of learning styles suggests that each learner comes to the learning environment with their unique traits, characteristics and behaviours. These include cultural dimensions (Hofstede, 1983), ethics of learning (Kwak, 2016), learning orientation (Beaty, Gibbs & Morgan, 1997) and habits (Lally, van Jaarsveld, Potts & Wardle, 2010). Moreover, each learner uses different approaches to learning (Entwistle, 1988), have different learning styles (Fleming, 2006; Kolb, 1984) and are at different stages of knowledge acquisition and use with each subject matter (Dreyfus & Dreyfus, 1984). Meta-analyses of individual learning theories and approaches found varying degrees of empirical evidence when it comes to learning theories that attempt to identify different characteristics and behaviours of learners (Pratt et al., 2009).

It is also important to note the substantial critique for the notion of learning styles in the literature. In 2004, Coffield et al. provided a systematic and critical review specifically highlighting the lack of unity within the field and conflicting assumptions that different learning style theories are built on. These fundamental critiques of the notion of learning styles are still present in the literature today. A common argument against the categorisation of students into learning styles today is that the process used to categorize students is subjective. Moreover, that studies using more objective and quantitative research methods have not found any evidence to substantiate the categorisation (Kirschner & van Merrienboer, 2013; Knoll, Otani, Skeel & Van Horn, 2016; Rawson, Stahovich & Mayer, 2016). The subjectivity of learning theory categorisation is attributed to the self-reporting nature of instruments. Rawson et al. (2016) claim that students do not have the ability or willingness to accurately assess themselves. Despite the substantial critique the intuitive notion that a student's beliefs, motivations, habits and past experience impact student's behaviour while learning is still intact. Perhaps the use of learning analytics in the examination of how student's mindsets, approaches to learning and learning history interplay in an experiential learning program could provide a more objective method of identifying a learners 'behaviour in real-time. Moreover, using learning analytics to perform the analysis in real-time may pick up the fluidity as students behaviour changes in response to the environment, task at hand and other factors known to influence a learner's behaviour.

An additional gap in the literature related to the concept of classifying learners based on their characteristics is in how research aggregates these characteristics, behaviours and preferences, particularly how they interplay in a learning experience (Narciss, Proske & Koerndle, 2007; van Seters, Ossvoort, Tramper & Goehart. 2012). Practera's EBP outlined above provides an opportunity to examine the behaviour of learners engaging in the EBP and identify relationships between particular behaviours and their self-assessment scores on validated instruments and their answers in a demographic survey. The data-set available from the EBP provides the opportunity to examine the relationship between learning history, approaches to learning and mindset and a learner's behaviour while participating in the EBP.

Learning History

Learning history brings into the equation the notion that a learner's history of learning or past learning context predisposes them to different learning outcomes and processes (Kwak, 2016). High and low context culture first introduced by Edward T Hall in the 1950's continues to be used today, as a vehicle with which to examine the differences between learners from different cultures (Bent, 2018; Qureshi et al., 2017). Yu (2005) proposes that a Socratic learner is encouraged to question social values as opposed to a Confucian learner who is encouraged to conform to social values. Moreover, Heng (2013) proposes that one of the fundamental differences between these two educational philosophies is their perspective on engagement in the political arena, insofar as Socrates preferred to "find truth within one's self" (p.86) and Confucius believed that "holding office in the government would be the best future" (p.87). This difference in perspective has contributed to the cultural difference of individualism (Socratic) and collectivism (Confucian) that underpin the approaches to education in each context.

Approaches to Learning

Marton and Saljo (1976) present two distinct learning processes humans use: surface learning that focuses on memorisation of facts and main points and deep learning that extends beyond memorisation of facts and points to meaning-making. A third learning process called strategic learning was introduced by Entwistle (2000). This third learning process suggests that learners who select the most appropriate learning process for the situation presented to them as opposed to always adopting the same learning process. In 2001, Biggs Kember and Leung (2001), published The Revised Two Factor Study Process Questionnaire designed to evaluate the learning approaches of students. This survey has been used to understand the nature of a student's approach to learning and how their approaches are impacted by their environment and learning content. Sengodan and Iksan (2012) found that intrinsic motivators like effort and self-efficacy are significantly linked with a students 'approach to learning. Dolmans et al., (2016) found that interest in a topic, having an appropriate amount of time and prior learning experiences that are positive can contribute to a student selecting deep approaches to learning. Alternatively, a lack of interest in the topic, not enough time and lack of background knowledge can contribute to a student selecting surface approaches to learning (Biggs, 1999; Entwistle, 1998; Ramsden, 1992).

Mindsets

'Mindset' is the term used by Dweck (2017) to describe the self-concepts people use to drive their behaviour. Dweck's theory suggests two different self-concepts related to learning ability that drive motivation and achievement:

1. Fixed Mindset: the notion that human abilities and intelligence are fixed traits;
2. Growth Mindset: the notion that human abilities and intelligence can be developed with persistence.

In 2015, De Castella and Byrne developed The Revised Implicit Theories of Intelligence (Self-Theory) scale in order to measure student's belief about their own intelligence. Holistically, people who lean towards a fixed mindset invest time proving their level of intelligence to others. Conversely, people who lean towards a growth mindset believe their intelligence is just a starting point and invest their time developing it (Dweck, 2017; Hochanadel & Finamore, 2015; Zhang et al., 2017).

Conclusion

Using the data from the EBP to aggregate learning analytics analysis and these learning theories will help me explore connections between what is known about learning history, approaches to learning and mindsets and learners' behaviour while engaging in an experiential learning program. This exploration will help me understand how technology might be able to identify these characteristics and recommend tailored interventions for individual learners that are underpinned by insights from learning theories.

The choice of learning theories is limited to these three as the surveys mentioned were already built into the design of the EBP program that produced the de-identified retrospective dataset. These learning theories are often positioned in the literature as binary choices. However, the use of learning analytics and regression analysis based on a learner's score that indicates a tendency towards fixed mindset, growth mindset, deep approaches to learning, surface approaches to learning, Confucian learning history and Socratic learning history enabled them to be dealt with on a spectrum instead of a binary choice.

Focusing on these theories also helps me explore how learning designers and facilitators can use these specific real-time insights about learners to tailor learning programs and support for students. Hence, a focus on these three theories, despite the limited choice, helps me to answer the research questions identified and discussed at the start of the next chapter.

Chapter 4: Methodology

This chapter explicitly works through the methodology and research methods used in this research project. Beginning with the hypothesis, the methodology outlines the philosophical foundations of the research design, my position and the lens I intended to look through when conducting this research and a detailed description of the research design. Finally some critical ethical issues are identified, and the following steps that were taken to mitigate the risks described.

The Hypothesis

The hypothesis at the heart of this research project; and the research questions and the objectives that have driven the research design (particularly the decision to use multiple regression analysis) as my method of analysis is: **that data created by learners and captured by an experiential learning platform can be predictive of learners 'perspectives, mindsets and skills.** Moreover that those perspectives, mindsets, and skills can impact the extent to which a learner acquires the technical skills of focus in an experiential learning program. Furthermore displaying the current state of learners' perspectives, mindsets, and skills to an experiential learning facilitator using a learning analytics dashboard could enable the facilitator to intervene in a student's learning experience with a more tailored support and feedback model. This tailored feedback could provide an increased positive impact on the extent to which a learner acquires the learning outcomes of the course.

Theoretical Justification for Hypothesis

The theoretical justification for the above-mentioned hypothesis that is driving this research, draws on the broad base of literature presented and discussed in Chapter 2: Literature Review. Specifically Heslin and Keating (2017) examined this phenomenon within the context of using experiential learning for developing leadership capability. They describe "how the extent to which leaders are in *learning mode* stems from salient mindset cues and guides whether they work through the experiential learning process with a predominantly self-improvement or self-enhancement motive" (Heslin and Keating, 2017, p. 367). Their research suggests that learners' mindsets impact their acquisition of knowledge in an experiential learning program. Suggesting that learners' mindsets are an important element for experiential learning facilitators to attend to. Perhaps being able to use learners data to identify mindsets and other components of learners behaviour would be valuable for both facilitators and students.

Educational research has a long history of examining learners' traits, perspectives, and behaviours; particularly developing and using self-reporting instruments. Araka et al (2020) and Covacevich (2014) use self-reporting instruments to measure the impact of an educational intervention and its intended learning outcomes. Conversely learning analytics researchers claim that "there is no real scientific basis" (p. 167) for the notion of learning style inventories and instruments (Kirschner, 2017). A prior study by Kirschner & van Merrienboer (2013) concluded that cognitive abilities rather than learner styles should be considered when designing interventions. Moreover that they "should be objectively measured on an ordinal scale" (p.6) rather than based on subjective and "more arbitrary criteria" (p. 6).

If learning **data created by learners and captured by an experiential learning platform is predictive of learners' perspectives, mindsets, and skills** it could be used as an objective measure of learners' styles, where learning styles are used in the broader sense of *dichotomous learning styles in the literature,* as opposed to the VAK learning styles specifically (Coffield et al., 2004). In addition to the value of this research for experiential learning facilitators, it could provide a specific point of collaboration for educational researchers and learning analytics research practitioners. A direct response to the call from both research communities for deeper integration and collaboration (Avella et al., 2016; Gasevic et. al., 2014; Gašević et al., 2016; Gasevic et al., 2017; Kirkwood & Price, 2013; Lockyer et al., 2013; Lodge & Corrin, 2017; Lodge & Lewis, 2012; McArthur et al., 2005; Reimann, 2016; Rogers et al., 2016; Wise, 2014; Wise & Shaffer, 2015).

Potential Impact on the Facilitation of Experiential Learning

At present to display the insights about learners' perspectives, mindsets and skills in learning management systems used to support experiential learning programs would require a significant amount of work for the facilitator. The facilitator would need to:

- select the insight they think is meaningful when supporting their students,
- examine the academic literature to find an instrument for measuring meaningful insight,
- embed the validated instrument in their course,
- use customizable data dashboard graphs to display the information in their interface.

At present, Jona and James (2021) embedded the PRO-SDLS (Stockdale & Broket, 2011) as a measure of self-direction to evaluate a 'Virtual Internship' intervention (James et al., 2020) and used the approach mentioned above to display the responses to each question on the teacher dashboard. In an analysis focused on the impact of teacher movements and how those movements are echoed in learners' behaviours (Jona & James, 2021), the study of teachers support did not suggest any usage of the displayed responses from the PRO-SDLS (Stockdale & Broket, 2011).

Suppose that the data created by learners and captured by an experiential learning platform predicts learners' perspectives, mindsets, and skills. In that case this analysis could be built into the technology itself and not require the use of the self-reporting instrument. Perhaps this analysis addresses learning analytics researchers concerns about the subjective nature of self-reporting instruments (Kirschner, 2017) and the ethical concerns raised about learning analytics being used in an evaluative way to predict performance (Ba Saleh, 2017; Mimis et al., 2019; Rojanavasu, 2019) and dropout (Simon et al., 2019; Sukhbaatar et al., 2018; Tasim et al., 2019).

One way to achieve this goal is to test the hypothesis; that is the cornerstone of this research, to examine whether any data from the eLMS has any predictive power when it comes to learner perspectives, mindsets and skills. If any learning data appears to have any predictive power the results of the analysis could be used as a baseline for developing machine learning algorithms (Li et al., 2020) for measuring perspectives, mindsets and skills. With the goal of testing the hypothesis and developing baselines for machine learning algorithms that measure perspectives, mindsets and skills in mind the objective of this research project is:

- To see if learning data from an eLMS could be used to predict a learners perspectives, mindsets and skills.

- Present baselines (Li et al., 2020) that could be used to develop machine learning algorithms for measuring students' perspectives, mindsets and skills.
- To gain insight from the relationships between the learners data and their perspectives, mindsets and skills that might lead to additional data and analysis techniques that could contribute to the algorithm development.

Research Questions

As mentioned above my aim for this research is to understand how data produced by a learner during an experiential learning program that is supported by experiential learning technology could be used to understand more about students' perspectives, mindsets and skills. A secondary aim is to examine whether this understanding could provide learning designers and experiential learning facilitators insights that could help them to tailor programs, designs and facilitator supports to improve student learning.

The learning program that provided the context for this research was a technology-enabled experiential learning program (outlined in Chapter 3) where students work in teams for three weeks to deliver a business project for a client.

The specific questions of focus are:

1. Which data captured by an experiential learning technology can be used to understand more about students' perspectives, mindsets, and skills?
2. How can data captured by experiential learning technology be used to understand more about students' perspectives, mindsets, and skills?

3. How can understanding more about students' perspectives, mindsets, and skills be used by learning designers and facilitators to support their practice in experiential learning environments?

Philosophical Foundations

To effectively present the methodological approach for this doctoral research project it is vital to understand my philosophical perspective. My philosophical perspective has driven the design and subsequently the data analysis and interpretation of the data. Cohen et al., (2007) presents two conceptions of social reality: the subjectivist approach and the objectivist approach. Which stems from Burrell and Morgan's scheme for analysing assumptions in social science research (2005). The subjectivist approach includes a normalist ontology and anti-positivist epistemology. Conversely the objectivist approach includes a realist ontology and positivist epistemology. Given my philosophical perspective, I leverage assumptions from both the subjective and objective dimensions. I believe that looking at a phenomenon from both vantage points can offer two truths that lie in tension with one another and perhaps offer more value when used together as opposed to denying one perspective for the other.

This doctoral research project stems from a realist, anti-positivist idiographic perspective (Cohen et al., 2007) that perceives agency (Bandura, 2001) as the driver of an individual's choice between determinism and voluntarism (Burrell & Morgan, 2005) at each point of actuality (Sachs, 2005). The anti-positivist idiographic epistemological and methodological stance comes from the subjectivist perspective that humans are unique, irrational and therefore unpredictable. This anti-positivist perspective suggests that using learning analytics and learning theory-based classification of learner behaviour is impossible. However, overlaying this with the human neurological behaviour of wiring synapses together causing chain-reactions and habits that are harder to break based on the duration and pervasiveness of the behaviour suggests that although humans are in essence unique and irrational our learned behaviour can be predicted (Wood & Runger, 2016). Neurological research (Mendelsohn, 2019) suggests that although we have the capacity for future goals to drive our decisions and actions, a significant amount of our daily behaviour is driven by habit. However as humans we can change the biological and behavioural functions of our brain (Ford, 1987) and at each point of actuality we either rely on habit (deterministic) or intentional choice (voluntarism) in our response. It is this perspective and notion that underpins the foundational stance of this research.

Positionality

Both my philosophical perspective and professional experience outlined in Chapter 1 have driven the intent, purpose, methodology and methods of this research design. However a secondary driver of the research design and specifically the methodology choice is for the research to impact my practice in eLMS design. My practice sits in the middle ground between computer science, learning analytics, instructional design, learning theory and experiential learning. Each of these domains has a common body of knowledge and community of practice, some of which conflict with each other. For example learning theory research practice is knowledge-driven, and learning analytics and machine learning research is data-driven (Kitchin, 2014). Experiential learning research tends to relegate technology to facilitating operational tasks (Beckem & Watkins, 2010; Pangelinan et al., 2018), whereas technology is an assumed element of learning analytics research. Furthermore both learning analytics research and educational research highlight the need for collaboration (Gasevic et al., 2017; Gašević et al., 2016; Lodge & Lewis, 2012; Rogers, Gašević, & Dawson, 2016; Wise, 2014; Wise & Shaffer, 2015; Avella et al., 2016; Gasevic, Dawson & Siemens, 2014; Kirkwood & Price, 2013; Lodge & Corrin, 2017; Lockyer, Heathcote & Dawson, 2013; McArthur, Lewis & Bishay, 2005; Reimann, 2016) but this collaboration is yet to emerge in any substantial way.

To build technology that not only aligns with but is integrated with experiential learning design and facilitation, requires computer scientists, learning analytics researchers, instructional designers, learning scientists and experiential learning facilitators to innovate collaboratively together. Kristinsson, Candi & Sæmundsson (2015, p. 464) found that "informational diversity is positively related to both idea generation and the implementation of ideas." Hence, the diversity of perspective of these Communities of Practice (Lave & Wenger, 1998) is an asset and holds the potential to not only generate ideas but implement them. However this potential cannot be realised without teamwork. Katzenback & Smith found that a team needs not only a common purpose and goals but a common approach (2015). The design of this research aims to show an approach that these diverse perspectives can use to collaborate to improve learning and teaching of 21st Century Skills through experiential learning.

Research Design

To achieve the research objectives and answer the research questions, I will use data produced by learners during an experiential learning program in several multiple regression analyses. Multiple regression analysis "allows researchers to assess the strength of the relationship between an outcome (the dependent variable) and several predictor variables as well as the importance of each of the predictors to the relationship" (Petchko, 2018, p 259). Researchers can use multiple regression analysis to predict outcomes and make causal inferences (Pederson, 2018). Two types of data can be used in multiple regression analysis, continuous variables (e.g. Likert scales) and categorical data (e.g. Categorisation of learning tasks) (Pederson, 2018). This research project will use continuous variables and categorical data for the dependent variables and categorical data for the independent variables. How I selected these variables, and the approach I used to categorise the data is described below.

Intuition that drives the hypothesis

When using multiple regression analysis in research a hypothesis is formulated based on the researcher's intuition or expert knowledge (Pederson, 2018). Pederson (2018, p 2) asserts that "researchers develop a hypothesis about how aspects of a particular phenomenon are related to one another and test those relationships by creating a model that explains the various relationships." In essence the hypothesis is the cornerstone of the research design. It drives the decision-making when it comes to the methodology, results reported, and the research implications for further research and in practice.

The hypothesis at the heart of this research design is that **data created by learners and captured by an experiential learning platform can be predictive of a learner's perspectives, mindset and skills**. This hypothesis stems from my years of experience designing and facilitating experiential learning programs in face-to-face and technology-mediated contexts. In essence my professional experience designing and facilitating experiential learning programs was where I developed my hypothesis "about how aspects of" this particular "phenomenon related to one another." This research project allows me to "test those relationships by creating a model that explains the various relationships" (Pedersen, 2018, p 2).

Throughout my professional practice (or hypothesis development phase) I invested time in designing experiential learning programs and facilitating and assessing students participating in them. Throughout this time I have seen patterns in my behaviour and the behaviour of the students. In my behaviour facilitating and assessing I noticed patterns in the way I framed feedback for different students. In students' behaviour I saw various common patterns in program engagement after feedback points from either peers or clients. This pattern identification suggests that students time on task could indicate a learners' engagement in the experiential learning program, similar to Kovanovic et al. (2015) and Stallings (1980) assertion that time on task contributes to learner success. Suppose students' engagement patterns were notably changing after feedback from peers and industry clients. This phenomenon is aligned to research into the impact of feedback on human behaviour from both a behavioural and cognitive perspective (Baker & Buckley, 1996), suggesting that perhaps time on *type of* task is a more specific unit of analysis to use in this research project.

This intuition was further confirmed in 2015 when I facilitated more than five cohorts of 50 students each, a total of 250 students, in an innovation and teamwork experiential learning program. At the same time I was undertaking a course of my EdD focused on learning theory and realised the differences in students' patterns of behaviour could be linked to the learning theory I was learning about in class. Furthermore I observed that time on *type of task* could contribute to closing the gap between educational research and learning analytics research and the explicit criticism by Kirschner (2017) that "there is no real scientific basis" (p. 167) for the notion of learning style inventories (discussed earlier in this chapter).

Since that time utilisation of these patterns and my understanding of learning theories like growth mindset (Dweck, 2017) and approaches to learning (Marton & Saljo, 1976) has helped me improve the design of multiple experiential learning programs. Moreover I intentionally consider these patterns of behaviour and my understanding of learning theory in my feedback to students when I am facilitating experiential learning programs. Ultimately my curiosity has led me to explore whether these behavioural patterns picked up in the learner data link to learners' perspectives, mindsets, and skills and whether they could provide a baseline (Lieu et al., 2020) for objective measurement of learning styles using a machine learning algorithm. Furthermore examining whether displaying this information for teachers could improve and perhaps enable the scalability of experiential learning programs.

Choice of data and learning theories used as dependent and independent variables

I did not have complete agency over the choice of learning theories focused on in this analysis or the instruments used in this analysis. As mentioned in Chapter 3: Learning Context, the questionnaire for learning history (Kwak, 2016) and instruments used for mindset (Dweck, 2017) and approach to learning (Marton & Saljo, 1976) where embedded in the Experiential Business Project (EBP) that the de-identified, retrospective data used in this analysis came from. Despite the lack of choice I did not feel that it limited my ability to answer the research questions or achieve the objectives outlined earlier in this chapter. In fact, similar to Callahan, Ito, Campbell and Wortman's (2019) study focused on career identity development in experiential learning programs, the choice of instrument is not critical to the analysis. The focus of this research is centred around whether learning data *could* measure learner preferences, mindsets and skills not *which* preferences, mindsets and skills it could be used to measure. Therefore I chose to use the de-identified and retrospective dataset that is available to me for this research. As a learning designer and facilitator of experiential learning programs in Practera I have used the company's eLMS Practera to design and facilitate experiential learning programs focused on 21st Century Skill development for five years. Use of this de-identified and retrospective data set in this study afford me an insider perspective that is useful for this project.

Beyond convenience I chose this context and this data because it is where the above-mentioned hypothesis emerged. As previously discussed Pederson (2018) highlights that when multiple regression analysis is used in research it is centred around a hypothesis that emerges from the researcher's intuition and expert knowledge. Since the hypothesis emerges within the context of the Experiential Business Project, outlined in detail in Chapter 3: Learning Context, it seems appropriate to conduct the research within this context. Additionally my intricate knowledge of the learning outcomes of the Experiential Business Project (EBP), the theoretical and pedagogical foundations of the EBP design and first-hand experience facilitating the program (in previous years before the data used in this research was captured) affords me a level of expert knowledge when it comes to the interpretation of the analysis.

Independent Variable: Learning tasks and their categorization

In a multiple regression model the independent variables can be used to predict an outcome (Pederson, 2018). The de-identified and retrospective data set acquired for this research includes:

- Student responses to learning theory survey instruments,
- Self and peer assessments on collaboration skills from the start, middle and end of the learning experience,
- Student responses to yes/no questions about team cohesion and project confidence,
- Learning content completion data,
- Client evaluations of team performance on project deliverables,
- Facilitator support intervention logs for teams and individuals,
- Post-program student reflections highlighting key learnings,
- The time and date learners started and completed each learning task in the EBP.

For this research project I chose to use the time a learner spends on different types of learning tasks as the independent variable. This choice stems in part from my intuition and experience facilitating experiential learning programs using the technology platform. Furthermore the choice is backed by learning theory research where time-on-task is acknowledged as a contributing factor of learning success (Kovanovic et al., 2015; Stallings, 1980). Kovanovic et al. (2015, p82) posit that "the amount of time students actually spent on learning has been identified as one of the central constructs affecting learning success." Time-on-task is a quantitative measure. Use of more qualitative data like reflective text analysis or industry client feedback on project artefacts could lead to richer predictions of learners' perspectives mindsets and skills. Selecting time-on-task as the independent variable in this research is achievable for the project and will provide insight into which additional data available in the data set could be useful to improve the baseline (Lieu et al., 2020), answer the research questions further or inform the development of a machine learning algorithm for measuring learners' perspectives, mindsets and skills.

Choosing time-on-task or more specifically 'time on *type* of task requires a layer of dummy coding to reduce each of the learning tasks in the EBP into candidate independent variables. As discussed earlier in this chapter the time on *type* of task centred around client and peer feedback points or lack of feedback points. Table 1: Candidate Independent Variables below lists each learning task (submission or learning content name) and the candidate independent variable category it was placed in (Independent Variable column). For example the Assessment_Draft category includes two items, both items are submissions (type column) of project artifacts (as per Figure 2 in Chapter 3: Learning Context). In contrast the Project_Draft (independent variable column) category contains the learning content embedded in the EBP to guide learners through the process of producing the Draft Project Report in the Assessment_Draft category. Similarly the Self_Peer_Assessment category (Table 1, independent variable column) includes the two submission items where students rate themselves and their peers teamwork skills (as per Figure 2 in Chapter 3: Learning Context) and the Skills_Teamwork category (Table 1, independent variable column) includes the learning content embedded in the EBP to guide learners through the self and peer assessment process.

Table 1

Candidate Independent Variables

Independent Variable	milestone	Type	Submission or Learning Content Name
Assessment_Draft	Week 2 - Project Report	Submission	Project Report (Draft) - Mentor
		Submission	Project Report (Draft) - Client
Assessment_Plan	Week 1 - Project Plan	Submission	Project Plan - Submit to Mentor
		Submission	Project Plan - Submit to Client
Assessment_Report	Week 3 - Project Presentation	Submission	Project Report (Final) - Mentor
		Submission	Project Report (Final) - Client
Orientation	Welcome	Learning Content	Welcome to the Program
		Learning Content	What You Will Learn
		Learning Content	How does this Program Work?
		Learning Content	Program Overview
		Learning Content	How do I get Help?
		Learning Content	Practera Tips
		Learning Content	Welcome to Global Scope!
		Submission	Photography Consent
		Learning Content	Next Steps and Orientation Details
		Learning Content	How does this program work?
		Learning Content	How do I get Help?
		Learning Content	Practera Tips
		Learning Content	Mentoring Tips
		Learning Content	Cross-Cultural Teams
		Learning Content	Welcome to Global Scope!
		Submission	Photography Consent
		Learning Content	Next Steps and Orientation Details
		Learning Content	How does this Program Work?
		Learning Content	How do I get Help?
		Learning Content	Practera Tips
		Learning Content	Practera’s Fair Work Policy - Summary
		Learning Content	Useful Resources
		Submission	First Team Submission on Practera
		Submission	First Individual Submission on Practera
		Submission	End of Orientation Checklist
Other	Welcome	Learning Content	How to Confirm your Participation

		Submission	Enrolment Form
	Conclusion	Learning Content	Engaging in continuing work
		Submission	Feedback Survey
		Submission	Participant Feedback and Certificate Survey
Project_Draft	Week 2 - Project Report	Learning Content	Week 2: Project Report Overview
		Learning Content	Project Report Outcomes
		Learning Content	Key Questions - Project Report
		Learning Content	Week 2: Project Report Overview
		Learning Content	Draft Project Report
Project_Plan	Week 1 - Project Plan	Learning Content	Week 1: Project Plan Overview
		Learning Content	Project Plan Outcomes
		Learning Content	Key Questions - Project Plan
		Learning Content	Week 1: Project Plan Overview
		Learning Content	Project Plan
		Learning Content	Project Plan Explained
		Learning Content	Project Plan Task List
		Learning Content	Seven Step Loop
		Learning Content	Minto Pyramid
		Learning Content	SCQ Analysis
Project_Report	Week 3 - Project Presentation	Learning Content	Week 3: Final Report and Project Presentation
		Learning Content	Project Presentation Outcomes
		Learning Content	Key Questions - Project Presentation
		Learning Content	Week 3: Final Report and Project Presentation
		Learning Content	Project Presentation
Self_Assessment	Welcome	Submission	Self-Assessment & Skill Development
	Week 1 - Project Plan	Learning Content	Attitudes of Learning Explained
		Submission	Attitude Towards Learning
		Learning Content	Attitudes Towards Learning and Your Project Team
	Week 2 - Project Report	Learning Content	Mindset for Learning
		Submission	Mindset for Learning
		Learning Content	Mindset for Learning and your Project Team?
Self_Peer_Assessment	Week 2 - Project Report	Submission	Self & Peer Assessment #1
	Week 3 - Project Presentation	Submission	Self & Peer Assessment #2
Skills_Aggregate		Learning Content	Aggregate Findings Task List

	Week 2 - Project Report	Learning Content	Project Report & Presentation Explained
		Learning Content	How to Synthesize Research
		Learning Content	Synthesis Tool: Mind Mapping
		Learning Content	Synthesis Tools: Finding Themes
Skills_Collaboration	Welcome	Learning Content	Introduction to Collaborative Project Learning
		Learning Content	Introduction to Self
		Learning Content	Emotional Intelligence
		Learning Content	Leading Self
		Learning Content	Skill Development Planning
		Learning Content	Key Collaboration Skills
Skills_Networking	Conclusion	Learning Content	Create your LinkedIn Profile
		Learning Content	Add Global Scope on Linkedin
		Learning Content	Add your program badge on LinkedIn
		Learning Content	Introduction to Networking
		Learning Content	Engaging in continuing work
Skills_Presentation	Week 3 - Project Presentation	Learning Content	Project Presentation Task List
		Learning Content	Project Report & Presentation Explained
		Learning Content	Presenting Tips: Know your Audience
		Learning Content	Presenting Tip: Powerpoint
Skills_Reflection	Week 2 - Project Report	Learning Content	Introduction to Learn
		Learning Content	Feedback
		Learning Content	Reflection
		Learning Content	Reflective Writing
		Learning Content	How to give Effective Feedback
Skills_Research	Week 2 - Project Report	Learning Content	Research & Analysis Task List
		Learning Content	Research Tools
		Learning Content	Research Tools: SWOT Analysis
		Learning Content	Research Tools: User Personas
Skills_Teamwork	Welcome	Learning Content	Actively Participates
		Learning Content	Communicates Effectively
		Learning Content	Demonstrates Reliability
		Learning Content	Exhibits Openness and Flexibility
		Learning Content	Solutions Orientated
	Week 1 - Project Plan	Learning Content	Introduction to Team
		Learning Content	Team Formation

		Learning Content	High Performance Teams
		Learning Content	Diversity in Teams
		Learning Content	Conflict in Teams
		Learning Content	Introduction to Project
		Learning Content	Project Fundamentals
		Learning Content	Goals & Objectives
		Learning Content	Approaches & Methods
	Week 3 - Project Presentation	Learning Content	Tips for Receiving Constructive Feedback
		Learning Content	Actively Participates
		Learning Content	Communicates Effectively
		Learning Content	Demonstrates Reliability
		Learning Content	Exhibits Openness and Flexibility
		Learning Content	Solutions Orientated

As mentioned in Chapter 3: Learning Context, in the EBP students engage with clients to deliver a real-world project. Therefore students participating in the EBP have to juggle both real-world project outcomes and learning outcomes focused on 21^{st} Century Skill development. Additionally students were required to complete administration tasks like photography release forms and feedback surveys. With this in mind, each task outlined in Table 1 above was considered through the lens of the following types of tasks:

1. Operational Task – An administration task required to participate in the EBP. For example pre-program surveys and program explanations.
2. Project Tasks – Tasks related to the effective delivery of the real-world client project. For example a project plan or project report.
3. Skill Development Tasks – Tasks related to students 21^{st} Century Skill development. For example learning content about collaboration skills, self-assessments and reflections.

This breakdown identified 30 operational tasks, 39 project tasks, and 45 skill development tasks. Table 2 shows the breakdown of learning tasks through this lens and which categories of tasks were considered operation tasks, project tasks and skill development tasks for the purpose of this research.

Table 2

Categorisation of Program Tasks

Category	Number of Tasks
Operational Tasks	**30**
Orientation	25
Other	5
Project Tasks	**39**
Skill_ Plan	10
Assessment_ Plan	2
Skills_Research	4
Skill_Aggregate Findings	5
Project_Draft	5
Assessment_Draft	2
Skill_Presentation	4
Project_Report	5
Assessment_ProjectReport	2
Skill Development Tasks	**45**
Skill_Collaboration	6
Self-Assessment	7
Skill_Teamwork	20
Self_Peer_Assessment	2
Skill_Reflection	5
Skill_Networking	5

Dependent Variables: Responses to survey instruments

In this research project I am using multiple regression analysis to test whether the candidate independent variables mentioned above in Table 1: independent variables are tested to see if they can contribute to an accurate prediction of five independent variables (outlined below). For this analysis to answer the research questions and achieve the objectives of this research project the dependent variables need to be representative of learners' perspectives, mindsets and skills. As outlined in Chapter 3: Learning Context the EBP has two survey instruments and a demographic questionnaire that could be used for this purpose.

As part of the EBP students complete the demographic data survey and two reflective activities that are designed to help develop their ability to learn from the experience. From the demographic data survey and the two instruments used in the reflective activities, demographic data about students learning history as well as information about student's self-perception of their mindset and approach to learning was extracted. The following section explains the three surveys mentioned in Chapter 3: Learning Context.

The demographic data survey is completed before students are allocated to a team. The reflective activity focused on approaches to learning is completed after students submit a project plan to their industry client. The reflective activity focused on mindset is completed after students submit their draft project report. The demographic data survey (hereafter referred to as Learning History Survey (Survey 1) captured a variety of questions about the student's age, area of study and educational background. The reflective activity focused on approaches to learning starts with students completing the Revised Two Factor Study Process Questionnaire (Survey 2) followed by students stepping through a structured reflection task designed to help them consider their responses to the survey in relation to their approach completing the Project Plan activity in the EBP. The reflective activity focused on mindset starts with students completing the Revised Implicit Theories of Intelligence Survey (Survey 3) followed by the same reflection task used for the Revised Two Factor Study Process Questionnaire activity.

The student responses to the demographic questionnaire, the revised two factor study process questionnaire and revised implicit theories of intelligence survey are captured in the de-identified and retrospective data used in this research project. The student responses to the two surveys and the questionnaire are reduced to five dependent variables:

1. Learning History
2. Deep Approach to Learning
3. Surface Approach to Learning
4. Fixed Mindset
5. Growth Mindset

How the students 'responses to the two surveys and questionnaire was reduced to these five dependent variables and why they were characterized with these names is outlined in detail below. However prior to outlining these five dependent variables and the data used one limitation requires acknowledgement, the sequencing of the questionnaire and surveys used to capture this data. Cognitive Load theory posits that the capacity and duration of a person's working memory affects learning (Zambarano et al. 2019). Furthermore Sweller et al. (2019, 2020) proposes that the success of educational technology is affected by human cognition particularly the extent to which human cognition is considered in instructional design. Cognitive load theory proposes the use of sequencing to facilitate knowledge acquisition (Clarke, 2005). The use of sequencing for good learning design suggests that when repeating a learning task, a portion of the improved performance could be attributed to prior knowledge and experience. Taking this into consideration it is relevant to examine how the sequence of the surveys and instruments were embedded in the EBP could impact the results presented and conclusions drawn from them.

Cognitive load theory suggests that students 'responses to the survey's and instruments could be impacted by how they are sequenced in the program design—for example, the reflective activity surrounding the Revised Two Factor Study Process Questionnaire (Survey 2) is identical to the reflective activity surrounding the Revised Implicit Theories of Intelligence Survey (Survey 3). Therefore students 'past experience completing the first reflective activity could have resulted in an improved performance in the second activity. It is possible to conclude that a student's ability to accurately self-assess their mindset could have been higher than their ability to assess their approaches to learning based on sequencing. Although this is a consideration, this research project is not measuring or comparing student's ability to accurately self-assess themselves or comparing the performance of the multiple regression models derived from each of the surveys. However it is worth considering cognitive load as a contributing factor when examining the multiple regression models specifically when it comes to outlier scores that appear to skew the models and when considering how the models could be improved.

Dependent Variables: Survey Questions, Data Components and Dummy Coding

The scoring of the student responses to the two validated survey instruments and demographic questionnaires used as dependent variables in the regression analysis are:

1. Learning History Questionnaire
2. Revised Two Factor Study Process Questionnaire (Biggs et al., 2001)
3. Revised Implicit Theories of Intelligence Survey (De Castella and Byrne, 2015)

As previously mentioned in detail, these surveys and questionnaire are embedded in the EBP program that the de-identified and retrospective data set used in this study comes from.

Dependent Variable One: Learning History

The Learning History Survey (Survey 1) is not a validated instrument designed to measure learning history. Taherdoost (2016) posits that a valid social science instrument is an instrument that measures what it is intended to measure. Based on this definition the Learning History questionnaire could be valid for measuring learning history. However the learning history questionnaire was not developed for this purpose and has not been tested for its ability to measure learning history. The Learning History questionnaire was developed as a part of the EBP to capture demographic data about student participants as opposed to being designed to measure a student's learning history. The intention of the Learning History questionnaire in the EBP was to give facilitators more insight so that they can more effectively support students. The questionnaire was added to the EBP in 2018, two and a half years after the initial design. At the time over 3000 students had participated in the program, with over 80% of participants identifying as international students. An evaluation of the program found that a large portion of the international students were not only struggling with transferring their theoretical knowledge to the real-world but transferring from a high context Confucian learning culture into Australia's Socratic and low context learning culture (Hall, 1976) and business environment.

Low context and high context are terms used to describe the way meaning is transferred in communication (Nam, 2015). In low context communication the majority of the meaning in a communication exchange is transferred in the verbal message whereas in high context communication the non-verbal cues matter more. Further what is communicated is more important than how it is communicated in low context communication, whereas this is reversed in high context communication. Students used to high context communication learning in technology-enabled low context cultures lose non-verbal cues they would use to interpret the meaning of an exchange (Westbrook, 2014). As a result it is more probable that students participating in the EBP who are transitioning from a high context culture to a low context culture experience a higher cognitive load than students who are not transferring context.

Transfer is the ability to take insight from one situation or context and apply it to another (Jackson et al., 2018) in experiential learning students are transferring theoretical knowledge from the classroom to real-life situations, switching physical contexts like this is considered far transfer (Kober, 2015). Adding a transition of social context to this already cognitively complex task (Irvine, 2017) increases the complexity to another order of magnitude and therefore, the cognitive load on each learner.

An example of the context shift required in the EBP for students is highlighted in the first engagement student teams have with their client. Australian industry clients tend to gauge their student team's understanding of the project by the clarifying questions students asked after reading the project brief. Students from high context cultures would find it essential to read between the lines of verbal communication and consider silence as golden (Nam, 2015) whereas an industry client from a low context culture would expect direct verbal messaging and all of the communication about the project to be explicit (Nam, 2015). This difference in understanding can result in subsequent actions of students not being aligned to the expected action of the client. In the EBP this often resulted in a lack of project confidence from the client and their subsequent disengagement.

To address this situation the instructional designers and facilitators developed the learning history survey in order to identify students they needed to provide additional support to in order to have a successful first client meeting. At present students who identify as completing the majority of their learning in a low-context Confucian culture in the survey received extra learning content and were encouraged to read the project brief in advance of the meeting with the specific intention of formulating questions to ask the client. The impact of this intervention is yet to be methodically measured however the EBP feedback surveys and program engagement data shows an anecdotal improvement.

The Learning History questionnaire developed to fill this need asks each student where they completed their primary education and secondary education. This data is categorical data, the dummy coding used in this survey for this research project and each of the location options were attributed to either a high-context Confucian culture or a low-context Socratic culture. A third category:' other', was used for locations that did not fit into either of these categories. The other category is less than 3% of the cohort. The ‘other ’category included students who had completed their education in African, Latino and Arab countries. Although most countries in these countries are considered high context cultures they were not discussed in the literature about Socratic and Confucian learning history so it was unclear which category they would fit best.

It must be acknowledged that while this questionnaire is not a validated instrument the questions are asking for facts about where the student completed their past studies. The survey is a demographic data questionnaire not a psychological instrument. The researcher transferred the survey data into the Socratic and Confucian groupings. The students completing the survey did not have to understand the theoretical concepts surrounding Socratic learning history, Confucian learning history, high context cultures and low context cultures in order to accurately answer the survey.

Dependent Variable Two and Three: Deep Approach to Learning and Surface Approach to Learning.

The Revised Two Factor Study Process Questionnaire (Survey 2) was developed by Biggs et al. (2001). The survey was designed as a tool for teachers to examine the learning approaches of students. In the EBP this survey is embedded in a reflective exercise where students examine their approach to learning. The survey contains 20 questions (see appendix one) that explore students ’attitude towards their study and their usual way of studying. Half the survey questions examine the student's deep approaches to learning, and the other half examine the students surface approaches to learning.

An individual who employs a deep approach to learning is focused on the meaning of what is being learned. In contrast an individual who employs a surface approach to learning is focused on capturing the entirety of the material that is currently being communicated (Jackson, 2012). Each question has five answers on a Likert Scale:

1. this item is never or only rarely true of me
2. this item is sometimes true of me
3. this item is true of me about half the time
4. this item is frequently true of me
5. this item is always or almost always true of me

The survey questions are action-based and in most cases, orient the individual to consider their past behaviour towards learning. For example question one is designed to understand the extent to which the individual has a deep approach to learning and asks "I find that at times studying gives me a feeling of deep personal satisfaction." In contrast question twelve (a surface approach to learning question) asked the individual to consider the phrase "I generally restrict my study to what is specifically set as I think it is unnecessary to do anything extra." A full list of the questions and their categorisation is available in appendix one.

This survey uses a Likert scale to capture students' responses and is a continuous variable. Multiple regression analysis is a statistical analysis method and is a procedure that requires the use of quantitative data to conduct the analysis (Pederson, 2018). With this in mind each students' responses to the survey questions were attributed a numerical value as per the scoring on the instrument (See Appendix 1). The scores were split into two groups. One group for the scores from questions identified as questions related to deep approaches to learning and one group for questions identified as questions related to surface approaches to learning. Each students' deep approach to learning question scores were summed to get a numerical value that could be used as the dependent variable for deep approach to learning. Each students 'surface approach to learning question scores were summed to get a numerical value that could be used as a dependent variable for surface approach to learning.

Dependent Variable Four and Five: Fixed Mindset and Growth Mindset

The Revised Implicit Theories of Intelligence Survey (Survey 3) was developed by De Castella and Byrne (2015) to identify fixed and growth mindset in learners. The scale was designed to "assess students 'belief about their ability to mould their own intelligence in contrast to their beliefs about the malleability of intelligence in general" (2015, p. 245). The survey contains eight questions (see appendix one) that explore students' belief about their ability to change their level of intelligence. Each question has six answers on a Likert scale. The instrument is presented as a list of eight questions that were divided into two sections. Questions one through four are designed to understand the extent to which an individual has a fixed mindset. Questions five through eight are designed to understand the extent to which an individual has a growth mindset.

An individual with a fixed mindset assumes their intelligence and character are static and unchangeable, whereas an individual with a growth mindset assumes their intelligence and character can be developed with intentionality (Dweck, 2019). Question one on the survey asks individuals to consider to what extent they agree with the statement "I don't think I personally can do much to increase my intelligence." Whereas question five asks individuals to consider to what extent they agree with the statement "With enough time and effort I think I could significantly improve my intelligence level." The questions focused on both fixed and growth mindset position the individual as the agent of change using phrases like "I think I have the capability" and "I personally can't". Finally the questions focus on current belief as opposed to past action. For example question six asks the individual to consider the statement "I believe I can always substantially improve my intelligence" as opposed to asking how often they have changed their intelligence in the past.

This survey uses a Likert scale to capture students 'responses and is a continuous variable. Each students 'responses to the survey questions were attributed a numerical value as per the scoring on the instrument (See Appendix 1). The scores were split into two groups. One group for the scores from questions identified as questions related to fixed mindset and one group for questions identified as questions related to growth mindset. Each students 'fixed mindset question scores were summed to get a fixed mindset dependent variable. Each students' growth mindset question scores were summed to get a growth mindset dependent variable. As mentioned above when discussing dependent variable two and three, a multiple regression analysis is a statistical analysis method and is a procedure that requires the use of quantitative data to conduct the analysis (Pederson, 2018)

Sampling

This study uses retrospective and de-identified data from Practera's eLMS. The eLMS is designed to support higher education learning programs that incorporate the experiential learning cycle as a core feature of the design. Practera uses real-time learning analytics analysis and data visualisation as a vehicle to extract learning issues for potential facilitator intervention.

Sample options were narrowed down through the use of a convenience sampling approach (Etikan et al., 2016). The learning programs in the sample were already run on the eLMS, designed by me and facilitated by Practera's facilitation team. The data extracted is already anonymised. The use of learning analytics and educational data mining processes in my study design enables a larger data set to be used for both the qualitative and quantitative analysis (Reinman, 2016) somewhat limiting the challenges of mixed-method research sampling strategies (Onwuegbuzie & Collins, 2007).

The sample for the study consisted of retrospective learning data of all learners, clients and facilitators in the EBP (explained in Chapter 3) that agreed to their data being used for research purposes. In the EBP students worked in teams of four or five on a project for an industry client. Selecting this learning experience resulted in a sample size of over 600 students and five facilitators.

Data Collection

The de-identified and retrospective data set available for this research project contained:

- Student responses to learning theory survey instruments;

- Self and peer assessments on collaboration skills from the start, middle and end of the learning experience,
- 'Pulse check' data used to highlight team dissonance,
- Learning content completion data,
- Client evaluations of team performance on project deliverables,
- Facilitator support intervention logs for teams and individuals,
- Post-program student reflections highlighting key learnings,
- Timestamped trace data for all inputs and outputs of students into the eLMS for the duration of the learning program.

Although all of this data is available in the data set the data used in the analysis includes the student responses to learning theory survey instruments (dependent variable) and the learning content completion data (independent variables). Combining these data sources allows for exploration into the three research questions. Firstly using these data sources as the independent and depended variables in a regression analysis will determine the extent to which there is a relationship between the learning data captured by the eLMS and the students' scores on the survey instruments. Furthermore which independent variables end up in the regression model could provide insight into additional data and analyses that could improve the accuracy of the model in predicting students' perceptions, mindsets and skills.

As mentioned previously this research stems from my work as an experiential learning facilitator and designer. As an insider I have a unique insight into the overall learning objectives, program design and facilitation strategies. The data collected by Practera's eLMS is rich in detail and is generated by students participating in an experiential learning program that I designed. In light of the research questions, I thought that the data selected showed potential for testing the hypothesis and answering the research questions.

Data Analysis Process

The following technology-enabled data analysis process and approaches are used in the following order in this research project.

Step 1: Identifying the Dependent Variable (Score and Code Learning Instruments Data)

As mentioned above, students participating in the EBP completed the Revised Two Factor Study Process Questionnaire R-SPQ-2F (Biggs et al., 2001) (Appendix 1) and The Revised Implicit Theories of Intelligence (Self-Theory) Scale (De Castella & Byrne, 2015) (Appendix 1). Furthermore they identified the context in which they completed their primary and secondary education in a Learning History Questionnaire. These instruments and learning history questionnaire were used to attribute a numerical value to each student for each of the five dependent variables:

1. Fix Mindset.
2. Growth mindset.
3. Surface approaches to learning.
4. Deep approaches to learning.
5. Learning history.

Step 2: Identifying the Independent Variables (Dummy Code Learning Data)

As mentioned above, each learning task students could complete while participating in the EBP was reduced into candidate independent variable categories (Table 1: Candidate Independent Variables). The following naming conventions were used for the different content categories:

1. Other – program informational data.
2. Orientation – Programmatic information about the learning experience.
3. Skills_x – Learning content on learning content related to a particular skill or capability (indicated by x).
4. Self_Assessment – a reflective task that is submitted for feedback.
5. Assessment_X – Experiential Task submissions related to particular assessment (indicated by x).

Table 3

Variables

Dependent Variables	**Independent Variables**

Learning History	Assessment_Draft
Deep Approaches to Learning	Assessment_Plan
Surface Approaches to Learning	Assessment_Report
Growth Mindset	Orientation
Fixed Mindset	Other
	Project_Draft
	Project_Plan
	Project_Report
	Self_Assessment
	Self_Peer_Assessment
	Skills_Aggregate
	Skills_Collaboration
	Skills_Networking
	Skills_Presentation
	Skills_Reflection
	Skills_Research
	Skills_Teamwork

Step 3: Multiple Regression Analysis

The first step in identifying whether learning data captured by the eLMS (candidate independent variables) can be used to predict the five dependent variables: learning history, deep approaches to learning, surface approaches to learning, growth mindset and fixed mindset is to examine the extent to which any combination of the candidate independent variables can predict any of the five dependent variables. This research project is an exploratory study that starts with seventeen candidate independent variables (outlined in Table 1: Candidate Independent Variables) for each of the five dependent variables. As a result of the size of the candidate independent variable pool it is likely there will be more than one viable regression model. Therefore the second step will be to use a systematic process to select the 'best fit' model (Ripley, 2003).

Ratner (2010, p. 65 asserts that "identifying the best subset among variables to include in a model – is arguably the hardest part of model building." The paper overviews the history of model selection from a time when the number of candidate variables and observations were small enough to use ordinary least squares (OLS) regression models that could be used alongside exploratory data analysis techniques to examine each data point and make adjustments for gaps, clumps and outliers. The paper further explores the characterised emergence of All-subset and Stepwise model selection processes and nine key limitations. Perhaps the most poignant limitation Ratner (2010) highlights is that "the data analyst knows more than the computer … and failure to use that knowledge produces inadequate data analysis" (p 66). The subsequent overuse of these approaches by those with limited formal training on statistics and experts who believe a "suitable computer program can objectively make substantive inference without active consideration of the underlying hypothesis" (p.66).

The number of candidate independent variables and observations in the data set used in this research rules out regression models like OLS builds and tested in a small-data set paradigm. This coupled with my positionality as a novice data analyst required me to leverage the expertise of seasoned data scientists and learning analytics researchers. After consulting the expert advice of learning analytics researchers I collaborate with on research projects that examine the use of learning analytics in work-integrated learning (James et al., 2018) and more specifically the importance of metacognitive regulation in work-integrated learning (Joksimovic et al., 2020).

I used a combination of the above-mentioned expert advice and learning analytics literature (Joksimovic et al., 2015; Van Sebille et al., 2018) to make key decisions in my approach to the multiple regression analysis, including software package choice and methods for 'best fit' model selection. As "the data analyst knows more than the computer … and failure to use that knowledge produces inadequate data analysis" (Ratner, 2010, p 66). I was fortunate enough to leverage the knowledge of the data scientists and learning analytics researchers mentioned above throughout each state of the regression analysis.

To conduct the multiple regression analyses used to answer the research questions in this research project I used Glmulti, an R package for automated model selection to find the optimal regression model for each of the five dependent variables. Glmulti implements information-theoretic methods for model selection and model inference (Calcagno & Mazancourt, 2010). Calcagno and Mazancourt (2010, p 5) assert that Glmulti "generates all possible model formulas, fits them with glm, and returns the best models" Leveraging the power of Glmulti means that each possible unique combination of independent variables is built and tested so that the best fit non-redundant models are identified.

Once all the possible combinations for each of the five dependent variables were tested the regression model with the best fit and predictive power was selected using Akaike Information Criteria (Hastie et al., 2009) and presented in the results (see tables 9,10 and 11, in chapter 5). When using Akaike Information Criteria for model selection, the model with the lowest AIC value is the best fit model. The AIC formula rewards goodness of fit, however it counters for overfitting by penalizing an increase in variables. AIC is calculated for each candidate 'best fit' model then the AIC for each 'best fit' model is compared to the lowest scoring model to identify the probability of information loss when comparing the two models. A ‘best fit’ multiple regression model is selected if the probability of information loss of all the comparison models is low. I chose to use Glmulti over OLS and stepwise regression analysis process and AIC because it enabled automated and systematic testing of each possible multiple regression model, including the consideration of main and interaction effects. Moreover this approach is used by learning analytics researchers (Joksimovic et al., 2015; Van Sebille et al., 2018) one of the educational research communities that has called for more integration of learning theory and learning analytics research (Gasevic et al., 2017; Gašević et al., 2016; Lodge & Lewis, 2012; Rogers, Gašević, & Dawson, 2016; Wise, 2014; Wise & Shaffer, 2015; Avella et al., 2016; Gasevic, Dawson & Siemens, 2014; Kirkwood & Price, 2013; Lodge & Corrin, 2017; Lockyer, Heathcote & Dawson, 2013; McArthur, Lewis & Bishay, 2005; Reimann, 2016).

One key interaction effect that is important to attend to when using multiple regression analysis is multicollinearity. Multicollinearity occurs when there is a high degree of correlation between variables analysed in a multiple regression equation (Allen, 1997). Existence of multicollinearity in a regression equation can impact the efficacy of the equation depending on how the equation is intended to be used. There are two types of multicollinearity. Perfect multicollinearity is when “one independent variable is a perfect linear function of one or more of the other independent variables in a regression equation” (Allen, 1997, pg. 176). Perfect multicollinearity can occur when one candidate independent variable is constructed out of other independent variables. In this research project none of the seventeen independent variables are constructed using part or all of other independent variables. As highlighted in Table 1 above, the time spent on each learning task is only attributed to one candidate independent variable.

Extreme multicollinearity is when “an independent variable is very highly correlated with one or more other independent variables” (Allen, 1997, p177). The presence of extreme multicollinearity in a regression model can be checked for by examining the standard error of the coefficients and the significance levels of the coefficients. In order for a regression coefficient to be statistically significant it must be larger than its standard error. In specific, at a 0.05 significance level the coefficient must be twice as large as the standard error. Furthermore, if there is interaction among the variables the significance level of the coefficients decreases. Akaike Information Criteria (AIC) attends to multicollinearity when scoring models to determine the best fit model (Polidori, 2020). Therefore, use of AIC in ‘best-fit’ model selection means that multicollinearity has been considered in the decision.

Ethical Considerations

Using learning analytics in educational decision-making is examined and debated in the literature and practice with the ethical issues surrounding the use of new technology in learning and teaching being no different. Slade and Prinsloo (2013) break down the ethical concerns surrounding learning analytics into three categories broadly related to where the data is captured, how it is used, and how it is stored. Rubel and Jones (2016, p. 147) specifically focus on the privacy concerns acknowledging that knowledge gained from the data is “exponentially more valuable for the institution than the data subject,” thus opening up the potential for institutions and the commercial enterprises they are working with to bias interventions and optimise for their own gain over the student benefit. This imbalance is further accentuated by Prinsloo and Slade (2016) who highlight both ethical challenges when it comes to the power balance between institutions and students and the complexities of student agency in learning that can be impeded by the use of learning analytics.

Sclater's (2017) discussion of the ethical issues surrounding the use of learning analytics includes concerns around insufficient data, invalid analytics, loss of autonomy and students' behaviour when using learning analytics in educational practice. Pardo and Siemens have explored the possibility of learning analytics being real-time research and requiring the same rules and ethics as any research (2014). In contrast Kay, Korn and Oppenheim (2012) highlight specific differences in consent parameters with research consent having an explicit direction and agreed outcome.

To more fully understand the potential of learning analytics, machine learning and educational data mining, for the purpose of designing educational practice that would lead to improved learning outcomes, my research addressed ethical concerns in the following manner:

- Data was fully anonymised before extraction from the eLMS (Practera) and used in any EDM, LA and ML processes;
- Data collected for this study was part of the regular operations of my organisation (Practera);
- Practera obtained consent from participants of the learning programs and the educational institutions they attend before their participation;
- No program coordinator or facilitator was aware of the consent status of each participant before, during or after the learning program.

A specific concern for this particular research project was the internationalised nature of the research and subsequent ethical and legal implications. The University of Liverpool was located within the European Union and is under the jurisdiction of the EU General Data Protection Regulation (GDPR). The data was captured in Australia and is under the jurisdiction of the Australian Privacy Principles (APP). Finally, the student researcher and thesis supervisor reside in the United States of America where there is no single principal data protection legislation but various laws enacted at the state and federal level. To examine the legal and ethical considerations of data privacy for this research, a Data Privacy Impact Assessment was conducted and is available in Appendix 2. The result of the Data Privacy Impact Assessment resulted in three key restrictions:

1. The de-identified data set in its entirety was not to be transmitted electronically over international borders;
2. If specific de-identified data was to be transferred electronically, only the minimum data required could be transferred, and traces of the transfer were to be deleted from email logs;
3. The de-identified data set was stored on an encrypted computer that the researcher cannot connect to the internet.

As a result, the student researcher had to travel from Boston to Sydney to collect the de-identified raw data and conduct the initial analysis. The de-identified raw data was provided on an encrypt MacBook Pro that could not be connected via wifi or Bluetooth to any other device or the internet without a password that was unknown to the student researcher. Initial data cleaning, scoring and coding of instruments and surveys, and initial regression analysis was conducted in Sydney. This was done to confirm which specific data from the data set was required for the analysis. Data that was not required for the analysis was removed from the encrypted MacBook

Pro before the MacBook Pro was physically taken back to Boston on a plane. Only the following data was physically transferred to Boston:

1. Scores of survey instruments.
2. Action Log.
3. Technical Program Map.

Conclusion

The research approaches employed in this study are underpinned by my philosophical foundation and beliefs about learning that emerged from my teaching practice and were refined, examined and iterated using the lens of learning theory. Moreover, the chapter explains the interaction between my philosophical foundation and positionality working at the intersection of education technology, learning analytics, learning theory research and experiential learning that led to the research hypothesis, research questions and methodological choices. Finally ethical issues, including data privacy and security, were addressed and controls added to limit the risks. This research methodology resulted in a research design that leverages strength from both learning analytics research and learning theory research in an integrated way.

Chapter 5: Results

Introduction

The analysis and findings presented in this chapter are from a de-identified and retrospective learning dataset captured by technology from the 612 students who participated in an experiential learning program. The results presented were produced by aggregating the data as a result of a deconstruction of the program design, analysing the student's behaviour engaging with the program and the students 'self-assessment scores on instruments and surveys that identify mindsets, approaches to learning and learning history. Specifically, students time-on-task, identified in the literature as a "constructs affecting learning success" (Kovanovic et al., pg 82), is used to derive seventeen candidate independent variables and student's responses to two validated survey's and a questionnaire is used to derive five dependent variables. The chapter presents the results of the self-assessment instruments and questionnaire. This is followed by a detailed overview of each of the five multiple regression models identified as the best fit model using Glmulti to test all possible models (Calcagno & Mazancourt, 2010) and Akaike Information Criteria (Hastie et al., 2009) to select the best fit model. This is a common approach used by learning analytics researchers (Joksimovic et al., 2015; Van Sebille et al., 2018). The discussion following the presentation of each of the five best fit regression models examines the models to highlight strengths and limitations of these quantitative models that are taken into consideration when using the model to answer the qualitative research questions in chapter six.

Throughout the chapter, analysis and results are presented through tables, graphs and text explanations. The results are presented, along with how these results relate to the research questions. The results are presented in the order the analysis was conducted so that the research process is clearly outlined.

The results chapter is organised into two sections. The first section, the scoring of the survey and questionnaire responses used as dependent variables, explains the nature of the five dependent variables derived from the two surveys and questionnaire. Presenting the results of scoring and a distribution graph of the scores gives an overview of the five dependent variables used and any considerations that need to be attended to in the qualitative discussion. The second section, the presentation of the multiple regression analysis, includes an explanation of the tests conducted, s the five regression models chosen and and how both these elements inform the answers to the research questions.

Dependent Variables: Survey and Questionnaire Scoring Results

Survey 1: Confucian and Socratic Learning History

As part of a pre-program questionnaire, students provided information on the location of their primary and secondary schooling in a learning history questionnaire (Survey 1). This data is categorical data and requires dummy coding to derive dependent variables (Pederson, 2018). The answers to these questions were used to distribute the learners into nine categories based on their learning history, these categories are displayed in Table 4 below.

Table 4

Learning History Categories

		Secondary		
		Confucian	Socratic	Other
Primary	Confucian	475	3	1
	Socratic	11	45	2
	Other	0	0	7

The coding of this data indicates a substantial weighting towards a Confucian education history. Furthermore, two categories have no data and four have less than ten. In regression analysis it is acknowledged that a minimum of 10 observations per category is required (Austin & Steyerberg, 2015). As a result I removed the "other" category and the sample data associated with that category and re-coded the data for use in an ordinal logistic regression (Harrell, 2015) with learning history represented in three groups that have a natural order: Confucian learning history, mixed learning history, and Socratic learning history depending on whether their K-12 education was entirely in a Confucian context, fully in a Socratic content or a combination of both. Table 5 presents the re-coding of the student responses to learning history questionnaire.

Table 5

Final Learning History Categories used as dependent variables

Confucian	Mixed	Socratic
475	14	45

Survey 2: Deep and Surface Approach to Learning

Table 6 shows the results of the Revised Two Factor Study Process Questionnaire (Survey 2) embedded into a reflection activity in the EBP, outlined in chapter 3. The student responses to the survey captured in the data set were scored based on the scoring process developed by Biggs et al. (2001) the authors of the survey. Figure 3 shows the asymmetrical distribution of the survey results indicating there is an orientation towards deep approaches to learning compared with surface approaches to learning. Over half of the cohort sit in the middle fifty per cent of the scoring on both deep and surface approaches to learning resulting in significant overlap of the distribution curves.

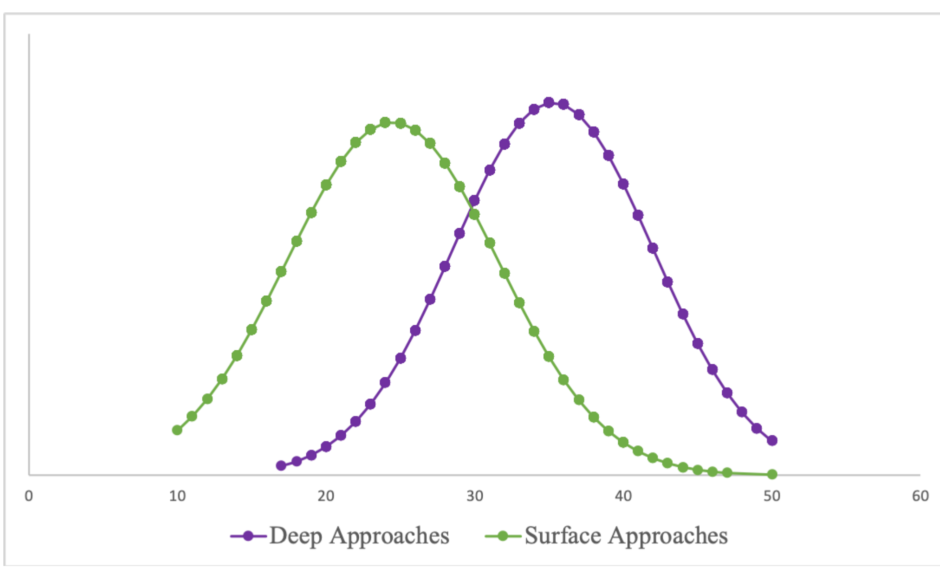
Table 6

Revised Two Factor Study Process Questionnaire

	<12.5	12.5 - 25	25 – 37.5	>37.5	No Score
Deep Approaches to Learning	0	42	304	212	78
Surface Approaches to Learning	3	344	179	32	78

Figure 3

Approaches to Learning Distribution



Students 'score of their self-perceived tendency towards surface approaches to learning and deep approaches to learning is used as the dependent variables two and three in this research study. The first regression analysis to identify the best fit model for predicting a learner score on the questions related to deep approach to learning (dependent variable 2) on the Revised Two Factor Study Process Questionnaire (Biggs et al. 2001). The second regression analysis to identify the best fit regression model for predicting a learner score on the questions related to surface approach to learning (dependent variable 3) on the Revised Two Factor Study Process Questionnaire (Biggs et al. 2001). If the time-on-task independent variable candidate categories (Outlined in detail in Chapter 4) can be reduced to regression models that can predict a learners scores on the Revised Two Factor Study Process Questionnaire it could be used as a proof of concept for learner behavior capture by an eLMS being used to identify a learners tendency towards deep approaches to learning and surface approaches to learning.

The regression model itself could be used as the baseline for a machine learning algorithm that monitors a learner's approach to learning. In machine learning research, "a baseline is a simple model that provides reasonable results on a task and does not require much expertise and time to build" (Li et al., 2020). A baseline can also help identify help identify the gaps in the baseline analysis that we can use to guide the development of a more complex and accurate model. Being able to predict a student's approach to learning using data captured by an eLMS could help facilitators identify students that may need more support with particular learning goals.

Survey 3: Fixed vs Growth Mindset

Table 7 shows the results of the Revised Implicit Theories of Intelligence survey (Survey 3) embedded into a reflection activity in the BPP. The student responses to the survey captured in the data set were scored based on the scoring process developed by De Castella & Byrne (2015), the authors of the survey. 335 of the 636 student participants scored above 19 of an available 24 on the growth mindset questions indicating that there is an orientation towards a perceived growth mindset in the sample. Figure 4 shows the normal distribution of the student participant scores. Students' score of their self-perceived tendency towards growth mindset and fixed mindset is used as the dependent variables four and five in this research study. The first regression analysis to identify the best fit model for predicting a learner score on the questions related to growth mindset (dependent variable 4). The second regression analysis to identify the best fit regression model for predicting a learner score on the questions related to fixed mindset (dependent variable 5).

Similar to the deep and surface approaches to learning, if the time-on-task independent variable candidate categories (Outlined in detail in Chapter 4) can be reduced to regression models that can predict a learner's scores on the Revised Implicit Theories of Intelligence survey (De Castella & Byrne, 2015) it could be used as a proof of concept for learner behavior capture by an eLMS being used to identify a learners tendency towards a growth mindset and fixed mindset and the regression model could be used a baseline for a machine learning algorithm (Li et al., 2020.

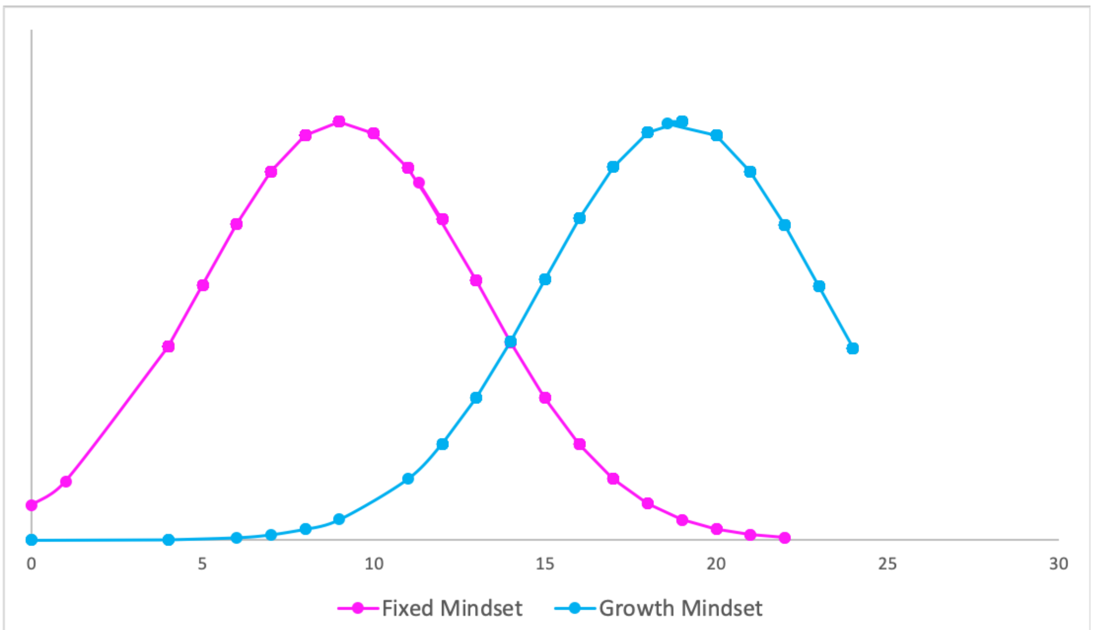
Table 7

Revised Implicit Theories of Intelligence Survey Results

	<6	7-12	13 - 18	19 – 24	DNC
Fixed Mindset	156	293	92	10	86
Growth Mindset	9	23	183	335	86

Figure 5

Mindsets Distribution



Further development of these analyses and displaying them to facilitators could help them provide more tailored support to each student. For example, facilitators could use this information to encourage students to complete learning tasks they do not naturally lean towards. Later in this chapter, the results highlight that students who identify as having a fixed mindset invest their time on learning tasks related to presenting or communicating their skills as opposed to learning tasks that will help them develop their skills. Facilitators could use this understanding about students with a fixed mindset and knowing which students in their cohort have a fixed mindset to encourage and even incentivise the completion of learning tasks that will help them develop their skills.

Multiple Regression Analyses

Use of Multiple Regression Analyses

Regression analysis is used to explain the relationship between variables (Pederson, 2018) and can be used to study how one variable changes as a result of its dependence on another variable (Weisberg, 2015). The variable under examination is the dependent variable, and the other variable or variables are the independent variables. Multiple regression analysis is a method of statistical analysis used to examine and understand the relationship between a variable (dependent) and multiple other variables (independent) (Allen, 2017). In this research project a suite of seventeen independent candidate variables is used to systematically identify the best fit multiple regression model for the five dependent variables outlined in Chapter 4 and presented in this results chapter. Glmulti is used to test all possible model combinations (Calcagno and Mazancourt, 2010) and the best fit model for prediction was selected using Akaike Information Criteria (Hastie et al., 2009)

The use of multiple regression analyses, a traditionally quantitative research method, is used in this thesis to infer qualitative insights that inform the research, present a proof of concept for how data captured by an eLMS can be used to identify and display a learners perspective, mindset and skills and potentially present one or more regression models that can be used as baselines for the development of machine learning algorithms for measuring mindsets and skills. g The characteristics of the best fit multiple regression models presented and discussed:

1. **Residuals:** Residuals are the difference between the student's actual score and the score the regression model predicted. The model's fit is determined by the symmetry of the points on the mean value of zero. Table 7 shows the Residuals for each of the five regressions run.
2. **Independent Variables in the Model**: Lists all of the independent variables that are in the best fit multiple regression models presented below.
3. **Estimate**: The estimate indicates the slope of the model. In this regression, the estimate indicates the effect of an increase of one point on each independent variable has on the dependent variable.
4. **p-value (indicated by significance codes)**: The p-value indicates how likely it would be to observe a value greater than or equal to t. In the results displayed below, the significance of the p-values for each independent variable in each of the five best fit models has been reported based on significance codes ranging from <0.001 through to 1.
5. **Standard Error:** The standard error indicates the average amount the model estimates vary from the actual averages of the data set. The lower the standard error means a lower the variance if the model was run again and again. An ideal model has a lower standard of error relative to the estimate.
6. **t-value**: The t-value indicates how many standard deviations the estimate is away from zero. The further the t-value is from zero, the higher the likelihood there is a

relationship between each of the independent variables in the best fit model and the dependent variable.

7. **Standardised Coefficient**: Standardising each of the independent variables enables the identification of which independent variable have the most significant effect on the dependent variable. In the reported regression models below, standardising the coefficients enables the identification of the independent variables that has the most significant impact on the students self-reported answers on the surveys and questionnaire.
8. **Adjusted R-Squared**: R- squared identifies how well the overall model fits the actual data. In multiple regression models, adjusted r-squared is used as it adjusted based on the number of independent variables in the model. In the reported multiple regression models, r-squared identifies the percentage of the variance in the students self-reported answers on the surveys and questionnaire that can be explained by the predictor variables.

Examination of the Residuals

The residuals for the five best fit multiple regression models for predicting the students self-reported answers on the surveys and questionnaire using independent variables using time-on-task are reported in Table 8. These models are the best fit models using a subset of the data available in the data set available to conduct this analysis.   The purpose of reporting and examining the fit of each of the multiple regression models produced by this analysis is to identify the strength of the model for accurately predicting a learner self-report responses on the survey's and questionnaires; without having to include the surveys in a learning program.

Additionally examining the nature of the relationship between the independent variables included in the best fit model and the dependent can offer insights into how the model could be improved with additional data or used as a baseline model for a machine learning algorithm Li et al., 2020.

As mentioned above a regression model is a good fit if the distribution of the residuals is symmetrical. The residuals "should show a trend that tends to confirm the assumptions made in performing the regression analysis or failing them should not show a tendency that denies them" (Martin et al., 2017, p 1). The residuals are calculated by subtracting the model's prediction from the actual score of each student. The residual indicates how far above or below the prediction line, each of the actual student scores is. Table 8 (below) highlights the distribution of the residuals for each of the five models. When using a regression analysis in a research project that stems from a positivist epistemological perspective an extensive regression diagnostic would be undertaken to verify observed discrepancies and check for model adequacy (Fernandez, 1992). However this study stems from an anti-positivist perspective (Burrell & Morgan, 2005) and is using a traditionally quantitative method to infer qualitative insights, to answer qualitative research questions and present a proof of concept that is not intended to be used without further development. It is from this lens and perspective that the results reported below are presented and examined.

Table 8

Residuals

Regression	Min	1Q	Median	3Q	Max

Learning History	-12.2785	-2.8880	0.5876	1.2311	14.2311
Deep Approach	-33.797	-2.039	1.5	1.5	20.101
Surface Approach	-22.6993	-2.6993	0.8362	0.8362	22.3007
Fixed Mindset	-7.9919	-0.9919	0.2937	0.2937	9.0081
Growth Mindset	-15.5038	-0.7297	0.2802	1.3140	6.4962

The regression model that is the best fit model for predicting the dependent variable used for **Learning History** is symmetrical. The residual median is 0.58, indicating that the model under predicts more than 50% of the student scores in the natural order. The model is symmetrical, indicating a fit and provides no indicators of ways the model itself could be further improved in order to provide a more consistently accurate prediction. However the data set itself is skewed toward students from a Confucian learning history and could be impacting the strength and the accuracy of the model. Moreover, the skewed nature of the data set should be attended to when using the model to draw qualitative insights and when answering the research questions.

The regression model that is the best fit model for predicting the dependent variable for **Deep Approach to Learning** is asymmetrical. Compared to the best fit models for Fixed Mindset, Growth Mindset and Surface Approach to Learning, the best fit model for Deep Approach to Learning appears to be less accurate. In one case, the predictive model has scored one student 33 points higher than their actual score and another student 20 points lower than their actual score. In the middle of the distribution, both the median value and 3Q value are 1.5, indicating that over 25% of the student's actual scores were exactly 1.5 points higher than their predicted score. This situation could indicate that an outlier score is impacting the predictive model. In a regression analysis "an outlier is an observation that is far removed from the rest of the observations" (Maddala, 1992, pg 89). In theory if the score that is 33 points below the predictive line is removed the predictive model line would be higher bringing the medium and 25% of the students' scores (150 students) closer to the predictive line.

The regression model that is the best fit model for predicting the dependent variable for **Surface Approaches to Learning** appears to be the most symmetrical of the models, specifically when looking at the full distribution. Similar to the best fit model for Deep Approaches to Learning, at least 25% of the cohort (150 students) have the same difference between their actual score and the model's predicted score. A median of 0.83 also indicates that over 50% of the cohort's actual Surface Approaches to Learning scores are exactly 0.83 points higher than the predictive model line. This situation could indicate an unbalanced model, or perhaps that students 'behaviour indicates a slightly lower use of surface approaches to learning than students 'self-perception. Additionally the Surface Approaches to Learning Model has the lowest R_squared of all the models (discussed in the next section), so although the model appears to be symmetrical, it is currently the weakest model when it comes to the accuracy of the predictions.

The regression model that is the best fit model for predicting the dependent variable for **Fixed Mindset** is symmetrical. The minimum and maximum residuals are similar whole numbers, and over 50% of the student's actual scores are within 1 point of the model's prediction. Despite the symmetry of the model, it does indicate that the prediction would score one student nine points above their actual score and one student eight points below their actual score. It is possible that these two students are outliers and removing their scores could result in a significantly lower minimum and maximum residual. The outlier status of these two students is a viable hypothesis considering that more than 50% of the students' actual scores are within one point of the predictive line.

The regression model that is the best fit model for predicting the dependent variable for **Growth Mindset** is symmetrical in the centre and asymmetrical at the extremities. A minimum residual of -15.5 indicates that for one student, the predictive model would have indicated they have a significantly higher growth mindset score than their self-evaluation. A recommended next step to improve this model would be to test whether this score is an outlier by removing it from the model. It is feasible that a student could inaccurately self-assess their mindset if they were in a situation of stress while completing the instrument. It is also feasible that there is an error in the data, and the student's score was miscalculated. Setting this potential outlier or error aside, over 50% of the models' predictions are within 1.5 points of the student's actual score.

The five ʻbest fit ʼmultiple regression models that emerged from this analysis

Dependent Variable 1: Learning History

Table 9

Dependent Variable 1: Learning History

Program Tasks	Coefficient Estimate	Error	t-value	Standardised Coefficients	Adjusted r.squared
Self_Assessment	0.3519.	0.2117	1.662	0.1618184	0.4951508
Assessment_Draft	0.4945**	0.1669	2.963	0.2111627	
Assessment_Plan	0.5484**	0.1944	2.821	0.2095597	
Skills_Collaboration	0.9351***	0.1934	4.834	0.3353930	
Skills_Presentation	1.3598*	0.5765	2.359	0.2849612	

Skills_Networking	1.3793***	0.2218	6.220	0.3881705
Project_Draft	29.0118***	4.8681	5.960	1.8917882
Self_Peer_Assessment	-0.5838*	0.2578	-2.264	-0.1259924
Skill_Aggregate	-0.7589.	0.4565	-1.662	-0.1967880
Other	-3.1002***	0.2352	-13.184	-0.7554623
Project_Report	-24.7071***	4.8682	-5.075	-1.6040895

Signif. codes: 0 '*** '0.001 '** '0.01 '* '0.05 '. '0.1 ' '1

The best fit multiple regression analysis for learning history was produced using students 'learning history on a sliding scale between Confucian and Socratic learning history. This was based on how much of their K-12 education was in a Socratic or Confucian environment. The coefficients with a negative slope (indicated by a negative coefficient estimate in Table 9) indicate that the higher the engagement with the learning category, the more likely the learner has a Socratic learning history. Conversely the coefficients with a positive slope indicate that the higher the engagement with the learning category, the more likely the learner has a Confucian learning history.

These results indicate that seven of the subcategories of learning tasks indicate a likelihood of Confucian learning history and four of the subcategories of learning tasks indicate a likelihood of Socratic learning history. However it does need to be noted that the dataset had significantly more students who identified having a Confucian learning history compared with those identifying a Socratic learning history. Perhaps a more evenly weighted data set would produce a different result or find more of the other subcategories having a relationship with Socratic learning history.

The adjusted R-squared of the learning history model is as high as that of fixed mindset, growth mindset and deep learning (reported below). However this result needs to be considered in light of the difference in the quality of the data used in the analysis. The mindset and approaches to learning regression models were developed using the Revised Two Factor Study Process Questionnaire (Biggs et al., 2001) and the Revised Implicit Theories of Intelligence survey (De Castella & Byrne, 2015). Both instruments are validated and designed to elicit a student's perception of their mindset and approaches to learning. In contrast the data used to develop this model was a questionnaire asking which environment they completed their primary and secondary education in.

Being able to identify a learner’s educational history could be useful for facilitators, particularly if the student is participating in an experiential learning program in a different learning context than their previous education. Understanding a student’s learning history and an awareness of common challenges students from different learning contexts have when participating in experiential learning programs could help facilitators provide tailored support to students who are switching contexts.

The results indicate that there is a relationship between some of the independent variables and the dependent variable representing a students ’learning history. However the questionnaire used is not a validated instrument. Either going through the process of validating the current instrument or using an already validated instrument would automatically strengthen the model. Once a validated instrument is used as the baseline for the analysis, richer data analysis like natural language processing of reflective writing could be used to improve its predictive ability.

Dependent Variables 2 and 3: Deep and Surface Approaches to Learning

Table 10

Dependent Variables 2 and 3: Deep and Surface Approaches to Learning

	Program Tasks	Coefficient Estimate	Error	t-value	Standardised Coefficients	Adjusted r.squared
Deep Approach to Learning	Assessment_Draft	-0.5902*	0.2978	-1.982	-0.13095622	0.5130537
	Assessment_Plan	0.4941	0.3411	1.449	0.09811586	
	Self_Assessment	2.9311***	0.4696	6.242	0.70020835	
	Skills_Aggregate	2.3972**	0.9211	2.603	0.32296613	
	Skills_Presentation	-2.4155*	0.9547	-3.530	-0.26299391	
	Skills_Reflection	-2.7036***	0.7290	-3.709	-0.35294767	
	Skills_Teamwork	0.6457**	0.2225	2.903	0.30373774	
Surface Approach to Learning	Assessment_Plan	0.3578.	0.1875	1.908	0.08858407	0.401287
	Self_Assessment	2.1854***	0.4168	5.243	0.65102940	
	Skills Reflection	-1.5743**	0.5203	-3.26	-0.25629591	
	Skills_Teamwork	0.3648 .	0.1960	1.861	0.21397742	
	Other	-0.4709	0.3186	-1.478	-0.07434800	

Signif. codes: 0 ‘*** ’0.001 ‘** ’0.01 ‘* ’0.05 ‘. ’0.1 ’ ‘1

Looking at the best fit models for the dependent variables for deep approaches to learning and surface approaches to learning presented in Table 10 there are more sub-clusters of tasks (independent variables) that are included in the best fit model for deep approaches to learning s than the number included in the best fit model for surface approaches to learning. It is of interest to note that there are independent variables (from the suite of 17 outlined in the previous chapter) that are used in both models and have a similar nature to their relationships and contribution to the model, particularly the independent variable - self-assessment. Self-assessment has the most significant effect on both models, as indicated by the standardised coefficients. Understanding the significance this category of tasks has on predicting students ’approach to learning could indicate a ‘hot-spot ’for more in-depth analysis and when using this regression model as a baseline for machine (Li et al., 2020).

The results indicate that students ’score on surface approach to learning has a negative relationship with operational tasks. This means that the more students engage with the operational tasks, the lower their surface approaches to learning score was. Although the significance is greater than 0.1, this independent variable has only four tasks, two before the start of the program and two after the completion of the program. A minor independent variable having any potential relationship with a learning category could be significant in itself.

The best fit regression model for dependent variable two suggests that 51% of variance in a student’s responses on the Revised Two Factor Study Process Questionnaire (Biggs et al., 2001) can be predicted by the seven independent variables listed in Table 10. This is 11% higher than the 40% proportion of variance the best fit regression model for dependent variable three can predict using the five sub-clusters listed in Table 10. The model for predicting a student’s tendency towards surface approaches to learning is by far the weakest of the five models and should be further developed.

Dependent Variable 4 and 5: Fixed and Growth Mindset

Table 11

Dependent Variable 4 and 5: *Fixed & Growth Mindset*

	Program Tasks	Coefficient Estimate	Error	t-value	Standardised Coefficients	Adjusted r.squared

Fixed Mindset	Assessment_ Draft	-0.2899*	0.1132	-2.560	0.1715	0.4964752
	Assessment_ Report	0.2416*	0.1045	2.311	0.1413	
	Self_ Assessment	0.3281*	0.1476	2.222	0.2090	
	Skills_Presentation	0.4960 .	0.2900	1.710	0.1440	
	Skills_Reflection	0.7288*	0.2827	2.578	0.2537	
Growth Mindset	Assessment_Report	-0.13925	0.08505	-1.637	-0.0544	0.4960319
	Self Assessment	1.03126***	0.19219	5.366	0.4390	
	Self_Peer_Assessment	0.49174*	0.22547	2.181	0.0982	
	Skills_Collaboration	-0.34408*	0.16144	-2.131	-0.1142	
	Skills_Reflection	1.69749***	0.30150	5.630	0.3949	

Signif. codes: 0 '*** '0.001 '** '0.01 '* '0.05 '. '0.1 ' '1

Comparing and contrasting the regression analysis of fixed mindset and growth mindset the independent variable - assessment_report - has a positive coefficient with the growth mindset dependent variable and a negative coefficient with the fixed mindset score. A positive coefficient means that as the independent variable increases the dependent variable increases and a negative coefficient means that the independent variable increases the dependent variable decreases (Frost, 2019). This situation indicates that the more learning tasks in the independent variable - assessment_report that students engage with the higher their score for fixed mindset on the Revised Implicit Theories of Intelligence survey is (De Castella & Byrne, 2015). Similarly, the more tasks in the independent variable - assessment_report that a student engages with the lower their score for growth mindset on the Revised Implicit Theories of Intelligence survey is (De Castella & Byrne, 2015). Conversely, the self-assessment and skill reflection independent variables have a positive coefficient with both fixed and growth mindset dependent variables. However, the significance of the relationship between self-assessment and skill-reflection and growth mindset dependent variable is much higher (between 0.000 – 0.001) than the significance of the relationship between self-assessment, skill reflection and the fixed mindset dependent varaible (between 0.01 – 0.05). Understanding what type of relation a student's engagement with a subcategory of learning tasks is predicted to have on a student's self-perception of their mindset could help facilitators tailor their support interventions.

The standardised coefficients indicate that the skill_reflection independent variable has the most significant effect on the model when it comes to predicting a learners self-perception score of fixed mindset on the Revised Implicit Theories of Intelligence survey (De Castella & Byrne 2015) and self-assessment has the most significant effect on the model when it comes to predicting a learners self-perception score of growth mindset. Understanding which of the independent variables has the most significant relationship with self-perception of mindset could help identify additional data and alternative analysis techniques could be used to further improve the ability to predict a learner’s mindset.

Overall these two multiple regression analyses found an almost identical proportion of variance (50%) in students’ self-perception of their fixed and growth mindset available in the data set can be attributed to the independent variables listed in Table 11, indicated by the adjusted R-squared. Understanding what percentage of the learners score on the Revised Implicit Theories of Intelligence survey can be predicted by the best fit regression model provides a baseline for developing and validating a machine learning algorithm that can do this analysis.

Conclusion

In summary, this results chapter presented the results from analysing an anonymised data set of 612 students participating in an experiential learning program designed to allow higher education students to complete a real-life industry project while simultaneously using the experience to develop their 21st Century Skills. The hypothesis driving this analysis is **that data created by learners and captured by an experiential learning platform can be predictive of a learner's perspectives, mindset and skills.** Furthermore, this quantitative method was employed to answer three qualitative research questions:

1. Which data captured by an experiential learning technology can be used to understand more about students' perspectives, mindsets and skills?
2. In what way can data captured by experiential learning technology be used to understand more about students' perspectives, mindsets and skills?
3. How can understanding more about students' perspectives, mindsets and skills be used by learning designers and facilitators to support their practice in experiential learning?

The first section of the chapter reported the results of scoring the Revised Implicit Theories of Intelligence Survey (De Castella & Byrne 2015), the Revised Two Factor Study Process Questionnaire (Biggs et al. 2001) and a learning history questionnaire. The second section of the chapter reported five best fit multiple regression models for predicting these dependent variables:

1. Learning History
2. Deep Approaches to Learning

3. Surface Approaches to Learning
4. Growth Mindset
5. Fixed Mindset

All five best fit regression models include multiple independent variables of time spent on learning tasks that can be used to predict these depended variables, with some independent variables having a 0.001 level of significance. The Adjusted R-squared of four out of five of the models was close to 50% providing a substantial baseline that could be used to develop a machine learning algorithm for measuring perceptions, mindsets and skills. Finally standardising the coefficients has identified independent variables that had the most significant effect on the model, this highlights the types of learning data and analysis techniques that could be used to develop machine learning algorithms that can identify a learners perspectives, mindsets and skills in real time. Further research and in-depth analysis could lead to an algorithm that has a reasonable automated performance according to Ameisen's (2018) four levels of performance and could then be embedded in the eLMS, deployed in a design-based research project to validate for use in the practice of experiential learning.

The results of this analysis provided valuable insight into the types of data captured by an eLMS that can be used to predict students 'perspectives, mindsets and skills. Based on which independent variables are in the best fit regression model and the nature of their relationship with the dependent variables, it is possible to see how knowing this information about individual learners could help facilitators. A potential use case for this is the provision of insights that help facilitators provide tailored support in the current learning program. Additionally the insights could be used to help students develop their lifelong learning capability.

Chapter 6: Discussion

Introduction

This chapter presents interpretations and insights from the analysis conducted and reported in Chapter 5. The chapter first provides a summary of the overall intention of the research and research questions. The summary is followed by a discussion about each individual research question and how the results of the analysis have contributed insight that helps provide an answer to the question and where potential gaps that require further analysis still lie. Additionally the interpretations and insights in this chapter reflect my philosophical perspective outlined in Chapter 4: humans are unique, can change and exercise free-will yet are driven by habits that result in subconscious predictable behaviour.

This chapter first discusses each of the three research questions in isolation, highlighting specific analysis results, the extent to which the questions have been answered and how they might be used within educational practice. Secondly the discussion brings the research questions together into a discussion on the overall objective of the research. The main focus of the discussion is an examination of how **data created by learners and captured by an experiential learning platform can be predictive of learners ʼperspectives, mindsets and skills**.

Furthermore, how using learning analytics dashboards to display these insights could be meaningful for facilitators. The discussion in this chapter extends into Chapter 7 where the implications of this research are highlighted within the context of my personal practice and more broadly for practitioners in higher education institutions using experiential learning pedagogies to develop students ’21st Century Skills.

Research Questions

My aim for this research was to understand how data produced by a learner during an experiential learning program, delivered using an eLMS, **can be predictive of learners’ perspectives, mindsets, and skills.** Furthermore to understand how these predictive analytics could be provided to a facilitator in a way that enables them to tailor support of students and subsequently improve student learning.

My research questions that will be discussed in this chapter are:

1. Which data captured by an experiential learning technology can be used to understand more about students’ perspectives, mindsets, and skills?
2. How can data captured by experiential learning technology be used to understand more about students’ perspectives, mindsets, and skills?
3. How can understanding more about students’ perspectives, mindsets, and skills be used by learning designers and facilitators to support their practice in experiential learning?

Research Question 1: Which data captured by an experiential learning technology can be used to understand more about students ’perspectives, mindsets, and skills?

As a part of the EBP students complete learning tasks that include content consumption, reflection activities, project deliverables and peer reviews. Practera's eLMS tracks the time students spend on each of these tasks, which tasks they complete and in what sequence. The best fit multiple regression models outlined in Tables 9, 10 & 11 in Chapter 5 indicate a relationship between students 'scores on self-perception instruments and demographic data questionnaires, used to generate the five dependent variables. In fact, the results indicate that the independent variables generated using time spent on task (Konovic et al., 2015) can predict a significant portion of the variance in learners responses to the self-perception instruments used in the program. The Revised Two Factor Study Process Questionnaire (Biggs et al., 2001) and the Revised Implicit Theories of Intelligence survey (De Castella & Byrne, 2015) are rigorously tested and validated instruments used to identify students 'mindsets and approaches to learning. If the independent variables derived by categorising the learning content in the program can to some extent predict learners 'scores on the instruments it is possible to conclude that time on task data can be used to understand more about students' mindsets and skills.

The following types of data created by learners participating in the EBP and captured by the eLMS were found to have a relationship with an element of predictive power towards one or more of the dependent variables - learning history, deep approaches to learning, surface approaches to learning and growth mindset, fixed mindset:

- **Learning content consumption**: Time spent on sub-categories of learning content including videos or text designed to help students complete project tasks, reflective tasks or feedback tasks.

- **Submission of project tasks**: Time spent understanding and completing submissions for project plans, draft and final reports related to the industry project.
- **Reflective task submissions**: Time spent on tasks including self-assessments of collaboration skills, skill development plans to identify how the student planned to develop their collaboration skills in each phase of the project.
- **Peer Feedback submissions**: Time spent on completing peer reviews of each teammate's collaboration skills.
- **Administrative tasks related to the program**: Time spent on post program surveys to provide feedback on the program, photography release forms and videos that explain the program and how the technology works.

Interestingly, no individual type of task itself appears to have a direct connection with a particular dependent variable. This is highlighted by the best fit multiple regression models reported in the results, found in Tables 9, 10 & 11 in Chapter 5. No one task type is connected to a specific perspective, mindset or skill. This indicates that it is the nature or context of the task that is relevant for categorisation, not the task type itself. For example independent variables that are present in the best fit regression model for growth mindset include learning content, project tasks, reflective tasks and peer feedback tasks. Furthermore, independent variables that had a relationship to deep approaches to learning include the tasks of learning content, project tasks as well as reflective tasks.

The following three subsections of this chapter examine the five best fit regression models reported in the results. In particular they will discuss the connectivity between what is known about learning history (Kwak, 2016), deep approaches to learning, surface approaches to learning (Marton & Saljo 1976), growth mindset and fixed mindset (Dweck, 2017) and the student's behaviour engaging with different types of learning tasks in the EBP. Further it will highlight how facilitators could use these insights to provide tailored support to their students.

Dependent Variable 1: Learning History

The emergent conversation about differences between learners from western cultures and eastern cultures is unfolding through the exploration of the difference between Confucian and Socratic educational philosophies and high and low context cultures. Kwak (2016) proposes that a learner's history in a Confucian or Socratic educational philosophy predisposes them to different learning outcomes and processes. Heng (2013) explains one of the fundamental differences between the two educational philosophies through the lens of politics. Socrates preferred to focus on self-development with public impact as a flow on effect whereas Confucius saw the public impact as the primary focus. This difference in perspective is believed to result in a cultural difference of individualism (Socratic) and collectivism (Confucian) that underpins education.

This understanding of the difference between Socratic and Confucian educational philosophies could explain why the results of this research indicate that data from students with a Confucian learning background indicate a positive relationship to learning tasks in the Skills_Collaboration, Skills_Presentation and Skills_Networking independent variables. Each of these tasks are focused on helping students engage more effectively with their team and client.

Additionally it could explain why coming from a Socratic learning background has a positive relationship with learning tasks related to actually completing the project.

Similar to the best fit multiple regression models for fixed mindset and growth mindset (discussed below), the learning tasks identified as having a relationship with a Socratic and Confucian learning history show connectivity to what is known about the different learning histories. For example a Confucian education philosophy builds a collectivist mentality, therefore positive perception of others is considered important. This aligns with the results of this research that highlight students 'engagement with learning tasks in the independent variables Skills_Collaboration, Skills_Presentation and Skills_Networking as having a positive relationship with the degree of orientation to a Confucian learning history. Understanding the individualistic vs. collectivist perspective that underpins the Socratic and Confucian learning philosophies suggests that educational technology could effectively categorise students into these learning categories if learning tasks were identified as either task-focused or relationship-focused.

It is essential to reiterate the limitations of the insight extracted from the results from the best fit multiple regression analysis for learning history based on the limitations of the data used to derive the dependent variable (discussed in Chapter 5: Results). However the alignment in the nature of the learning tasks in the independent variables that are in the best fit multiple regression model and knowledge about the differences between Confucian and Socratic learning history (Kwak, 2016, Yu, 2010) and high and low context cultures (Bent, 2018; Hall, 1976; Qureshi et al, 2017) reinforces the ability of the data captured by technology to predict this variance however a more robust questionnaire and a more evenly distributed sample would be of value y. The above-mentioned limitation aside, the results of this research do indicate that data captured by an eLMS could be used to predict a learners perceptions and specifically a learners learning history. If the analysis was re-done with the caveats discussed about and the best fit model was used as a baseline to develop a machine learning algorithm for identifying students 'learning history and the algorithm was used to display insights to facilitators they could use the insights to encourage or even incentivise students to complete learning tasks that they do not naturally lean towards.

Dependent Variable 2 and 3: Deep and Surface Approaches to Learning

The notion that learners approach learning using deep or surface approaches to learning was first introduced by Marton and Saljo (1976). Surface learners focus on acquiring the knowledge they perceive as the primary learning objective. while in contrast deep learners explore the knowledge for what can be gained beyond the primary learning objective. The objective of the EBP is completion of the client project. However the client project also provides a real-world context for 21st Century Skill development. The best fit multiple regression model presented in Chapter 5 in Table 10 show that students 'completion of both project-based tasks and skill development tasks have a relationship to their reported self-perception scores on the Revised Two Factor Study Process Questionnaire (Biggs et al., 2001). For example time spent on reflection tasks as indicated by the Skills_Reflection independent variable have a negative relationship with Deep Approaches to Learning score on the Revised Two Factor Study Process Questionnaire, used as the dependent variable in the analysis. Whereas self-assessment tasks, indicated by the y independent variable Self_Assessment, have a positive relationship with the

Deep Approaches to Learning score, used as the dependent variable in the analysis. These two sub-categories of tasks are similar in nature. Both sets of tasks require the learner to consult learning content about competencies that will assist them in the completion of the project, reflect on their own understanding and application of those competencies and consider how they could use the next stage of the EBP to improve their understanding or application of the competency. However one has a negative relationship with the deep approaches to learning score (the dependent variable) and the other has a positive relationship with the deep approaches to learning score. Compounding the complexity the y independent variable Self_Assessment also has a positive relationship with surface approaches to learning (indicated by a positive coefficient) and the Skills_Reflection (y independent variable) has a negative relationship with surface approaches to learning score (indicated by a negative coefficient).

Perhaps this complexity as mentioned above is explained by the link between approaches to learning and motivation. Sengodan and Iksan (2012) found that intrinsic motivators like effort and self-efficacy are significantly linked with a student's approach to learning. This suggests that in order for an eLMS to accurately predict a student's approach to learning using a multiple regression model additional data related to the learner's intention for participating in the learning program needs to be collected.

In statistics adjusted r.squared is the coefficient of determination or the percentage of variance in the depended variable that is predictable from the independent variable (Allen, 2017). The results presented in Chapter 5 highlight that the best fit multiple regression model reported for deep approaches to learning has the highest (51%) adjusted r.squared of all the regression models, displayed in Table 12 below, whereas the best fit multiple regression model for surface approaches to learning has a significantly lower adjusted r.squared. In fact surface approaches to learning has the lowest r.squared of all five of the regression models. Perhaps this result coupled with Sengodan and Iksan's (2012) research indicates that asking students why they signed up for the EBP as part of the course design could provide the data needed to improve the multiple regression model for surface approaches to learning.

Table 12

Adjusted r.squared

Regression Model	Adjusted r.Squared
Deep Approach to Learning	0.5130537
Surface Approach to Learning	0.401287
Fixed Mindset	0.4964752
Growth Mindset	0.4960319
Learning History	0.4951508

When discussing the fixed and growth mindset multiple regression models below there appears to be a relationship between what is known about the nature of a fixed and growth mindset and the types of tasks that had a relationship with students 'scores on the Revised Implicit Theories of Intelligence Survey (De Castella & Byrne, 2015). However the independent variables identified as having either a positive or negative relationship with either a deep or surface approach to learning do not have any explicit pattern to them. In addition to this there does not seem to be any link between what is known about the nature of deep approaches to learning, surface approaches to learning and the types of independent variables of learning tasks that have a relationship with students 'scores on the Revised Two Factor Study Process Questionnaire (Biggs et al., 2001). As mentioned above both deep and surface approaches to learning scores have a negative relationship with the Skills_Reflection independent variable and a positive relationship with the Self_Assessment independent variable.

Perhaps this can be explained by factors identified as having an impact on students ' approaches to learning. There is tension in the literature when it comes to whether a learner's approach is a relatively stable pattern of behaviour or is malleable based on the learning context. There is a body of literature that highlights interest in a topic, having an appropriate amount of time and positive prior learning experiences can positively encourage deep approaches to learning (Dolmans et al., 2016). In contrast a lack of interest in the topic, not enough time and lack of background knowledge can positively encourage surface approaches to learning (Biggs, 1999; Entwistle, 1998; Ramsden, 1992). This notion of malleability (based on context), differentiates the approaches to learning model from the concept of learning styles that suggests that a learner's style is stable and fixed (Dolmans et al., 2016). The EBP is a fast-paced learning program. Students have three weeks to complete a business project with an additional week at the start for onboarding and orientation. Additionally students are assigned to a project at random. In some cases engineering students have completed marketing projects. Based on the notion that a learner's approach to learning is malleable based on the learning context it could be said that the conditions of the EBP itself is creating an environment that encourages surface approaches to learning.

Taking all of this into consideration, an analysis that identifies and displays whether a student is employing deep or surface approaches to learning in real time could be beneficial to a facilitator. For example it could help facilitators identify students whose approach to learning transitions from a deep to surface approach at a particular point in the EBP. This insight about the changing nature of a student's approach to learning in the program coupled with what the literature highlights about the contextual pressures that impact students 'approaches to learning could help educators not only identify the change but offer insight into why the change is happening and how they can intervene. In addition to the teaching and learning implications facilitators could also use this information to identify whether a particular learning program or element of the learning program is too difficult or complex for the student cohort in general. For example if a learning program consistently shows students exhibiting surface approaches to learning in one particular phase of the program it could indicate that the instructional design of the learning program needs adjusting.

Dependent Variable 4 & 5: Fixed and Growth Mindset

Research on fixed and growth mindset (Dweck, 2017; Hochanadel & Finamore, 2015; Zhang et al., 2017) identifies the fundamental difference between the two mindsets to be whether an individual believes their skills and performance can be developed or not. These two mindsets drive human behaviour when it comes to challenges, effort, feedback and success of others. Holistically people who lean towards a fixed mindset invest time proving their level of intelligence to others. Conversely people who lean towards a growth mindset believe their current level of skill is just a starting point and invest their time developing it.

Overlaying this understanding with the results of the multiple regression analysis could explain why the independent variables included in the best fit multiple regression model for fixed mindset tended to focus on things that others can see (submissions) and tasks that helped them 'present 'better to others. For example one of the two skill-based independent variables included in the best fit multiple regression model for fixed mindset is skill_presentation. This independent variable does not require the students to directly engage with others but it is designed to help students present their project to clients better. Conversely the independent variables included in the best fit multiple regression model for growth mindset had more consumable learning content that focused on 21st Century Skill development, learning tasks that have an indirect impact on the project outcome. In addition to the indirect connection to the project outcome, completion of these tasks is invisible to everyone else in the learning collaboration (team members or client). There is no identifiable extrinsic motivator to incentivise the completion of these task.

The learning tasks identified as having a relationship with a fixed or growth mindset align with what is known about the nature and subsequent behaviours of each of the mindsets in the literature (Dweck, 2017; Hochanadel & Finamore, 2015; Zhang et al., 2017). Embedding an analysis of this nature and displaying the results for facilitators could add value to the teaching and learning process. Identifying and displaying whether a student's behaviour indicates a fixed or growth mindset could give insights to facilitators that help them intervene more effectively in each student's learning process. For example facilitators could encourage specific students to complete learning content they do not naturally lean towards or use their understanding of the particular mindset a student is exhibiting to more clearly explain the connectivity of each learning task to the student's overall learning and development.

Conclusion

This research project has used data captured about students 'learning tasks completion and students 'scores on self-reporting instruments to see whether this data could be used to predict a learners perceptions, mindsets and skills without relying on the self-reporting instruments being embedded in the learning program. The results indicate that there are relationships between students' behaviour while participating in an experiential learning program and their scores on self-reporting instruments designed to identify mindset and approach to learning and a demographic survey used to identify learning history. The results of this research suggest that there is value in such self-report instruments in terms of identifying stable patterns of behaviour. Moreover the analysis method developed and used in this research could be applied to test the predictive value of other self-report instruments.

The results of the research suggest that objective evidence may be available to support students 'ability and willingness to accurately assess themselves. Furthermore the results indicate that experiential learning technology could use data analysis of this nature to identify students 'mindset, approach to learning and learning history and display the results for facilitators. The literature surrounding mindsets (Dweck, 2017; Hochanadel & Finamore, 2015; Zhang et al., 2017), approaches to learning (Marton & Saljo, 1976) and learning history (Kwak, 2016) already examines and highlights the usefulness of understanding these perceptions, mindsets, and skills for educators (Gaservic et al., 2017; Hochanadel & Finamore, 2015; Herrmann et al., 2017; Zhang et al., 2017). Therefore if experiential learning technology could accurately identify these perceptions, mindsets and skills and display the results for facilitators they could use these insights to tailor their support of students.

In conclusion the results presented combined with an understanding of the existing literature surrounding mindsets, approaches to learning and learning history indicate that it is possible for experiential learning technology to use predictive analytics to understand more about students 'perspectives, mindsets, and skills. However in order to do this effectively the technology needs to capture data not only about the type of tasks students focus on but the skill each task relates to (mindset), students 'motivation or intention for undertaking the learning program (approach to learning) and whether the learning outcome itself is task-or relationship-focused (learning history). Additionally the discussion has highlighted areas where additional data, analysis and testing could lead to better fit multiple regression models for surface approaches to learning and learning history.

Research Question 2: How can data captured by experiential learning technology be used to understand more about students ' perspectives, mindsets, and skills?

The results reported in Chapter 5 and answer to the previous research question suggest that data currently captured by experiential learning technology can contribute to the understand more about students 'perspectives, mindsets and skills. In particular, understand more about a students 's mindset, approach to learning and learning history. But in order for the technology to predict and display insights about students' further development is required including:

1. Data not yet captured by experiential learning technology;

2. A framework for classifying learning tasks,
3. Further development of the best fit regression models.

Data not yet captured by experiential learning technology

For technology to automatically predict a students ’perceptions, mindsets, and skills using the multiple regression models developed and presented in Chapter 5, the process of classifying the learning tasks into independent variables needs to happen prior to students starting the program and to be captured within the technology’s database. This classification of learning task could be done using metadata tagging. Tags are machine readable traces that can be used by analytics tools to detect patterns (Duval, 2011; Sharma, 2017). In its simplest form, tagging is used in learning technology to recommend additional learning content based on learning pattern and learning style of the student (Sharma, 2017). Tagging can also be used to visualise learning goals and track achievement of those goals (Duval, 2011). Additionally research suggests that tagging and the use of learning analytics can be used to develop metacognition, one’s ability to examine one’s own thinking process (Marzouk et al., 2016).

If instructional designers and facilitators building learning programs were able to attribute each learning task to a subcategory during the program design process the additional layer of post program coding would not be required. The technology would be able to conduct the analysis and display the predicted perceptions, mindsets and skills. At present, the technical capability to classify learning content using tags exists in Practera’s eLMS. This feature could be used to tag learning content. However the tagging functionality would need to extend beyond learning content to submissions and reflection points in order to tag all of the learning tasks required to automate the regression analysis conducted in this research project.

A Framework for Classifying Learning Tasks

If instructional designers and facilitators are responsible for effectively tagging each learning task into subcategories used as independent variables in the multiple regression models it is essential that learning content, submissions and reflection tasks are accurately tagged. When using tagging to recommend learning content for consumption in e-learning, a knowledge map is used. A knowledge map is a hierarchical tree structure which resembles the prerequisites of concepts (Sharma, 2017). These knowledge maps need to be developed for each individual course delivered by e-learning technology.

Based on the insight from the research reported in chapter 5 and discussion related to the previous research question it is possible to use a meta understanding of mindsets, approaches to learning, learning history and the nature of a learning task to develop a system wide framework for accurate tagging of learning content. Perhaps supervised machine learning could be used to recommend tags in order to establish consistency and improve the accuracy of tags.

Ciurez et al (2019) have applied this approach to tagging learning content to another well-known learning styles model (VARK) and are working to improve the accuracy of the machine learning based recommendation. Ciurez et al (2019) are training a machine learning algorithm to analyse learning content based on learners ’preferences for how content is delivered: reading, listening, seeing or experiencing. Training a machine learning algorithm to analyse learning content based on what type of content display the learner appears to prefer is likely to be much simpler than training a machine learning algorithm to accurately tag based on its ability to predict learners mindset, approach to learning, and learning history. This could be overcome by embedding the learning theory-based instruments and demographic questionnaire to test the tagging prior to educators being able to use the newly tagged course in the analysis.

In order to start this process a framework or knowledge map for the tagging needs to be developed and disseminated. The classification framework used in this analysis includes three categories of tasks and 17 subcategories of tasks. Although this is a comprehensive list for the EBP it is by no means exhaustive when it comes to experiential learning in general. Therefore the framework would need to be extended and be adaptable as the regression models are further developed and as the diversity of experiential learning programs using the experiential learning technology expands.

Another important element to consider when developing a classification framework is the agreement and acceptance of the framework by the community of learning designers and facilitators using the technology. Irrespective of whether this research suggests that the technology can accurately predict a learners perceptions, mindsets and skills is possible, the classification and the process used to produce the classification needs to be accepted by the learning professionals using the technology in order for it to produce any value for students in experiential learning programs. The review of literature surrounding the use of developmental technologies in education identified a lack of focus on the adoption and implementation of the emerging capabilities that research is identifying (Santur, Karakose & Akin, 2016; Soobramoney & Singh, 2019; Sohail, Khanum & Alvi, 2018; Kondo, Okubo & Hatanaka, 2017; Aulck et. al., 2016; Pang et.al., 2017). Therefore the task classification framework needed for experiential learning technology to automatically conduct the regression analysis needs to be developed and tested in partnership with instructional designers and facilitators.

Development of the predictive classification model

Once learning tasks are effectively classified and the categories used as independent variables in the regression models is stored within the experiential learning technology database, the technology will contain all the data required to conduct the analysis without human intervention. Capturing the classification of learning tasks using tags will enable automatic analysis of students ’behavioural data using the multiple regression models developed by this analysis and reported on in Table 9, 10 and 11. This automatic analysis could predictively identify learners' perceptions, mindsets and skills and display them for use by facilitators.

As mentioned above the results of this research suggest that predictive learning analytics could be used to identify learners' perceptions, mindsets, and skills using their past and current behaviour in an experiential learning program. These predictions could then be used by facilitators to provide tailored support, structure and incentives in order to support each individual student to extract as much learning as possible out of the learning program. Moreover the insights about the different mindsets, approaches to learning and learning history could be displayed alongside the predictions in order to provide the learning facilitator real-time learning theory knowledge that could assist them in deciding how best to support each student.

Displaying the learning theory insights alongside the predictive analysis could address utility and increased workload issues raised by teachers (Herodotou et al, 2017).

In order to automate the predictive identification of learners' perceptions, mindsets and skills reported in this research, the categorisation of learning tasks needs to be stored in the experiential learning technologies' databases. More importantly more research and development is needed before the predictive learning analytics are used in practice.

The overarching result of the analysis reported in Chapter 5 is five best fit multiple regression models that attempt to predict learners' self-perception of their mindset, approach to learning and learning history using their behavioural data while engaging with a learning program. Multiple regression analysis is a statistical method that uses two or more variables to predict a dependent variable. To date multiple regression analysis has primarily been used to predict academic performance in a course (Ellis et al, 2017; Mwalumbwe & Mtebe, 2017; Yamada et al, 2016). Although predicting performance has utility in teaching and learning it does not offer any insight into the cause of the outcome that could possibly support the facilitator with insight on how to effectively intervene. Predictively identifying learners' perceptions, mindsets and skills based on their current behaviour and displaying this, along with real-time learning theory insights, for facilitators could offer not only useful data but actionable insights that could lead to a change in behaviour and a change in performance.

In this study students 'engagement with subcategories of learning tasks in the learning experience were used to predict a learner's score on self-perception instruments and a demographic questionnaire. The best fit multiple regression models report a significant correlation between students' scores related to their self-perception of their mindset, approaches to learning and learning history and their behaviour engaging with the learning tasks in the EBP. The adjusted r.squared for each regression model highlighted between a 40 - 50% attribution of the subcategories of learning tasks in the model towards the students' self-perception scores. This means that 40 – 50% of the student's self-perception score can be explained by the predictive model. Although this is only half of the self-perception score that can be explained by the variables the significance of the relationship between the variables currently in the models and the self-perception score coupled with the insights gathered about the nature of the different mindsets, approaches to learning and learning histories offer insight into other available behavioural data that could be used to improve the models.

At present the models do not take into consideration students' response to peer and client feedback, students' reflective writing captured in reflection assessment submissions or students' feedback to peers. To use these elements of the student's behavioural data in the multiple regression model would require text analysis, a significant time investment that was outside of the scope of this research project. However the significance of the relationship between the variables and students' self-perception of their mindsets, approach to learning and learning history coupled with the explanatory power of these models suggests that adding these additional variables to improve the models is a worthy investment.

Technology tools like natural language processing, a subcategory of artificial intelligence that combines linguistics and computing power to analyse human language (Ciolacu et al., 2018) could be used to analyse reflective writing. Machine learning is a class of artificial intelligence that employs a self-adaptive algorithm that improves with time. Naïve Bayes Classifier is a machine learning algorithm used to classify objects. In higher education learning and teaching, it has been applied to the assessment of learners' cognitive presence (Hayati et al., 2018) and to determine the sentiment of learners' writing (Sivakumar & Reddy, 2017). Naïve Bayes Classifier could be used to analyse the sentiment of reflective writing and peer feedback of learners in experiential learning programs and tested to see if there is a relationship between reflective writing sentiment and peer feedback sentiment and their self-perception scores on learning theory-based categories, though probably different learning theories than those used here.

To extend the utility of the multiple regression models even further deep learning techniques could be used. Deep learning is a form of machine learning which uses a complex structure of artificial neural networks to examine raw data to progressively extract high level features (Deng & Yu, 2014). The artificial neural networks used in deep learning are built like the human brain and mimic human cognitive processes to explore and make meaning out of big data (Goodfellow et al., 2016). Deep learning could be used to explore the data set and find its own relationships between learner behaviour and their self-perception of their mindset, approach to learning and learning history. More specifically deep learning could be used to extend the model by exploring not only what learning tasks students invested time on in the learning program, but the sequences or order in which learners looked at learning content in relationship to project submissions. Deep learning is currently being used in higher education administrative data to predict dropout (Berens et. al, 2018). Perhaps this same process could be used by experiential learning technology to categorise students so that facilitators can provide better support instead of accelerating attrition as it is currently being used.

Research Question 3: How can understanding more about students' perspectives, mindsets, and skills be used by learning designers and facilitators to support their practice in experiential learning?

This research suggests that data captured by experiential learning technology can be used to predictively identify learners' perspectives, mindsets, and skills using learning analytics analysis. However being able to predictively identify learners' perspectives, mindsets, and skills about particular students is not a compelling enough argument for doing it. In order for value to be extracted from the prediction, it should be meaningfully used by facilitators for the purpose of supporting students and improving the design of learning or more holistically, to examine the nature of learning itself.

At present the main use case for predictive learning analytics in higher education is in predicting a learner's performance in a whole degree program (Herodotou et al, 2017; Herodotou et al, 2019; Sclater et al., 2016; Williamson, 2016) or specific course (Ellis et al, 2017; Mwalumbwe & Mtebe, 2017; Yamada et al, 2016). In fact, the emergent definition or explanation of predictive learning analytics is "to improve learning by identifying students at risk of failing their studies" (Herodotou et al, 2019, p. 85). However predictive analytics itself is the use of statistical techniques to analyse both current and historical data in order to make predictions about the future (Gandomi & Haider, 2015). This understanding suggests that predictive learning analytics could be much broader than the definition implies.

The results reported in Chapter 5 and the above discussion highlight which data can provide actionable insights for facilitators and how data can be used to identify learners' perspectives, mindsets, and skills. In response to this research question a potential use case for predicting a learner's perspectives, mindsets, and skills and the subsequent predictions in the customisation of support, incentives and learning tasks in real time.

The data reported in Chapter 5 suggests that predicting a learner's perspectives, mindsets and skills using learning analytics is possible. In addition to the analysis providing statistical results about how data collected could be used in this prediction also provides insights into the nature of learners behaviour as they participate in an experiential learning program. Perhaps this insight could be used by facilitators and instructional designers to further integrate and support the learning of 21st Century Skills in experiential learning programs. The learning analytics literature highlights the use of learning analytics for the development of learning content (Kovanović, Joksimović, Gašević, & Siemens,2017; Lockyer & Dawson, 2012; Lockyer, Heathcote & Dawson, 2013) but perhaps it could extend beyond content to structure and support. The following discussion will explore this by focusing in on the results of the Revised Implicit Theories of Intelligence instrument (De Castella & Byrne, 2015) and the best fit multiple regression models for predicting students' scores on the instrument.

The research results highlight that there is a significant relationship between growth mindset score and the learning tasks in the skill_reflection and self-assessment independent variables. Also of note there is a significant yet weaker relationship between a fixed mindset score and the same two groups of learning tasks, indicated by the results in Table 11. In fact the Revised Implicit Theories of Intelligence survey used to self-assess growth and fixed mindset was a part of the independent variable skill_reflection. The results of the survey completion in Table 7 show a significantly higher number of students who completed the survey leaning towards a growth mindset. In contrast to this there are 86 students (13% of the cohort) who did not complete the survey. Based on the results of the multiple regression analysis, particularly the significance of the relationship between the skill_reflection and self_assessment sub-categories of tasks and growth mindset score, one could speculate that students who did not complete the survey would be more likely to lean towards a fixed mindset.

This insight about learners who lean towards a growth mindset and learners who lean towards a fixed mindset could be used by facilitators and instructional designers to:

1. customize support based on the mindset they are exhibiting;
2. incentivise completion of learning tasks that students may not naturally complete on their own,
3. adapt the framing of learning content to connect it better with a learner's objectives.

For example if a student participating in the EBP exhibits behaviour that classifies them as exhibiting a fixed mindset the facilitator could use this information to intervene early on in the program in order to encourage the student to extract all of the available learning out of the program. Specifically the facilitator could engage with the student and more explicitly explain how each learning task in the EBP will support their ability to demonstrate their skills. Essentially this is facilitating what is known about the nature of a fixed mindset to drive learning outcomes. Knowing that learners with a fixed mindset give up easily when facing obstacles and see effort as fruitless (Dweck, 2017) facilitators could intervene with proactive encouragement and support when they are in the midst of grappling with an obstacle that is designed into the learning program.

In addition to the facilitator support, instructional designers could use insights about learners who lean towards a fixed or growth mindset to alter the design of the learning program. Understanding that students who have a fixed mindset will focus on proving their skills could be used to add customisation to the design of the learning program for these students; for example, building in badges or other publicly available incentives based on the completion of learning content. This would offer them a mechanism to show proof of skills as an incentive to complete learning tasks that will develop their skills. Learning designers could also re-frame the titles and introduction of learning tasks for learners with different mindsets, for instance reframing tasks designed to develop their skills as tasks that will help them present their project better to their client.

Conclusion

This chapter has presented interpretations and insights from the analysis conducted and reported in Chapter 5 in order to systematically address these three research questions:

1. Which data captured by an experiential learning technology can be used to understand more about students’ perspectives, mindsets, and skills?

2. How can data captured by experiential learning technology be used to understand more about students' perspectives, mindsets, and skills?
3. How can understanding more about students' perspectives, mindsets, and skills be used by learning designers and facilitators to support their practice in experiential learning?

This chapter discussed each individual research question and how the results of the analysis have contributed insights that help provide an answer to the question and where potential gaps that require further analysis still lie. Additionally the discussion has identified some potential future developments of the research that could help further improve the teaching and learning of experiential learning in higher education. The interpretations in this chapter stem from my philosophical perspective outlined in Chapter 3 and are by no means exhaustive in terms of what could be derived from the results. However it has provided insight into how data captured by experiential learning technology can be utilised to predict learners' perceptions, mindsets and skills. Furthermore it shows how this prediction could be used by experiential learning facilitators and designers to customise real-time support, incentives and learning content.

The discussion in this chapter has highlighted not only how the results of this research could be used to impact the practice of experiential learning facilitators but more broadly it has discussed the potential of this research to further operate as a propulsion point for further research into how experiential learning technology could be used to support 21st Century Skill development in experiential learning programs. The content of this chapter has identified how both the results of this research and further development of experiential learning technology based on the results of this research could support the practice of experiential learning facilitators. In the next chapter the results and insights discussed here will be used to examine how the outcomes of this research could impact my practice as an experiential learning technology designer and as a researching practitioner. It will also examine the implications of this research for practitioners in higher education institutions using technology enabled experiential learning pedagogies to develop students ’21st Century Skills.

Chapter 7: Implications for Practice

Introduction

The discussion in the previous chapter examined and interpreted the research results within the context of how they could improve the ability of technology to support experiential learning programs designed for 21st Century Skill development. The chapter concluded with an examination on how the results of this research could be used by facilitators and instructional designers to improve their practice of experiential learning design and facilitation. This chapter will extend on the insights generated from the discussion and consider potential implications for the integration of real-time analysis that integrates learning theory and learning analytics, within the practice of experiential learning in higher education, and within my own personal practice.

It is essential to note that this study is a proof of concept aimed to present the potential power of aggregating learning theories and emerging technology enabled processes like machine learning and learning analytics. The results themselves are not generalisable outside of the EBP program because they are dependent upon this specific context, technology and course design. Despite these limitations the study does present a case for the use of learning analytics in experiential learning facilitator and for more generalizable research at the intersection of learning theory and learning analytics.

This chapter will discuss how the improvements to education technology that stem from this research could contribute to improvements in higher education experiential learning programs. Specifically it will discuss ways the results of this research could be used to increase the volume of students each facilitator can support in experiential learning programs, support experiential learning facilitators with real-time insights that help them provide better support to students, help student extract more of the available learning out of an experiential learning programs and perhaps even help students develop their lifelong learning capability.

The second section of this chapter will address the call located in both learning analytics literature and education research literature (Gasevic et al., 2017; Gašević et al., 2016; Gasevic, Dawson & Siemens, 2014; Reinmann, 2016) for aggregation of learning analytics with learning theory that was highlighted in Chapter 2. The section will discuss how this research project provides a response to this call for the aggregation of learning analytics and learning theory, and demonstrates what is possible when learning theory and learning analytics research are combined.

Finally the implications of this research on my own practice will be discussed. The discussion will start with my current practice in experiential learning facilitation, design and technology development, then switch to my intended practice in the development of learning programs, technology and research that focuses on the potential for implementation of scalable learning solutions in low resource economies.

Implications for experiential learning in higher education

The literature review of the 4th Industrial Revolution (4thIR) and 21st Century Skill development identified the need for higher education institutions to shift their focus towards more 21st Century Skill development (Andrade, 2016; Chamorro-Premuzic & Frankiewicz, 2019; Hodgman, 2018). Literature about work in the 4thIR suggests that automation will disrupt physical and cognitive work (Perry, 2018; WEF, 2015). This disruption will shift the role of humans away from repeatable tasks to problem-solving, innovation and collaboration (Ghislieri et al, 2018; Kazancoglu & Ozkan-ozen, 2018; Shvetsova & Kuzmina, 2018). In addition the literature highlighted that jobs that students would have in the future do not exist yet, resulting in higher education institutions needing to shift away from preparing students for a specific career towards developing capabilities and competencies that help them adapt and evolve as the nature of work changes throughout their career (Mphuthing, 2019; United Nations, 2015). The results of this research and further development of the findings could play a role in this transition towards 21st Century Skill development required in order for higher education institutions to play a useful role in the 4thIR. This could be achieved by further improving the predictive categorisation models and building the predictive categorisation models into experiential learning technology. This would enable experiential learning designers to use learning analytics insight to improve the design of the experiential learning programs. Perhaps more importantly experiential learning facilitators could use the insights from the predictive models to support larger cohorts of students without increasing the time invested. This could reduce the cost of delivery and open up access to the experiential learning programs to more students.

The results of this research presented in Chapter 5 suggest that data from experiential learning technology can be used to predict learners 'perceptions, mindsets and skills . Moreover, the discussion in Chapter 6 highlighted how predicting learners' perceptions, mindsets and skills and displaying these predictions alongside learning theory insights could help experiential learning facilitators and instructional designers. Here the results and discussion will be drawn upon to examine how prediction of learners' perceptions, mindsets and skills and displaying this prediction alongside learning theory insights could help experiential learning facilitators with actionable insights that help replace affective cues lost when students are not physically in front of them (Crawley et al., 2009). Moreover the discussion will examine how displaying the prediction and learning theory insights could assist learning designers to improve the design and introduce a layer of learner-centred adaption into experiential learning programs. Specifically how the results of this research could enable increased use of experiential learning, as a vehicle for curriculum development and delivery, enable facilitators to provide more tailored support, and help students extract more of the available learning out of experiential learning experiences and perhaps even support the development of lifelong learning capability.

Support for Experiential Learning Facilitators

Enable Experienced Experiential Learning Facilitators to support more students

Experiential learning programs are used across a broad spectrum of the higher education ecosystem (Mills & Teagust, 2003; Widiastuti & Budiyanto, 2018; Dixon, 2014; Henderson, 2018; Leal-Rodrigues & Albort-Morant, 2019; de Groot et al., 2018, Graber et al., 2017; Pangelinan et al. 2018). The literature continues to validate the positive impact of experiential learning on students 'learning (Henderson, 2018, Jackson, 2013, Tiessen et al., 2018). However it is commonly understood that experiential learning programs are labour-intensive, complex and therefore expensive to deliver (Beckem & Watkins, 2012; Henderson, 2018; James et al, 2020). Perhaps real-time theory-based insights about the perceptions, mindsets and skills of students participating in experiential learning programs could play a role in reducing the complexity and the time a facilitator needs to invest in each individual student. For example if the experiential learning technology could identify students who have switched from exhibiting behaviours (attributed to deep approaches to learning) to exhibiting behaviours attributing to surface approaches to learning and highlight this to the facilitator they can jump in and provide support without the time investment of identifying the issue themselves. Leveraging the experiential learning technology and predictive models for problem identification could reduce the time facilitators invest in dealing with an individual issue.

Increasing the volume of students a facilitator can effectively support without decreasing the quality of the learning outcomes could also enable more experiential learning components in foundational courses that tend to have higher student to teacher ratios. Being able to offer foundational courses using experiential learning pedagogies could mean that students have more opportunities to develop their 21st Century Skills much earlier in their degree and more times throughout their degree.

Support for Less Experienced Experiential Learning Facilitators

One of the barriers to the use of experiential learning in higher education, highlighted within Chapter 2 is the complexity and associated costs to deliver quality experiential learning programs (Henderson, 2019). Yet higher education institutions are under pressure to provide more experiential learning, particularly experiential learning that develops 21st Century Skills and prepares students for a career in the 4thIR. The literature cautions that these two challenges can result in a consumerist orientation or *white washing* of experiential learning that does not actually have the learning impact (Tiessen, Grantham & Cameron, 2018; Jorgenson & Shultz, 2012; Qiubo, Shibin & Zha, 2016). Additionally, the increase in non-traditional students accessing higher education not only increases the need for real-world experiential learning programs (Burns & Danyluk, 2017; Buglione, 2012) but adds to the complexity of the delivery and the support each student needs to be successful.

This contextual pressure could result in institutions strongly encouraging faculty to embed more experiential learning elements into their courses without effective training and support. If the regression models developed in this research were further enhanced and results displayed for experiential learning facilitators in real-time perhaps it could help less experienced facilitators have more insight into each student and their team composition. This data-driven insight could help them develop their ability to facilitate experiential learning.

How the experiential learning technology could support facilitators

When looking specifically at the best fit regression models for predicting fixed mindset and growth mindset, visualization of the models 'prediction, coupled with interpretations of how mindset can play out in a learner's behaviour based on learning theory, could help facilitators provide data and examples to the student team to help understand and overcome a challenge. For example if a diverse team were experiencing team-dissonance with students highlighting frustrations about other team members 'behaviours; having insight into the student's mindset and interpretations of known challenges a diversity of mindsets can cause, could be utilised by facilitators in real-time to coach the team through the dissonance.

Developing experiential learning technology to augment the facilitator's ability to gather insight about each student's experience and learning context, followed by the ability to leverage the research and science of human behaviour in real-time to offer support, could help institutions ensure their experiential learning programs are generating the learning for which they are intended. The learning theory augmentation would also help experiential learning facilitators leverage learning theory about their diverse student cohort and personalise feedback, support and perhaps even the overall learning program structure for each student.

Support for Students engaging in Experiential Learning Programs

Enable facilitators to provide more tailored support for individual students

Experiential learning offers an opportunity for students to learn from experience. This transitions the role of the facilitator from 'expert 'to 'guide. 'Embedding technology that provides a theory-based analysis of students' learning behaviour while participating in experiential learning could help facilitators identify when guidance is needed and provide theory-based insight into the student's mindset, approach to learning and learning history that would enable more tailored guidance and support.

For example the discussion in chapter 6 identified that students who exhibit behaviours that correlate with a Socratic learning history appear to focus more on project-based learning content and tasks as opposed to relationship-based content and tasks. An experiential learning facilitator can use this insight to engage specifically with students who are exhibiting behaviours correlating to a Socratic learning history and encourage or incentivise the completion of relationship-based tasks. Within the EBP facilitators could use learning theory-based insights to proactively encourage students that identify as being from a Socratic learning history to complete learning content about communicating and presenting their ideas. This encouragement might help prevent all the value generated in their task based work from being lost because students were unable to communicate it effectively.

Help students extract more out of an experiential learning program

The experiential learning cycle is a structured process for extracting knowledge from experience (Botelho et al. 2015; Kolb & Kolb, 2005a; Kuk & Holst, 2018; Miller & Maellaro, 2016; Sandlin et al, 2018). The experiential learning cycle steps a learner through four phases:

1. Concrete experience: For example, a business project;
2. Reflective observation: looking back on the business project in order to consider what went well and where improvement is required;
3. Abstract conceptualisation: consideration of how theory from class could offer more in-depth insight into what happened;
4. Active experimentation: planning what could be done differently next time and implementing that plan at the next phase of the business project (Kolb, 2015).

An experiential learning program that leverages the experiential learning cycle offers an opportunity for students to extract a larger volume of knowledge and meaning from a real-life situation. The Practera EBP, the context for this research is an example of an experiential learning program that leverages the experiential learning cycle in its design. Students participating in the program have the opportunity to:

1. Develop their collaboration skills,
2. Apply theoretical knowledge and technical skills to a real-world project,
3. Learn how to engage an industry client effectively,

4. Learn how to manage and deliver a project effectively,
5. Develop their networking skills,
6. Test out a particular career.

all by using the four phases of the experiential learning cycle. Experiential learning programs like the EBP offer a large volume of available knowledge for extraction however extracting it all simultaneously is cognitively complex (Irvine, 2017). In addition to the volume of knowledge available from an experiential learning program, students are also required to transfer past learning from the classroom to current real-world contexts (Jackson et al., 2018).

The results of this research project indicate that students that have particular mindsets, approaches to learning and learning histories tend to focus on different types of learning tasks. For example, the discussion in chapter 6 highlighted that students who self-identified as having a surface level approach to learning tended to focus on learning tasks that had a direct connection to the industry project. If a student who identified as having a surface level approach to learning continued to lean towards specific learning tasks, they might be leaving a valuable learning opportunity on the table.

Embedding technology and specifically the ability to analyse students' behaviours in real-time in order to understand the mindset, approach to learning, and learning history they are exhibiting could help facilitators encourage students to focus on learning that they do not naturally lean towards and result in them extracting more of the available learning from the experience. Moreover experiential learning designers could use the information to create more explicit links between knowledge acquired in a past classroom setting that could be transferred into this current real-world context.

In time and with more development and research, the insights from this research could be used to adapt reflective writing tasks to focus students on particular skills that they may not naturally focus on. For example, the reflective writing task could be adapted for a student who identifies a fixed mindset to focus them on elements of the available learning that are not directly connected to their original intention for signing up for the learning experience.

Development of Lifelong Learning Capability

An additional and somewhat more abstract and future focused implication for this research is the ability for it to impact the development of a student's lifelong learning capability. Lifelong learning is acknowledged as learning that is ongoing, self-motivated and pursuant of either personal or professional goals (Commission of European Communities, 2006; Laal, 2011; Longworth, 2019). Functionally effective and intentional lifelong learning requires metacognition; to examine how one thinks (Lai, 2011) or as Socrates put it, to *know thyself,* and learning flexibility, the ability to intentionally use a non-preferred approach to learning if that is what is required (Petersen, DeCato & Kolb, 2015). But in order to enact this change these capabilities need to be underpinned by a belief that change is possible (Dweck, 2017). Perhaps being able to predict learners 'perceptions, mindsets and skills could play a role in developing these attributes required for lifelong learning.

As highlighted in Chapter 4, the epistemological perspective that underpinned this research is that humans are unique, can change and exercise free-will. Yet the method used in this research design is positivist and deterministic. The tension within this choice is explained by the neuroscience of habit and the notion that although we can choose in the moment, we acquire habits that automate our choices and behaviour (Gardner, de Bruijn & Lally, 2011). Perhaps the ability to predict a learners perceptions, mindsets and skills in an experiential learning program could unearth subconscious learning habits by triggering metacognition about their learning process. This could enable students and facilitators to examine the approach to learning being used and whether it is the most effective for the knowledge, skill or ability being acquired. This process could help facilitators support not only the foundational skill development outcomes of the experiential learning program but also the student's development of their learning flexibility.

The research data reported in Chapter 5 indicates that education technology could be used to identify a student's approach to learning while they are participating in an experiential learning program. Perhaps displaying this identification to the facilitator, and even the student, they could engage in a meaningful conversation about whether this approach to learning is appropriate for the task at hand or the experiential learning program overall. This could be made possible by displaying the learner's approach to learning on their dashboard and providing reflective tasks that are personalized to each student's approach to learning, learning history and mindset. Each reflective task could be structured to focus each student to not only what they are learning and producing but how they are doing it. This reflection task could then be reviewed by the facilitator who would also be aware of the learner's approach to learning; mindset, learning history and could provide tailored feedback.

Conclusion

As mentioned above, the ability to predict learners perceptions, mindsets and skills according to relatively stable learning characteristics and preferences while in an experiential learning program by analysing students' behaviour holds lots of potential for supporting learning designers, facilitators and students. This potential is particularly relevant for the practice of experiential learning in higher education institutions. Implementation of technology-enabled real-time analysis of students' behaviour can leverage both theory and the expert knowledge of experiential learning facilitators to augment facilitation.

Implications for the integration of Learning Analytics and Learning Theory

Learning analytics literature indicates a potential for real-time learning analytics, driven by machine learning algorithms, to augment teaching (Hernandez-Lara, Perera-Lluna & Serradell-Lopez, 2019; Alblawi & Alhamed, 2017). However, both the educational research and learning analytics research communities indicate a need for learning analytics research that is underpinned by learning theory (Gasevic et al., 2017; Gašević et al., 2016; Lodge & Lewis, 2012; Rogers, Gašević, & Dawson, 2016; Wise, 2014; Wise & Shaffer, 2015; Avella et al., 2016; Gasevic, Dawson & Siemens, 2014; Kirkwood & Price, 2013; Lodge & Corrin, 2017; Lockyer, Heathcote & Dawson, 2013; McArthur, Lewis & Bishay, 2005; Reimann, 2016). Bronniman et al. (2018) explicitly call for learning analytics to ask clearer pedagogical questions, and Gasevic et al. (2017) feel that learning analytics research should build on learning theory. Despite the call for more integration, there is still little learning analytics research that is focused on teaching and learning (McKee, 2017) and even less that integrates learning theory with analytics.

Perhaps the most significant implication of this research for learning analytics and learning theory research is its ability to offer an example of what is possible if they are both combined. My doctoral thesis is a solo research project. However I did seek feedback, insight and research from both the learning analytics and learning theory research communities in order to leverage the perspectives of both bodies of literature and communities of practice. Throughout the process of completing this doctoral thesis; the analysis and report, I engaged with multiple scholars including education researchers and learning analytics researchers. Although there is interest in my research project from both perspectives, I was also confronted with passionate arguments against it. Kirschner (personal communication, February 2018) found the learning theories I chose problematic, claiming that the learning theories I was using had no objective validity. The learning analytics researcher that was mentoring me through the research design process was supportive yet apprehensive, sending me research articles that suggested I should not expect much from the results. On the educational research side, I was under pressure to change the nature of the research to fit in better with existing education research practices.

Walking down the line between learning analytics and learning theory research has been challenging and insightful. Despite the somewhat challenging journey, I hope this project offers insight into what innovation and impact might be possible if learning theory and learning analytics research were more integrated. Research into what produces better innovation outcomes acknowledges that bringing together more diverse perspectives produces more innovative outcomes (Diaz-Garcia, 2014). However this lift in innovation is only realised if the diverse perspectives can be integrated into a common purpose (Katzenbach & Smith 2015). Integrating these perspectives in this doctoral thesis has led to interesting and useful insights that were likely not possible without combining the different perspectives and research approaches.

Research into high performing teams identifies that a common purpose is not enough, a team also needs a common approach for how the purpose will be achieved (Katzenback & Smith 2015). As an individual researcher bringing perspectives from learning analytics and learning theory research together, I did not have to deal with conflicting perspectives on purpose and approach. As an individual researcher I had a single purpose and chose an approach that I thought was appropriate for the research project. However bringing a team of learning theory researchers and learning analytics researchers together to collaborate on a larger project would have to address their differences in purpose, perspective and approach in order to collaborate effectively. Perhaps exploring and reporting on effective collaboration models for learning analytics researchers and learning theory researchers could result in more research projects that aggregate learning theory and learning analytics research.

Limitations

The results, discussion and implications chapter of this doctoral thesis have attempted to address three research questions:

1. Which data captured by an experiential learning technology can be used to understand more about students' perspectives, mindsets, and skills?
2. How can data captured by experiential learning technology be used to understand more about students' perspectives, mindsets, and skills?

3. How can understanding more about students' perspectives, mindsets and skills be used by learning designers and facilitators to support their practice in experiential learning?

Although the research has resulted in some interesting and novel insights about the nature of data captured by experiential learning technology and how it can be used to improve and scale the practice of experiential learning in high education institutions, it is important to acknowledge the limitations. This research project used retrospective de-identified data from one experiential learning program and one technology to conduct the analysis and generate insights. Using retrospective and de-identified data meant that learning tasks, structure and learning theory-based instruments used in the learning program were pre-designed into the learning program.

In addition to the limitations of the research method itself it is also important to reiterate that the purpose of this research project was not to examine or validate existing learning theory but to examine one way learning theory and learning analytics could be aggregated to see if this integration hold potential for the improvement and scalability of experiential learning programs in higher education institutions. The learning theories used in the categorisation and regression models were already existing in Practera's experiential business project program and technology. All the insights and discussion about the value of integrating learning theory and learning analytics would be increased through using the best possible learning theory and more complex learning analytics processes.

Implications of this research on my personal practice

I am a first-generation university student. I am the second in my extended family to gain a master's degree and to date the only one to be at the final stages of a doctorate. This opportunity was afforded to me because I was born in Australia. Australia is a nation that places value on higher education, invests into it and has implemented legislation and financial structures that make it accessible and affordable.

Earlier in my career I was a social innovator in Australia, the USA, China and Tanzania. I became increasingly aware of how lucky I was to be born and raised in a context that valued higher education. In parallel, I was acutely aware that problems I was solving as a social innovator were caused by a lack of quality and accessibility in education systems. As a result, I examined what systemic changes were required in order to enact scalable change to education systems. My conclusion was to focus on 21st Century Skill development and how technology could play a role in facilitating 21st Century Skill development.

This transition began in 2013 with the purpose of understanding how emerging technologies could be used to improve the quality and accessibility of 21st Century Skill development in higher education, leading to my current *practice* designing experiential learning programs and technology that support 21st Century Skill development. In the future I will use insight from my current practice and knowledge from this research to improve the scalability of quality experiential learning and 21st Century Skill development in low resource economies.

Current Practice

In order to build education technology and specifically experiential learning technology that can augment facilitators' skills in a meaningful way, an understanding of how students learn is required. The process of completing this doctoral thesis and the results of the research have increased my understanding of how students learn and, in particular, how students learn 21st Century Skills.

The World Economic Forum 21st Century Skill framework (2015) breaks down sixteen skills into foundational literacies, competencies and character qualities. The foundational literacies are focused on how technical expertise is applied to everyday tasks, for example, how an understanding of marketing theory applies to the practice of marketing in the real-world. The competencies include critical thinking and are skills used to approach complex problems, for example, skills required to respond to technology disruption in an industry. The character qualities include adaptability and are skills used to approach one's environment more holistically. Finally, lifelong learning is the wrap-around skill of the framework, the ability to continuously acquire new skills, knowledge and capabilities required to respond to the ever-changing environment.

The process of this doctoral research project and the results of the research have helped me understand the nature of these three subsets of skills and how they are developed. The exploration of whether mindset (Dweck, 2017) and approach to learning (Marton & Saljio, 1976) can be identified using the behavioural data of learners going through an experiential learning program gave me further insight into the nature of these mindsets and approaches to learning. My heightened understanding based on the results of this research will have a significant impact on my teaching, designing, technology development and research.

Future Practice

As mentioned, I intend to transition my attention towards the accessibility of quality experiential learning and 21st Century skill development in low resource economies. Three significant challenges to making technology and, subsequently, technology-enabled learning accessible in low-resource economies are the technology infrastructure, cost and confidence in teaching ability (Zamani et al., 2016). The biggest barrier to technology-enabled scale in low-resource economies is access to WiFi and cost of data. This is outside the scope of my current research. However, the other two challenges, cost and confidence in teaching ability, can be addressed by designing for scale and using real-time learning analytics to augment the facilitator. If one learning facilitator can effectively support 1000 students through an experiential learning program designed to develop 21st Century Skills, without decreasing the learning outcomes gained by each student, then it makes the program more cost-effective for the institution and accessible to more students. Moreover, real-time learning analytics augmentation of inexperienced facilitators or facilitators who lack confidence could support with facilitator development and boost confidence knowing they are supported by theoretically sound insights and analysis.

The results of this research offer insights that will contribute to the re-development of learning programs and technology to enable facilitators to increase the volume of students they are supporting without decreasing the learning experience or outcomes for each student. For example, the Practera EBP is currently delivered at a ratio of one facilitator to 500 students. One of the barriers to scale is the ability of facilitators to understand how each student and team is progressing through the learning program in order to provide bespoke and tailored support. Re-development of the technology to include real-time analysis that identifies a student's mindset, approach to learning and learning history that can be displayed to the learning facilitator could increase the volume of students they can effectively support. Moreover, using an understanding of learning theory to offer facilitators real-time learning theory insights could save facilitators time and improve their practice and support to another magnitude of scale. This ability to augment the facilitator with real-time theory-based insights using machine learning and learning analytics could enable higher education institutions in low-resource economies to access solutions for 21st Century Skill development that are cost-effective and high-quality.

In addition to the results of this research and insight gained from completing this doctorate enabling a transition in focus to scalability and accessibility in low-resource economies, it has also transitioned me from a practitioner to a practitioner-researcher (Jupp, 2006). The results of this research project have provided a baseline for multiple follow-up research projects that could improve the teaching and learning of experiential learning programs that are designed to develop 21st Century Skills. Perhaps, more importantly, it has developed my ability to take a research-based approach to my practice. The ability to engage with the current academic literature in order to inform my practice, design research questions, conduct a research study and methodically consider the outcomes and how they can be implemented are invaluable skills for an innovator focused on driving real-world outcomes.

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Appendix 1 Instruments

Revised Implicit Theories of Intelligence (Self-Theory) Scale

The following questions are exploring students' beliefs about their personal ability to change their intelligence level. There are no right or wrong answers. We are just interested in your views. Using the scale below, please indicate the extent to which you agree or disagree with the following statements.

	Strongly disagre e	Disagre e	Mostly disagre e	Mostly agree	Agree	Strongl y agree
1. I don't think I personally can do much to increase my intelligence.	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5	☐ 6
2. I can learn new things, but I don't have the ability to change my basic intelligence.	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5	☐ 6
3. My intelligence is something about me that I personally can't change very much.	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5	☐ 6
4. To be honest, I don't think I can really change how intelligent I am.	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5	☐ 6
5. With enough time and effort I think I could significantly improve my intelligence level.	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5	☐ 6
6. I believe I can always substantially improve on my intelligence.	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5	☐ 6
7. Regardless of my current intelligence level, I think I have the capacity to change it quite a bit.	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5	☐ 6
8. I believe I have the ability to change my basic intelligence level considerably over time.	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5	☐ 6

The Revised Two Factor Study Process Questionnaire: R-SPQ-2F

This questionnaire has a number of questions about your attitudes towards your studies and your usual way of studying.

There is no right way of studying. It depends on what suits your own style and the course you are studying. It is accordingly important that you answer each question as honestly as you can. If you think your answer to a question would depend on the subject being studied, give the answer that would apply to the subject(s) most important to you.

Please fill in the appropriate circle alongside the question number on the "General Purpose Survey/Answer Sheet". The letters alongside each number stand for the following response.

A — this item is never or only rarely true of me
B — this item is sometimes true of me
C — this item is true of me about half the time
D — this item is frequently true of me
E — this item is always or almost always true of me

Please choose the one most appropriate response to each question. Fill the oval on the Answer Sheet that best fits your immediate reaction. Do not spend a long time on each item: your first reaction is probably the best one. Please answer each item.
Do not worry about projecting a good image. Your answers are CONFIDENTIAL.
Thank you for your cooperation.

1. I find that at times studying gives me a feeling of deep personal satisfaction.
2. I find that I have to do enough work on a topic so that I can form my own conclusions before I am satisfied.
3. My aim is to pass the course while doing as little work as possible.
4. I only study seriously what's given out in class or in the course outlines.
5. I feel that virtually any topic can be highly interesting once I get into it.

6. I find most new topics interesting and often spend extra time trying to obtain more information about them.
7. I do not find my course very interesting so I keep my work to the minimum.
8. I learn some things by rote, going over and over them until I know them by heart even if I do not understand them.
9. I find that studying academic topics can at times be as exciting as a good novel or movie.
10. I test myself on important topics until I understand them completely.
11. I find I can get by in most assessments by memorising key sections rather than trying to understand them.
12. I generally restrict my study to what is specifically set as I think it is unnecessary to do anything extra.
13. I work hard at my studies because I find the material interesting.
14. I spend a lot of my free time finding out more about interesting topics which have been discussed in different classes.
15. I find it is not helpful to study topics in depth. It confuses and wastes time, when all you need is a passing acquaintance with topics.
16. I believe that lecturers shouldn't expect students to spend significant amounts of time studying material everyone knows won't be examined.
17. I come to most classes with questions in mind that I want answering.
18. I make a point of looking at most of the suggested readings that go with the lectures.
19. I see no point in learning material which is not likely to be in the examination.
20. I find the best way to pass examinations is to try to remember answers to likely questions.

Scoring is in the following cyclical order:
1. Deep Motive, 2. Deep Strategy, 3. Surface Motive, 4. Surface Strategy 5. " etc.
Deep Approach Score: Σ All Deep Motive scores + all Deep Strategy scores
Surface Approach Score: Σ All Surface Motive scores + all Surface Strategy scores

Note: The A – E response options in the survey where converted into numerical values for scoring. A was given the value of one, B was given the value of 2 and so forth through to E being given the value of 5.

Appendix 2 Data Privacy Impact Assessment

Data Privacy Impact Assessment for Thesis Research Data

Documents Read

- Practera Privacy Policy -
- GDPR.eu
- OAIC Privacy and OAIC Guide to data analytics and the Australian Privacy Principles -
- Australian Privacy Principles
- GDPR changes the rules for research
- Australian Department of Education Privacy Policy

Insight

- GDPR explicitly caveats for research that is for scientific, medical or public research
- Australian Higher Education institutions are not bound by Australian Privacy Legislation but choose to comply in their Privacy Policy
- Australian legislation does not explicitly address data for the purpose of research.
- Australian Department of Education has a Data Privacy Impact Assessment process they use and have a register listed on their website.
- The main issue with storing, transferring to third party or processing is 'personal information' and there is a specific list including name and other demographic details.
- There is specific language around anonymized and pseudo anonymize. Anonymized sits outside data privacy legislation and pseudo anonymized sits inside.
- There is specific information about only using/transferring data that is necessary to be transferred and processed.
- Anonymized data is considered anonymized if more than reasonable effort is required to re-identify the subject.
- Australian legislation and GDPR both say that data can be used for improvement of services (which we have included in our privacy statement) and GDPR says that data can be used for research even if it is not explicitly outlined in the privacy statement if it does not impact the owner of the data and is for scientific, medical or public research.

Transferring to a third party

- There is no information around documentation or agreements
- Both GDPR and APP talk about transfer (including across boarders) being okay if the people or organization that it is going to is bound by the APP/GDPR or another national legislation that is similar to the APP/GDPR
- The Australian Department of Education and UniSA's policy on data transfer to a third party (including across boarders) aligns to this

Based on all of this information my conclusion on how to share data with researchers to provide feedback on the analysis is:

1. The data being transferred is anonymized (and cannot be reversed with reasonable effort)

   a. All data listed as personal data in Privacy Legislation has been removed
   b. Additional layer of de-identification can be added by the researcher giving each 'user' a new code for the transfer to the third party.
2. The data being transferred is only what is needed to execute the analysis
   a. 3 data tables out of 9 available
   b. No data table includes userID, free text or direct assessment items (assessment items were coded manually and only the table with the results of the coding would be transferred.
3. Third Party
   a. UniSA's Privacy Policy is APP and GDPR compliant
4. Data Security
   a. Zip Files are password protectable and passwords can be transferred using a different channel to avoid them being able to be connected together or vice versa.

There is no legal requirement to have a contract or legal terms, but I recommend a Research Ethics Statement that includes:

- A statement justifying all of the above (Privacy Impact Assessment)
- Acknowledgement of being bound by APP legislation
- Acknowledgement that data will only be stored for the duration of the review and feedback
- Acknowledgement that the data will be stored, used and destroyed using the universities policy for academic research data

Appendix 3 Experiential Learning Program Content Map

Category	milestone_name	order	duration	model	Order	story_title/Assessment_name
Assessment_Draft	Week 2 - Project Report	3	7	Assess.Assessment	0	Project Report (Draft) - Mentor
		3	7	Assess.Assessment	1	Project Report (Draft) - Client
Assessment_Plan	Week 1 - Project Plan	2	7	Assess.Assessment	0	Project Plan - Submit to Mentor
		2	7	Assess.Assessment	1	Project Plan - Submit to Client
Assessment_Report	Week 3 - Project Presentation	4	7	Assess.Assessment	0	Project Report (Final) - Mentor
		4	7	Assess.Assessment	1	Project Report (Final) - Client
Orientation	Welcome	1	41	Story.Topic	0	Welcome to the Program
		1	41	Story.Topic	1	What You Will Learn
		1	41	Story.Topic	2	How does this Program Work?
		1	41	Story.Topic	3	Program Overview
		1	41	Story.Topic	4	How do I get Help?
		1	41	Story.Topic	5	Practera Tips
		1	41	Story.Topic	0	Welcome to Global Scope!
		1	41	Assess.Assessment	1	Photography Consent
		1	41	Story.Topic	2	Next Steps and Orientation Details
		1	41	Story.Topic	3	How does this program work?
		1	41	Story.Topic	5	How do I get Help?
		1	41	Story.Topic	6	Practera Tips
		1	41	Story.Topic	7	Mentoring Tips
		1	41	Story.Topic	8	Cross-Cultural Teams
		1	41	Story.Topic	0	Welcome to Global Scope!
		1	41	Assess.Assessment	1	Photography Consent
		1	41	Story.Topic	2	Next Steps and Orientation Details
		1	41	Story.Topic	3	How does this Program Work?
		1	41	Story.Topic	4	How do I get Help?
		1	41	Story.Topic	5	Practera Tips
		1	41	Story.Topic	0	Practera’s Fair Work Policy - Summary
		1	41	Story.Topic	1	Useful Resources
		1	41	Assess.Assessment	0	First Team Submission on Practera
		1	41	Assess.Assessment	1	First Individual Submission on Practera
		1	41	Assess.Assessment	2	End of Orientation Checklist

Other	Welcome	1	41	Story.Topic	0	How to Confirm your Participation
		1	41	Assess.Assessment	0	Enrolment Form
	Conclusion	5	7	Story.Topic	0	Engaging in continuing work
		5	7	Assess.Assessment	0	Feedback Survey
		5	7	Assess.Assessment	4	Participant Feedback and Certificate Survey
Project_Draft	Week 2 - Project Report	3	7	Story.Topic	1	Week 2: Project Report Overview
		3	7	Story.Topic	2	Project Report Outcomes
		3	7	Story.Topic	3	Key Questions - Project Report
		3	7	Story.Topic	0	Week 2: Project Report Overview
		3	7	Story.Topic	1	Draft Project Report
Project_Plan	Week 1 - Project Plan	2	7	Story.Topic	1	Week 1: Project Plan Overview
		2	7	Story.Topic	2	Project Plan Outcomes
		2	7	Story.Topic	3	Key Questions - Project Plan
		2	7	Story.Topic	0	Week 1: Project Plan Overview
		2	7	Story.Topic	2	Project Plan
		2	7	Story.Topic	0	Project Plan Explained
		2	7	Story.Topic	1	Project Plan Task List
		2	7	Story.Topic	2	Seven Step Loop
		2	7	Story.Topic	3	Minto Pyramid
		2	7	Story.Topic	4	SCQ Analysis
Project_Report	Week 3 - Project Presentation	4	7	Story.Topic	1	Week 3: Final Report and Project Presentation
		4	7	Story.Topic	2	Project Presentation Outcomes
		4	7	Story.Topic	3	Key Questions - Project Presentation
		4	7	Story.Topic	0	Week 3: Final Report and Project Presentation
		4	7	Story.Topic	1	Project Presentation
Self_Assessment	Welcome	1	41	Assess.Assessment	7	Self-Assessment & Skill Development
	Week 1 - Project Plan	2	7	Story.Topic	0	Attitudes of Learning Explained
		2	7	Assess.Assessment	1	Attitude Towards Learning
		2	7	Story.Topic	2	Attitudes Towards Learning and Your Project Team
	Week 2 - Project Report	3	7	Story.Topic	0	Mindset for Learning
		3	7	Assess.Assessment	1	Mindset for Learning
		3	7	Story.Topic	2	Mindset for Learning and your Project Team?
Self_Peer_Assessment	Week 2 - Project Report	3	7	Assess.Assessment	8	Self & Peer Assessment #1
	Week 3 - Project Presentation	4	7	Assess.Assessment	2	Self & Peer Assessment #2

Skills_Aggregate	Week 2 - Project Report	3	7	Story.Topic	0	Aggregate Findings Task List
		3	7	Story.Topic	1	Project Report & Presentation Explained
		3	7	Story.Topic	2	How to Synthesize Research
		3	7	Story.Topic	3	Synthesis Tool: Mind Mapping
		3	7	Story.Topic	4	Synthesis Tools: Finding Themes
Skills_Collaboration	Welcome	1	41	Story.Topic	0	Introduction to Collaborative Project Learning
		1	41	Story.Topic	1	Introduction to Self
		1	41	Story.Topic	2	Emotional Intelligence
		1	41	Story.Topic	3	Leading Self
		1	41	Story.Topic	5	Skill Development Planning
		1	41	Story.Topic	6	Key Collaboration Skills
Skills_Networking	Conclusion	5	7	Story.Topic	0	Create your LinkedIn Profile
		5	7	Story.Topic	1	Add Global Scope on Linkedin
		5	7	Story.Topic	2	Add your program badge on LinkedIn
		5	7	Story.Topic	3	Introduction to Networking
		5	7	Story.Topic	4	Engaging in continuing work
Skills_Presentation	Week 3 - Project Presentation	4	7	Story.Topic	1	Project Presentation Task List
		4	7	Story.Topic	2	Project Report & Presentation Explained
		4	7	Story.Topic	3	Presenting Tips: Know your Audience
		4	7	Story.Topic	4	Presenting Tip: Powerpoint
Skills_Reflection	Week 2 - Project Report	3	7	Story.Topic	0	Introduction to Learn
		3	7	Story.Topic	2	Feedback
		3	7	Story.Topic	3	Reflection
		3	7	Story.Topic	4	Reflective Writing
		3	7	Story.Topic	7	How to give Effective Feedback
Skills_Research	Week 2 - Project Report	3	7	Story.Topic	1	Research & Analysis Task List
		3	7	Story.Topic	2	Research Tools
		3	7	Story.Topic	3	Research Tools: SWOT Analysis
		3	7	Story.Topic	4	Research Tools: User Personas
Skills_Teamwork	Welcome	1	41	Story.Topic	0	Actively Participates
		1	41	Story.Topic	1	Communicates Effectively
		1	41	Story.Topic	2	Demonstrates Reliability
		1	41	Story.Topic	3	Exhibits Openness and Flexibility
		1	41	Story.Topic	4	Solutions Orientated
		2	7	Story.Topic	1	Introduction to Team

	Week 1 - Project Plan	2	7	Story.Topic	2	Team Formation
		2	7	Story.Topic	3	High Performance Teams
		2	7	Story.Topic	4	Diversity in Teams
		2	7	Story.Topic	5	Conflict in Teams
		2	7	Story.Topic	6	Introduction to Project
		2	7	Story.Topic	7	Project Fundamentals
		2	7	Story.Topic	8	Goals & Objectives
		2	7	Story.Topic	9	Approaches & Methods
	Week 3 - Project Presentation	4	7	Story.Topic	0	Tips for Receiving Constructive Feedback
		4	7	Story.Topic	1	Actively Participates
		4	7	Story.Topic	2	Communicates Effectively
		4	7	Story.Topic	3	Demonstrates Reliability
		4	7	Story.Topic	4	Exhibits Openness and Flexibility
		4	7	Story.Topic	5	Solutions Orientated