Employee Motivation To Learn: An Innovative Hybrid Approach By Combining Traditional And Machine Learning Methods

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B.Sc. Hons. Computing

Master of Business Administration (MBA)

Submitted in fulfilment of the requirements for the degree of Doctor of Business Administration (DBA)

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DECLARATION

"I, **Audrey Sin** declare that the DBA thesis entitled **'Employee Motivation To Learn: An Innovative Hybrid Approach By Combining Traditional And Machine Learning Methods'** is no more than 65,000 words including quotes and exclusive of tables, figures, appendices, bibliography, references, and footnotes. This thesis contains no material that has been submitted previously, in whole or in part, for the award of any other academic degree or diploma. Except where otherwise indicated, this thesis is my work".

"I have conducted my research in alignment with the Australian Code for the Responsible Conduct of Research and Victoria University's Higher Degree by Research Policy and Procedures.

[redacted]

Audrey Sin

23-06-2022

ACKNOWLEDGEMENTS

The greatest pleasure of completing this thesis is acknowledging the efforts of many people whose names may not appear on the cover but without their cooperation and support, this thesis would not be successful.

Firstly, Dr. Alan Keoy Kay Hooi, Dr. George Koshy, Dr. Selvi Kannan and the panellists evaluated my performance and provided me with valuable feedback. They gave me opportunities to grow in research. The last 24 months (2020 & 2021) cannot be compared with any other years in my DBA journey. It has been an incredibly tough year balancing a burst of work-life under lockdown at an accelerated speed and managing wellness. This acknowledgement is more important now knowing the sacrifices my supervisors must make supervising me virtually under the same lockdown while managing their other commitments.

My sincere gratitude to my principal supervisor Prof. Dr. Sardar M. N. Islam (Naz) who is an extraordinary supervisor. He is an exceptional professor; talented, committed, passionate, and dedicated toward the university, students, and communities. He is such an inspiration. Every step I take in the research journey is making me nervous. From not knowing and following him along the dark path of literary studies to completing the thesis. He was there from the start. His constant trust in me to deliver my thesis on time despite hundreds of other commitments I have is encouraging even at times I was doubting. He showed me the possibilities and provided his invaluable pieces of advice and encouragement throughout the thesis progression. His philosophy of being a robot to be successful resonates well with himself. He is an excellent robot, but he is built with much empathy. He gave me the freedom to work on my own accord and to be able to craft my thoughts in the thesis. He shaped me to be an independent researcher.

Special thanks to Associate Prof. Dr. Catherine Prentice, who generously reviewed and provided constructive feedback on the multiple drafts of the articles and thesis. She has the eyes of an eagle with her professionalism even the smallest creases, she ensures it is ironed out. She stepped in to lend a hand with her expertise at the most critical time and every time.

Associate Prof. Dr. Feng Xia, thanks for calming the boat when it rocks and for generously pouring in so much time, more than I deserve reviewing the multiple drafts of articles and thesis. Appreciate his contribution to bringing the island near and pulling me onshore.

Special thanks to the editor, Ong Gek Suan for the editing and proofreading services rendered, roughly responding to the clarity of expression and logical connection, per the standards cited in the Australian Standards for Editing Practice.

I would also like to thank the Australian Government and the Australian Commission's Workforce Performance team for the scholarship and for making the APS employee census dataset publically available for the public and researchers.

Not forgetting my perseverance and my family's unconditional sacrifices and support over the years. I would also like to take this opportunity to express my sincere gratitude and thanks to my incredible group of coursemates. They continuously inspire me with their research and motivated me to do better from every angle. Now at the finish line, I owe them every thanks for keeping me sane throughout the journey.

The research journey portrays the complexities and struggles one must face when confronted with unknowns and uncertainties in life. As a reflection, I have learned to filter criticisms and coped with imposter syndrome. Nothing is perfect, so long as I have given my best.

THANK YOU!

PUBLICATIONS FROM THIS THESIS

Sin, A.L.Y. (2019). Employer of choice as an extrinsic motivator and self-determination as an intrinsic motivator in fostering employee learning. Paper presented at the Victoria University Three Minute Thesis Conference, Melbourne, Australia.

Sin, A.L.Y. (2020). AI-driven employee learning. Paper presented at the Victoria University Visualising Your Thesis Conference, Melbourne, Australia. People's Choice Award.

Sin, A.L.Y. (2020). AI-driven employee learning. Paper presented at the Victoria University Higher Degree by Research (HDR) Student Conference, Melbourne, Australia.

Sin, A.L.Y. (2021). Prediction of employee motivation to learn using machine learning and ensemble methods. Paper presented at the Victoria University Higher Degree by Research (HDR) Student Conference, Melbourne, Australia.

Sin, A.L.Y., Islam, S.M.N., & Prentice, C. (2022). SEeMS: Kernel-based Deep Extreme Learning Machines for Employee Learning Motivation Prediction. (Paper submitted and accepted by IEEE).

Sin, A.L.Y. Prentice, C., & Islam, S.M.N. (2022). Gender equality and employer of choice: A systematic literature review. (Paper submitted to Scandinavian Journal of Managements).

OTHER PUBLICATIONS/ CONTRIBUTIONS BY THE CANDIDATE

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ABSTRACT

Employee learning is vital for professional and business success. The technological disruptions are prompting organisations towards radical transformation, but organisations are struggling to motivate employees to learn. The turning point to organisational crises caused by agency dilemmas and environmental factors are an employee learning management strategy and a robust decision-making framework. It is necessary and critical to promote employee motivation to learn for sustainable employee job satisfaction, performance, and well-being.

Existing literature on employee learning has been controversial; coming to a different conclusion as to how attitudinal and environmental motivation influences employee learning. Many empirical studies are done using traditional statistical methods but still missing a hybrid approach that uses both traditional and machine learning methods to automatically identify the indicators and predict future occurrences of employees' learning motivation. Various learning theories have advanced through the years but still lack a comprehensive approach to solving the issue of unmotivated employees in learning.

This thesis aims to design a comprehensive theoretical framework for employee learning motivation. Using a hybrid approach that includes traditional quantitative and machine learning methods to assess the relationships between perceived Employer Of Choice (EOC) utility, SelfDeterMination (SDM) and AI support and validate the autonomous and cost-effective predictive model. Data analysis is further enhanced with some machine learning techniques for model optimisation. A customised activation function of ReLu and Sigmoid called BSigReLu was formulated and introduced to create a robust optimisation model to enable efficient predictive analytics. Measurement indices are used to provide an unbiased model comparison and validation.

The results of regression analysis show that EOC utility perception, SDM and employee learning are positively related. The extent to which AI support plays a role in motivating employees to learn has been hypothesised and statistically validated. The stronger the AI support, the higher employees' sense of attitudinal and environmental motivation to learn. The hybrid model was selected based on model good-fit indices. An unbiased estimate using the 2-fold cross-validation operationalised with 5 iterations paired t-test indicate the use of the hybrid method can achieve better generalisation performance than the state-of-the-art conventional method. Results show that the introduction of predictive analytics could proactively capture the issue earlier so that intervention can be introduced earlier to avoid unmotivated employee learning crises vii occurrence. The findings from this research are new because of the hybrid approach adopted that improves computational efficiency.

This thesis highlights some important considerations at a practical level for practitioners, researchers, academics, and policymakers to improve employee learning outcomes using award citation, AI support and an innovative machine learning approach. It provides insights on the considerations needed to promote greater utility on the employer of choice award citation, practices, and policies. This thesis also expanded on the influence of AI support and established its capability to reengineer employees' motivation by strengthening human-machine collaboration in the context of employee learning.

This thesis makes several contributions to the theory and practices in employee learning motivation. An integrative framework is developed using Self-Determination Theory (SDT) and agency theory. Given the dynamics and complexity involved in the employee learning context, combining different approaches provides a more comprehensive approach to addressing the given problem. New variables called AI support and perceived EOC utility are introduced, and their motivational relationships have been validated. The hybrid approach provides an analytical robust approach that has not been attempted before. The use of machine learning is contemporary and capable of automatically and effectively classifying employee learning motivation signals for early intervention.

The models presented are the first step in designing the multi-agent strategies toward achieving self-motivated employee learning outcomes based on the role of EOC utility, SDM and AI support that contributes to employer competitiveness and most importantly employee job satisfaction, performance, and well-being. Keywords: motivation, employer of choice, employee learning, self-determination theory, multi-agent system, AI, Python, machine learning, deep learning, extreme learning machines, ensemble learning, kernel, activation function, hybrid.

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LIST OF ABBREVIATIONS

AI	Artificial Intelligence
APS	Australian Public Service
AUC	Area Under the roC
BSigReLu	Blending of Sigmoid and Rectified Linear activation function
CE	Computation Efficiency
CFA	Confirmatory Factor Analysis
CFI	Comparative Fit Index
CNN	Convolutional Neural Networks
CV	Cross-Validation
DELM	Deep Extreme Learning Machines
DL	Deep Learning
DT	Decision Template
EFA	Exploratory Factor Analysis
EL	Ensemble Learning
ELM	Extreme Learning Machines
EOC	Employer Of Choice
EOFGE	Employer Of Choice For Gender Equality
IDE	Integrated Development Environment
IoP	Internet of People
IoT	Internet of Things
IQR	InterQuartile Range
IR	Industrial Revolution
KDELM	Kernel-based Deep Extreme Learning Machines
KMO	Kaiser-Meyer-Olkin
KNN	K-Nearest Neighbours

LDA	Linear Discriminant Analysis
LR	Likelihood Ratio
LO	Learning_Outcome_new
ML	Machine Learning
MSE	Mean Squared Error
NN	Neural Networks
OECD	Organisation for Economic Cooperation and Development
OHS	Occupational Health and Safety
PCA	Principal Component Analysis
PS	Percentage of Similarity
RBF	Radial Based Function
ReLu	Rectified Linear activation function
RMSE	Root Mean Square Error
RMSEA	Root Mean Square Error of Approximation
ROC	Receiver Operating Characteristic
SD	Standard Deviation
SDM	Self-DeterMine
SDT	Self-Determination Theory
SRMR	Standardised Root Mean square Residual
SVM	Support Vector Machine
TLI	Tucker-Lewis Index
VU	Victoria University
WE	Working Environment_new

CHAPTER 1 INTRODUCTION

This thesis develops a self-motivated predictive employee learning outcomes model by statistically examining the motivational factors on employee learning outcomes of job satisfaction, performance and well-being using the convergence theory of traditional statistical learning, machine learning (ML) and deep learning (DL). The scope of this thesis is to statistically analyse employees' experiences from a random sample of 93,199 Australian Public Service (APS) sector workforce to identify the motivational factors and establish the relationship between perceived Employer Of Choice (EOC) utility, AI support, and self-determination leading to employee learning outcomes signals.

Chapter 1.1 presents the research background and the rationale for the research. Chapter 1.2 presents the aim and objectives of the research, while research questions are lay-out in Chapter 1.3. The dedication of Chapters 1.4 and 1.5 are towards contributions to knowledge and statement of significance. Chapter 1.6 briefly discussed the methodology. The last part of the introductory Chapter 1.7 outlined the remaining chapters of this thesis.

1.1 Background and rationale of the research

Employee learning is an essential organisational tool to engage top talents. Scholars (Dachner et al. 2021; Mielniczuk & Laguna 2017) have established that employee learning is a vital component for organisations to compete in the knowledge economy. An employee is a source of competitive advantages from the resource-based view perspective. The resource-based theory (Barney 1991, 2000) articulates that organisations are capable to implement a value-creating strategy that sets them apart from existing and potential organisations by having resources that are inimitable, valuable, non-substitutable and rare resources to achieve sustained competitive advantage. Employees are intangible resources exhibiting these characteristics which could bring value to the organisation, but employees have expectations. Employees expect continuous development so organisations are keen to employ them for their skills (Johnson 2014). Herman, Roger E. and Gioia (2001) affirmed that employees are interested to work for an organisation that provides opportunities for personal development to grow professionally through learning to reach their fullest potential contributing to employee job satisfaction, performance and well-being that indirectly contributes to employer competitiveness.

The problem is that some recent statistics show employees are stressed, disengaged and unmotivated to learn (Busby 2018; Oehler & Adair 2018). There are also signs of labour skill shortages, whereby 41% of organisations are complaining of difficulty in recruiting the right talent (ManpowerGroup 2019). The emerging era of the Fourth Industrial Revolution (IR 4.0); is a shared vision of technological transformation based on a range of integrated autonomous resources (Wilkesmann & Wilkesmann 2018) such as the Internet of People (IoP), Internet of Things (IoT), robotics, big data, Artificial Intelligence (AI) among others is a disruptive frontier of technology further widen the skill gap dilemma. Not forgetting the historic COVID-19 pandemic that is having an adverse impact on employee learning motivation. However, it must be noted that the pandemic-related disruptions are not in the scope of this thesis.AI is the mantra in today's digital age. McCarthy, the father of AI coined the term in 1956 (Peart, 2017), defining it as the art of making intelligent machines. AI can also be described as the intelligence of the computer to imitate, extend, and augment human intelligence. More and more businesses are joining the fray to be powered by AI, wanting to gain competitive advantages as businesses enter a fiercer competition to achieve their business objectives. It is forcing organisations to be digitised and shifting the management of organisations, including how employees work. At this current point of rapid technological advancement, it has been predicted that existing employee skills and knowledge will be outdated (Ceniza-Levine 2018; Shank & Sitze 2004). A study by PwC has forecasted in the UK approximately 7 million ongoing jobs will be undertaken by AI with 7.2 million new jobs created (Talerngsri 2019). Similarly, an industry expert has estimated that 3.5 million Australians going out of a job over the next decade (Livingston 2019) and the need for 0.1 million specialists to build the AI industry capability (Braue 2019). The digital space presents an accelerating need for employees to be motivated to learn but there seems to be no clear path in pursuit of it.

The current literature on employee motivation has gone into a deepening development and coming to a full circle from exploiting employees (Schaufeli, Bakker & Salanova 2006) to politicising outcomes (Shuck, B. et al. 2016). Grounded by Kahn's three-dimensional construct of meaningfulness, availability, and safety, researchers have openly reconstructed and re-established the boundary; operationalising the experience of employee engagement (Fletcher, Bailey & Gilman 2018; Shuck, Brad, Adelson & Reio 2017). It is in this context; that the experience of employees drives motivation in learning instead of the widely used construct of dedication, vigour, and absorption (Schaufeli, Bakker & Salanova 2006). Joosr (2015) affirmed a workplace with lots of perks could fair very well in the organisational survey, but it will not reveal the quality of employees. The literature is still lacking a comprehensive framework, and a proactive and generalisable approach for any possible corrective actions. More interestingly, the motivational factors leading to employee workplace learning are still not completely understood. AI-powered systems that dazzle us with their intelligence skills continue to be a major challenge for many organisations. The challenge of bridging humans and computers into our everyday life has been viewed by some as subservient while another more prosaic viewpoint is the creation of a new branch of employee motivation.

According to Locke and Latham (2004, p.388) motivation refers to external factors that can act as inducements to action and internal factors that impel action. Some progress has been made over the years, affirming employees' degree of motivation could vary, and there are also different kinds of motivations (Aworemi, Abdual-Azeez & Durowoju 2011). Predominantly, attitudinal and environmental motivation has been identified in dualistic theories (Reiss 2012). Environmental motivation requires intervention such as reward and accreditation to achieve the desired outcome. For example, an employee engages in learning to receive monetary compensation or recognition. The focus of this thesis is now limited to the Employer Of Choice (EOC) as an environmental factor based on the definition from Locke, EA and Latham (2004).

EOC refers to the employer who can attract the most talented employees by possessing attractive attributes (Bellou et al. 2015). EOC is a prestigious award acknowledging the citation organisation having the benchmark qualities of an employer. Trend observation of EOC (WGEA 2019) suggested that the award recognition is gaining momentum and popularity, year on year 18% award citation increment and a drastic 86% award citation increment since its inception in 2014. EOC has increasingly become the focus of organisations (Herman, Roger E. & Gioia 2001) because it is a winning strategy in the war of talent. The literature on EOC (Branham 2005; Rampl 2014) has thus far arrived at identifying the characteristics of EOC, but not the influence of EOC on employees' motivation to learn. Therefore, it will be examined in this thesis together with self-determination as attitudinal motivation.

Ryan and Deci (2000a, p.55) defined attitudinal motivation as 'doing something because it is inherently interesting or enjoyable.' That is when an employee is keen on upskilling simply because that is what the employee wants to do and finds joy in discovering new knowledge. Self-determination theory (SDT) is a meta-theory of human motivations. The limited discussion that exists in the workplace context and the motivating factors of SDT are the basis for this thesis. Ryan and Deci (2000a) have identified three basic psychological needs: autonomy, competence, and relatedness. Employees' motivations could vary based on various factors and employees have an innate desire to learn, and mastering new skills (Ryan & Deci 2000b). Much attention has been given to attracting employees with EOC branding; however, little is done to retain and develop talent which is critical in achieving competitive advantages. SDT delineates between environmental and attitudinal motivations thus providing a theoretical framework to be further explored in this thesis. When employees are motivated, both organisational and personal goals are intertwined that mutually benefit each other, therefore creating a sustainable eco-system. According to Maas (2017), an effective strategic management system maintains a pivotal role in achieving the objective of building a sustainable competitive advantage regardless of time-space.

A strategic management system is the creation of interrelated processes working together to achieve the desired outcome. It starts with planning by analysing the internal and external organisational environment before moving on to the formulation of the corporate mission and vision (Maas 2017). These defined long and short-term goals are then communicated within the organisation so that they could be translated into workable objectives and continued to be adapted to the changing business environment to achieve the set business goals. Organisation implementation failure happened when these objectives are unclear, leading to misinterpretation (Barrett 2004). Conflict of interest between employers and employees can be resolved with an effective strategic management system.

This employer-employee relationship often is described in terms of agency theory (Azevedo & Akdere 2011; Donze & Gunnes 2018; Eisenhardt 1989). The agency relationship occurs when the principal-agent (employer) employs the agent (employee) to perform a task on their behalf. In most of these relationships, conflict of interest will arise because of asymmetric information such as differences in goal orientation, obligation, risk, and self-interest. The issue of difficulties in motivating employees to learn in the best interests of the employer rather than for their interests is an agency dilemma. The dilemma arises when the employer cannot determine the employees' effort level; hence, even if employees have put forth the maximal effort, it can be regarded as insufficient. Although employers/ stakeholders own the organisation, employees are performing the operational tasks in the organisation; therefore, they are in the ideal position to follow their interests at the expense of other entities. The employer-employees dilemma is a typical issue in the organisation. These agents are bound to have conflicts in the organisation, especially in the decision-making process whereby self-interest supersedes other agents in the organisation. The combating interests in the employment cooperation are bound by the employment contract.

The contract theory posits that contractual clauses are used to bind these players' cooperation (Watson 2013) to avoid asymmetry pay-off whereby one party is gaining advantages over the other. It is especially true when agents are negotiating to achieve the notion of contractual equilibrium. The theory specifies the responsibilities and requirements of employers and employees working towards the same goal in the organisation. The clauses help to remedy an employment dispute when it arises and the incentives for a long-term contractual relationship between employer and employee.

Due to the fact, that agents in organisations are not necessarily rational during the decision-making process, this leads to poor decisions and less promising outcomes. Organisations need to be proactive and reflexive in adapting to the changing business environment, including management practices. This thesis has been designed to point us towards a new paradigm of strategic and cognitive motivation in employee learning. It explores self-determination theoretical foundations of contemporary issues, and the investigation of the relevance of agency theory substantiates the presence of the thesis problem of unmotivated employees in workplace learning. It also provides methodological improvements to search for new findings with hypothesis-testing and an effort for the generalisability of findings with the machine learning model developed from employees' insight. It is timely now for the concepts of motivations to receive the much-needed academic attention in the employee learning framework because they are essential for organisational survival to reshape the polarised traditional employer-employee relationship and the orthodox way of learning especially in this digital era.

1.2 Research aim and objectives

The general goal of this research is to reshape the traditional employer-employee relationship through an effective strategic multi-agent management system. The specific aim of this thesis is to statistically assess the associations between EOC utility, self-determination, and the role of AI support in these relationships to devise an autonomous and economical predictive model of self-motivated employee learning outcomes.

The objectives of this thesis are:

(a) To design a comprehensive theoretical framework of employee learning motivation.
(b) To statistically assess the relationships between EOC utility, SDT constructs and AI support to model the employee learning motivational problem.
(c) To use a hybrid approach to examine the error rates of the models investigated in this thesis and validate the employee learning motivational model to improve policy, practices, and program consideration on EOC, employee learning agenda and development.

1.3 Research questions

1) What are the relationships between EOC utility perceptions and self-determination motivators in the context of employee learning and the motivational features that affect employee learning outcomes?

2) What are the mechanisms through which these effects manifest themselves or to what extent AI support mediates the relationship between employee motivation (EOC utility perception and self-determination) and employee learning outcomes?

3) How does AI support interact with EOC utility perceptions, self-determination, and employee learning, or does AI support moderate the relationship between EOC utility perception, self-determination, and employee learning?

1.4 Contribution to knowledge

1. A comprehensive framework

   Researches on EOC (Sedighi & Loosemore 2012; Smith, Gregory & Cannon 1996; Tanwar & Kumar 2019), employee learning (Lancaster & Milia 2014; Wan, Compeau & Haggerty 2012) and SDT (Sie, Phelan & Pegg 2018) are at their individual infancies streams. Integrating contemporary topics of EOC and employee learning that build on SDT and agency theory is rare, with no research sighted thus far. A limited effort to date in investigating the subject matter, which is growing in influence and needed in the digital age and knowledge economy. The contribution of this present thesis is the understanding of how to effectively encourage employee learning through motivations and AI support.

2. Empirical research on employee learning

   There is limited empirical research on motivation based on SDT field studies (Gagné & Deci 2005) but primarily on laboratory experiments (Deci, E. L., Koestner & Ryan 1999). Studies on the utility of SDT as a framework have been multi-disciplinaries (Cuevas et al. 2018; Lavergne & Pelletier 2015; Mosteller & Mathwick 2014; Peters, Calvo & Ryan 2018). However, its presence in the organisational behaviour and human resource management domain is limited. For example, a review of related articles from Human Resource Development Quarterly (HRDQ) journals in 2020 over the past five years have found no relevant items while reviewing materials from the Journal of Organisational Behaviour within the same period has identified only two related articles (Conway et al. 2015; Hewett & Conway 2016). This thesis also aligns with calls for more investigation on the practical experience of employee learning (Purcell 2014).

3. Use of the hybrid approach

   Three of the most recent, related SDT articles in various disciplines identified in 2019 involved quantitative analysis (Huang, YC et al. 2019; Ju et al. 2019; Krause, North & Davidson 2019). These studies showed evidence of the role of basic psychological needs on empowerment (Ju et al. 2019), the relationship between engagement and well-being (Krause, North & Davidson 2019) and the influence of psychological needs on behavioural intention (Huang, YC et al. 2019). However, these studies lack qualitative details and context. Therefore, the present thesis will not only compensate for the relevance of the theory in the workplace but is also innovative in employing a mixed-method. Consistent with the nature of mixed-method studies (Creswell & Plano Clark 2011), the integration of qualitative and quantitative methods in this thesis will move away from the well-established approaches. The debate over the relative virtues of a qualitative or quantitative method has been around for more than 15 years and has gained considerable impetus. The constitution of mixed-method is arguable, but there is substantial agreement about the fundamental antinomies that the use of both methods is mutually complementing. This thesis will also use the hybrid approach by combining both traditional and contemporary statistical learning methods to inform the theoretical framework and elaborate on key aspects of the thesis questions in finding new solutions. This thesis contributes to the understanding of employee self-determination learning within the SDT framework. It adds insight and enables refinement of the theoretical framework to use self-determination to increase perceived ECO on employee learning utility, which in part moderate's attitudinal motivation of employees.

4. Use of machine learning approach

   Previous research on motivation is done using traditional statistical methods. The usage of the convergence theory of machine learning and deep learning analysis together with PCA and a customised activation function of ReLu and Sigmoid in this thesis is another contribution. It allows the refinement and development of a theoretical framework adequate to hypothesise models of employee learning outcomes. AI tools such as Hadoop, Pycharm, Juypter and others are sophisticated theoretical tools that can effectively and statistically compute a range of multivariate analyses such as factor analysis, regression, and variance analysis to make predictions of employee learning which standard statistical tools may be unsustainable in terms of its statistical integrity (Huang, G-B, Zhu & Siew 2006; MacLean & Gray 1998). Therefore, utilising contemporary machine learning techniques to achieve the aims of this thesis extends the theory.

5. New variables

   AI has been the buzzword causing disruption worldwide however, the role of AI support in motivational relationships has not been discovered. Therefore, in this thesis, a new variable called AI support has been introduced. Past studies on EOC are mainly to discover its characteristics based on potential employees' views (Arachchige & Robertson 2011) rather than the insights of existing employees and mostly on a specific industry (Sedighi & Loosemore 2012; Smith, Gregory & Cannon 1996) coming from the practitioner and consulting firms (Clayton 2018; Lanier 2018; Robak 2007). This thesis will take an Australian country-wide public sector view to determine the extent of the phenomenon in the employee learning context. Despite the critical need for a highly engaged workforce, Australia is facing with employee engagement crisis with a score of 14% (Busby 2018) which is low compared with other OECD countries such as Canada 69% and the United States 64% (Oehler & Adair 2018). This thesis will fill the gap here incorporating large representative samples of existing APS employees, and sample data will be statistically assessed to propose a good-fit model of self-motivated employees' learning outcomes where no prior attempt is identified to date with the variables offered on the selected unique APS population.

1.5 Statement of significance

The Australian government has committed to a 25% reduction of the gender workforce participation gap by 2025 (Madgavkar, Ellingrud & Krishnan 2016). Since 1974, Australia has boosted its economic activities by 22% with the rise in female employment and it is anticipated that Gross Domestic Product (GDP) index would be raised by 11% with another 6% increase in female participation (JBWere 2009). Findings from this thesis, provide insights for government entities in setting legislative measures to improve EOC award citation with the development of targeted intervention strategies through SDT and AI. Therefore, it is timely to deep dive into this contemporary issue to proactively react to closing any potential gap from the findings of this thesis.

This thesis will also contribute economically to the organisational roadmap for creating returns, maximising loyalty among employees and optimising performance (Clarke 2001) because when employees are motivated to learn, they will be empowered to achieve greater things and willing to be retained in the organisation that offer such opportunities. Thus, contributing to retraining cost reduction while optimising new training initiatives costs to drive the organisation forward. According to Duncan (2018), employees need to move in the learning curve from the lowest to the highest point and be put into another learning curve to keep them engaged. When employees are engaged, they would be able to contribute and innovate in their own spaces resulting in individual and organisational performance improvement.

Designing an effective strategic management system, through the understanding of relationships and motivational factors between EOC and self-determination, will be beneficial in improving the overall management practices for organisational efficiency. Therefore, such an emerging topic may resonate with professionals who are involved in organisational changes (Herman, Roger E. & Gioia 2001). Leadership teams such as HR, communication and marketing teams could define strategies, policies, and programs targeting existing and potential employees and start impacting the organisations' bottom line with increased productivity and talent pool out of engagement in learning.

Potential and existing employees will also benefit from this thesis because individuals who are engaged in what they are doing; in this case, learning will experience greater well-being as demonstrated in SDT research (Ryan & Deci 2000b) and overall job satisfaction and performance improvement. It is significant due to the impact this could make on improving management practices and overall employer-employee relationships by formulating efficient management systems and practices within the research context. This thesis is expected to enable practitioners to become aware of the motivational factors that foster employee learning and how to successfully implement management practices to motivate the employees to learn through AI either to support continuous development or to take proactive corrective actions. For those in a more scholarly setting, this thesis can be a recommended reading for the broader understanding it provides. Hence, regardless of the findings, there is something to be learned from this thesis.

1.6 Methodology

The author has adopted a mixed-method to investigate the links between EOC utility perception, AI support, and self-determination in the context of employee learning. Lopez-Fernandeza and Molina-Azorin (2011) affirmed the findings in the field of organisational behaviour that the quantitative method dominated the research literature. Therefore, the use of the quantitative and qualitative methods in this thesis helps to advance this field and is an adequate mechanism to investigate the thesis problem. There is a growing body of studies for business and management research (Cameron & Molina-Azorin 2011; Lopez-Fernandez & Molina-Azorin 2011; Molina-Azorin & Fetters 2019) acknowledging the use of the mixed-method provides a better understanding of the research problem than using a single approach.

Besides, this thesis utilises secondary data for analysis. A secondary source of data is those readily available data that can be repurposed for another study and does not involve additional primary data collection efforts such as focus groups, interviews, surveys, and other instrumentation. This thesis's primary data was the latest census collected in 2018 by the Australian Public Service (APS) Commission through survey research as part of the APS employee census. It is to inform the planning and improvement initiatives of APS employees' working conditions. The data is publicly available on the web, and it is from an ethical and reliable source. The census data was then downloaded and critically assessed to determine its usability in this thesis (refer to Appendix 2). The selection criteria were data addresses characteristics of EOC, self-determination constructs, AI support and employee learning outcomes. The data was not categorised for this specific research because it was not the intention of the original study, but it can be easily realigned to suit this thesis.

The only limitation of secondary data is that the customisation is done post-data collection and not prior. Therefore, data analysis is performed only after the realignment and adaptation of thesis questions, hypotheses, and selection of questionnaire items that are relevant to this thesis. Nevertheless, it was the preferred choice because it outweighs the challenges involved in getting access to the organisations to conduct survey research as it might cause unnecessary interruption to business operations and foreseen difficulty to recruit sufficient participants to achieve the desired sample size for statistical analysis. Therefore, at the exponential growth of IR 4.0, this thesis innovatively leverages big data to answer new thesis questions. As with Netflix and Amazon that analyses billions of past choices datasets to make suggestions on movies that will be of interest to customers and predict purchases based on online buying behaviour.

This thesis uses a hybrid approach to an existing dataset to predict employee learning outcomes using various machine learning (ML) and deep learning (DL) algorithms with the traditional regression method. Literature on employee motivation to learn has thus far been investigated using the traditional regression method. An attempt to use a contemporary and proactive approach has not been evident to the best of the author's knowledge. How this is done will be further elaborated in Chapter 4.

1.7 Thesis Organisation

Figure 1 depicts the structure of the seven chapters in this thesis. A summary of each of the chapters is outlined below:

Chapter 1: Introduction – Background of the thesis

Consists of brief background and rationale for this thesis highlighting some organisational issues, an overview of the research design, ethical and risk considerations, academic and practical contributions as well as the organisation of the thesis.

Chapter 2: Literature Review

It contains the definition and synthesises the relevant literature to identify the constructs of EOC utility, self-determination, AI support and employee learning outcomes. The literature review provides an in-depth examination of the historical beginnings of the concept. It discusses the differences between employer brand, EOC and EOCGE, the gap in previous studies and the link between motivations and employee learning. This chapter aims to situate SDT and EOC concepts in the employee learning context and to explore the literature, both past, and present, for any gaps that may be significant. It is perceived that this chapter will provide a theoretical foundation for this study and highlight any emerging themes which can be examined further within this study.

Chapter 3: Theoretical Framework

Presents the thesis framework and relevant theory developed based on the literature review that could be applied in understanding the phenomenon in the workplace.

Chapter 4: Research Design and Methodology

This chapter consists of an introduction, the thesis model and the design of the data collection method which will be processed and analysed in the next chapter. Information about the various approaches to research philosophy and justification of the choice of research philosophy within the context of this thesis.

Chapter 5: Data Analysis and Findings

This is about data analysis and empirical findings. It provides the empirical result of the research, that is, the relationship between self-determination and EOC as attitudinal and environmental motivators leading to employee learning. The findings of the quantitative analysis, which has been performed on the secondary data collected from the census.

Chapter 6: Discussions

This chapter provides a synthesis of all the findings and discusses their implications on organisations and employees. It reviews the results of the findings of this thesis, some theoretical background on motivations and employee learning, the limitation of the current thesis and possible future directions are detailed.

Chapter 7: Conclusions

This chapter draws upon the previous chapters to present a summary to conclude the thesis.

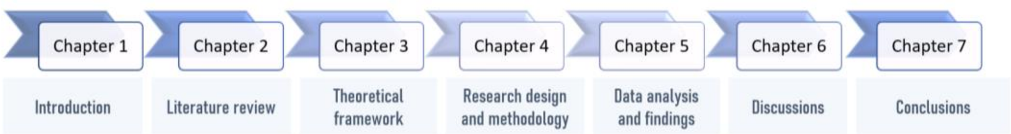


Figure 1. *Organisational of the thesis*

CHAPTER 2 LITERATURE REVIEW

The preceding chapter gave an overview of the thesis, in this chapter the author aims to share the findings from the key literature which were explored with regards to EOC, self-determination, and learning to provide a summary of discoveries and debates in the research area both for knowledge building and as evidence to support the outcome of this thesis. The literature review is divided into three parts. Chapter 2.1 examines employee learning and the translation process is guided by social cognitive theory providing sufficient background to answer how to promote employee learning. Next, the motivational influence specifically self-determination theory and its benefits are discussed in Chapter 2.2. The remainder of the chapter is devoted to the consideration of the environmental elements exploring the key concept of EOC and why organisations are interested to become one that influences the employee learning outcomes.

2.1 How to promote employee learning?

This chapter of the employee learning literature review is to provide, some reference to selective literature, a clearer understanding of the learning background and its development over time as well as how to promote employee learning.

2.1.1 Method

A qualitative study was initially conducted to identify the related literature on 2nd May 2019 and then periodically updated. The source of published studies was electronic databases on the VU library system (Health Business Elite, Business Source Complete, Scopus, PsycARTICLES, Academic Search Premier, ScienceDirect). First screening inclusion criteria: (a) be published in a peer-reviewed journal; (b) be in the English language, and (c) use the keyword “learning” in abstract/title/keywords. Second screening inclusion criteria: discuss learning and the related learning theory as the main topical theme. Articles are removed from consideration when it does not meet any one of these mentioned criteria. The search was focused on the last 10 years, however, there were no population, geographical cultural, or language restrictions on the search. The review was then organised theoretically, moving from a broad understanding of various learning theories to focusing on self-regulation theory looking at how it was applied and the mainstream versus alternative viewpoint with regards to the theory.

2.1.2 A survey of the recent development of literature

Scholars and practitioners have not identified factors that influence employees' learning. Learning at work is a process based on increased awareness of one's capabilities and aptitudes (Raelin 1997). Many theories have advanced through the years trying to explain employee's learning behaviour.

In the 20th century, theories were focused on behaviourism. Behaviourists such as Skinner (1976) posit that the learner is passive acting on a principle of 'stimulus-response'. There are generally two entities in learning; the sender and the receiver as well as two types of learning: formal and informal. Informal learning occurs naturally while formal learning expects effort from the educator to create optimal stimulus and response or 'operant conditioning' (Skinner 1976). It can be regarded as a carrot and stick metaphor; when you behave according to the pre-defined rules you are rewarded else punished. This is evident in the study of employee absenteeism and enactive mastery experiences (Frayne & Latham 1987; Hong et al. 2019). The findings from Frayne and Latham (1987) show, that job attendance is higher when the perceived self-efficacy is higher, while time series and correlations analysis from Hong et al. (2019) implied participants' cognitive and affective factors can be improved when learning by practising calibration. The behaviour is reliant on environmental motivation which can be argued for ignoring the attitudinal motivation role. Out of dissatisfaction with behaviourism, scholars like (Liao, Chen & Shih 2019; Oommen 2020; Perry 1999; Piaget 1968) have contributed to cognitive constructionism. Contrary to a behaviourist, theorists of cognitive constructivists argued that learners are actively constructing their knowledge and meaning from their encounters hence, it is a repetitive process of discoveries. Learners are attitudinally motivated by setting their own goals, instead of being environmentally motivated. Arguably, attitudinal motivation alone may not be enough to fulfil the goal-related needs.

In the 21st century, the integration of cognitive and social learning; also called social constructivism (Hassard & Cox 2019; Lombardo & Kantola 2021; Vygotsky 1978) has become evident in a comparative study on three models of innovative knowledge communities (Paavola, Lipponen & Hakkarainen 2004) and has been tested in a small group classroom activity (Knapp 2019). The authors claimed that learning is an informal process. New knowledge can be created by socialising with people. This creates the third metaphor of learning and can be regarded as pull and push learning which is in the same vine as acquisition and participation (Sfard 1998). In the workplace context, employees are either learning through acquiring knowledge formally or learning by participating in the activity which is often referred to as on-the-job learning. Unconsciously, casual employee interactions are also a form of learning; sharing and exchanging knowledge through experience that builds on the knowledge creation metaphor. Comparatively, behaviourism is motivated environmentally, constructionism is motivated attitudinally while social constructionism addresses both attitudinal and environmental motivations. SRT is grounded in the pioneering work of Bandura's (1991); social cognitive theory and can be understood as a process that mediates the effect of environmental influences to pursue goal-related needs (Mawritz et al. 2017), it is a self-directed process that helps individuals to learn more effectively (Lombardo & Kantola 2021; Papamitsiou & Economides 2019; Toering et al. 2012).

The mainstream view suggests that those with high self-efficacy would better engage in learning (Bandura 1991; Yoon & Kayes 2016). Overall SRT contributions to learning are evident across multi-educational domains, such as physical, art and even academically (Anshel & Porter 1996; Cleary, Zimmerman & Keating 2006; Papamitsiou & Economides 2019). A recent meta-analysis of SRL in formal training contexts illustrated the extent to which SRL theories have shaped our understanding of how individuals adapt their learning behaviour (Sitzmann & Ely 2011; Verma, Ahuja & Hermon 2019), emphasizing particularly the goal-oriented nature of work-related learning. Self-regulation impairment provides a strong explanation for the breakdown of employee learning. Therefore, there is an increasing need, to understand theoretically and practically how employees are motivated to learn in the workplace context.

2.1.3 Result and discussion

Drawing from some recent studies (Table 1) among all the learning theories, social constructivist theories are the ones widely cited in the field of educational research. Seventy per cent of the studies emphasise social constructivist ideas while the others discussed behaviourist and cognitive constructivism. It has become evident that quantitative studies are dominating the field of study with 70% of studies cited and two (20%) are using the mixed-method and one (10%) using qualitative with insights from students and organisations equally investigated. By analysing the publication timelines there is a consistency of publications in the educational context but not in the organisational context. More specifically, the relevance of this present thesis in building the momentum of learning in an organisational context is compelling research.

Table 1. Summary of learning theories investigated in this thesis

Author	Aim	Employee learning categorisation investigated	Motivational Factor	Sample/ Methodology	Location	Category
Sitzmann and Ely (2011)	This review examines the current state of research on self-regulated learning and gaps in the field's understanding of how adults regulate their learning of work-related knowledge and skills.	Social constructionism	Attitudinal & environmental	Quantitative 369 research reports	Not mentioned	Organisational
Toering et al. (2012)	The study examined the reliability and validity of the Self-Regulation of Learning Self-Report Scale (SRL-SRS).	Social constructionism	Attitudinal & environmental	Quantitative 601 and 600 adolescents aged 11 to 17 years	Netherlands	Student
Yoon and Kayes (2016)	This paper identified employees' self-efficacy as a potential antecedent to their perception of individual learning in the context of teamwork.	Social constructionism	Attitudinal & environmental	Quantitative 236 team supervisors and 1397 employees	South Korea	Organisational
Mawritz et al. (2017)	Investigate the differential strength of supervisor self-regulation impairment versus social exchange as mediating mechanisms.	Social constructionism	Attitudinal & environmental	Quantitative Study 1 & Study 2 (supervisor and subordinates)	United States	Organisational

Author	Aim	Employee learning categorisation investigated	Motivational Factor	Sample/ Methodology	Location	Category
Hong et al. (2019)	Participants' cognitive and affective factors can be improved when learning Traditional Chinese Pinyin by practising calibration.	Behaviourist	Environmental	Quantitative Time series analysis and correlation analysis were used to test the interplay between online learning interest, learning self-efficacy, cognitive anxiety, and cognitive certitude of calibration.	Southeast Asia	Student
Knapp (2019)	A small group classroom activity using coloured shapes that offer a concrete way to introduce these principles to students and provide them with opportunities for subsequent scaffolded discussion and reflection.	Social constructionism	Attitudinal & environmental	Mixed method 18 undergraduate introductory classes in educational psychology, each comprised of 20–25 mostly first- and second-year students	Not mentioned	Student
Weinert et al. (2022)	To design a co-creation system to support employees in the co-creation of work-process-related learning material under the consideration of cognitive load	Cognitive constructivism	Attitudinal	Mixed method	Germany	Organisation

Author	Aim	Employee learning categorisation investigated	Motivational Factor	Sample/ Methodology	Location	Category
Liao, Chen and Shih (2019)	The use of an instructional video in collaborative digital game-based learning (DGBL) significantly influence learning achievement, intrinsic motivation, cognitive load, and learning behaviours of students learning Newtonian mechanics.	Cognitive constructionism	Attitudinal	Quantitative 109 students	Taiwan	Student
Papamitsiou and Economides (2019)	Utilising the learners' trace data for measuring the learners' autonomous interactions, and investigates the effects of four SRL strategies on learners' autonomous choices to bridge that gap between SRL strategies and autonomous learning capacity	Social constructionism	Attitudinal & environmental	Quantitative 113 undergraduate students	European	Student
Corlett, Ruane and Mavin (2021)	To explores how senior executives learn (not) to be different in Action Learning Set spaces (ALSS) as part of a business school Executive Education programme	Social constructionism	Attitudinal & environmental	Qualitative 13 senior executives	Ireland	Organisational

The main agreement is that motivation can influence employee learning however the disagreement in the literature is on the type of motivation, whether it is attitudinally or environmentally motivated. Apart from motivation, the profiling of employees seems to have been ignored to a large extent in the discussion. Multi-faceted theory (Hartnett, George & Dron 2011) suggests that employees are not the same from one individual to another. Hence, there are various needs and various degrees of learning capabilities. An employee can be motivated for several different reasons rather than attitudinally or environmentally, and these may not be mutually exclusive.

2.2 What is the self-determination theory and its benefits?

This part of the literature review is devoted to understanding the various motivational theories and identifying the knowledge gap in self-determination theory.

2.2.1 Method

A comparison was done between traditional and contemporary motivational theories using constrain snowball sampling (Lecy & Beatty 2012). Qualitatively, the seed article was collected on 25 Apr 2019 at the first level, then articles that cite the seed are collected at the second level, and so on. A network of relevant articles formed around the seed facilitates insights into the broad context of the research rather than the narrow set of publications that are returned based on keyword searches. VU library databases were searched to source the published studies: Health Business Elite, Business Source Complete, Scopus, PsycARTICLES, Academic Search Premier, ScienceDirect. The following screening inclusion criteria were selected to identify the seed article: (a) be published in a peer-reviewed journal; (b) be in the English language; and (c) use the keywords "self-determination theory" or "motivation" and "in the workplace", in abstract/title/keywords. Second screening inclusion criteria: discuss employee learning or learning in an organisational context as the main topical theme. The absence of at least one of these criteria determined the removal of the article from further consideration. This review is organised theoretically moving from a broad understanding of various motivational theories to focusing on self-determination theory looking at how it was applied and the mainstream versus alternative viewpoint with regards to this theory.

2.2.2 A survey of the recent development of literature

Motivation is derived from the word motive referring to the reason or reasons a person is behaving in a particular manner. In another word, it refers to 'internal factors that impel action and to external factors that can act as inducements to action' (Locke, EA & Latham 2004, p. 388).

However, Vroom has referred to it as a person's conscious choice (Vroom 1964). When we refer to someone as being motivated, it means to be moved to do something according to Ryan and Deci (2000a). Employees are motivated differently and the motivation level varies (Aworemi, Abdual-Azeez & Durowoju 2011). The current view is the explication of the two streams of motivation theories, one looking at content and the other at the process. Content theories are related to identifying people's needs and their goal-related efficacy. In contrast, process theories emphasise cognitive influence on behaviour. In general, content theories help to answer the 'what' questions while process theories address the 'how' questions. For example, what are the factors that influence employee learning and how people are motivated? Figure 2 depicts some of the motivational theories in the 20th century and their respective thematic categorisation.

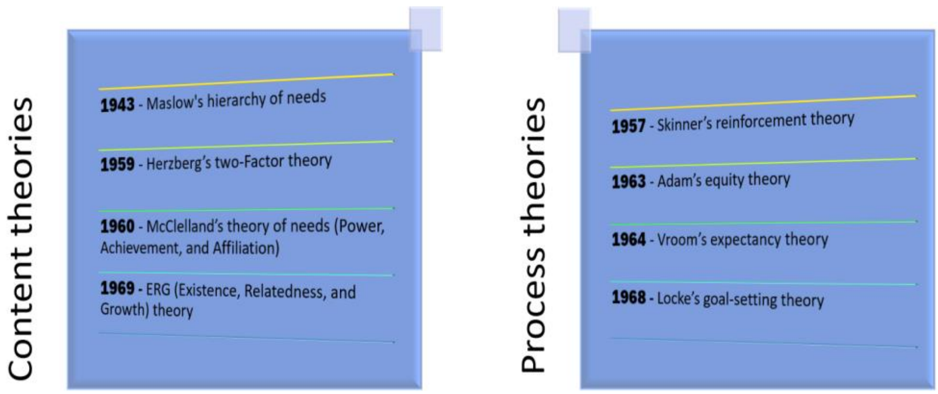


Figure 2. *Motivational theories*

In this writing, it is possible to find descriptions and analyses of three popular motivational theories: Maslow, Herzberg and Vroom's expectancy theory which this thesis does not intend to match. Maslow and Herzberg, two-factor theory have been regarded as a content-based theory while Vroom's expectancy theory is process-based. Each of these theories will be further elaborated in the following sub-topics.

2.2.2.1 Maslow's hierarchy of needs

Figure 3 depicts Maslow's model that comprises five levels of needs (Maslow 1943, 1970, 2013; Pichere & Cadiat 2015). Moving from the lowest tier which is more concrete to the highest which is more abstract. It is when individuals achieved a state of personal accomplishment or self-actualisation. This is also known as growth needs. Physiological, security, belonging, and esteem, are the first four levels. Physiological needs are the survival essentials such as food, air, water, and others. Security needs are the need to be safe from any harm, stable in terms of employment and orderly of resources among others. When an individual has satisfied the lower levels of needs then the individual would be able to share with others in the relationship. Hence, the need for belonging. The fourth level is the esteem level, this is achievable when the individual feels comfortable with their achievement and ready to boost their confidence, respect, and success. These four levels are generally known as deficiency needs. A deficit of the lower level of needs will hinder the movement to a higher level of needs. The longer an individual stays on a certain level, the stronger the motivation to progress higher in the hierarchy (McLeod 2018).

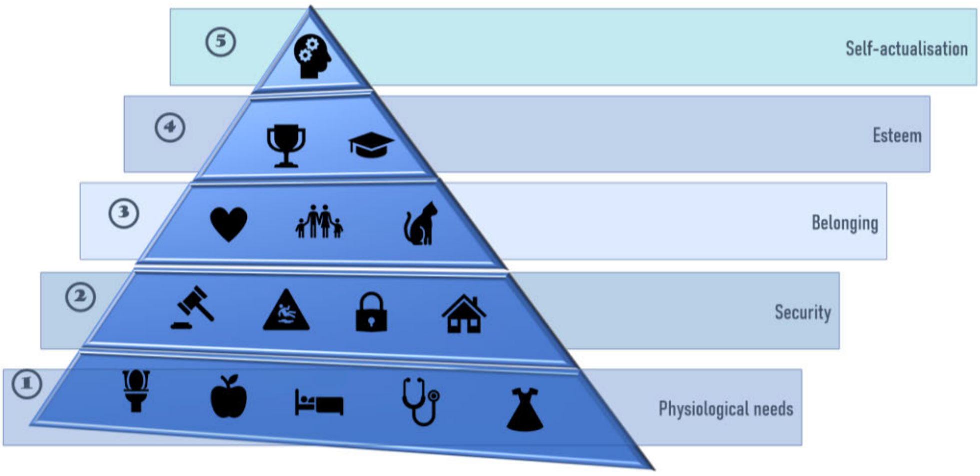


Figure 3. *Maslow's hierarchy of needs (five-stage model)*

In Maslow's original study (Maslow 1943), he initially emphasised that individuals need to satisfy the lowest level of deficiency needs before progressing to unlock the neighbouring growth needs. However, later Maslow acknowledged that the movement is not as rigid as implied; individuals do not necessarily need to fully satisfy one level of needs before the emergence of the next level (Maslow 1987). These needs can be fulfilled simultaneously and there is a domino effect from one that needs fulfilment to another. For example: in a busy workplace with a lack of workstations, sharing a workstation with a colleague meets the love and belonging need of the employee in the organisation and at the same time it is also providing a safe place for the employee to work.

The pioneering work of Maslow's model has been repeatedly challenged; however, the model has been timeless. For close to a century now that sets a solid foundation for other scholars. The seven and eight-level of the hierarchy of needs model were developed to modernise and correct the misconception of the initial five-level model however, the four preliminary levels of deficiency needs have remained. A cross-country survey affirmed the elusiveness of Maslow's hierarchy of needs model which is universally supported (Tay & Diener 2011). The main departure from Maslow's theory is that personal accomplishment can still be achieved even when the lower level of needs is not fulfilled yet. The controversy of Maslow's theory still exists, and an update of the model proves to be timely in supportive of the contemporary lifestyle even when the Maslow theory remained widely popular and acceptable.

2.2.2.2 Herzberg, two-factor theory

An extension of Maslow's most celebrated hierarchy of needs theory (Maslow 1970, 2013) is Herzberg. Herzberg posits two-factor to enhance workplace motivations; lower-order and higher-order need also known as hygiene factors and motivators respectively (see Figure 4) (Herzberg, Mausner & Snyderman 1959).

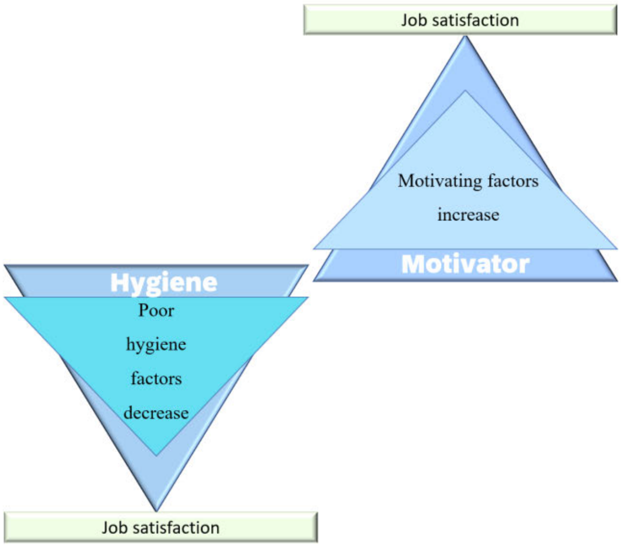


Figure 4. Two-factor theory

According to Herzberg, Mausner and Snyderman (1959), motivators are found within the job itself i.e. job satisfaction, achievement, recognition, and opportunity for growth. Hygiene factors are the environment around the job which if absent will cause dissatisfaction such as salary, company policy, supervision, peers' relationship, working conditions, and security. However, remedial for dissatisfactions will not create satisfaction. They do not sit in the same polar. In the study of Indian salesforce motivation in the retail sector, salesmen are dissatisfied with motivation factors but are more satisfied with hygiene factors (Kotni & Karumuri 2018). A study at a ski resort in Sweden on seasonal employees' motivation, found there are different levels of motivation within the same hygiene factors depending on individual and subgroup (Lundberg, Gudmundson & Andersson 2009). Hygiene factor was of greater importance to the resident community members than to those of the migrant community as evident in Lundberg, Gudmundson, and Andersson's (2009) findings. Herzberg's work influenced a generation of scholars and practitioners. It has attracted a lot of criticism and also attention regarding the distinctions between hygiene factors and motivators as well as individual and workgroup influences on these factors. The universality of this seems to be too simplistic to understand the complexity in practice especially in the context of employee learning. Despite its limitations, the theory has been a valuable aid to be extended in the process-based theory.

2.2.2.3 Vroom expectancy theory

Whereas the content theory looks at the relationship between needs and goal-related efficacy, Vroom's expectancy theory focused on the cognitive antecedents and their outcome (Vroom 1964). Vroom postulated that individuals make conscious choices, and decision-making is based on the choice the individual perceived leading to the best possible outcome (Lloyd, R & Mertens 2018). In Vroom's seminal work, the motivational force that drives behaviour is the product of expectancy, valence, and instrumentality as depicted in Figure 5.

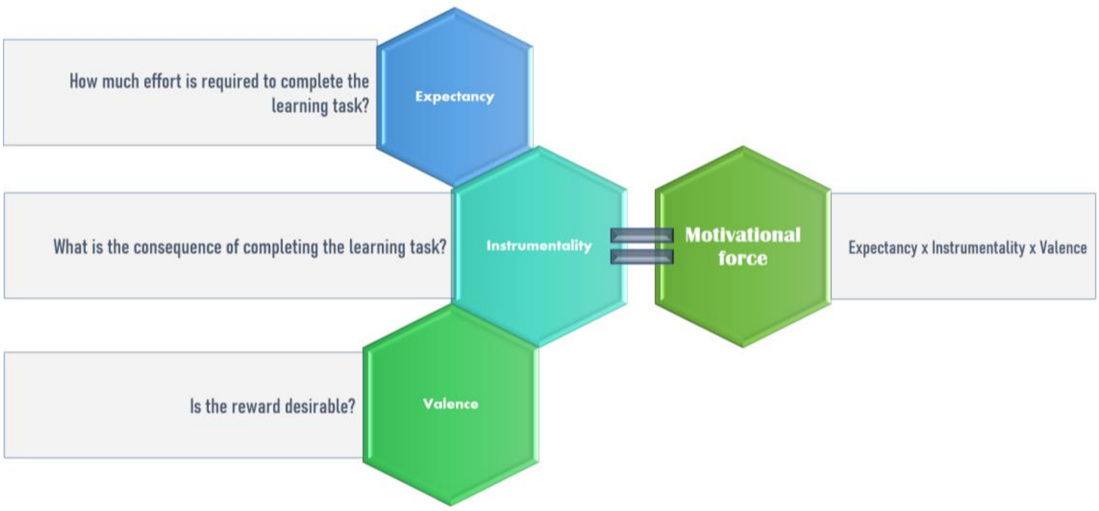


Figure 5. *Vroom expectancy theory*

Following the seminal work publication, the expectancy theory has sparked substantial debate on the subject. Like Herzberg's theory, the major criticism is on the simplicity of the theory that did not take into consideration of the different levels of effort that will influence the outcome and have generally assumed that reward will encourage greater effort. One of the greatest strengths of the theory is also one of its weaknesses because it has omitted the fact that there are other factors besides rewards that people get motivated.

Porter and Lawler's theory has emerged out of Vroom's critiques (Porter & Lawler 1968). It aims to provide a more comprehensive theory of motivation. Similarly, most recent time scholars have developed their expectancy theory and also extended and integrated theories to have a complete framework (Harris et al. 2017; Kiatkawsin & Han 2017). So far, two of the salient developments within motivation theories have been highlighted. However, in the context of employee learning, it is still murky if it is based on content or process motivation. The focus is now limited to one which is the self-determination theory (SDT). The motivating factors of SDT and the limited discussion that exists in the workplace context are the basis for this thesis.

2.2.2.4 Self-determination theory

It all began in 1977 when two young psychologists met and had a conversation that has since changed how we view human motivations (O'Hara 2017). SDT is a psychological theory that has been studied for more than 40 years in a variety of contexts. It is a meta-theory, within this, Ryan and Deci (2000b) have identified six sub-theories: Cognitive Evaluation Theory (CET) concerns attitudinal motivation, Organismic Integration Theory (OIT) concerns environmental motivation, Causality Orientations Theory (COT) concerns individual differences in people’s tendencies to orient toward environments and regulate behaviour in various ways, Basic Psychological Needs Theory (BPNT) concerns psychological needs and their relations to psychological health and well-being, Goal Contents Theory (GCT) concerns distinctions between attitudinal and environmental goals and their impact on motivation and wellness and Relationships Motivation Theory (RMT) concerns development and maintenance of close personal relationships**.**

Dualistic theories divide motivation into two types: attitudinal and environmental (Reiss 2012). The locus of this study is on attitudinal and environmental motivations. Attitudinal motivation is most commonly defined as ‘doing something for its own sake’ (Reiss 2012, p. 152). That is when an employee is keen on upskilling for no reason other than because that is what the employee wants to do and finds joy in discovering new knowledge. Domenico and Ryan (2017, p. 1) defined it as ‘spontaneous tendencies… even in the absence of operationally a separable rewards’. According to Reiss (2012), environmental motivation, in contrast, refers to the pursuit of an instrumental goal. That is when an employee contributes to knowledge sharing to receive a monetary reward or when employees are engaged in learning to receive recognition. People certainly can be motivated environmentally by reward or certification of achievements, for example – but Ryan and Deci (2020) contented that is a form of controlled motivation which will eventually be diminished and thwart the objective of the intention and undermine attitudinal motivation. According to SDT, the employee is likely not going to contribute to the knowledge sharing in the absence of the environmental reward, similarly, will not participate in any training when there is no monetary reward in return for the effort contribution. The undermining of attitudinal motivation has been controversial since it first debuted which leads to hot debate from time to time. Threats (Deci, Edward L. & Cascio 1972), deadlines (Amabile, DeJong & Lepper 1976), directives (Koestner et al. 1984) and competitive pressure (Reeve & Deci 1996) too could lessen attitudinal motivation. Despite the controversy, a meta-analytic review examining the antecedents and consequences of basic need satisfaction of 99 studies with 119 distinct samples, empirical evidence is supportive of SDT (Broeck et al. 2016). SDT has been clear in attitudinal motivations positing three characteristics as depicted in Figure 6.

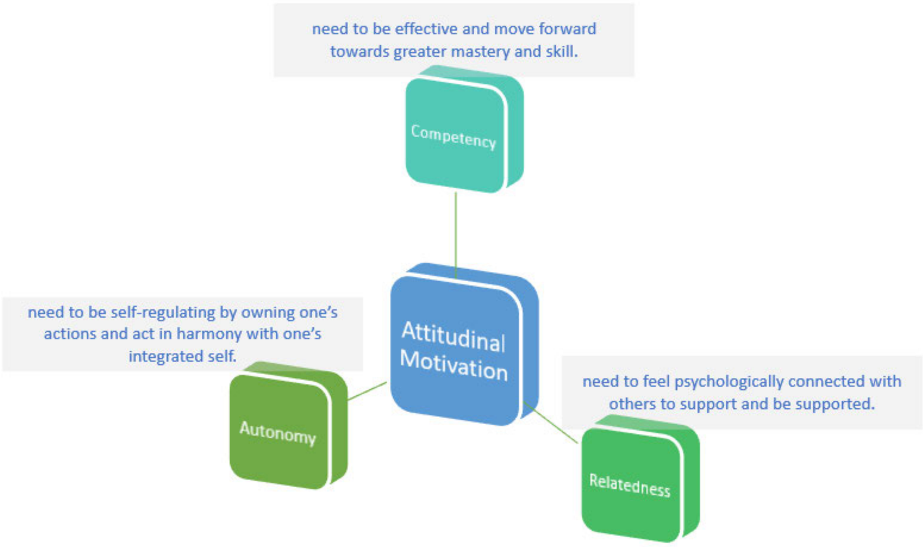


Figure 6. Characteristics of attitudinal motivations

SDT argued that satisfying these three needs will lead to individual psychological growth, internalization, and well-being in addition to greater persistence, a better quality of engagement, performance, more positive self-perceptions, creativity, psychological wellness, and optimal development among others (Broeck et al. 2016; Domenico & Ryan 2017; Ryan & Deci 2000a). Collectively, the findings indicate that SDT offers a useful theoretical framework for understanding the relationship between motivation and employee learning. Further, the pattern of findings reiterates the positive link being found in the study of mindfulness contributing to positive work-related outcomes (Olafsen 2017) such as enhanced deep-level learning (Aelterman et al. 2019) and employee's intention to start new training (Mielniczuk & Laguna 2017) with broad implications for people involved in the facilitation of employee learning. However, the role of different types of motivations in fostering employee learning has not been examined and employee motivation in learning sometimes lacks a well-articulated theoretical base. Therefore, the well-established SDT that differentiates types of motivation can be applied in the context of employee learning in this thesis.

Considering the central role of these needs and their benefits, many studies have been done to further extend and understand how to nurture these psychological needs. However, most research conducted is qualitative empirical evidence from the laboratory. SDT has been silent in terms of the order of these needs as in whether attitudinal or environmental motivation plays a more distinctive role. SDT has broadly used attitudinal motivation referring to various behaviour including but not limited to curiosity, mastery behaviours and exploration (Ryan & Deci 2017). This clearly explained why the majority of SDT studies including a recent study on the role of basic psychological need satisfaction in the employee work passion appraisal process (Thibault-Landry et al. 2018) used self-reported measures. Their study provided empirical evidence showing that employees' cognitive appraisals of work characteristics such as job autonomy, task variety, meaningful work, and performance expectations were positively related to basic psychological need satisfaction, which, in turn, positively impacted their work intentions, thus indicating the subjective experience of work passion. Another study using multi-source and time-lagged data investigating how leaders can break employee silence found that when employees have high levels of job autonomy, they are more willing to break the silence at work (Ju et al. 2019). If autonomy-supportive leads to attitudinal motivation to achieve goal-related needs, then it would be reasonable to suggest that the absence of self-determination could lead to rejection of self-regulated learning outcomes. Therefore, the author anticipates that self-determination influences employees' motivation to learn.

This thesis will innovatively attempt quantitative empirical research with practical evidence to understand which of these three needs are of the highest importance in fostering employee learning, moving away from previous reviews of mostly narrative and theoretical (Pedro et al. 2012). Beyond just theory, SDT's growth has steeply accelerated over the past two decades. SDT has been applied in multi-disciplinary fields including education, health care, technology, marketing, nature and environmental sustainability (Cuevas et al. 2018; Lavergne & Pelletier 2015; Mosteller & Mathwick 2014; Peters, Calvo & Ryan 2018; Smit et al. 2017) and the latest development is in neuroscience (Domenico & Ryan 2017). Today, SDT has spiked out and is growing with increasing depth and reach in both basic types of research and practical applications. However, SDT is still in its infancy and has not been extended in the organisational behaviour and management disciplines. This study will build on SDT by filling this knowledge gap to make a theoretical and empirical contribution to the field of organisational behaviour and management.

According to SDT, an employee will engage in learning not only because of attitudinal motivation but also because of environmental motivators such as promotion, salary increment or simply because of self-regulated action that is satisfying. In both cases, the intensity of motivation can be identical and result in satisfying goal-related needs but the reason why an employee is engaged in learning is completely different. However, SDT has only addressed environmental motivations in a continuum ranging from amotivation (not motivated) to integrated motivations but has not identified the factors that contribute to the low engagement of employee learning. Scholars have had little to say on the relationship between employee learning and motivation; this black hole will be addressed in this study.

Referring to the taxonomy of human motivation in learning as illustrated in Figure 7, amotivation is at the lowest level which shows the employee is not motivated to learn to a large extent and there is no regulation. Next to amotivation is environmental motivation with varying degrees of environmental motivation. External regulation is closer to being not motivated; it represents the least autonomous form of environmental motivation. For example, an employee who is doing training only because the employee fears demotion for not doing it is environmentally motivated because the employee is doing the work to attain the separable outcome of avoiding demoted or when there is a reward. Introjected regulation is similar to external regulation. An employee who does the training because the employee personally believes it is valuable for the employee's personal career development is also environmentally motivated because the employee is doing it for its instrumental value rather than the enjoyment it brings. Both examples involve instrumentalities, yet the latter case entails personal endorsement and autonomy instead of mere compliance with management control.

The two types of environmental motivation represent intentional behaviour but vary in their relative autonomy. Moving upward on the hierarchy of environmental motivation is identified as regulation. It is when employees are starting to understand the value of regulation. This can be considered as somewhat attitudinally motivated but at the lowest level as an employee is consciously valuing learning but is not enjoying it. At the highest level of environmental motivation, the continuum is integration regulation. This is when the identified regulation of learning is congruent with the employee's value and need. However, they are still environmental because it is an employee's behaviour motivated by integrated regulation where employees are learning because of its presumed instrumental value concerning some outcome that is separate from the behaviour, even though it is volitional and valued by the self. Despite putting the environmental motivation in a continuum, (Ryan & Deci 2000a) have warned that by no means the individual will go through each phase sequentially and integrated motivation will not turn into attitudinal motivation over time. Given that employee learning in the workplace is not designed to be attitudinally interesting, a central question remained as to how to motivate an employee to value and self-regulate learning, without external pressure but to carry them out on their own. To this end, SDT proves to be a helpful framework to be investigated. If this study is successful, and a relationship is established with employee learning then much is owed to Ryan and Deci (2000a).

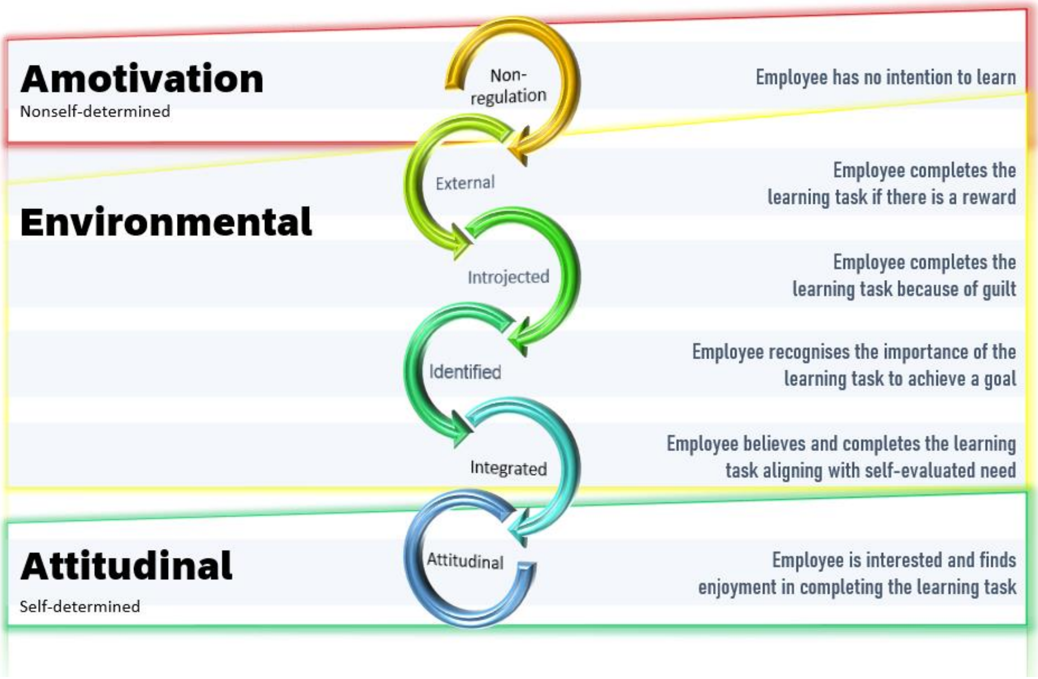


Figure 7. *A taxonomy of human motivation in learning*

2.2.3 Result and discussion

Table 2 provides a summary of motivational theories investigated in this thesis.

Table 2. Summary of motivational theories investigated in this thesis

Author	Aim	Motivational theory	Motivational theory categorisation	Sample/ Methodology	Location	Category
Lundberg, Gudmundson and Andersson (2009)	To understand work motivation in a sample of seasonal workers at a ski resort strongly steered by seasonality.	Herzberg	Content	Mixed-method Questionnaires and in-depth interviews	Sweden	Employees
Tay and Diener (2011)	The study examined the association between the fulfilment of needs and subjective well-being (SWB), including life evaluation, positive feelings, and negative feelings.	Maslow	Content	Mixed-method Phone interview and door to door interview	Multi-country	Others
Aworemi, Abdual-Azeez and Durowoju (2011)	The ranked importance of the following seven motivating factors: (a) job security, (b) personal loyalty to employees, (c) interesting work, (d) good working conditions, (e) good wages, (f) promotions and growth in the organisation, and (g) full appreciation of work done.	Multiple	Content & Process	Quantitative 300 randomly selected employees of the 15 randomly selected targeted population	Nigeria	Employees

Author	Aim	Motivational theory	Motivational theory categorisation	Sample/ Methodology	Location	Category
Pedro et al. (2012)	To examine the empirical literature on the relations between key SDT-based constructs and exercise and physical activity behavioural outcomes.	SDT	Content & Process	Qualitative 66 empirical studies	Not mentioned	Others
Mosteller and Mathwick (2014)	To examine the impact of a retailer-managed ranking system on product reviewers' well-being and its relationship to customer engagement.	SDT	Content & Process	Qualitative 189 reviewers generating 949 posted comments in Amazon's Top Reviewer Forum	Multi-country	Employees
Lavergne and Pelletier (2015)	To examine how people, resolve inconsistencies between their pro-environmental attitudes and their counter-environmental actions.	SDT	Content & Process	Quantitative N = 2209	Canada	Others

Author	Aim	Motivational theory	Motivational theory categorisation	Sample/ Methodology	Location	Category
Broeck et al. (2016)	To examine the antecedents and consequences of basic need satisfaction.	SDT	Content & Process	Mixed-method a meta-analytic review of 99 studies with 119 distinct samples e	Multi-country	Students
Harris et al. (2017)	The research investigates motivational theories concerning employee compliance with food safety inspection expectations.	Vroom & Hertzberg	Content & Process	Quantitative 755 restaurant managers and employees	United States	Employees
Kiatkawsin and Han (2017)	To examine young travellers' pro-environmental behaviours.	value-belief-norm & Vroom	Process	Quantitative 538 responses were from young group travellers	South Korea	Students
Mielniczuk and Laguna (2017)	To provide insight into motivational factors that are important for training initiation.	SDT	Content & Process	Quantitative 155 employees	Poland	Employees

Author	Aim	Motivational theory	Motivational theory categorisation	Sample/ Methodology	Location	Category
Olafsen (2017)	To investigate the antecedents and outcomes of state mindfulness in a self-determination theory model in the work domain.	SDT	Content & Process	Quantitative Online questionnaires 428 municipalities	Norway	Others
Smit et al. (2017)	To develop and validate the virtual climate care questionnaire (VCCQ), a measure of perceived autonomy-support in a virtual care setting.	SDT	Content & Process	Quantitative 230 Dutch adults who drink alcohol (occasionally) 228 Dutch students using cannabis	Netherlands	Students
Kotni and Karumuri (2018)	To find out the satisfiers and dissatisfiers among the salesmen motivation techniques adopted in the retail sector.	Herzberg	Content	Quantitative 150 salespeople working in the 15 leading retail outlets in the city of Visakhapatnam	India	Employees

Author	Aim	Motivational theory	Motivational theory categorisation	Sample/ Methodology	Location	Category
Thibault-Landry et al. (2018)	To investigate the relations between employees' cognitive appraisals of their work environment characteristics (work cognitions), their basic psychological needs satisfaction, and their work intentions.	SDT	Content & Process	Quantitative 1,456 full-time employees	United States	Employees
Aelterman et al. (2019)	An integrative and fine-grained analysis of teachers' classroom motivating style (i.e., autonomy support, structure, control, and chaos) to resolve existing controversies in the literature, such as how these dimensions relate to each other to an educationally important student and teacher outcomes.	SDT	Content & Process	Quantitative Six independent samples of teachers (N = 1332) and/or students (N = 1735)	Belgium	Students

Author	Aim	Motivational theory	Motivational theory categorisation	Sample/ Methodology	Location	Category
Cuevas et al. (2018)	To test an explanatory model based on self-determination theory, which posits that pressure experienced by teachers when they are evaluated based on their students' 4 academic performance will differentially predict teacher adaptive and maladaptive 5 motivation, well-being, and ill-being.	SDT	Content & Process	Quantitative 360 Spanish physical education teachers	Spain	Students
Ju et al. (2019)	To study how leaders can break employee silence.	SDT	Content & Process	Quantitative 1000 full-time employees in 19 companies of a large multi-national electronics group	China	Employees
Chiu (2021)	To investigate how the perceived psychological needs in SDT affected student engagement in online learning	SDT	Content & Process	Quantitative 1201 Grade 8 and 9 students from 2 schools that participated in online learning	Hong Kong	Students

A total of 18 articles within 12 years of threshold in recent years were included in the analysis. The majority of the studies (67%) were quantitative research while 17% were mixed-method and the remaining 16% were done qualitatively. The geographical focus of these studies is mainly on the United States and Europe with only 10% of the studies conducted in Asia. The study samples were both in educational and organisational settings with sample sizes ranging from 66 to more than 2000.

Motivational theories are abundant but what motivates employees to learn and how to motivate employees to learn remains unclear. Among the various motivational theories, SDT stood up as an interesting and comprehensive framework. The main agreement is that SDT brings about invaluable benefits and disagreements about SDT is self-defeating but still ongoing debate is whether environmental goal diminished and thwart the objective of the intention and undermine attitudinal motivation. Apart from that, studies are confined to laboratory experiments mainly in the educational field. Further research could build on SDT with field studies of different settings. Therefore, SDT fully supports the aim of this thesis as it is the dualist theory that makes a distinction between attitudinal and environmental motivations. It also addresses the condition that enhances or diminished these motivations. Therefore, it has constructed both the content and process theory by suggesting that an individual has innate psychological needs for learning (content) and only by fulfilling the three needs of autonomy, competence, and relatedness (process), the individual will achieve self-determination in the goal pursuits (employee learning). By drawing on SDT, this study will help clarify whether attitudinal or environmental motivation has a more distal or proximal factor in employee learning and can predict future occurrences of employee learning.

2.3 Why organisations are interested in becoming 'Employer Of Choice' and their characteristics?

Employer of choice is growing in influence and literature review shows there is a gap, particularly at the academic level, rarely a comprehensive review of Employer Of Choice (EOC) have been conducted using a systematic method.

2.3.1 Method

To capture all the relevant citations, various electronic databases were used. The source of published studies was electronic databases on a VU library system such as Health Business Elite, Business Source Complete, Scopus, PsycARTICLES, Academic Search Premier, and ScienceDirect. The following screening inclusion criteria were selected to identify the seed article: (a) be published in a peer-reviewed journal (b) academic journal (c) be in the English language, and (d) use the keyword "employer of choice" in abstract/title/keywords. Second screening criteria: (a) discuss employer of choice as the main topical theme, and (b) use either a quantitative, qualitative, or mixed approach to investigate employer of choice in an organisational context. The absence of at least one of these criteria determined the removal of the article from further consideration.

In keeping with a pre-defined set of inclusion and exclusion criteria, studies were reviewed for relevance and excluded if they did not meet those criteria. Data are then summarised and tabulated as part of data synthesis. The efforts put forward in searching multiple databases provide some safeguard against missing relevant articles. Thus, the quality of evidence summarised in this review is likely to be better in the foreseeable future.

2.3.2 A survey of the recent development of literature

Even though the employer branding statement is abounding in literature, its conceptually precise definition is elusive. Ambler & Barrow (1996) defined an employer brand as a package of psychological, functional, and economical benefits provided by the employer. It is also a process of creating a unique employer identity and building an employer brand as a differentiating concept (Backhaus & Tikoo 2004). In the same vein, Sutherland, Torricelli & Karg (2002) has defined it as the process of establishing and creating a company brand message while Bellou et al. (2015) have a closer definition to Amber & Barrow (1996) referring to it as the package of the benefits provided by an employer, playing the role of identifiers of an employer. Generally, the root is Kotler, Philip's (2007, p. 188) traditional product branding definition; 'essentially a seller's promise to consistently deliver a specific set of features, benefits, and services to the buyers'; the seller represents the organisation while the buyer represents the employees. Table 3 provides a summary of a few definitions of employer branding. Taken these defintions together, the employer brand can be regarded as a unique employer identity in the eyes of employees.

Table 3. Employer branding definition

Employer brand definition	Authors
As the package of functional, economic, and psychological benefits provided by employment and identified with the employing company	(Ambler & Barrow 1996)

Employer brand definition	Authors
Essentially a seller's promise to consistently deliver a specific set of features, benefits, and services to the buyers	(Kotler, P. 1997)
The process of identifying and creating a company brand message	(Sutherland, Torricelli & Karg 2002)
The process of building an identifiable and unique employer identity, and the employer brand as a concept of the firm that differentiates it from its competitors	(Backhaus & Tikoo 2004)
As the package of the benefits provided by an employer, playing the role of identifiers of a particular employer	(Bellou et al. 2015)

Another term, 'Employer Of Choice' (EOC) is often used interchangeably and without precision. Alternatively, EOC has also been referred to as 'A great place to work', 'The best place to work' and 'World's Most Admired Company' (WMAC), which are all generally referring to the same meaning. EOC has only started to garner considerable attention in the 21st century with much literature from practitioners and consulting firms. It has been regarded as the strategy to become the winner in the war of talent. Hence, 67% of the papers following the full-text assessment were removed as they are not academic journals.

Finding the right talent has remained a challenge until today. Bellou et al. (2015) have referred to EOC as the employer who possesses attractive attributes to attract the most talented employees while Herman, Roger E. and Gioia (2001) have revealed the intention to attract talent is to retain them for long tenure out of employees' choice. Clarke (2001) has stressed outperforming its competitors in attracting, developing and retaining employees. All of these completely adhere to Lloyd, S (2002) definition of EOC as a desirable place to work. Table 4 provides a few citations of EOC definitions.

Table 4. Employer of choice definition

Employer of choice definition	Authors
an employer of any size in the public, private or not-for-profit sector that attracts, optimises, and holds top talent for long tenure… because the employees choose to be there.	Herman, R.E. and Gioia (2000, p. 11)
an organisation that outperforms its competition in the attraction, development, and retention of people with business-required talent, often through innovative, and compelling human resource programs.	Clarke (2001, p. 21)
the sum of a company's efforts to communicate to existing and prospective staff that it is a desirable place to work	(Lloyd, S 2002)
an employer who can attract the most talented employees by possessing attractive attributes	(Bellou et al. 2015)

Comparing the two terms from the above discussion, a significant difference has been found. It has been understood that any organisation can create an employer brand but only a few will be regarded as EOC; whereby employees are chosen to be retained by the employer because of the perceived employee value proposition (EVP). It is the relative benefits the employees received in return for the capabilities, skills, and experience employees bring to a company (Page 2019).

Research on EOC has always been taken from a potential candidate perspective with insights mainly coming from university students. One example among many is the study of business student perceptions of a preferred employer (Arachchige & Robertson 2011). The study was conducted with a sample of students from Sri Lanka university to identify the significant factors that attract the graduates to potential employees. The authors further posited eight dimensions of employer attractiveness drawing on the research results the job structure, corporate environment, relationship, personal growth, organisational dynamism, enjoyment, social commitment, and environment. This study will compensate for the gap by providing existing employees working in EOC organisations with insights into the context of employee learning.

Furthermore, as many as 33% of the studies sighted from the pool of literature are industry-specific. For example, Smith, Gregory and Cannon (1996) were assessing commitment in the hospitality workplace and identified four predictors of overall job satisfaction: organisational support, supervisor relations, job environment and attitude towards management. In the software industry, Pattnaik and Misra (2014) presented a study on EOC by developing a scale to measure the level of employer attractiveness. Another industry-specific study was the one conducted in Germany; the management consulting industry, on how to become an employer of choice (Rampl 2014). Out of this 33% of industry-specific, 42% are reflecting on the public sector such as the study of civil service as EOC in Belgium (Vandenabeele, Hondeghem & Steen 2004), organisational readiness to be EOC in India (Maheshwari & Singh 2010) and the attractiveness of public-sector jobs to youth in Egypt (Barsoum 2016). Hence, a study of countrywide EOC in the Australian context will do justice in filling the gap.

Herman, Roger E. and Gioia (2001) have urged organisations to invest in obtaining the official EOC designation to thrive in the challenging labour market and economic turbulent times. These labour market conditions and competitive pressure are forcing organisations to invest in various resources for top talent attraction and retention (Schuler & Jackson 2006) including investment in the EOC award citation. Organisations must remain focused on attracting and retaining talented employees because having a great team is the core of success for any organisation (Kusuma & Madasu 2015). The authors added, that employees are actively engaged to move the company forward by creating an awesome experience that will increase satisfaction and retention of customers. It is a strategic investment for a sustainable competitive advantage. Looking through the resource-based view, organisational resources need to portray four characteristics: valuable, rare, inimitable and non-substitutable resources to achieve sustained competitive advantage (Barney 1991). Employees are intangible resources exhibiting these characteristics; an invaluable asset for any organisation.

Hence, organisations are investing in EOC to attract employees, honing employees' skills to impact the organisational bottom line. However, it has become apparent if the organisation has a 'true intention' or pure 'impression management' (Jonsen et al. 2019). Agency theory popularised in the financial-economic field (Jensen & Meckling 1976), could well explain this agency relationship. Employment contract provides a framework defining the employer and employee relationship; the employer is paying for the employee to work hence it may not be of interest for the employer to invest in employee learning. Similarly, looking at the agency theory perspective (Pandey & Chermack 2008), the employer is always looking at ways to cut costs while employees are looking for quality employment. Therefore, it is critical to address this value gap (Cording et al. 2014), to create an equilibrium utility for both employer and employees. This study will try to delineate this in the context of employee learning.

As with the eight factors of EOC posited by Arachchige and Robertson (2011), Herman, Roger E. and Gioia (2001) stressed the importance of company profile such as reputation, quality of products and services, company culture and leadership. Branham (2001) on the other hand has identified the characteristics as opportunities for rapid advancement, a high-risk reward profile, exciting challenges, and improved lifestyle benefits while Rampl (2014) has identified six factors: salary, advancement, location, reputation, work content and culture of which work content and culture stand out as key drivers. Sutherland, Torricelli and Karg (2002) using a two-phase study involving 274 knowledge workers has identified 6 communication channels for EOC: current employees, word of mouth, media, first-hand experience, branding, and the internet. They have established eleven EOC attributes: the corporate culture of career growth, personal training and development, pay, innovative product, job rotation and diversity, successful company based on strong products, challenging work, like the work and industry, value-based organisation, benefits, and comfortable working environment. Table 5 presents a list of EOC characteristics. There is a diversity of EOC characteristics but what stands out is training and development, consistent with SDT, employees have an innate psychological need for learning.

Table 5. Employer of choice characteristics

Employer of choice characteristics	Authors
Company profile, company culture, and leadership	Herman, Roger E. and Gioia (2001)
Opportunities for rapid advancement, high-risk reward profile, exciting challenges, and improved lifestyle benefits	Branham (2001)
A corporate culture of career growth, personal training, and development pay, innovative product, job rotation and diversity, a successful company based on strong products challenging work, like the work and industry, value-based organisation, benefits, and a comfortable working environment	Sutherland, Torricelli and Karg (2002)
Corporate environment, job structure, social commitment, social environment, relationship, personal growth, organisational dynamism, and enjoyment	Arachchige and Robertson (2011)
Salary, advancement, location, reputation, work content and work culture	Rampl (2014)

The EOC is an evolving interest for Australian businesses and has taken on a new dimension of employer branding with the introduction of Employer of Choice for Gender Equality (EOCGE); strategically aligned with the nation's gender equality agenda. In this study, EOC and EOCGE will be used interchangeably (unless specified), because the review of the literature suggested that it is just another form of EOC branding to allow organisations to position themselves in the targeted segment of potential employees.

#MeToo and #TimesUp among other movements (Andersen 2012; Subedar 2018), are not just any social campaigns but signify a cultural change (Kotler, Philip & Zaltman 1971). Gender equality has become a hot topic not only in the global humanitarian agenda but also in the corporate context and millennium workforces are expecting gender equality in the workplace. Scholars have successfully built the business case for a gender-diverse workforce (Churchman & Thompson 2008; Herring 2009, 2017) linking to positive organisational and financial performance (Campbell & Mínguez-Vera 2008; Conyon & Hec 2017; Dwyer, Richard & Chadwick 2003; Low, Roberts & Whiting 2015; Reguera-Alvarado, Fuentes & Laffarga 2017; Wiley & Monllor-Tormos 2018), improved corporate social responsibility scores (Alazzani, Hassanein & AlJanadi 2017; Ben-Amar, Chang & McIlkenny 2015; Kyaw, Olugbode & Petracci 2017) and some evidence of improved innovativeness (Ruiz-Jiménez, Fuentes-Fuentes & Ruiz-Arroyo 2016). Unfortunately, the progress has been far too slow, yet the steady improvement seems to have plateaued. Organisations continue to fight the long battle of improvement with little progress toward a sustainable solution. At the current rate of progress, gender equality in the workplace will take 217 years an economic monitoring group has suggested (BBC 2017). EOC is seen as an avenue to address this gap.

The EOCGE award is honoured by the Workplace Gender Equality Agency (WGEA) which has been established by the Australian government based on the *Workplace Gender Equality Act 2012* (WGEA 2018). According to the award citation guide, the validity of the award citation is 2 years which is non-renewable. This means, that a new application is to be submitted on expiry and a new application is accepted yearly for a fee, which covers the Agency's cost of administering the citation and assessing applications. The organisation representative is to submit an online application which is open yearly on 1st June and closes on 30th Sept, and the list of successful applicants will be announced in mid-February of the following year. This list will also include employers who are in their intervening year, where an application submission is not required. Part of the assessment is having a management interview and evidence of consultation with the employee through an employee survey. Overall, the citation award is viewed as a prestigious award that sets the organisation apart in having the baseline features of a leading organisation for gender equality (WGEA 2018).

The list of 2019 EOCGE award citation holders was announced recently (WGEA 2019). A total of 141 organisations across 16 industries, with 26 first-time citation holders. This is an 18% increment from 2018 and a booming 54% since the citation commenced in 2014. Statistics show there are continuous momentum and progress toward gender equality in Australian workplaces. Figure 8 shows the EOCGE trend.

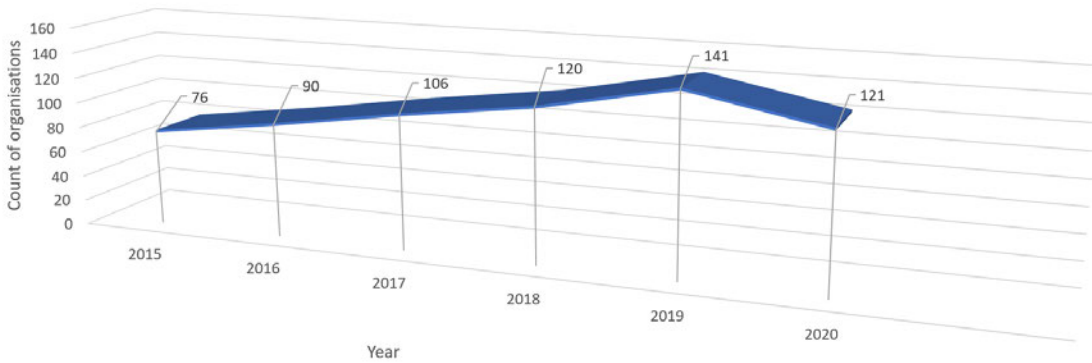


Figure 8. Employer of Choice for Gender Equality trend

In the assessment of the EOCGE award citation, the agency used seven factors' indicators as a benchmark: (1) leadership, accountability, and strategy; (2) developing a gender-balanced workforce; (3) gender pay equity; (4) support for caring; (5) flexible work; (6) preventing gender-based harassment and discrimination, sexual harassment, and bullying and (7) driving change beyond the workplace. As highlighted earlier, in the discussion of SDT, an employee has an innate need for competence to develop mastery over tasks that the employee value, comparatively to the characteristics of EOC, it has become evident that a key factor around training and development should be included as part of EOCGE indicators for assessment which has been left out. This is critical to support the employee's need for professional development and career growth. The 7-dimensions model will be adopted in this study to include support for professional development.

Arguably, Herman, Roger E. and Gioia (2001) have boldly categorised EOC attributes as tangible and intangible. The authors also claimed that companies are relying heavily on tangible, easy-to-implement solutions rather than strategically investing in intangible solutions such as good management and culture. Regardless, according to signalling theory (Connelly et al. 2011), information asymmetry is present, whereby organisations know about their quality, but outsiders (e.g. investors, potential employees) do not, so EOC is an environmental signal to show what the organisation could offer. Against this background, it is important to note that the present work does not aim to examine the drivers of EOC rather, the focus is on EOC as an environmental motivator and the EOC indicators will be assessed to establish the relationship with employees learning. Both employee engagement in learning and EOC are important aspects of employee and organisational success. Much has been written and discussed on employee learning and EOC in a silo, but no study has attempted to link employee learning and EOC.

The main agreement is that EOC has the potential in bridging the employment gap hence organisations are interested to get recognition as evident in the statistics. However, literature thus far has only arrived at identifying the characteristics of EOC and has not gone any further in identifying how to tap on this EOC branding to retain resources to achieve the said competitive edge in the employment slump. Resulting in some organisations not seeing the benefit of investing in the EOC recognition and those who have the award citation may not be obtaining the desired result. Therefore, even though many organisations are coming on board with the EOC award citation, there are many more who are not interested in the renewal of the EOC award citation following the expiry. Only 10% of the EOC are repeated award citation holders for more than 2 years. More academic research is required in this area to fully understand the phenomenon. There are plenty of opportunities for further research in this area such as understanding:

a) Who is accountable in the organisation to deliver on the employer of choice for the gender equality award?
b) How relevant is the award citation to the employees?

Overall, this thesis will only be attempting to address the tip of the iceberg concerning the relationship between EOC as an environmental motivator and its impact on employee learning.

2.3.3 Result and discussion

Table 6 provides a summary of the EOC literature investigated in this thesis.

Table 6. Summary of Employer of Choice literature investigated in this thesis

Author	Aim	Sample/ Methodology	Location	Category
Smith, Gregory and Cannon (1996)	To find if there was a positive correlation between overall job satisfaction and commitment to the organisation.	Quantitative - primary data 7504 employees	United States	Organisation
Sutherland, Torricelli and Karg (2002)	To establish the factors knowledge workers regard as important organisational attributes when seeking an employer and what communication channels signal these attributes to knowledge workers.	Mixed-method - Primary data A two-phase study involving 274 knowledge workers	South Africa	Organisation
Stroh (2003)	To examine how one Fortune 500 organisation is changing its culture, policies, practices, and procedures to become an employer of choice, especially for women in the organisation.	Mixed-method - Primary data Interview and focus group 164 senior, middle-, and lower-level managers	Not mentioned	Organisation
Vandenabeele, Hondeghem and Steen (2004)	A three-factor solution is extracted from the factor analysis and used in explaining the attractiveness of an employer.	Mixed-method - primary data Interview and online survey 741 final-year students of a master's program at two universities and nine colleges	Belgium	Organisation

Author	Aim	Sample/ Methodology	Location	Category
Branham (2005)	To examine how several companies turned around high turnover with retention and hiring strategies geared to the particular needs of critical talent—managers, professionals, or front-line workers.	Qualitative - secondary data 7 companies	United States	Organisation
Li, X and Bryan (2010)	To measure CUL employees' perceptions of the library's workplace climate.	Quantitative - primary data 305 valid employee response	United States	Organisation
Maheshwari and Singh (2010)	The study provides a framework to analyse the organisational readiness in the case of the Government of India employees to implement PRP systems.	Qualitative - secondary data	India	Organisation
Arachchige and Robertson (2011)	The paper identifies the significant factors which attract Sri Lankan university graduates to potential employees, both on a general basis and for specific student segments.	Quantitative - primary data 221 final year business course students	Sri Lanka	University

Author	Aim	Sample/ Methodology	Location	Category
Franca and Pahor (2012)	To establish how the image of an employer, communicated to the job market through the employer brand, influences the pool of candidates that a company gets.	Quantitative - primary data 7000 potential employees	Slovenia	Organisation
McGrath-Champ and Jefferson (2013)	The purpose of this article is to explore gender pay equity policies at an organisational level within a professional business services firm (‘ProServ’, a pseudonym) to gain insights for future policy and research on pay equity.	Mixed-method -Secondary data	Australia	Organisation
Pattnaik and Misra (2014)	To empirically investigate how to measure the level of employer attractiveness within Indian software organisations.	Mixed-method	India	Organisation
Rampl (2014)	To investigate employer brand associations that predict status as an employer first-choice brand (FCBe), and by determining how these associations are transferred into preference.	Mixed-method	Germany	University

Author	Aim	Sample/ Methodology	Location	Category
Bellou, Rigopoulou and Kehagias (2015)	To extant knowledge by delineating the content of employer of choice (EOC) regardless of sector and shedding light on the role of gender in the EOC profile.	Quantitative - primary data 896 valid online survey replies	Greece	University
Bellou et al. (2015)	Determining the Employer Brand of Choice and its core components.	Mixed-method 12 semi-structured interviews 896 valid online survey replies	Greece	University
Jepsen, Knox-Haly and Townsend (2015)	To examine practitioner and peer-reviewed literature on the current Australian recruitment context.	Qualitative - secondary data	Australia	Not applicable
Kusuma and Madasu (2015)	To study the Employee Engagement Practices of the top 5 companies rated by Great Places to Work (India) 2013.	Qualitative - secondary data 5 companies	India	Organisation
Barsoum (2016)	Seeks to explain the attractiveness of public-sector jobs to this group, embedding this experience within the literature and theorization on public service motivation (PSM) and discussing its relevance.	Mixed-method	Egypt	Organisation

Author	Aim	Sample/ Methodology	Location	Category
Saurombe, Barkhuizen and Schutte (2017)	To explore management perceptions on a higher education institution as a brand for the attraction of talented academic staff.	Qualitative	South Africa	Organisation
Lanier (2018)	To provide ideas for institutionalizing an “employer of choice” culture.	Qualitative	Not mentioned	Not applicable
Ronda, Valor and Abril (2018)	To propose a novel employee-centric framework for the study of employer brand attractiveness.	Qualitative	Multi-country	Not applicable
Jonsen et al. (2019)	Examine the websites of 75 major companies in five different countries (France, Germany, Spain, United Kingdom, and United States).	Qualitative Secondary data	Multi-country	Organisation
Dahiya (2021)	To examine the association between organisational virtuousness and perceptions of employer branding with the psychological mechanism of 314 employee happiness	Quantitative – primary data	India	Organisation

A detailed inspection of the studies identified by the earlier mentioned search engines found that 145 studies were related to the EOC. Some duplications of papers were found resulting in 37 papers being removed from the initial pool. The full text of 108 papers was retrieved and assessed following the pre-defined inclusion criteria, of these 44 were identified, and 64 papers were excluded after the full-text analysis resulting in 21 papers included in the final qualitative synthesis.

2.4 Summary

Following the discussion above, this thesis offers a theoretically grounded, yet previously unexamined pattern of predictors explaining how employee learning may occur. The thesis builds on and contributes to work in employee motivations and employee learning, hinging on SDT as an attitudinal motivator and EOC as an environmental motivator. Although SDT, learning, and EOC have been examined in many disciplines they have not been looked at as an integrated framework. As such, this study provides additional insight into organisational behaviour. The analytic focus on correlations enables another contribution. This study analyses the relationship between perceived EOC utility, self-determination, AI support, and employee learning. Although numerous studies have looked at motivation and employee intention to learn, little analytic attention has been paid to identifying which of the motivators play a greater contribution to fostering employee learning and the influence of AI support. This thesis also differs from all previous research highlighted above in the fact that the author is targeting current employees, thus providing an organic work experience that is invaluable. In the next chapter, a theoretical framework will be presented.

CHAPTER 3 THEORETICAL FRAMEWORK

The key literature regarding EOC, motivation and, learning was reviewed in the preceding chapter. In this chapter, the theoretical framework, and the links between variables under investigation will be provided. These links and concepts will be guiding the development of a new theoretical model of AI support and employees' motivation to learn with the thesis questions and hypotheses derived from the framework. Despite much empirical evidence over the last decade establishing the links between attitudinal and environmental motivation, there is not one that looked at EOC, self-determination and the influence of AI on employee learning outcomes. This thesis devotes its attention especially to EOC utility perception and self-determination respectively in fostering employee learning. And given that AI has enormous relevance today and is enjoying its resurgence it is timely to also investigate the influence of AI in motivating employees to learn where no research has been done in this direction as of today in an organisational context.

This thesis takes an initial step in establishing its link to the employee learning outcomes of job satisfaction, well-being, and performance. Whilst many studies looked at the controversial relationship between attitudinal and environmental motivation there is still much to be discovered and it is worthy to see this in the light of the APS population because there is an urgent need to reform this aging population. In 2012, employees aged over 45 years old represented 14.8% of the APS population (APSC 2012), this has at least doubled if not tripled in the 2018 census. Like the Australian population, the APS workforce has been aging rapidly, posting challenges in workforce management. This includes keeping them motivated to learn and developing new skills and knowledge that are critical in this rapidly technologically driven changing environment. As such, the proposal in this thesis is that positive learning outcomes resulting from perceived EOC utility and self-determination fulfilment may be further enhanced with the presence of AI. In this chapter, a theoretical model of employee attitudinal and environmental motivation in fostering learning is developed and investigated together with the influence of AI.

3.1 Theoretical background

In this thesis, employee learning is conceptualised by drawing on concepts derived from EOC and SDT (see Figure 9). The author postulates that an employee's self-determination and EOC utility perceptions will influence employee learning together with this AI support plays a role too.

3.2 Theoretical framework

In this thesis, the author will build on Zimmerman's self-regulated learning (SRL) model and agency theory to integrate with SDT and EOC constructs because of its similarity envisioned within Bandura's triadic model of social cognitive theory (Bandura 1991) as described in Chapter 2.1 about learning. In this model (Figure 9), the cyclical arrow has been replaced to indicate an iterative process instead of a cyclical process where one happens after another, both environmental influences and attitudinal influences can present simultaneously, and the employee is continuously evaluating to balance between value and benefits as postulated in the social-exchange theory. In the original model, Zimmerman (1989) has three constructs: person, behaviour, and environment, in this framework the three constructs have been reworded as self-determination, employee learning outcomes, and perceived EOC utility respectively. Besides, AI support was introduced into the framework.

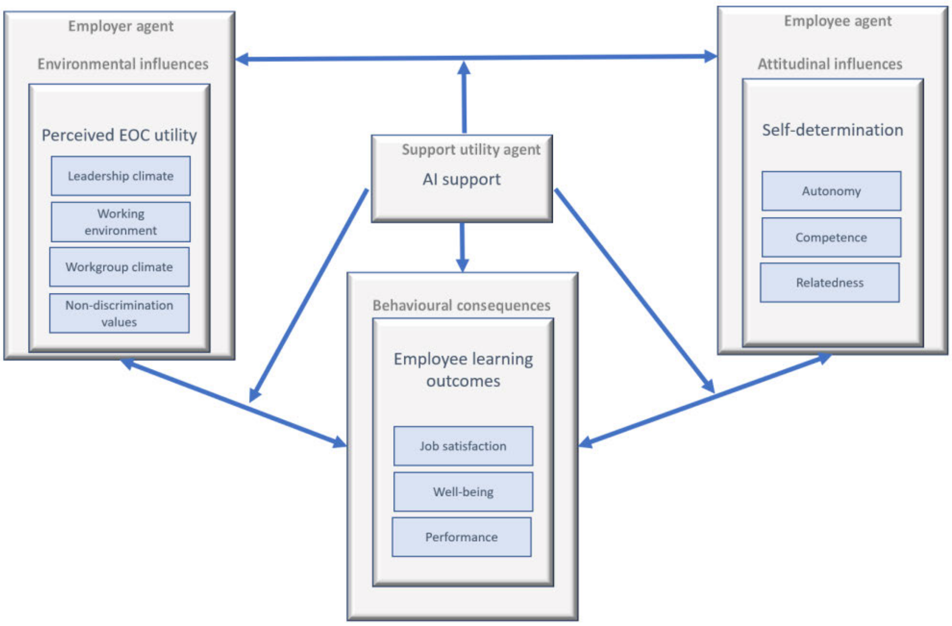


Figure 9. A theoretical framework of employee self-determination in learning

3.2.1 Employee learning outcomes

Behaviour refers to performance evaluation and strategic adaptation (Zimmerman 2013). The variables used are job satisfaction, well-being, and performance referring to the positive fulfilment of a work-related state of mind (Schaufeli, Bakker & Salanova 2006). Job satisfaction, according to Locke, E (1976) is an emotional state of being positive. This is a result of the evaluation of one's work. Well-being on the other hand is notoriously difficult to define precisely. The dictionary defines well-being as a state of being satisfied with one's welfare such as being happy, prosperous, or healthy (Dictionary.com, 2020). This definition is indeed subjective and independent of the context where it is used. In a family context, well-being could refer to a harmonious relationship among family members. In an educational context, well-being is achieved through the feeding of knowledge to the learner. In an organisational context, the innovative introduction of robotics has brought about simplification of work but arguably impacted the labour market causing insecurity among employees and affecting employees' well-being (Acemoglu & Restrepo 2020). Hence, it is clear that the dimension of well-being is vast but not clearly defined. Fabio (2017) gave a novel definition of well-being referring to an equilibrium state between an individual's resource pool and the challenges psychologically, socially, and physically. The other variable included in the employee learning outcomes factor is performance. It refers to the ability of employees to be productive and accomplished the given tasks. To achieve the employee learning behavioural outcome, they need to be motivated.

3.2.2 Self-determination

Self-determination as an attitudinal influence has been added as an additional factor that influences employee learning. It has the variables: competence, relatedness, and autonomy. Autonomy, competence, and relatedness represent the dimension of the attitudinal motivation constructs in SDT. According to Ryan and Deci (2000a), autonomy refers to an employee's need to self-regulating one's actions and act in harmony with one's values. Competency refers to an employee's need to be effective and advance towards greater mastery skills and relatedness refers to an employee's need to feel psychologically connected with peers for support.

3.2.3 Perceived EOC utility

While attitudinal motivator variables are from SDT, the environmental motivator is derived from EOC characteristics. Zimmerman (2013) defined the environment as monitoring the dynamic of environmental conditions and controlling strategically. The variables that emerged out of perceived EOC utility are the work environment, workgroup climate, non-discrimination, and leadership. Prentice (2004, p. 102) defined leadership as 'the accomplishment of a goal through the direction of human assistant' while Koohang et al. (2020, p. 3) defined leadership as 'the process of interactive the influence that occurs' when the follower is inspired to achieve a common goal. Both definitions underscore leadership as an individual trait. Individual traits theory states that certain individual characteristics can position one to be a leader by driving the followers to achieve the desired goal. Atmojo (2012) found evidence that leadership influences employee performance, satisfaction, and commitments. Contradictingly Supriyanto, Ekowati and Maghfuroh (2020) found leadership has a significant indirect effect on employee performance mediated by work satisfaction. This means employees will tend to contribute to the organisational performance only when they are satisfied. In this thesis, the leadership variable refers to the general quality of supervision of employees in the organisations.

The other variable is the work environment. It is widely defined as the professional place where the employees perform their functions (Paguio & Yu 2020). For example, the work environment for the nurse is in the hospital and the police officer is in the police station. Similarly, the work environment in this thesis refers to the APS organisations and it is seeking to understand the employees' general impression of the APS organisations and employees' willingness to be retained in the organisations. A study on Domino's pizza, conducted in Jaipur city found evidence that the work environment is one of the most influential factors in employee satisfaction and degree of motivation among employees (Jain & Kaur 2014). This evidence is supported by a study on merchant banks in Ghana too (Agbozo et al. 2017). These findings emphasise the need for organisations to improve physical work ambience; to be vibrant to boost employees' satisfaction and performance. As such, it is anticipated that employee learning outcomes would likely be enhanced with an improved work environment.

Whilst the work environment refers to the place itself, the workgroup on the other hand refers to the people working within a subgroup daily. It is also referred to as teams of two or more individuals interacting dynamically (Shuffler et al. 2018). It has been widely recognised (Jing, Avery & Bergsteiner 2019; Lacerenza et al. 2018) that teams are the basic building block of organisations. Therefore, organisations are investing significantly in tools and resources to cultivate a harmonious team culture including organizing team building. Employees' work performance-enhanced when employees maintained good interpersonal relationships at work. There is indeed no lack of theory and research on teams and their development. Consistent with these findings, in this thesis, there is an intention to discover the general impression of employees of diverse backgrounds in APS organisations perceiving each other as behaving acceptably within their direct workgroup will influence the employee learning outcomes.

The act of discrimination and bullying of any kind harms the harmonious relationships between individuals and teams in addition to contributing to mental health issues (Nauert 2018). Discrimination is defined as beliefs and attitudes of individual or group inferiority based on some characteristics according to Martinez et al. (2020). Employee discrimination could be due to age, gender, ethnicity, disability, and others. In this new knowledge economy, the ever-deepening discrimination of individuals and groups has not abated. In Australia, discrimination of ethnicity and religion has been reported to be rising including gender discrimination. The empirical findings from Carangio et al. (2020) shed light on racism and discrimination due to skin colour affecting the non-white skilled immigrant women's careers in Australia. It is not the intention of this thesis to dive into the issues of discrimination but to highlight that any kind of discrimination negatively affects the workgroup climate which in return influences and impacts the employee learning outcomes. Therefore, there is broad acceptance that the discriminatory act could be minimised with the adaption of organisational policies falling under the rubric of law and order (Einarsen et al. 2020). As such, it has been assumed in this thesis that APS organisations value non-discrimination with a policy that applies to everyone in the organisation and is fair. That is no one individual or group is treated less favourably than another based on their background or certain personal characteristics. It would be interesting to statistically evaluate if employees perceived their immediate workgroup is acting per the APS values in their daily work activities. Apart from the above-mentioned, given the rapid technological advances, the question of how AI is changing employees' motivation and learning outcomes is highly salient for scholars of organisational behaviour.

3.2.4 AI support

The process by which employees decide whether to adopt or reject the use of the AI system is often based on the costs-benefits analysis of the innovation diffusion (Lee, Hsieh & Hsu 2011). Innovation diffusion theory postulated the adoption of innovation usually starts slowly but eventually gains momentum and diffuses through the population. The diffusion of innovations has been widely applied in multidisciplinary such as education, medical, and businesses. Regardless, organisations need to quickly adapt to technological advances or risk losing out to competitors. A recent report claimed that disruptive technology poses a greater threat to organisations than economic uncertainty or change in regulations (Violino 2018). Successful adoption of the AI system, in general, helps to improve employee satisfaction subsequently bolstering business performance (Gil D. et al. 2020). As we move into the IR 4.0 era, many sophisticated systems are deployed hence, there is a pressing need to understand the contribution of AI support in the employee learning context. Therefore, the AI support variable has been included in this thesis referring to the general impressions of employees if the current employer provides access and support to effective learning and development using AI. In this thesis, it is proposed that positive reactions resulting from employee learning outcomes may be enhanced with AI support. That is the support rendered on AI influencing employees' motivation and learning outcomes implicitly.

3.3 Hypothesis development

Hypothesis 1 (H_1): Employee EOC utility perceptions are positively associated with the employee learning outcome.

Hypothesis 2 (H_2): Employee self-determination is positively associated with the employee learning outcome.

Hypothesis 3 (H_3): Employee EOC utility perception is positively associated with employee self-determination.

Hypothesis 4 (H_4): The relationship between EOC utility perception as an environmental motivator and employee learning outcomes is mediated, at least in part, by AI support.

Hypothesis 5 (H_5): The relationship between self-determination as an attitudinal motivator and employee learning outcomes is mediated, at least in part, by AI support.

Hypothesis 6 (H_6): The relationship between EOC utility perception as an environmental motivator and self-determination as an attitudinal motivator is mediated, at least in part, by AI support.

Hypothesis 7 (H_7): The relationship between perceived EOC utility and self-determination motivation is moderated by AI support. That is, employee learning outcomes will be higher following AI support when EOC utility perceptions are high than when they are low.

Hypothesis 8 (H_8): EOC utility perceptions, self-determination, and AI support significantly predict employee learning outcomes.

3.4 Summary

In this chapter, how self-determination theory illuminates the linkages between attitudinal and environmental motivators and individual outcomes have been articulated. Drawing upon self-determination theory, a model is proposed which suggests that employees' self-determination is created under the influence of employees' EOC utility perceptions and AI support leads to an increase in employee learning outcomes. To this end, the theoretical framework for empirical research has been delineated. It described the proposed associations among the variables and presented the theory underlying the conceptual model. Finally, this chapter concluded with the hypotheses for the present program of research. This framework was applied to the APS population in Australia. In the next chapter, the methodology undertaken in this thesis will be discussed as they serve to quantify each of the constructs described in this chapter included in the theoretical framework. The research process, data analysis, and issues related to the quality of the research will also be outlined.

CHAPTER 4 RESEARCH DESIGN AND METHODOLOGY

In the previous chapter, the theoretical framework and hypotheses for the model used in this empirical research were established. Following on from this, in the present chapter, the methodology used in the thesis to examine and test the model presented in Chapter 3 is developed. The material discussed here is a result of the preceding chapters that assist with the determination of the appropriate research design from data collection to the choice of tools used to test the research hypotheses resulting from the proposed model.

4.1 Research methodology

There is a lot of research methodology that can be employed for answering the research questions. The choices made to execute the research are dependent on the nature of the research. The nature of the research can be visualised as a funnel as depicted in Figure 10.

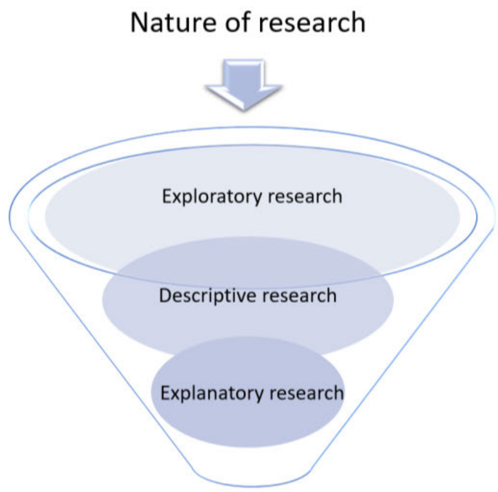


Figure 10. Nature of the research

At the beginning of the research, when little is known about the research there were a lot of questions asked. Exploratory research as the name implies is basic research that helps the author to research the topic to better formulate the problem. Following exploratory research, such as through literature review, when the author had more clarity on the problem, there is a tendency to want to learn more by describing the research problem. Hence, the name of descriptive research. In descriptive research, the author attempts to explore and explain by describing the interrelated variables. The correlations of variables are established however, a correlation does not mean causation. As such, moving further into the funnel, the author is looking at the causation which has been described as explanatory research. That is researching how and why the relationship among variables occurs. In this thesis, there is also the intention to statistically analyse and predict future occurrences hence, this is known as predictive research. In contrast to experimental research, it is non-experimental research that includes hypotheses, and variables that can be measured, calculated, and compared with no intention to control or manipulate the variables but relies on the interpretation of the correlations to conclude.

4.2 Research approach

Inductive and deductive reasoning are the two broad categories of reasoning approaches (Hayes et al. 2018). Deductive reasoning is a logical process of obtaining a conclusion about a specific instance based on something known to be true or a known general premise. For example, fruits have torn, and that durian is a type of fruit that deductively means durian is a fruit with torn. If we know that birds can fly, and parrots are birds then deductively it follows that parrots can fly. The task in deductive reasoning is to find a theory and try to apply it to a specific phenomenon.

Inductive reasoning on the other hand is a logical process involving the assessment of probability drawing inferences from general propositions through the observation of particular facts or instances. For example, we know durian has torn it may seem likely that this observation is shared by other fruits, but this inference is not logically valid. Similarly, when it is observed that parrots can fly would imply that all birds can fly. Truly inductive research does not rely on any theoretical background, it takes the data and tries to formulate a theory. Notably, inductive and deductive reasoning tasks often overlapped (Hayes et al. 2018).

In this research, both deductive and inductive approaches are used. Deductive approach because of the need for some presumptions based on theory and hypotheses utilisation for this thesis. Based on the available data, the author induces the hypothesis, modifies the model to be tested, and redefined the problem. The findings from data analysis and interpretation of the findings are then fed back to enhance the model which is an inductive approach. Even though the inductive elements exist in this thesis but predominantly it is utilising the deductive approach. Overall, employing both approaches allow a more complete understanding of the thesis topic.

4.3 Research process

The research process refers to the step-by-step procedures taken to successfully conduct the research. Figure 11 illustrates the steps taken in this research.

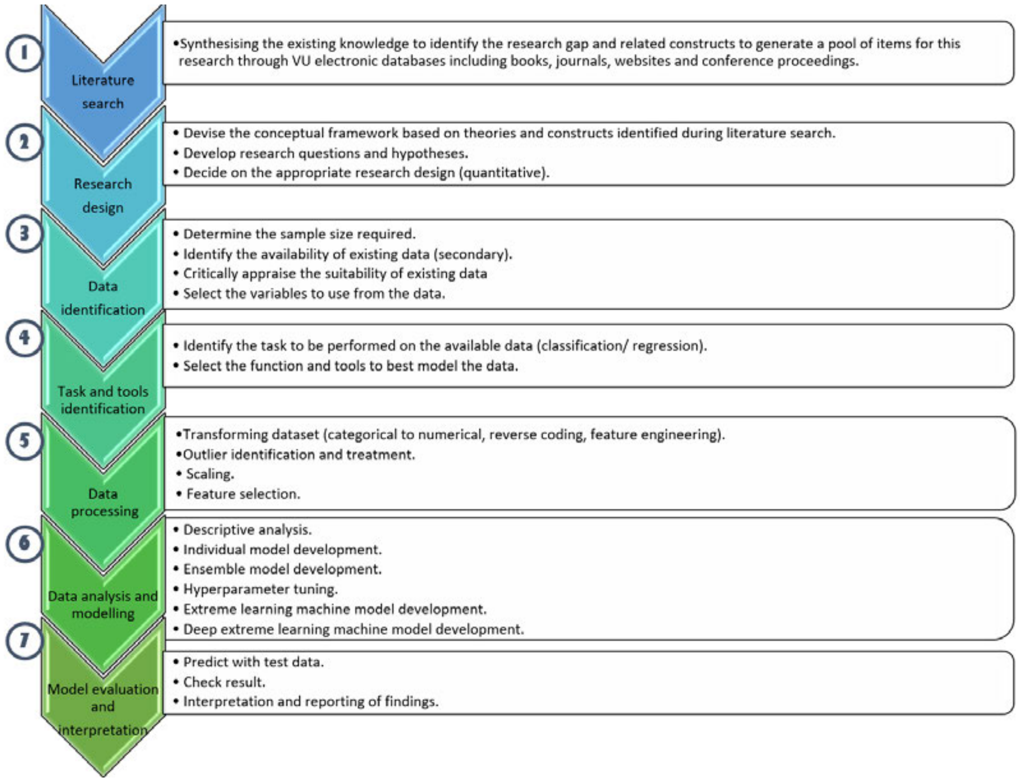


Figure 11. Steps in the research process

As a first step, a literature search was conducted to gather and synthesise the existing knowledge to identify the research gap and the related constructs. The search was conducted through VU electronic databases. This step is necessary to generate a pool of items for the next step which is the research design. Here, a theoretical framework was devised based on the result of the literature search. Then a set of research questions and hypotheses was generated. It was subsequently decided to conduct a quantitative research design.

Next is data identification. Data identification is to ensure effective and purposeful data collection. According to Ragsdale (2015), a general rule of thumb can be used to determine the size of data required. The author's recommendation is between 10 to 15 x *p* where *p* is the count of variables. There are 13 variables in this thesis (leadership climate, working environment, workgroup climate, non-discrimination values, autonomy, competence, relatedness, AI support, job satisfaction, performance, well-being, gender and age), hence following Ragdale's guidance, more than 100 data is required to perform the analysis. Next is to identify if primary or secondary data is to be collected. This research utilised secondary data. It was then critically appraised the suitability of the secondary data. Following data identification, it is time for task and tool identification.

There are two considerations. Firstly, the existing data collected is based on Likert scales which are widely considered categorical. Secondly, the research is to find relationships between variables. Therefore, the task is to perform regression analysis. However, in machine learning regression analysis is to be done using continuous data but the data collected for this thesis is ordinal or widely known as categorical in nature. Hence, in machine learning, this regression analysis is to solve a classification problem. Classification is applicable if data is in the categorical or discrete group such as gender, marital status, questions with yes or no answer and ordinal data. Finding a function that best models the data and involves the prediction of discrete values can solve the classification problem.

There are many techniques and tools available that can be applied to address the classification or regression problem. Some of the techniques are logistics regression, discriminant analysis, KNN, SVM and neural networks. There are various tools available to execute these techniques such as Jupyter Notebook, Pycharm, Spyder, Google Colab and others. Since the dataset is categorical, the next step is to perform data processing such as removing missing data, transforming categorical strings data into numeric data and reverse coding to cleanse the data. The next step in the process is data modelling once data is prepared.

Firstly, various individual models were developed and then ensembled. Ensembling is a technique to combine different algorithms for predicting tasks to make a more accurate classification. Hyperparameter tuning was done to all the individual models and the best was selected. The data was also being modelled with the extreme learning machines and deep extreme learning machines for evaluation. In the model evaluation and interpretation step, the selected ensemble model and the rest of the models trained were then used for prediction with the test dataset and the accuracy was checked. The final step is interpreting and reporting the findings.

4.4 Research method

There are generally three clusters of research methods, either multi-method, mono-method or mixed-method (Saunders, Lewis & Thornhill 2019). A mixed-method is combining both qualitative and quantitative methods while a multi-method is the adoption of more than one of the methods such as two qualitative methods. For example, interviews and observation in single research can be considered multi-method. Mono-method implied either quantitative or qualitative.

Qualitative research is concerned with a deep understanding of non-numerical data that is subjective to interpretation and involves inductive hypothesis-generating while quantitative research is concerned with collecting and analysing numerical data to quantify the social phenomena (Tuli 2010) to allow hypothesis testing. The research undertaken helps to determine the choice of the appropriate method. The centre of the attention of this thesis is on the relationships between motivations and employee learning. The proposed framework has a whole set of semantic relations defined in an ontology that can be augmented to compute relatedness with the help of the statistical tool. Semantic relations are concerned with the association between two concepts while semantic relatedness considers a broader range of relations.

Employing the quantitative method allows the author to define the research problem in a very specific term to achieve high reliability of gathered data due to mass surveying for an objective conclusion to remove any judgemental bias (Kealey & Protheroe 1996). However, motivation is abstract, exploring employee perception quantitatively and elaborating it qualitatively help to extend the nature and impact of current understanding. Both quantitative and qualitative approaches have their relative merits that have been debated (Gelo, Braakmann & Benetka 2008) and they differ along several important dimensions. In this thesis, a mixed-method and a hybrid approach using machine learning and traditional statistical learning will be adopted to statistically establish the relationship between EOC and self-determination motivations on employee learning as well as the influence of AI to conclude the hypotheses derived from the theory to subsequently enhance the theoretical model.

4.5 Research paradigm

The research paradigm or philosophy refers to the set of beliefs concerning the reality being investigated (Bryman 2016). The choices that were made in the process of this thesis with regards to the research nature, approach, and design imperatively pre-determine the ontological and/ or epistemological assumptions for a coherent research strategy and methodological validity. The research method and methodological considerations help the author to understand the real-world and practical resources to conduct the research. Ontology and epistemology are the other two elements of research philosophy apart from the research method and methodology (Abdul Rehman & Alharthi 2016). Even though research ontology and epistemology are often not mentioned in the research, understanding the assumptions based on the theories allows the author to appreciate and be able to make a comparison between different areas of research more sophisticatedly. The point to be made here is that even though the assumptions beneath the research are often not elaborated, epistemological issues and ontological concerns exist and implicitly the belief is represented throughout the research, and most evident in the method used for the research. Therefore, a discussion on this is an important one but it must be stressed that no one paradigm is better than another.

4.5.1 Ontology

Ontology deals with the understanding of the nature of reality which determines what can be discovered about it. The primary question is what is the nature of reality? Should it be perceived as objective or subjective? Accordingly, there are generally two ontological streams of either objectivism or subjectivism.

Subjectivism is the belief in the non-existence of a single reality which means there is more than one reality to how the phenomenon should be interpreted. Subjectivism is also referred to as constructivism which means that reality can be constructed, and it is dependent on an individual's experience. Subjectivists deal with qualitative data where the reality is symbolically constructed with a sense of empathy which could be different from one person's experience to another. Research is focused on seeking to understand why a phenomenon occurs rather than if the phenomenon occurs. A subjectivist belief could bring a certain degree of chaos as the reality changes to fit the subject of research because there is multiple reality of truth. For example, an interview with an employee who has experienced gender discrimination in the organisation would reveal that the employee was embroiled in many conflicts due to gender bias. This could result in more questions such as how many genders there are and if the reality heard is indeed a reality.

As opposed to subjectivism, objectivism is also referred to as positivism as the name suggested there is a single reality, and its existence is independent of human consciousness and experience. Objectivists deal with quantitative data where authors engage with the world objectively through the interpretation of the statistical analysis. For example, the voice of customer survey, and consumer survey. These are quantitative surveys driven; a huge amount of data is used for statistical analysis to understand how the variables are correlated. The results give a snapshot of what the truth is. Objectivism believes that reality is through experience and it is measurable objectively. In an organisational context, the reality is governed by organisational rules and policies. For example, during recruitment to ensure no candidates are discriminated against based on the individual's age, race, gender, and colour, organisations are governed by the equal employment opportunity policy. The intention is to ensure all candidates regardless of the individual's characteristics are given an equal opportunity to be considered for a position. The ontological position will influence the decision-making process. Bryman (2016) pointed out the association between ontology in formulating the research question and research procedure however, it is understood neither objectivism nor subjectivism is better in any way than the other. In this thesis, the author has an objectivist view of the nature of reality as such retaining the belief that reality is represented in the data collected that can be statistically analysed for a better understanding of the thesis topic.

4.5.2 Epistemology

While ontology looks at the nature of reality, epistemology is heavily influenced by the ontological assumptions focusing on how knowledge is gathered and investigated to best represent reality. According to Bryman (2016), depicted also in the research onion of Saunders, Lewis and Thornhill (2019) (Figure 12), one end of the first layer of the onion is pragmatism and the other end is positivism. Table 7 provides an overview of the four principal paradigms of epistemology.

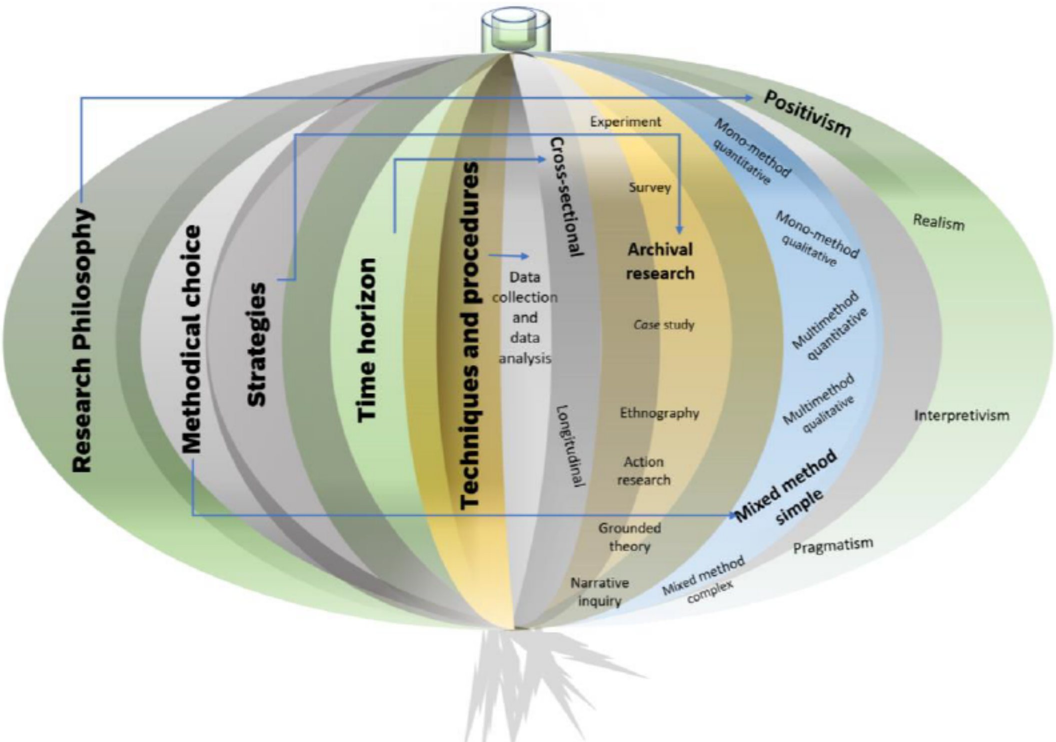


Figure 12. Research onion applicable in this thesis

Table 7. Overview of the four principal paradigms of epistemology

Epistemology	Description
Positivism	The research is not influenced by the researcher's value. The method used is highly structured and statistically measurable. Method: Quantitative
Realism	The research is influenced by the worldviews and the researcher's own experience.

Epistemology	Description
	There are two forms of realism. 1) Direct realism: what has been previously experienced by the researcher forms reality. 2) Critical realism: what is the immediate experience of the researcher triangulating between the researcher and the research object. Method: Qualitative and quantitative
Interpretivism	The researcher believes deep insights can be gathered from a group to discover the subjective meaning of the research. Method: Qualitative
Pragmatism	The researcher believes there are multiple realities and there is no single source of truth in the findings of practical consequences. Method: Qualitative and quantitative

Source: Adapted from Bryman (2016) and Saunders, Lewis and Thornhill (2019)

Although there are four epistemology positioning, the positivism paradigm is best suited for use in this thesis. This is because, there is a theory describing how things work, and hypotheses were developed and tested objectively. In this thesis, hypotheses are presented by gathering secondary data on the concepts of EOC utility perceptions, self-determination, AI support, and, employee learning outcomes, before conducting the data analysis using the statistical tool. Therefore, the quantitative data sought to provide the hypothetical-deductive generalisations of the theory testing and validating objectively. Accordingly, on this positivist view, survey research using secondary data is proposed. It allows the respondents' perceptions of several constructs in this thesis to be represented numerically.

4.6 Sampling design

4.6.1 Research setting

Research setting refers to the environment where the research is set to be conducted. A laboratory experiment research is often conducted in a confined environment due to the need to control the research conditions. For example, Limonero et al. (2015) did a study in the Autonomous University of Barcelona laboratory to investigate 67 students' stress and emotional intelligence using the Mayer-Salovey-Caruso emotional intelligence test. On the other hand, when research is done in a natural setting, it is called a field study. During a field study, the researcher is examining and observes various factors in the field. According to Aziz (2017), correlational studies in an organisational context is often field study to enable the hypothesis to be tested in the organisation set to allow natural events in the organisation to unfold. One of the limitations of performing a field study is the issue of environmental distraction that influences on the researcher's evaluation. To overcome this limitation, in this thesis, archival research was done using secondary data obtained from the 2018 APS census to investigate the correlations among the constructs under research and subsequently develop a model to predict employee learning outcomes. As such, the initial primary data collection observation and events are independent of this thesis. In another word, the natural settings of the earlier study done in the APS organisations do not influence the author in any way.

4.6.2 Target population

The full set of cases from which the sample is taken is called the population (Saunders, Lewis & Thornhill 2019). For this thesis purpose, the author has a specific target of the population; they are employees of APS. APS has an elaborate setup of about 100 organisations with employees ranging from as small as ten employees to as large as 40000 employees. Although the population of interest for this thesis could have been any employees working for any organisation, however, several considerations point to the APS as an appropriate choice. Firstly, Australia is sprinting into an aging population. The APS organisations are no exception to the phenomenon, to the point that seniors accounted for 63% of the 2018 APS workforce (APSC 2018). This is a challenge for organisational workforce management, especially in this digital age and needs immediate intervention or this group of aging employees will be struggling to cope and eventually left to join the unemployment.

Secondly, the 2018 census data was readily available, and the variables measured can be tailored for the current thesis. The census was completed on Friday 8 June 2018 at 5:00 pm AEST. The biggest challenge initially revolves around finding ways to repurpose the data and thesis questions to fit this thesis. O'Leary (2020) recommended four steps to secondary research guidelines to critically appraise the appropriateness of using secondary data. This is tabled and adapted in Appendix 2.

Thirdly, the thesis examines relationships between employees' EOC utility perceptions, their self-determination, and the influence of AI to evaluate their learning outcomes. There is no concern about population selection. However, McDonnell et al. (2020) have criticised restricting the research to a single population to be lacking generalisability. Hammersley, Foster and Gomm (2000) contested, that the greater the heterogeneity of the population the more complex the empirical generalisation. Therefore, it can be argued research focusing on a single population provide some control for variation between jobs across various industry. Thus, focusing on a single target population gives the much-needed heuristic view of APS organisations.

Hence, the thesis provides a nuanced, holistic insight and empirically rich information about the APS population. Therefore, it is important to stress that the target population is an appropriate context for testing the theoretical model rather than questioning if the research is generalisable. In any way, Watt and Berg (2002) claimed that generalisation is uncertain and impossible in the real world because it is not feasible for the researcher to totally scrutinise the whole population but only get a representation of the population which is referred to as the sample population. As such, generalisation should be expressed in a continuum rather than absolute. Research conducted in natural field settings is often associated with greater generalisability (Aziz 2017). Even though the thesis is utilising secondary data, the result is not lacking in its validity and reliability hence findings are highly relevant and generalisable. After all, generalisation is the aim of any quantitative research and in this thesis, analytic generalisation is implicitly embedded within theory-driven quantitative research (Polit & Beck 2010) and statistical generalisation can be enacted through sampling. According to Aziz (2017), Polit and Beck (2010), the validity of the data collection and analysis is a result of strong research design in terms of framing the action plan for the research, choosing the appropriate research method, reflecting on the setting, the participants, the data including sampling.

4.6.3 Sample techniques

Sample refers to a subset of the population (Bryman 2016). Sampling is an important concept regardless of whether the research is qualitative or quantitative, whether it is sampling interviewees, newspapers, magazines, or questionnaires. Therefore, it is necessary to define the principles used in sampling because it has broader relevance to the purposes of the investigation. There are two methods of sampling: non-probability (non-random) and probability (random) (Bryman 2016). Non-probability sampling is a subjective consideration of selecting sampling units such as based on convenience and personal judgment while probability sampling is where every entity of a target population has a non-zero or known probability of being included in the sample (Kitchenham & Pfleeger 2002). In this thesis, both probability and non-probability sampling were used for different purposes. There are a vast variety of techniques that can be selected for both sampling approaches.

Figure 13 depicts some common techniques that can be used on their own or in combination (Wilson, J 2014). There are five probability sampling techniques: simple random, stratified random, systematic, clusters, and multi-stage (Quinlan et al. 2019) and seven non-

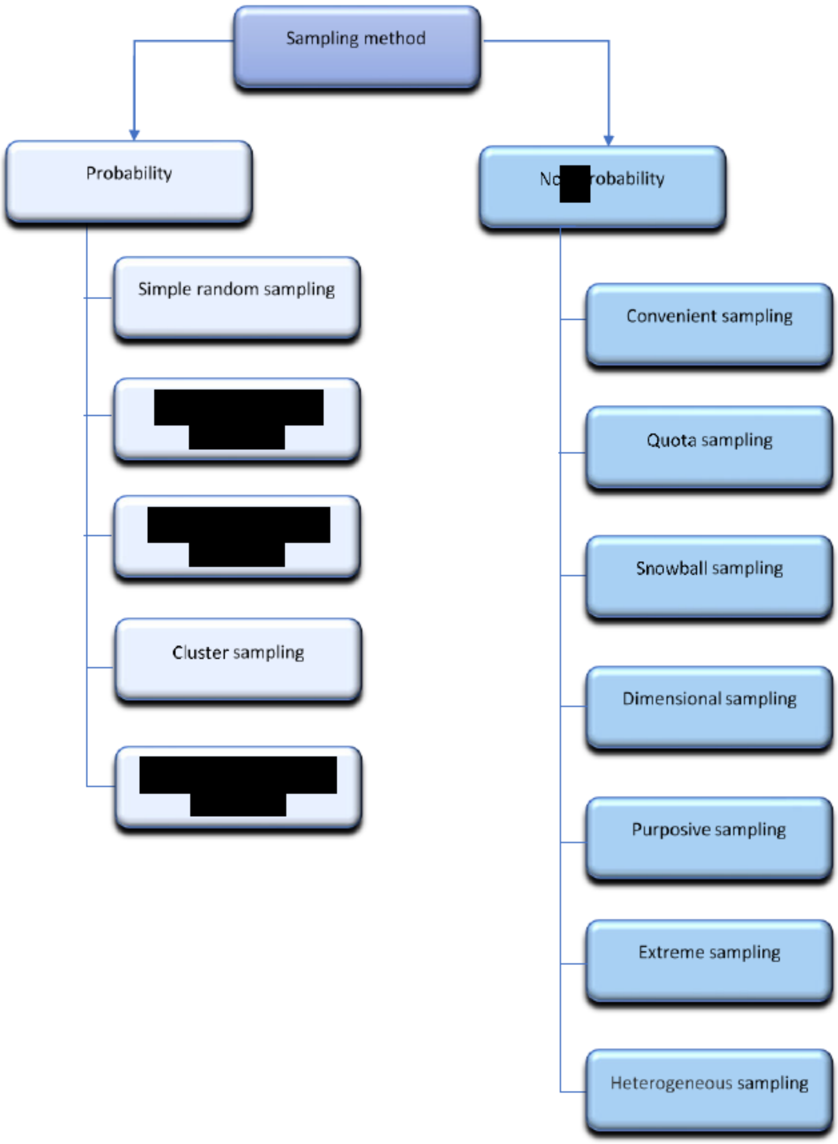


Figure 13. Sampling techniques

probability sampling techniques: convenient, quota, dimensional, snowball, purposive, extreme and heterogeneous sampling (Bryman 2016; Wilson, J 2014). In general, probabilistic, or random sampling methods are preferred over non-probabilistic as they are considered more rigorous and accurate. However, at times there may be circumstances where it is not practical, feasible, or theoretically sensible to do random sampling because it usually consumed more time and resources to cover the whole population. This is when a wide range of non-probabilistic alternatives are available for consideration.

In this thesis, for the literature review, systematic sampling is used together with snowball sampling. Systematic sampling is used especially for the comprehensive literature review on the EOC topic to capture all the relevant citations. The first article is randomly selected in no particular order but reviewed one by one thereafter. This approach is rather time-consuming and required a lot of effort. Hence, the snowballing technique was used for the rest of the literature review whereby, the first article was identified based on the selected criteria then the potential candidate was identified through the initial article and moved on until enough samples are obtained. Snowball sampling is extremely useful especially when the researcher is finding difficulties in identifying samples of a population (Wilson, J 2014). Similarly, the researcher was overwhelmed by the number of citations on learning and self-determination that it would be difficult to sample the whole population hence resulting in snowball sampling to allow the author to experience conducting the various methods of sampling in the research initiative.

For hypothesis testing, a secondary analysis of data derived from census-based on a large sample from APS organisations was used. Due to the use of census data, it was assumed that the enumeration of the APS population where data is collected concerning all units in single survey research. However, as the author has no control of the primary source and to eliminate any possible sampling bias, in this thesis a probability sampling was done. According to Bryman (2016), probability sampling allows the researcher to make inferences about the sample from which it was selected. This thesis uses the simple random sample technique in selecting the respondent from APS so that the sampling frame element has a known and equal chance of selection. Simple random sampling was used to ensure the population has gender and age representative characteristics. The advantage of simple random sampling is having the least bias and offering high generalisability of findings (Blas et al. 2020). This is achieved with the configuration of the data analysis tool to enable random sampling. The sample size plays a role in the extent to which statistical sampling can accurately capture population heterogeneity (Hammersley, Foster & Gomm 2000).

4.6.4 Sample size

Sample size refers to the count of the unit in the population. A sampling unit is an element that has an interesting property. In this research, the sampling unit is the employee and the sample size refers to the count of employees. In the study to identify the significant factors attracting university graduates to potential employers in Sri Lanka, Arachchige and Robertson (2011) conducted survey research using a sample size of 221 final-year students from various course streams. Ronda, Valor and Abril (2018) on the other hand, conducted a systematic and critical review of the literature using a sample size of 85 articles to propose a novel employee-centric framework for the study of employer brand attractiveness. On a smaller scale, Kusuma and Madasu (2015) analysed the top 5 companies from the 'Great Place to Work' in India to compare employee engagement practices. As demonstrated, there seems to be no agreement about sampling size (Bryman 2016; Hunt, Sparkman & Wilcox 1982).

According to Bryman (2016), some consideration is needed on the degree of homogeneity and heterogeneity of the population to achieve the desired representation of the population. The more homogeneous a population, the smaller a sample will be needed. For example, when a study is looking at a population of university students or a selected organisation having a certain characteristic will require a smaller sample because of the lesser variation in the population. Hence, such studies do not need a big sample whereas else studies looking at a bigger scale such as a country or state will be needing a bigger sample size due to the level of variation expected in the population.

This research is looking at APS organisations covering employees across Australia, there is a certain degree of homogeneity. However, big sample size is needed because it is looking at a country level and it is a requirement for statistical analysis to minimise any possible sampling error. Often, Type I and Type II errors are unavoidable in hypothesis testing, and the probability of error occurrences in any way should be minimised. The rejection of the true null hypothesis and failure to reject a true false null hypothesis is classified as Type I and Type II errors respectively. The formula can help to quickly determine the sample size required (Yamane 1973).

$$n = \frac{N}{(1 + Ne^{2)}} \tag{1}$$

where *n* is the sample size; *N* is the target population, and *e* is the percentage of error.

$$n = \frac{103137}{(1 + 103137(0.05^{2)}} \tag{2}$$

$$n = 398 \tag{3}$$

As there are no definitive recommendations on the sample size to obtain a reliable result, a general rule of thumb was used in this research. Sideridis et al. (2014) suggested that 50-70 samples as sufficient for a model involving a few variables. Where else more complex models such as mediational models require even larger sample sizes. For mediational analyses, Miočević et al. (2018) suggested that sample sizes of around 500 are optimally required. Looking at some similar past studies at the country level, done in northern Greece, Zahariadis, Tsorbatzoudis and Alexandris (2006) had 343 responses from young athletes while a recent study in China has used a sample of 125 employees to understand how the perception of organisational commitment to learning and attitudinal motivation could enrich employee absorptive capability (Tian & Soo 2018). Based on the APS 2018 census, the final sample size is 93,199 following the removal of non-respondents is deemed to be statistically reasonable.

4.7 Research design

The research design refers to the plan to facilitate the collection of data to be analysed (Pandey & Pandey 2015). Vaus (2001) described research design as the overall strategy of integrating the different research components logically and coherently. Thus, the problem and research design are interrelated (Sarstedt & Mooi 2019). The research question is the driver of the selection of the research design to effectively address the research problem. Therefore, in this thesis, a correlation research design is adopted. It is a type of non-experimental research where at least two variables are measured to assess the correlations between them. This thesis will also encompass a causal intent when addressing the hypothesis that motivation will predict employee learning outcomes. According to Zikmund (2003), causal research is conducted to identify cause-and-effect relationships between variables when the research problem has already been narrowly defined. Following the formulation of the research problem and framing of the hypothesis, a plan is needed to allow optimum effort in data collection, time spent in the process, and expenditure required in conducting the research. Considering the hypothesis, the association between EOC utility perceptions and self-determination with employee learning outcomes will be established within the research timeframe.

According to Saunders, Lewis and Thornhill (2019), the research could either be a cross-sectional or longitudinal study. A cross-sectional study is relevant for this thesis because it is carried out at one point in time for a short period with the outcome of interest for a given population, which is the employees in the workplace. Besides, the purpose of the thesis is descriptive in the form of a survey and there are hypothesises to be tested to investigate associations between motivations and employee learning. The advantage of this cross-sectional research selection is that it is relatively inexpensive and takes up little time to be conducted compared to longitudinal research (Levin 2006).

Data comes in many forms; structured and unstructured. Structured data as the name implies refers to orderly data that can be retrieved from a fixed field within a database or files while unstructured data refers to myriad formats without any predefined schema that allows easy extraction for processing such as voice, images, video, and others. Big organisations like Google, Facebook, and Amazon have an abundance of data to harvest the analytics going far beyond our imagination. For example, offering customer products bundled in an attractive value deal that is irresistible to the customer such as when a customer purchases a car wash shampoo from Amazon, it also recommends the microfibre cloth and the rain repellent solution as a bundle. Another example is when you search for flight tickets on Google, it quickly learned your desire to travel and starts sending you flight and hotel promotions details including travel insurance.

With IR 4.0, we are looking at big data that is famously known as 3Vs: volume, variety, and velocity which consist of both structured and unstructured data that makes the analytic extremely challenging. Every day, millions of people are using social media such as Twitter, Instagram and Facebook. You can imagine the amount of data available for processing. Not only pictures but also voice messages and videos among others. Unfortunately, small firms suffer because they do not have the resources to acquire the needed data thus, hindering the ability to generate any deep understanding of insights that are important for business success.

One option for these small organisations is to spend a big amount on acquiring the data however, risks sustainability as we live in a dynamic economy. The interest and needs of individuals are constantly changing. Even if these small organisations can get the initial budget to bypass the data collection hurdle, it will be difficult to fund the ongoing need for data to run an AI program because data are constantly needed to train and test the model for program maintenance and optimisation. An interesting alternative would be to generate synthetic data with the machine learning algorithm. This technique is not new but still in its budding phase. Not only the small organisations can reap the benefits of artificial data, but giant organisations such as Google is also an adopter. Waymo, the Google self-driving car is an AI project that has completed over 3 million miles of driving in simulation utilising synthetic data before going to market (Fingas 2018). Therefore, the initial first step is to find the data.

Various techniques are available such as experiments, case studies, archival data, and surveys. Survey research is widely used in the positivism paradigm where the primary data will be obtained with a questionnaire that can consist of both open-ended and close-ended questions to provide both quantitative and qualitative information. Saunders, Lewis and Thornhill (2019) defined a questionnaire as a general term to include all techniques of data collection in which each person is asked to answer the same set of questions in a predetermined order. An online questionnaire has become a common data collection technique in the era of technological advancement.

With broader internet connectivity and device accessibility as well as more computer literate respondents, the choice of online questionnaires is widely used and is highly suitable for this thesis. This is because firstly, respondents are working adults who will have access to the internet and devices. Secondly, the research would be cost-effective because there are many free and open-source online questionnaire software that can be used to support the data collection. Thirdly, the research will benefit from anonymous immediate responses. Studies show that the online questionnaire response rate improved on average by 4.2 days compared to postal questionnaires (Granello & Wheaton 2004; Sheehan 2001). Finally, the collected data can be directly loaded into the data analysis software which saves time and resources needed for the data entry process.

Survey research via online questionnaires could be an ideal option however, it can be extremely time-consuming to research because the target population is working adults. No doubt they have technical literacy to support the data collection process, but this group of people can be difficult to approach with ethical considerations. Given that large amounts of quantitative data are required, this drawback has led to archival research being preferred compared to survey research.

Archival research is a data collection technique involving a broad range of activities investigating documents and textual materials that already existed (Ventresca & Mohr 2017). This could be referred to as historical information but may not necessarily be a relatively distant past. For example, census reports, annual reports, newsletters, and other documents of recent years are often used as a good source of data. Whilst online questionnaire is focused on primary data, archival research is mainly reliant on secondary data. Generally, the data is collected for other purposes not necessarily related to the current thesis topic under investigation. As such, utilising archival reports has its challenges.

The criticism is around no control of the data collection process. However, it can be argued there is no such concern in this thesis because the APS commission and agencies use the results of the original survey to inform planning and initiatives. Therefore, it has been assumed that the census data is of high validity and reliability. That is capturing the 2018 APS employees' experience and insights working in APS organisations at that specific period. Besides, having the needed industry statistical expertise overseeing the whole data collection process including the ethical considerations. Additionally, the census data used in this thesis has gone through the hassle of data collection and was successfully published. Therefore, again saves resources and time both for collection and the preliminary basic data organisation and preparation for analysis.

More importantly, the challenge of ethical consideration in getting employees' consent to participate in the survey research is no longer a major concern in archival research. This is because there is no direct contact with the research participants and any emotion and biasness are eliminated. At the same time, covering a wider geographic area and reaches more people effectively where it would not possibly have reached otherwise yet discovering patterns and relationships that the original research would have not investigated. Therefore, archival research compensates for the shortfall of online survey research.

Additionally, in the current booming technological information age, the author can innovatively leverage the availability of archival data. Even though the original intention of the data collected is not purposefully designed for this thesis, the data existed and remained relevant and hence could be repurposed for this thesis. This approach is not new but rare especially for a contemporary research topic because often it is difficult to look for the required materials. The archive has been regarded as a treasure trove of materials (Desmarais 2017) hence, it could be time-consuming to locate the right dataset. However, with technological advancement, we are benefiting from the availability of a vast variety of data through the Internet hence, it is becoming easier to search through the repository effectively and it is a less daunting task.

It is timely and not surprising that scholars and practitioners are slowly turning to archival research these days and should be highly recommended due to the explosion of big data availability. Archival research is often used in the study of ethnography which enables the longitudinal element of the study to be investigated. Baiyere, Salmela and Tapanainen (2020) conducted a recent study conducted using archival data covering the period from 1986 to 2019 for an ethnographic case study. The research unpacking their dynamics in the context of digital transformation contributed to the rethinking of the dominant business process management logic. Therefore, when making the selection of data collection techniques, the use of archival data stood out among the rest.

Sometimes, secondary data obtained is lacking the features needed to perform analysis. According to Mueller and Massaron (2021), when the right information is unavailable, feature creation is needed. For instance, the modelling of the price of a property. Usually the bigger the property, it tends to be costlier. However, should the size of the property information be unavailable, but the latitude and longitude of the property are available, the size of the house could be calculated. Fortunately, suitable secondary data is available for this research to enable analysis hence, there is no need to generate synthetic data. However, the art of humanising is needed to determine the suitability of the data and the need for data reengineering. Piscopo, Siebes and Hardman (2017) used secondary government data to predict a sense of community and participation. Talukder and Ahammed (2020) on the other hand, used secondary Bangladesh Demographic and Health Survey data to predict the malnutrition status among under-five children in Bangladesh. Therefore, in this thesis, the APS data is used for data analysis. Regardless of whether primary or secondary data is used, the golden rule is to use the data collected responsibly, thoughtfully, and critically. The relationships between the constructs to be investigated in the thesis can then be examined using various statistical techniques.

4.8 APS data

Data source for this thesis is the APS census (APSC 2018). It is important for researchers to be familiar with the variables used in this thesis. Appendix 30 presents the tabulated list of variables and the mapping to the selection of APS data.

4.9 Data analysis techniques

Various techniques can be used for both data collection and analysis. For this thesis, the secondary data was obtained from the 2018 APS census (APSC 2018) using a questionnaire to collect information from APS employees. Saunders, Lewis and Thornhill (2019) defined a questionnaire as a general term to include all techniques of data collection in which each person is asked to answer the same set of questions in a predetermined order. Even though, the original data collected consisted of both open-ended and close-ended questions when it was repurposed only the close-ended questions were selected and analysed using PyCharm 193.5662.61 built with an Anaconda environment. PyCharm is an Integrated Development Environment (IDE) (Gonzalez 2020). Essentially, programmers use IDE to effectively write, compile and execute programming codes including debugging. Apart from PyCharm, Spyder is the other most competitive IDE that can be used. Ideally, any IDE that the researcher is comfortable with should be chosen. For this thesis, the PyCharm was selected because it offers comprehensive smart assistance such as code completion, error detection while coding and recommending quick fixes. There are generally two versions of PyCharm that can be installed: either community or professional. The professional version has full-fledged of PyCharm features while the community version excludes the connectivity to Jupyter notebook, SQL, and web development support as well as support for interactive scientific analysis of data. The community version was used in this thesis because it is a free version that has all the needed functionality sufficient for the scope of this thesis.

PyCharm supports many programming languages such as R, Javascript, HTML, Python, and others. Python was selected for coding the program because it is an incredibly dynamic and versatile object-oriented programming language that is often used for the development analysis of machine learning models (Gonzalez 2020). It is a trending open-source programming language which means it is free and widely used among researchers and data scientists. It has an extensive availability of data science package libraries including libraries to support deep learning and has been widely used in many practical applications such as Google, YouTube, and others. Some leading-edge deep learning frameworks are being explicitly developed targeting Python (Amaratunga 2021). Python is easily extensible. In other words, it is easily integrated into website applications, games development, database management, IoT and others. Therefore, considering the flexibility and maturity of Python, it was chosen to investigate the statistical relationships among the dependent and independent variables in this thesis as well as make predictions.

4.9.1 Preliminary analysis

As a preliminary step before any data analysis, the initial first step is to select all the variables of interest in this thesis based on the available census data because the original data was not collected for the intention of this thesis. Data coding is done in parallel by assigning numbers to the available dataset (see Appendix 3). Converting questionnaire data into meaningful categories helps to facilitate data analysis (Williams 2003). Once data are coded into PyCharm and cleaned, descriptive statistics are used to provide an overview of the basic features of the data in a study (Boslaugh 2012). Descriptive statistics are important to allow the examination of whether certain subgroups were over or under-represented in the sample based on those invited to participate. It is useful in data cleaning. An analysis of the differences between gender and age will be included and presented with graphs including the test of reliability and validity of measurement (e.g. skewness and kurtosis). Following the descriptive analysis, inferential analysis is done to answer cause-and-effect questions and make predictions (Texas 1995). It is used to generalise the author's findings to a broader population group. The inferential analysis consists of a test of association and a test of relationship which provides more detailed information than descriptive statistics and yields insight into relationships between variables. These are done using machine learning (ML), deep learning (DL), extreme learning machines (ELM) and deep extreme learning machines (DELM).

4.9.2 Feature selection and factor analysis

Feature selection as the name implies is the selection of features relevant to the output variable. The objectives are data reduction and determining the underlying data structure between the variables (Wheelwright et al. 2020). The data selected for data modelling has a direct influence on the model performance. When an inaccurate data feature is selected, the model generated could be negatively impacted by overfitting issues, inaccuracy, slowness and undesirable statistical error. The objective of factor analysis is data reduction. That is reducing the dimensionality of the variables to a few manageable ones. Figure 14 illustrates the steps taken to perform factor analysis in this thesis.

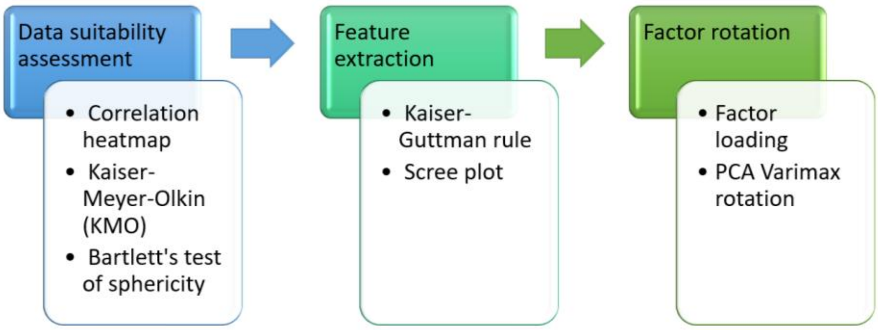


Figure 14. Steps involved in factor analysis in this thesis

Factor analysis is generally classified as exploratory or confirmatory. Exploratory Factor Analysis (EFA) is mainly used to find the underlying influences on a set of observed variables. In another word, it is to create hypotheses. Confirmatory Factor Analysis (CFA) is to confirm the hypothesised structure. In this thesis, the correlation heatmap was created first and features were further accessed for suitability with EFA and then CFA.

The Principal Component Analysis (PCA) was used in this thesis to aggregate the given variables into factors. The PCA class in the scikit-learn Python library was invoked to perform the data reduction. Yong and Pearce (2013) recommended that the sample size should be about 300. Ewing and Park (2020) suggested that PCA with a smaller small size could be carried out however, the larger it is the sample size the more stable the estimated result. Therefore, to evaluate if PCA is appropriate for the data two tests were conducted: Kaiser-Meyer-Olkin (KMO) and Bartlett's test of sphericity. KMO test is used to indicate the proportion of variance in the features that might be caused by the underlying factor. A KMO test result is in the range of 0 to 1, any value that is more than 0.05 indicates the adequacy of sampling. Hsu, Lin and Jhang (2020) suggested a value of more than 0.06 as necessary for good factor analysis. Bartlett test on the other hand required a value of lesser than 0.05. A small value suggests that there are correlations between the features and the identity matrix is not visible thus appropriate for factor analysis.

Many criteria have been suggested to determine the number of factors to be extracted. Xia (2021) asserted that despite the various methods, there is no one method outperforms the others. As such, in this thesis, the criteria for the count of factors to be extracted were based on eigenvalue, scree plots, percentage of variance, the significance of factor loading, and assessment of the structure. Firstly the Kaiser-Guttman rule was applied (Kaiser 1970) to determine the factors to be retained. According to the rule, the principal component factors with an eigenvalue of more than 1 are to be retained. The rationale is that since the sum of eigenvalue is p, then an eigenvalue of greater than 1 represents the greater importance of the components compared with the other components. Only the factors with eigenvalues ≥ 1 and with scree plots that supported these factors were considered significant for this thesis while the rest of them are considered insignificant and were disregarded.

After which, the scree plot is used to plot the selected features based on the eigenvalue to determine the correct count of features for further analysis. A scree plot is a visual representation of all the eigenvalues in descending order plotted into a graph. Cattell (1966) suggested that the factors before the slope should be retained while factors after the slope could be removed. It is rather arbitrary in determining the correct number of factors to be retained. The general rule is that if the slope begins at the f^{th} factor, then f is the appropriate number of factors to be retained.

The next step in factor analysis is deciding on the factor loading cut-off and rotation method. The rules of thumb can be used when deciding on the factor loading cutoff which generally ranges between 0.3 to 0.55 to be considered a strong coefficient (Swisher, Beckstead & Bebeau 2004). For a sample size of 300, a factor loading of at least 0.3 is required to be considered significant (Tabachnick, Fidell & Ullman 2019). Ahad et al. (2021) used a factor loading cut-off of 0.50 on a sample size of 263. Similarly, Rezapouraghdam, Akhshik and Ramkissoon (2021) have used a 0.50-factor loading cut-off on a bigger sample. Christensen-Salem et al. (2020) used a factor loading cut-off of 0.40 on a sample size of 795 employees. Howard (2016) recommends retaining factors above 0.40. The 0.40-factor loading cut-off is considered ideal irrespective of sample size as observed in various studies similarly being used as a reference for the present thesis.

The rotation method is used along with PCA. The rationale for factor rotation is to transform the initial solution of unrotated factor analysis into an interpretable mapping between variables and factors. That is to make it clear, which variable belongs to which factor. The

Varimax rotation method was employed for the present thesis because it is a common method (Howard 2016) for creating the new factor called the varimax factor. Varimax focuses on maximising the spread in loadings to minimise the variables on each factor. When the loading is high after extraction becomes higher and low loading becomes lower after rotation. Therefore, a distinctive correlation can be identified for ease of interpretation.

4.10 Machine learning

This thesis further investigates the predictive validity of the model with ML techniques. The first ML program was developed during the 1950s. Samuel in 1959 (Fermor 2018) coined and defined the term as a field of study that can create AI programs that give the computer liability without explicitly programming. ML is a subset of AI using a computer program to perform a given task that mimics human intelligence of planning, reasoning, and solving among other human behaviours known as AI. The algorithm used in the AI-powered program to accomplish a task or solve a problem is known as ML. ML can learn and be trained to find the underlying pattern of a complex dataset to solve a given task or problem which otherwise would be difficult to be discovered with classical rule-based programming algorithms relying mostly on conditional statements. ML is an exciting concept that not only has the ability of any traditional computer program to perform data analysis but also can process an immense amount of data for predictive analysis. The discovery of patterns and relationships of the data could then be modelled with supervised, unsupervised, semi-supervised and reinforcement learning to predict outcomes.

4.10.1 Reinforcement learning

Reinforcement learning is when an agent is introduced to explore the environment and subsequently feedback either to reward or punish the agent. The overall objective of the agent is to cumulatively maximise the reward outcomes to propose the best fit model to achieve an optimised prediction. It is widely used in robotics to trace paths or to automate the robot as well as in gaming to decide the player’s next move based on the conditions selected.

4.10.2 Semi-supervised learning

Semi-supervised learning as the name suggested is a hybrid learning combining both supervised and unsupervised learning. It is highly used in simple data, documents, handwriting classification and the like where there are both labelled and unlabeled data available to support building the model.

4.10.3 Supervised learning

Supervised learning, on the other hand, relies on the mapping of information; input variable (x) and output variable (y) using a learning algorithm on a training dataset. The input and the desired output are specified so that when a new input dataset is available, the output is predictable based on what the machine has been trained to learn (Johnston, B & Mathur 2019). For example, the pictures that were captured with the mobile phone can be easily and quickly sorted into various folders such as places, food and person automatically. The input data in this example is the picture. They are then manually labelled as food, place and person name as the output information. Next, the picture-sorting algorithm will take the pictures to be trained to return the right label which has already been programmed to be correct. This is the same algorithm that Facebook is using for friend tagging. Initially, when it started, each friend was manually tagged, over the years the supervised learning algorithm has already learned to identify a person automatically hence friend tagging on Facebook is a seamless feature without any manual effort.

There are many supervised learning algorithms, and their usages are dependent on the problem needed to be resolved. These problems are generally categorised as classification and regression. As both the names of the groups implied when dealing with a regression problem, output data is not discrete such as price, temperature, and height, the regression is a more appropriate technique in treating the problem. The classification problem expects the output variable with categorical data such as the colour group: red, blue, green, and yellow. K-nearest neighbours (KNN) and support vector machines (SVM) are two examples of single classifier methods that can be used to resolve the classification problem. Both KNN and SVM will be used as the base classifier for comparative analysis.

4.10.4 Individual learning

Individual learning as the name implies is to use a single classifier that best models the sample data to predict future occurrences with the least error. Figure 15 shows the overview of the single classifier structure. The goal of the classification is to use several of the independent variables to predict employee learning outcomes. Many classifiers can be used each with its strengths and weaknesses. Two selected classifiers; KNN and SVM are discussed below.

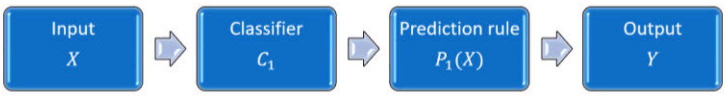


Figure 15. Structure of a single classifier

4.10.4.1 K-Nearest Neighbours

K-nearest neighbours (KNN) is a classic and popular algorithm of nonparametric statistics. It is widely used to solve both classification and regression predictive problems and will be used in this thesis as a based classifier because it is simple and reliable (Li, S, Harner & Adjeroh 2011). The basic idea of the algorithm is to look in the training dataset with a minimum distance to the object to be recognised. The assumption is the sample's class with the closest proximity to the selected data point is taken as the recognition result. The distance between two points (a,b) and (x,y) can be calculated with the formula:

$$D = \sqrt{(a - x)^2 + (b - y)^2} \tag{4}$$

Similarly, the same can be extended to calculate multiple points. For a three-dimensional space, the formula can be further extended and is denoted as:

$$D = \sqrt{(a - x)^2 + (b - y)^2 + (c - z)^2} \tag{5}$$

Based on the feature similarity, through a voting mechanism, the algorithm makes a prediction. Therefore, in KNN, it has been noted that selecting the right value of k is important for better accuracy. The general rule of $\sqrt{n}$ was used to avoid biases in the k value selection. As such, before the calculation of the k factor, the full dataset of 93199 is split into test (10%) and train data (90%). The model will fit in the training data to predict the test data. The Pareto rule (80/20) can be used. However, in this thesis, the 90/10 rule was used to avoid overfitting and underfitting issues that affect the predictability of the model. Both the 80/20 and 90/10 rules were tested for comparability and the 90/10 rule produced a slightly higher accuracy hence it was selected to be ideal. Therefore, the k value was calculated based on the 10% test dataset resulting in an output of 96.

$$n = \sqrt{9319} \tag{6}$$

$$n = 96 \tag{7}$$

However, as it is an even number, optimally the leave one out method was chosen, and the k value was taken as 95 as the initial value.

4.10.4.2 Support vector machine

Like the KNN, the support vector machine (SVM) algorithm is used to solve both classification and regression predictive problems. It is based on the statistical learning theory which has received attention in establishing models for solving real-world problems. Researchers have acknowledged the difficulties of obtaining the dimension of research that is mostly constrained due to the large sample requirements and the assumptions taken. SVM is extremely powerful in solving tractable datasets especially when there is a lack of knowledge of the underlying problem and overcoming the difficulties in data analysis. SVM has very strong theoretical standing and empirical results (Sha'abani et al. 2020); prides itself on performing better than logistic regression, decision trees, and KNN. The logic is relatively simple, the goal is to find an optimal hyperplane in a two-dimensional space or a multidimensional space to classify the sample.

A hyperplane is a line linearly separating the feature space with each class laying on each side of the line (plane). Therefore, it indicates there are positive and negative classes. Let H, be the hyperplane, if H_0 is the optimal hyperplane, there are two other hyperplanes H_1 and H_2 with H_0 having an equidistant from H_1 and H_2. The equation to obtain a line is denoted as:

$$y = wx + b \tag{8}$$

where w is the slope and b is the y-intercept and $x\ is\ the\ set\ of\ features$. In SVM, the equation (5) is represented as:

$$w^T\text{x} = 0 \tag{9}$$

that is equivalent to

$$y - wx - b = 0 \tag{10}$$

Therefore,

$$w^T\text{x} = y - wx - b \tag{11}$$

It is expected that changing the value of w and b can model an infinity possibility of lines. Therefore, an algorithm such as SVM is used to find the value of w and b that best produces y with the minimum error. SVM is the frontier that best segregates the classes. The findings of data points that defined the hyperplane with the maximum margin that minimises the prediction error are the support vector. It implies that only the support vectors are important whereas other data points are ignorable.

4.10.5 Ensemble learning

The KNN and SVM algorithms described above are some examples of how individual machine learning models are developed. Each of the algorithms has its strengths and weaknesses. Cross-validation and hyperparameter tuning are required to evaluate the individual model performance and find the best set of hyperparameters that produces the best performance model. Apart from the combination of cross-validation and hyperparameter tuning, in this thesis, multiple algorithms will be ensembled to improve model performance. EL can be achieved with various techniques such as bagging (Guo, Boukir & Aussem 2020), boosting (Hastie, Tibshirani & Friedman 2009; Sigrist 2021), and stacking (Pavlyshenko, B 2018), and other methods. It has been understood that the way EL happened is the same as individual learning, however, with an additional voting feature before a final prediction is made. Figure 16 depicts the ensemble learning structure.

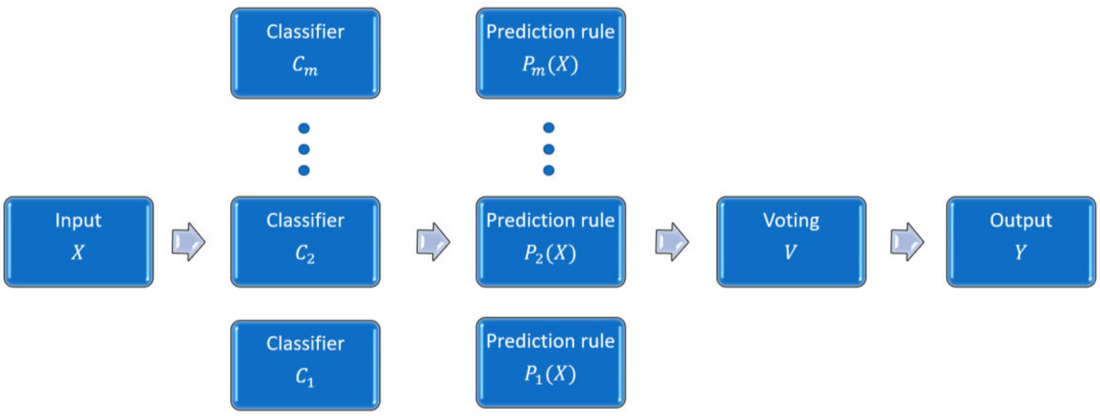


Figure 16. Ensemble learning structure

The motivation to use the ensemble ML technique came from recent various multi-disciplinaries empirical studies that find improved classification performance (Pavlyshenko, B 2018; Qutub et al. 2021; Xu, R et al. 2021). Despite its successful applications in various fields, ensemble ML methods are a less applied methodology in the management and especially employee learning domain. Hence, it is being investigated in this thesis in the quest to develop a more reliable, robust and generalised predictive model with higher computational speed and accuracy performance.

4.10.6 Unsupervised learning

Unsupervised learning takes no output data to train but only relies on input data to learn the patterns and relationships in the dataset. In unsupervised learning, algorithms are left to discover knowledge on their own. Hence, it can deal with a more complex real-life dataset where the data are not labelled. However, since the output data are not labelled and trained therefore unsupervised learning is less accurate than supervised learning and takes a longer time to process. Taking the Facebook tagging example, the algorithm can put the pictures into various groupings such as happy celebrations, birthdays and others without needing any predefined labelling. This can be achieved with two popular unsupervised learning techniques: clustering and association.

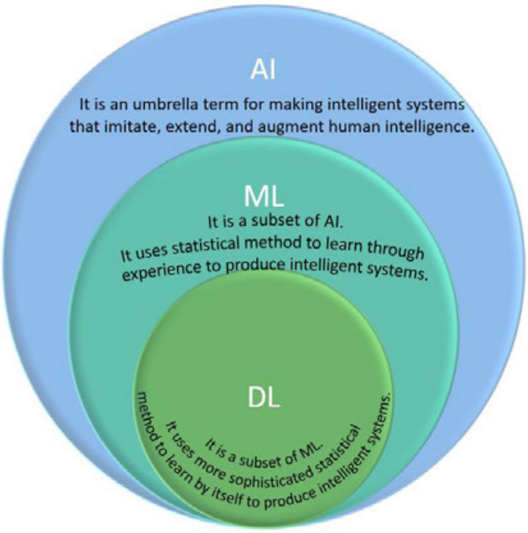
Clustering as the name suggested puts the given dataset into various groups. Amazon uses clustering algorithms to give a user-specific recommendation. The clustering model divides the customer into various segments and groups them into clusters based on vectoring or voting to describe the strength of their relationship from one cluster to another (Linden, Smith & York 2003; Ungar & Foster 1998). The algorithm will then either merge or split the cluster further to propose recommendations. Some of the cluster algorithms are K-means and expectation maximisation.

Association, on the other hand, refers to finding the relationships between the dataset (Ahmad et al. 2018). For example, an interesting relationship between purchases can be revealed through analysing supermarket transactions. If customers are consistently purchasing chips and soft drinks together then the store layout can be adjusted to relocate the associated products together. Similarly, to promote cross-selling and marketing based on statistics. Unlike clustering where similar products are grouped, in an association, the Apriori algorithm is used to define the rules to be considered when deciding on the associations. This includes identifying the fraction of transactions containing the item, probability of occurrence and ratio of confidence to propose the relationships between variables.

Even though unsupervised learning helps to discover unknown data patterns, the biggest disadvantage is that precise information and accuracy of the information are doubtable because it is left for self-learning without supervision. As such, the method taken to calculate the output is unclear and the time taken fluctuates considerably given a different set of data despite data similarities. Nevertheless, there is evidence that unsupervised learning outperformed human capabilities such as in terms of speed and solving complex problems (Amaratunga 2021). And it has become popular with several remarkable breakthroughs in recent years with deep learning such as image processing, text generation, language translation, generative adversarial networks and more (Weidman 2017).

4.11 Deep learning

As with ML being a subset of AI, deep learning (DL) is a subset of ML. The representation of the relationships between AI, ML and DL is presented in Figure 17 all working with one common goal of building intelligent machines. A significant difference between ML and DL is that DL can process a lot more features and capabilities to solve more complex problems than ML. DL builds upon the features and concepts from simple to complex in a hierarchical architecture as with how the biological human brain works. Figure 18 illustrates the hierarchical representation of the deep learning structure whereby multiple levels of feature extraction are done in the hidden layer without any supervision to make the prediction. Multiple ensemble learning models are not considered deep learning. It is when the learning takes place in a hierarchy structure whereby each node receives input and is connected to the next layer of nodes by weights forming a network to arrive at a final prediction. The passing of information from one node of one layer to another node in another layer is known as a feed-forward (Sewak, Karim & Pujari 2018). The feed-forward network is the most popular topology (Mirjalili 2019).



AI: Artificial Intelligence; ML: Machine Learning; DL: Deep Learning

Figure 17. The relationships between AI, ML and DL

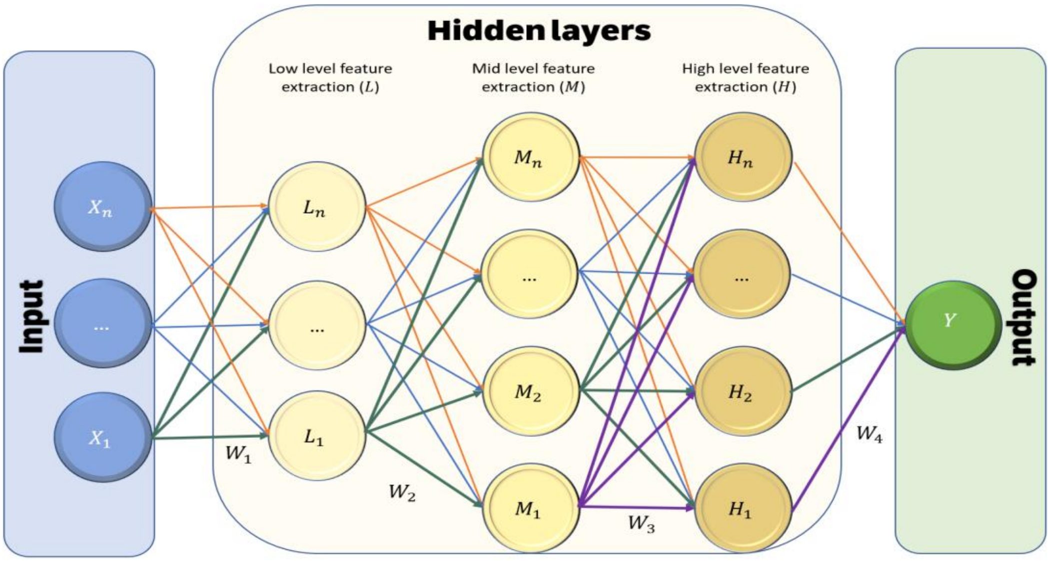


Figure 18. Hierarchical deep learning structure

One of the most distinctive features of deep learning is its scalability. It consumes a big amount of data to optimise performance. Unlike, traditional ML algorithms that have upper-bound data restrictions that set a limit to the amount of data it can comprehend hence, creating a plateau in performance (Amaratunga 2021). Over time, these traditional algorithms would also impact the performance of the predictive model because the model has learned the noise in the training dataset. Hence, it is a weak helper in the decision support system. Due to such limitations in ML algorithms, neural networks (NN) have emerged as an alternative to conventional ML (Amaratunga 2021). Convolutional neural networks (CNN) are the prime example of DL but there are more such as Boltzmann machines, stacked autoencoders, transformers and others (Mirjalili 2019). In these NN models, there is generally a two-step approach. Firstly, using an unsupervised learning algorithm to train the parameters of each layer subsequently tuning occur using supervised learning. With the advancement and significant improvement in the classification-related NN models over the years, the curse on performance remained (Rehman et al. 2020). Under a variety of phenomena, Michie, Spiegelhalter and Taylor (1994), and Liu, R (2018) have empirically compared the performance of traditional and NN classifiers. Without a doubt, the accuracy is higher compared to traditional classifiers but it is rather time-consuming due to the complex structure that requires tuning iteratively causing a bottleneck on the model performance as evident in the findings of Li, W, Yin and Chen (2020). Hence, in this thesis, apart from the traditional classifiers, extreme learning machines (ELM) will be executed as a comparison.

4.12 Extreme learning machines

The term Extreme Learning Machines (ELM) has surfaced since 2006 (Huang, G-B, Zhu & Siew 2006) based on Universal Approximation Theorem (Afzal, Nair & Asharaf 2021). Extreme refers to moving extremely closer to the biological learning mechanism from the AI mechanism (Huang, G-B 2014). It is not replacing ML and DL, but ELM converges the theories to produce a tuning-free technique to overcome the suboptimal performance issue identified in traditional ML and DL. The basic idea is to use a single hidden layer with randomised nodes to arrive at the final prediction. Unlike traditional DL that passes through hierarchical structures, a single hidden layer creates an extremely simple network as depicted in Figure 19. The existing network parameters are kept as-is when a new node is added to the network. The optimal value of the newly added node that links the newly added node to the output node will be calculated and considered as the optimised output.

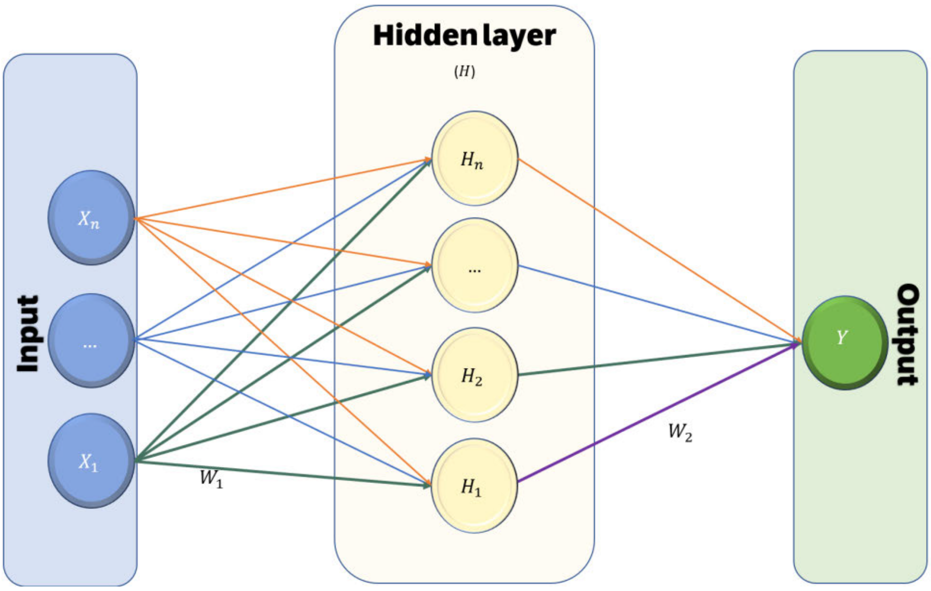


Figure 19. Extreme learning machine's structure

In this thesis, in addition to the traditional classifiers, the ELM and the DELM algorithm will be executed to provide a comparative insight to choose the best-fit model to answer the thesis questions.

4.13 Deep extreme learning machines

The deep extreme learning machines (DELM) are an evolution of ELM. Multiple ELMs are used to create the deep architecture to predict the final output as illustrated in Figure 20. DELM provides a promising way of overcoming the drawback of traditional ML and DL as evident in the study of intrusion detection (Li, W, Yin & Chen 2020) and fault diagnosis (Jia, Liu & Cai 2021). Despite the enthusiasm, DELM is still in its infancy. Therefore, it has been proposed in this thesis to extend the theory especially in supporting decision-making in the employee learning context. The specific tests and parameters applied for each model using Python are detailed in the next chapter.

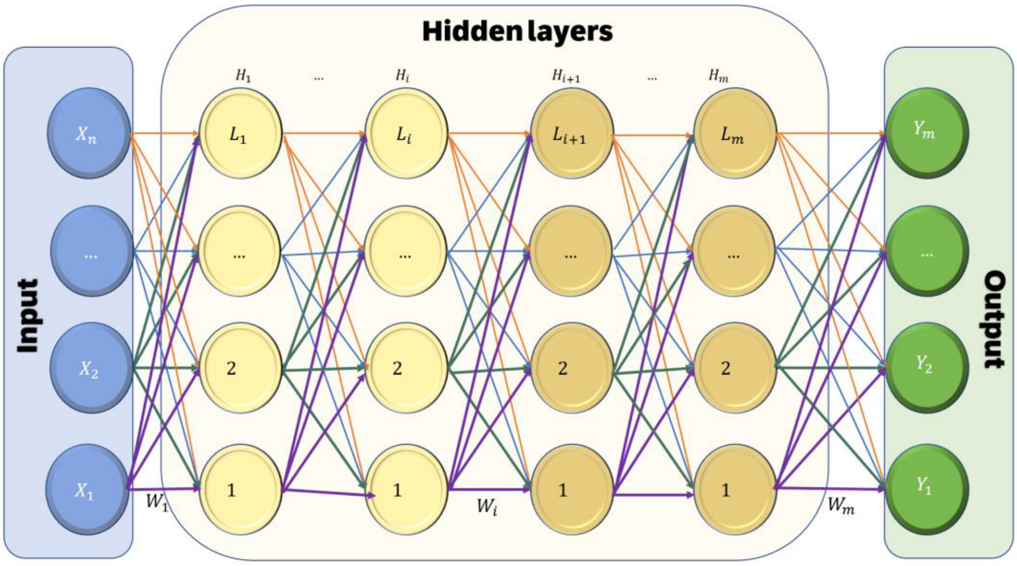


Figure 20. Deep extreme learning structure

4.14 Summary

An overview of the research process and a discussion on the adopted theoretical paradigm were presented in this chapter to provide a philosophical base for conducting this thesis. To achieve the thesis objectives and answer the thesis questions, the adoption of archival research using a secondary quantitative research design was rationalised providing the basis for testing the hypothesis. Further, the technique used to analyse the data have been evaluated to justify the soundness and appropriateness of the selection. Issues concerning the generalisation and reliability of the research were assumed and discussed. The method of analysis used in this thesis from data screening to predictive modelling will be discussed and applied in the next chapter to examine the interrelationships between EOC utility perceptions, self-determination, AI support and employee learning outcomes. The discussion with issues relating to data screening, the examination of descriptive statistics and demographic characteristics of the chosen sample, and the examination of the results using ML, DL, EL and DELM are elaborated in Chapter 5.

CHAPTER 5 DATA ANALYSIS AND RESULTS

In Chapter 4, the methodology adopted for this thesis was discussed and justified. In this chapter, the result of the descriptive analysis, and predictive analysis will be presented and discussed. Starting with Chapter 5.1 on examining the dataset including data coding moving data screening where missing data are treated, and the steps taken to remove any outliers including the representations of the samples under descriptive analysis and visualisation of the data structure in Chapter 5.2. Chapter 5.3 touches on the ML, DL, ELM and DELM, KDELM analysis including training the model to be able to predict the employee learning outcomes. Finally wrapping up the chapter with Chapter 5.4 which is the presentation of the chosen model.

5.1 Data processing

5.1.1 Transforming the dataset

The machine learning algorithm works by converting input data into meaningful output. As highlighted earlier that data comes in many formats. The original dataset of this thesis has a mix of data formats, both categorical and numerical. Categorical data such as gender and age group while numerical data is data expressed in digits. When the dataset has both categorical and numerical data, these are known as irregular data frames where data manipulation will be needed before it can be useful for the computer to generate any meaningful analysis. This is because the machine learning algorithm relies on the mathematical calculation to derive a predictive model and solution. Hence, ideally, numeric data is used for analysis. Therefore, the transformation of the dataset is needed for data cleansing and standardisation of format for ease of model training and analysis to allow an erroneous model. This can be easily achieved with the pre-processing function in Python of the scikit-learn library. It is a machine learning technique to remove any inconsistency. In this thesis, pre-processing was done by converting the responses which are recorded in categorical strings data to numerical data points. The label encoder followed by the fit_transform function is used to compute the mean, and standard deviation, and auto-scale the data to enable data to pass on to the next function for modelling. All 13 variables were transformed from strings to numeric data.

Reverse coding was then performed; converting positively worded answers with the highest scoring while the negatively worded get a lower scoring. Twelve items were reverse coded. The five-point and six-point Likert scales were reverse coded to allow consistency between the variables. Strongly disagree, disagree, neither agree nor disagree, agree and strongly agree are coded as 1 for strongly disagree and the number runs sequentially with 5 as the highest value on a five-point scale indicating a positive response. Similarly, this was repeated for the six-point Likert scale. After this, the dataset was re-examined to see if there is any missing data. Missing data can occur for many reasons in a real-world scenario, it is not uncommon, and it is not a setback. There are many ways to deal with missing data and not anyone way is better than another (Tunguz 2019). Therefore, in this thesis, the author chose to treat the missing data by removing them because there is sufficient data to train and test the model. When data are limited, it is best to replace the missing value with a mean or median value of the feature so that no further leakage of the limited dataset could obstruct a meaningful data analysis.

Variables in machine learning are also known as features. One new variable was created as part of feature engineering; an important part of data transformation before starting any machine learning processes (Ippolito 2019). Aggregating the existing features which have been identified as associated based on the understanding of the theory creates the new feature. After the removal of missing data, outliers are to be identified and treated before moving on with data analysis and modelling.

5.1.2 Outlier identification and treatment

In agreement with Press (2016), generally, 80% of the time is used in managing and preparing the data for analysis. This includes the time spent on treating outliers. The observation that lies outside the overall pattern is known as an outlier (Moore, McCabe & Craig 2017). It simply means observations with distant values that are noticeably different from the rest. It is important to identify outliers and treat them accordingly so that the outliers will not distort the statistics. According to Kovach and Ke (2016), outliers could impact skew the statistical result and reduce the power of the statistical test. Three methods were used to identify the outliers for treatment in this thesis as a way to cross-reference and finally chart the demographic profiles.

5.1.2.1 Interquartile range (IQR)

An interquartile range (IQR) was calculated first to see the range of data for each of the variables and the boxplot is created to visualise the outliers. Each of the variables/features was computed with the IQR. IQR is the measurement of dispersion or variability by splitting the data into a quartile. The formula to calculate IQR is:

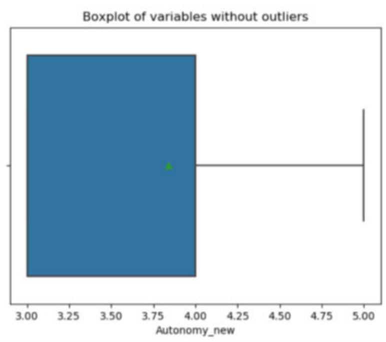
$$IQR = Q_3 - Q_1 \quad (12)$$

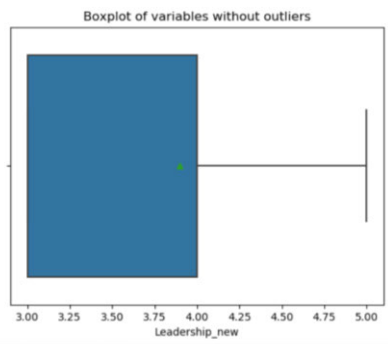
where Q_1 denotes the first quartile of the dataset that holds 25% of the value below it while Q_3 denotes the third quartile with 25% of the value above and the difference between Q_3 and Q_1 is the IQR (Haldera, Bhattacharya & Sarkar 2019).

The determination of the outlier is often a subjective debate. A general rule of 1.5 IQR (Nair 2019) was adopted in this thesis to provide the range by calculating the lower and upper bound. Only when a datapoint falls out of the range is to be considered an outlier. The lower and upper range for the autonomy feature is 1.5 and 5.5 respectively with 1.0 IQR which means any data points below 1.5 and above 5.5 are considered outliers. The lower and upper range for the Learning_outcome variable is the same being 4.0 with 0.0 IQR which means there are no outliers identified in the dataset.

5.1.2.2 Boxplot

The boxplot is then used to summarise the statistical information more synthetically (Abramowitz & Stegun 2014) and also to have the needed visualisation of the structure of the data to determine if any points were sitting extreme out from the range. Figure 21 shows the boxplots for Autonomy_new, Leadership_new, Artificial_Intelligence_new, and Learning_outcome_new. The boxplot can be called with the seaborn function in Python. Seaborn is a library that is closely integrated with pandas to provide statistical visualisation (Waskom 2020). According to the author, different questions are best answered by different kinds of visualisations. Figure 21 boxplot shows that Autonomy_new has a minimum of 3 and a maximum of 5 with 3.8 as the mean. The Leadership_new variable has a minimum of 3 and a maximum of 5 with 3.8 as the mean. The Artificial_Intelligence_new variable has a minimum of 3 and a maximum of 5 with 3.75 as the mean. The Learning_outcome_new variable has a minimum of 4.0 and a maximum of 5.0 with a mean of 4.2. A similar approach was done for the rest of the features used in this thesis. It was noted there were no outliers detected in the dataset. Now that the data is cleansed, scaling or normality assumptions are to be addressed next.





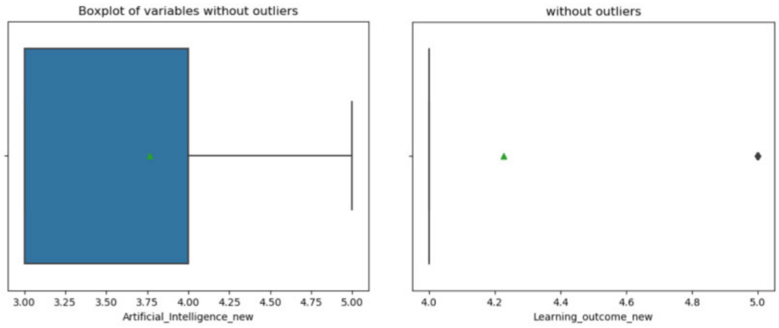


Figure 21. Boxplot of selected features used in this thesis

5.1.2.3 Scaling

Before examining the hypotheses and doing data modelling with ML and DL algorithms, the data for this thesis needs to be normalised or scaled. This is because the APS employee census dataset consists of 5-point and 7-point Likert scale variables that cannot be processed efficiently by the ML technique. KNN requires normalised data to calculate the Euclidean distance to find the nearest neighbour. SVM algorithm works best on scaled data otherwise the statistical analysis would be biased towards certain features in the dataset causing unreliability of the test result. It implies that the test would be more valid if the normality assumption is not violated especially in the parametric test when the distribution between groups should be balanced. According to Knief and Forstmeier (2021), the violation of normalisation is ignorable when the sample size is large. Similarly, Ghasemi and Zahediasl (2012) asserted that a small deviation from normality is acceptable when the same size is large. Koh and Ahad (2020) empirical study suggested that the general rule of the central limit theorem that required 30 samples or more can be violated but the more skewed the distribution of sample implies a larger sample size is needed to achieve normality. The dataset (n = 93,199) available for this thesis is considered large therefore could tolerate normality violation. Nevertheless, normalisation or scaling are performed to avoid any statistical errors. After all, real-world data are naturally unstructured and not normally distributed (Das & Imon 2016). The MinMaxScaler from the scikit-learn library was invoked on the dataset of this thesis to normlise the data. The default configuration of a minimum 0 and a maximum of 1 were used. Figure 22 presents the histogram of the scaled dataset distribution extracting the first 1000 datasets.

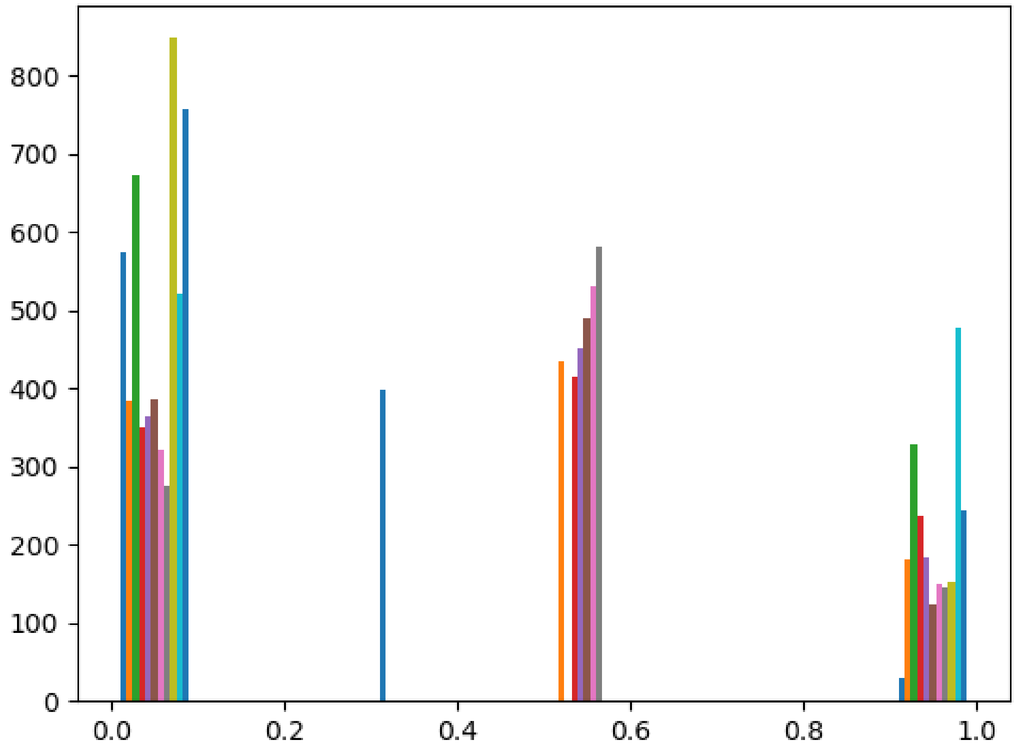


Figure 22. Histogram of scaled dataset distribution

Many other techniques can be used for normalisation such as bagging, sub-bagging, and bragging. Lee, T-H, Ullah and Wang (2020) discussed the theory and applications of these techniques. It was noted that the variants of the normalisation method are rooted in the bootstrap method. Bootstrapping is used for statistical resampling with multiple smaller datasets by repeatedly drawing and replacing the data source to establish a population parameter. It implies that the findings can be generalised to the entire population through the testing of several subsets of the dataset without needing to explicitly test it on each datapoint in the population. This general method is used in many leading ML algorithms and has proven to be efficient and accurate (Sukhanov et al. 2015). Similarly used in this present thesis for resampling the dataset for ML and DL analysis. According to Johnston, MG and Faulkner (2021), the bootstrap method is superior to other non-parametric tests. Even though the non-normality issue is not trivial, in this thesis, the multivariate non-normality was evident, as such, for robustness and performance improvement of ML and DL algorithms bootstrap was conducted. Zhang, Y and Xu (2021) drew 9000 bootstrap samples in the study of superconductor doping mechanisms and changes in critical temperature. Monjaras-Gaytan et al. (2021) suggested the use of 200 bootstrap samples in the study of critical consciousness. The Bollen-Stine bootstrap in this thesis was invoked with the random() function to generate 5000 bootstrap standard errors with 95% confidence intervals for the model parameter estimates. A similar 5000 bootstrap was used in the study of consumer behaviour during a pandemic (Jin et al. 2021) and deemed to be reliable. To determine whether the model estimated is a good fitting model, the Bollen-Stine bootstrap *p*-value is observed whereby *p* should be less than 0.001. Table 8 shows a summary of fit indices. A decision based on a good fit model is important to ensure the model is not misleading. Other fit indices beyond the *p*-value such as RMSEA, TLI and CFI will be evaluated to provide additional info on the usefulness of the model presented.

Table 8. The goodness of fit measures

Measures	Level of acceptable fit
Likelihood ratio (LR) Chi-square (x^2) statistics (p)	$p > 0.001$
Root mean square error of approximation (RMSEA)	< 0.05
Standardised Root mean square residual (SRMR)	< 0.10
Tucker-Lewis index (TLI)	≥ 0.9
Comparative fit index (CFI)	≥ 0.9
Normed Chi-square (CMIN/DF)	$1.0 \leq x^2/\text{df} \leq 5.0$

Next, the characteristics of the dataset are examined. In Python, a powerful feature of pandas called describe() can produce a descriptive analysis with the quartile information as well which can be used as an alternative to the IQR method.

5.2 Data analysis and modelling

5.2.1 Descriptive analysis

The descriptive analysis as the name implies seeks to describe the data by providing a summary of information such as mean, median, percentile, standard deviation, and other statistical information but does not attempt to make inferences about the whole population from the sample (Narkhede 2019). The sample size is 93,199. The original sample size was 103,137 whereas 9,938 was removed due to missing data as mentioned in Chapter 5.3. The means for Autonomy is 3.6 while the Workgroup is having a mean of 4.1. The AI variable has a mean of 3.5 and the Learning_outcome variable has a mean of 3.9. Apart from the mean, the describe() function also shows the standard deviation value. Standard deviation (SD) refers to the variability or dispersion of data from the average population in the study. Dispersion refers to the idea that there is a second number that tells how widely spread all the measurements are from that central number (Boeree 2005). SD can be calculated with the formula:

$$\pi = \sum_{i=1}^{N}(x_i - \mu)^2 \tag{13}$$

where μ refers to the mean of the variable, N refers to 93,199 and x_i is the data point. Taking the Learning_outcome variable as an example, the variance can be calculated by:

$$\pi = 1/93199\ ((x_1 - 3.92)^2 \text{ to } (x_{93199} - 3.92)^2) \tag{14}$$

and the SD is simply the square root of the variance. For any data, the lesser the dispersion is always desirable because a smaller value represents the data is more or less consistent with the average. Autonomy, Workgroup_climate, AI support, and Learning_outcome have SD of 0.93, 0.77, 1.0, and 0.8 respectively. Comparing the four variables, the Workgroup climate has the lowest value of SD which indicates that the data points are close to the mean and do not have a lot of spread. Table 9 displays the descriptive analysis such as means, standard deviations, skewness, and kurtosis for all variables of this thesis.

Table 9. Means and standard deviations for all variables of this thesis

Variable	Mean	SD	25%	50%	75%
Leadership	3.780008	0.978472	3	4	4
Working environment	3.656853	0.995886	3	4	4
Workgroup climate	4.188682	0.768870	4	4	5
Autonomy	3.693044	0.928104	3	4	4
Competency	3.865149	0.750710	4	4	4
Relatedness	3.811865	0.807041	3	4	4
Job satisfaction	3.725576	0.982307	3	4	4
Well-being	3.811232	0.974018	3	4	4
Performance	3.284188	1.091596	2	4	4
Non-discrimination	5.313587	0.863523	5	5	6
Artificial Intelligence	3.524673	1.058094	3	4	4

Most of the items were measured using 5-point Likert scales except non-discrimination feature using 7-point Liker scales, the means could range from one to five and one to seven respectively. This means approaching five on a 5-point Likert scale is considered as high similarly means approaching seven on a 7-point Likert scale is considered as high while means approaching one are considered as low. A mean of three on a 5-point Likert scale can be considered the midpoint and four can be considered the midpoint on a 7-point Likert scale. It is important to note that the means for all the items for the attitudinal and environmental motivation were higher than the midpoint. These appear to indicate that most employees tend to be motivated by learning. It is also important to note that when the means for items are less than three would mean otherwise. There are no conclusions that can be drawn by observing the mean alone. Furthermore, given that comparable means for other industries are not readily available, it must be noted that meaningful and conclusive interpretations of the means presented in Table 9 are rather difficult.

Comparing the min with the first quartile (25%) and the max with the third quartile (75%) can determine the outliers. Since the missing data was handled by removing them from the dataset as described earlier, to avoid further leakage of data, the outliers were replaced. As with the subjectivity of whether to remove or replace the outliers, it is also rather subjective which value to take for replacement. The outliers in this thesis were replaced with the min or max value instead of the mean value because the mean calculated is exposed to the risk of distortion from the presence of the outliers themselves.

5.2.2 Demographic profiling

The demographic profiles of the sample population include gender and age group. Figure 23 shows the histogram of gender split by age groups investigated in this thesis.

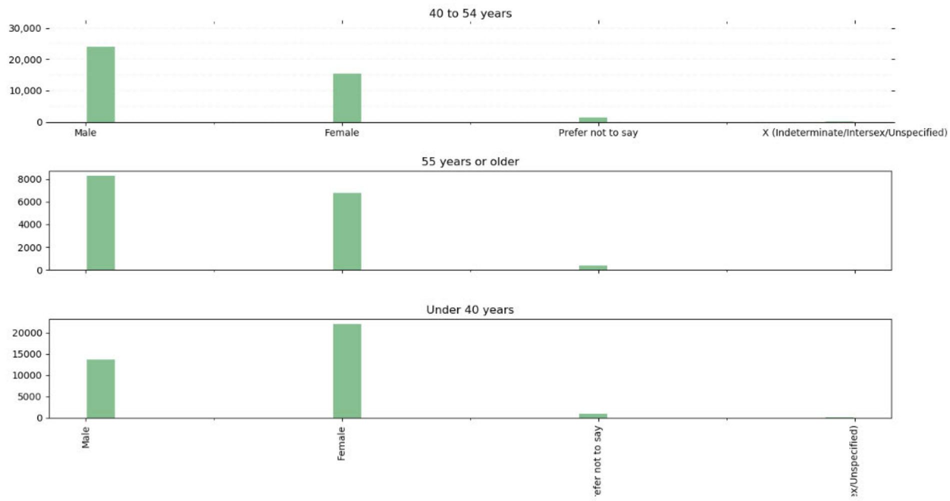


Figure 23. Histogram of demographic profiles

The histogram is an effective graphical technique for showing both the skewness and kurtosis of the data set. This is often useful in describing the characteristics of the sample or population that is being studied. Referring to Figure 23, the female representation is the most with more than 20,000 under 40 years old and drops significantly to 7,000 for the age group of 55 years or older. The majority of the workforce is between the age of 40 to 54. In this age group, close to 25,000 are male and 15,000 are female.

5.2.3 Principal Component Analysis (PCA)

Before conducting PCA, the data were assessed for suitability as discussed in Chapter 4. The correlation heatmap, KMO and Bartlett's test of sphericity are executed, and the results are presented below.

5.2.3.1 Correlation heatmap

Correlation is a statistical technique to show the relationship between variables including their strength. A correlation can be presented in a matrix table which is called a correlation matrix. It is mainly used to summarise the correlation coefficient between variables. The correlation coefficient is the result of the correlation, and it ranges from -1 to 1. The closer the correlation coefficient to -1 or 1 indicates the variables are closely related. A positive correlation means when one variable increases the other increases together while a negative correlation means when one variable decreases the other increase. This is also known as an inverse correlation. When there is no correlation, the correlation coefficient is 0. In a correlation matrix, the x and y-axis are presented with the same variables. When both rows and columns variables perfectly correlate with themselves, it is indicated as 1.0. And this is observed from the top left to the bottom right diagonally. The matrix is said to be symmetrical, that is when the variables act as a mirror of the same output between the upper and below the diagonal line. Therefore, since the matrix is symmetrical, it is common to display the upper triangle or the lower triangle of the matrix. Regardless, it must be noted that when one variable correlates with another variable it is never assumed that it is a causation relationship whereby a change in one variable causes a change in another. Besides, it does not explain the total variance of a construct as needed in theory testing. Therefore, the interpretation of results and their generalisability should be made with caution.

Apart from the correlation matrix, correlations can be visualised with a heatmap. A correlation heatmap is an interesting visualisation method that can provide detailed insights like the correlation matrix. It provides a high information density where all the information from the original data is presented in a gradient to show the relationships that exist between the variables.

The correlation heatmap of the pairwise correlation of the variables in this thesis is presented in Figure 24 including the annotation of *p-value*.

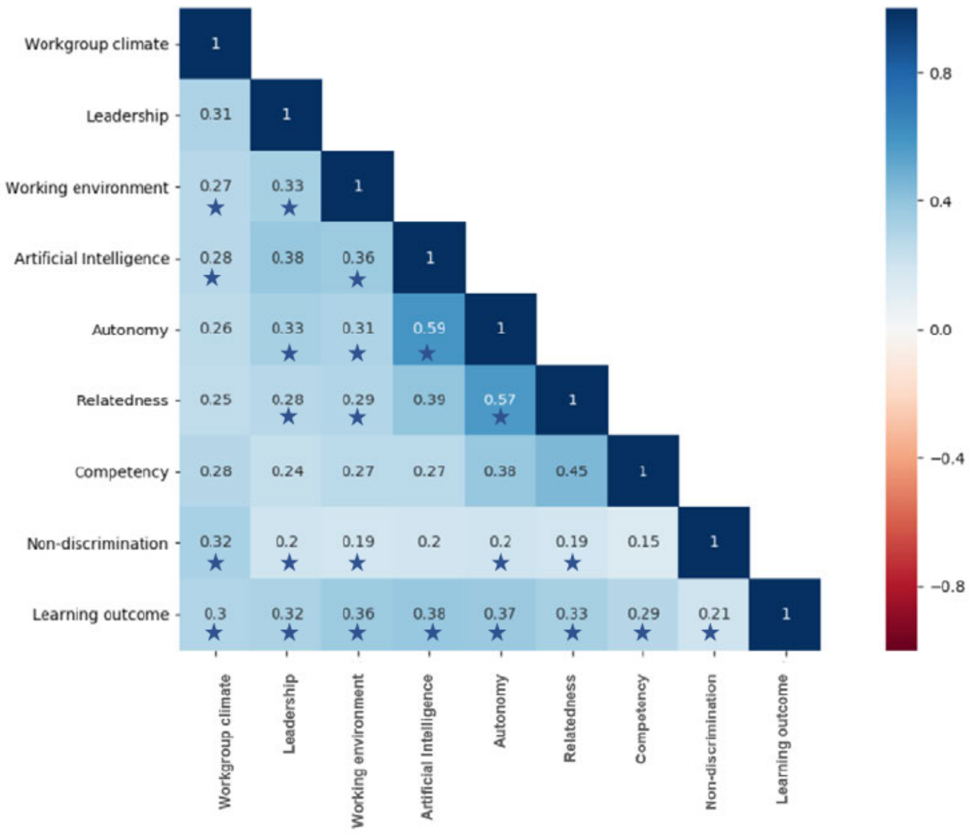


Figure 24. The correlation heatmap of pairwise correlations of variables

In the colour bar on the right of Figure 24, the neutral white is showing no correlation. The darker shades of blue and red indicate higher positive and negative correlations respectively. All the variables observation are positively correlated which means as a variable increases, the other variable varies on the same direction. The correlation heatmap was interpreted using the rule of thumb whereby the scoring of r more than 0.70 is considered strong and below 0.30 is considered weak (Hinkle, Wiersma & Jurs 2003; Schober, Boer & Schwarte 2018). Results indicate weak to moderate significant correlations between all the variables and the learning outcomes ratio. There seems only to be a connection or extremely weak correlation between the non-discrimination and competency ratio. Despite the correlation heatmap showing all variables scoring nonzero value, there is a possibility of no correlations actually exists. Given that the r value is abstract and does not provide a precise interpretation of the correlation coefficient, the *p-value* is used to show the statistical significance of the r and the random chance of observing the given r value even when there is no real correlation exists. For example, a correlation coefficient as small as 0.19 between non-descrimination and relatedness can be significantly different from 0 at $\alpha = 0.05$. In other words, the relationship exists between the variables is statistically significant. The variables annotated with * indicates that the observed variable provides ample evidence to conclude that the population correlation coefficient is not equal to 0. These relationships presented in the correlation heatmap help to check the assumption of multicollinearity.

Multicollinearity is a state where two or more independent variables intercorrelate with each other (Kline 2015). According to the author, multicollinearity occurs when the correlation coefficient has values exceeding 0.85. In this thesis, the highest correlations between the independent variables are 0.59 which is between Autonomy and Artificial Intelligence, which is significantly lesser than the 0.85 ratios. This suggests that the assumption of multicollinearity has not been violated. The reason multicollinearity occurs is because of a structural issue such as duplicated variables or inaccurate usage of dummy variables. The other reason is because of poorly collected data or manipulation of data. In this thesis, the instrument used provided reliable measures of the variables of interest that are free from instability or extremely sensitive or unreliable models. While the correlations heatmap provides valuable insights about the possible relationships among variables, other tests are conducted to better judge whether there is a possible dependency and if factor analysis is feasible on the dataset.

5.2.3.2 KMO and Bartlett's test of sphericity

Bartlett sphericity test and KMO were conducted to examine the intercorrelation and proportion of variance between variables. Referencing Hsu, Lin and Jhang (2020), the Bartlett sphericity test with a significant *p*-value of less than 0.05 and KMO of 0.60 would be considered appropriate for factor analysis. The Bartlett sphericity and KMO test conducted on the APS census dataset produced a significant *p*-value of 0.0 and KMO of 0.85 indicating data suitability to proceed with factor analysis. Table 10 confirms the appropriateness and reliability of all the items in the dataset used in this thesis. The next step is extracting the factors.

Table 10. KMO and Bartlett's test of sphericity output

Test on all items	Result
Bartlett's test of sphericity	Chi squared value = 200494.53349078418 (p = 0.0)
KMO measure of sampling adequacy	0.8496668848585214

5.2.3.3 Features extraction

The KMO statistics of more than 0.60 confirms the adequacy of sampling and the Bartlett test of 0.0 indicates the appropriateness of the factor model. The next step in PCA is to select the features with Varimax rotation along with eigenvalues and scree plots to determine the number of factors to be retained. An eigenvalue of >1 is required to be retained as a factor to proceed with further ML and DL analysis. Figure 25 depicted the scree plot of eigenvalues for perceived EOC utility and Self-DeterMination (SDM). The scree plot shows a steep slope at the 2nd factor and a gradual shrinking appears to start at factor 3 and then tail off. The result from the scree plot suggested that 2 factors with eigenvalues of 2.8 and 1.0 are to be retained while others can be eliminated. These 2 factors described the variance of about 3.8 variables.

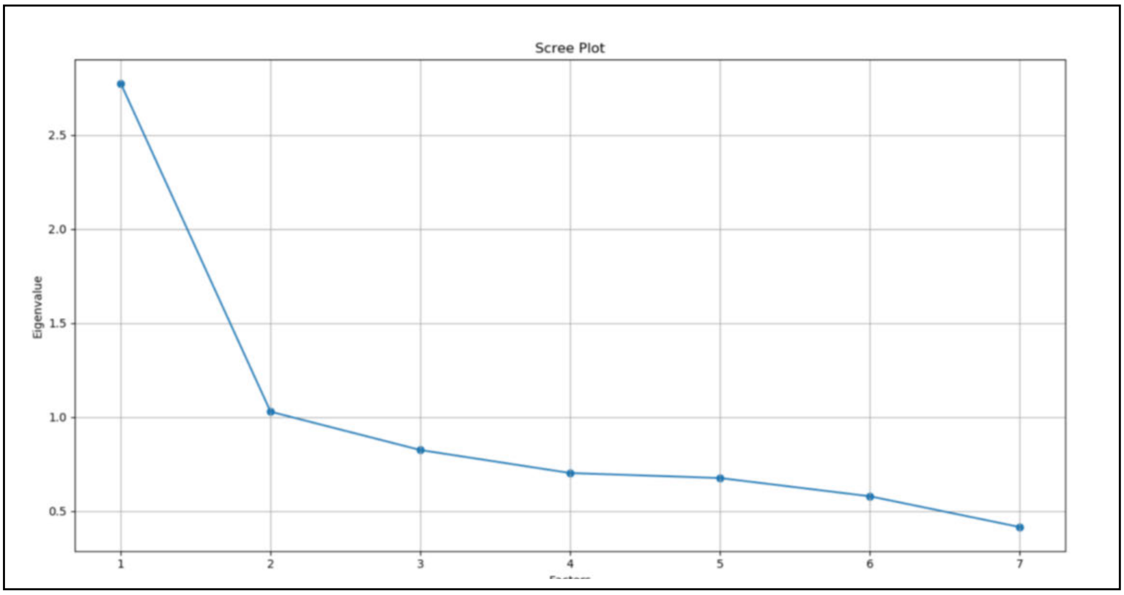


Figure 25. Scree plot of initial factor solution for EOC utility and SDM

A factor loading cutoff of equal to or greater than 0.50 (Rezapouraghdam, Akhshik & Ramkissoon 2021) was used when determining the practical significance of the variable to be included in the 2 factors identified (see Appendix 4). For instance, the first factor (PCA1) contains variable autonomy, relatedness, and competency with loadings of 0.65, 0.80, and 0.49 respectively while the second factor (PCA2) contains workgroup climate, leadership, working environment and non-discrimination variables with the loading of 0.62, 0.45, 0.40 and 0.43. The alphas are evaluated at 0.72, and 0.59 which indicates that they are useful and coherent. An alpha coefficient of a minimum of 0.50 is needed for accepting the reliability and internal consistency of a factor (Hair et al. 2019). These new factors are then concatenated with the rest of the data frame to create four factors (EOC, SDM, AI and LO) new data frame for subsequent analysis and prediction with ML and DL algorithms.

5.2.4 Predictive modelling using individual machine learning

The detailed process applied to employee learning outcomes prediction using KNN and SVM is described here.

5.2.4.1 K-nearest neighbour

The objective of KNN is to locate the nearest neighbour of the feature space to predict the target label of the input data. To do this, firstly, python libraries such as NumPy, pandas, sklearn, matplotlib and time are imported. After the needed packages are imported, the new data frame created because of PCA was loaded using the read_csv command. Next, identify and place the selected input and output data into arrays. Then, the datasets were partitioned into train and test datasets. Here the Pareto rule of 80/20 split was initially used. The training dataset is used for training hence was assigned the bigger portion while the test dataset was used for testing and a smaller portion was allocated. Then both the train and test datasets were scaled and fitted before applying the KNN classifier. The value of k was initially set to 5. The predictive model accuracy was 79%. The model was tested again with an adjusted train and test split using the 90/10 rule. The model produced a higher accuracy of 80% hence the data partitioning was set as a 90/10 rule. The reason this is happening is that a bigger training dataset is used to train the model. The more complex the problem is, the more data is needed to train the model so that the model will be able to learn the good patterns in the data. Therefore, apart from dataset partitioning, it is important to cleanse the data so that the model will not learn bad data patterns. Figure 26 depicts the steps taken in executing the KNN algorithm. Hyperparameter tuning was done on the k value. Different values of k were used to test the performance of the proposed model.

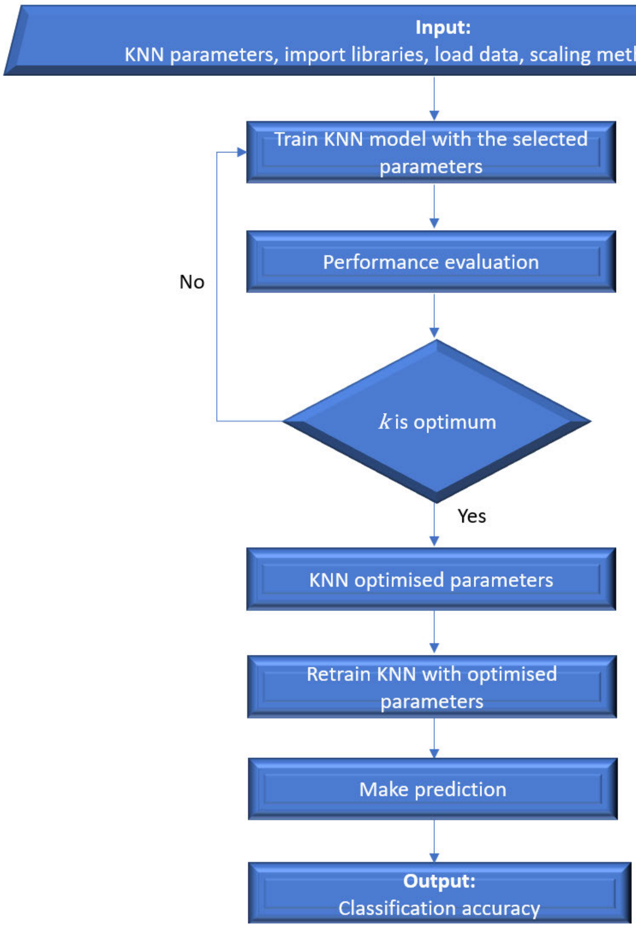


Figure 26. KNN execution flowchart

The performance was valuated using the accuracy scores generated and plotted into the graph as presented in Figure 27.

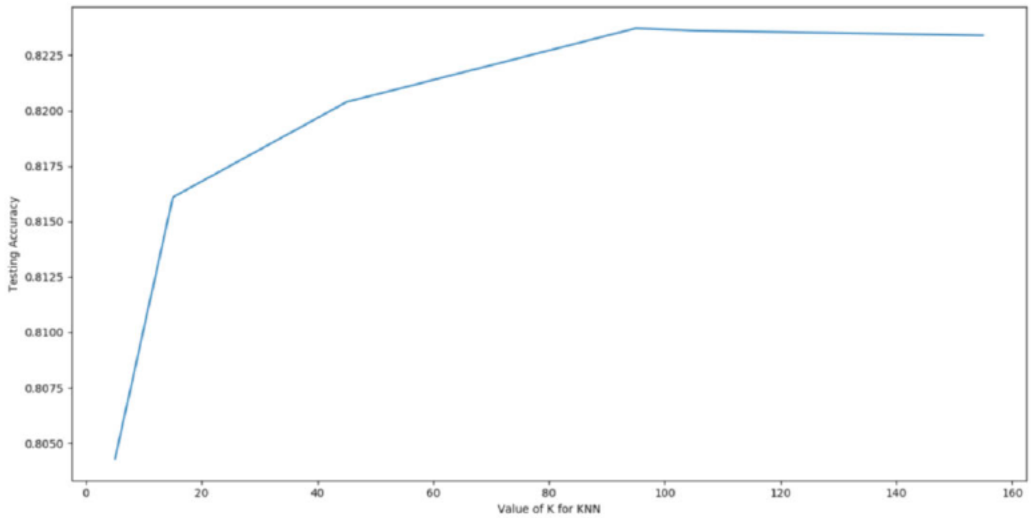


Figure 27. Relationship between k value on accuracy scores

The influence of different k on the classification accuracy of the KNN model is tabulated in Table 11. The misclassification is highest when the k value is low (5) with 19.57% misclassification and the KNN model improved with a higher k value as evident with the classification accuracy. However, despite further increasing the k value beyond 95 the accuracy did not improve. Hence, as described in Chapter 4 and demonstrated here using the rule of thumb.

$$k = \sqrt{n} \tag{15}$$

when determining the value of k yields a good model. Nevertheless, hyperparameter tuning is an important step in finding the best model using KNN as the result differ significantly even with slight parameter adjustment. In this thesis, the k value is optimum when it is set at 95 and the model was retrained and made a prediction on the test dataset producing 82.37% of classification accuracy. This means the prediction is fairly fitted to the model but with room for improvement. The KNN model generated was used as a benchmark to compare with other models. As the KNN was based on Euclidean distance, the comparison with other algorithms was done aiming to improve the classification performance. The SVM will be explored next to see if it produces a better result.

Table 11. A comparison of k-value

Classification accuracy (%)					
$k = 5$	$k = 15$	$k = 45$	$k = 95$	$k = 105$	$k = 155$

Classification accuracy (%)					
80.43	81.60	82.03	82.37	82.36	82.34

5.2.4.2 Support vector machine

The objective of SVM is to find the optimal hyperplane that maximises the separation of the dataset of n-dimensional space. Specifically, to produce an efficient SVM model, hyperparameter tuning of various parameters are a vital task to find the optimum model. This includes the C parameter tuning and kernel selection among other parameters that required tuning (Duan, Keerthi & Poo 2003; Sha'abani et al. 2020). The C parameter is the penalty for misclassification. In other words, it represents the trade-off between misclassification and the width of the hyperplane margin.

The kernel parameter on the other hand is used to accommodate a non-linearly separatable dataset. Implicitly transforming it into a higher dimensional space so that it can then be linearly classified. Adding more dimensions to the dataset helps to transform the inseparable planes into separable planes. To achieve this, different kernel tricks computation is used for different non-linear mapping. An unoptimised decision boundary could result in the misclassification of new data. Generally, kernel selection is done through trial-and-error experimenting with various kernel tricks.

The aim is to obtain a classifier or a model that can provide a confidence measure. The process of finding the confidence measure is a standard ML problem involving the training and testing phase to produce the appropriate SVM model. Firstly, the sample is evaluated to see if it is linearly separable by visualising it with a scatter plot. The scatter plot generated is depicted in Figure 28. It shows a linearly separatable dataset hence the linear kernel is selected to build the SVM model. Other SVM parameters are also required tuning. This is often done randomly and manually with various combinations to find the appropriate parameters. The search procedures are often time-consuming and computationally expensive to be executed.

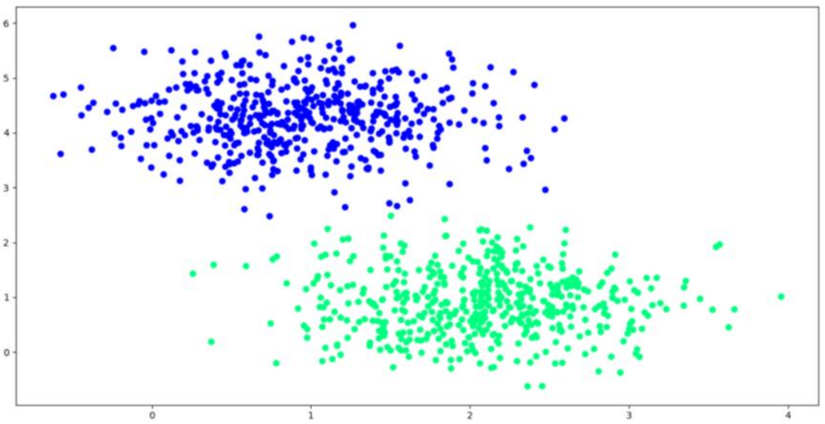


Figure 28. Scatter plot of the APS dataset used in this thesis

In this thesis, the initialisation of the parameters is performed by applying the grid search technique to find the optimum combination of the hyperparameters to be applied in the predictive model. The motivation for using this technique among others such as the randomised grid search (Kulkarni et al. 2017) came from Paper (2020). In agreement with Fu, Nair and Menzies (2016), the choice of the optimisation algorithm is based on the problem to be solved on hand. Various studies suggested that a randomised grid search could be more effective taking lesser time to compute compared to the grid search (Roodposhti, Hewitt & Bryan 2020; Sowmya et al. 2021; Yang et al. 2014), the dependency is on the search space dimensionality. The result of using a more advanced or randomised grid search technique on a low-dimensional search space could be as effective as the exhaustive grid search technique (Fu, Nair & Menzies 2016). Another consideration is the number of hyperparameters for optimisation. The more parameters required for calibration the longer it takes to complete the execution. Given in this thesis, the search space is inherently low dimensional and the number of hyperparameters required is not many, therefore, the exhaustive grid search with k-fold cross-validation was applied.

The *k*-fold cross-validation is a technique to take the APS census dataset by splitting them into *k*-number of subsets for training and testing. The objective is again to improve the model performance. The default 10-fold was taken in this thesis and will be calibrated through sensitivity analysis of various *k*-folds. The steps taken to execute the SVM algorithm with parameter optimisation using the grid search technique with cross-validation are presented in Figure 29.

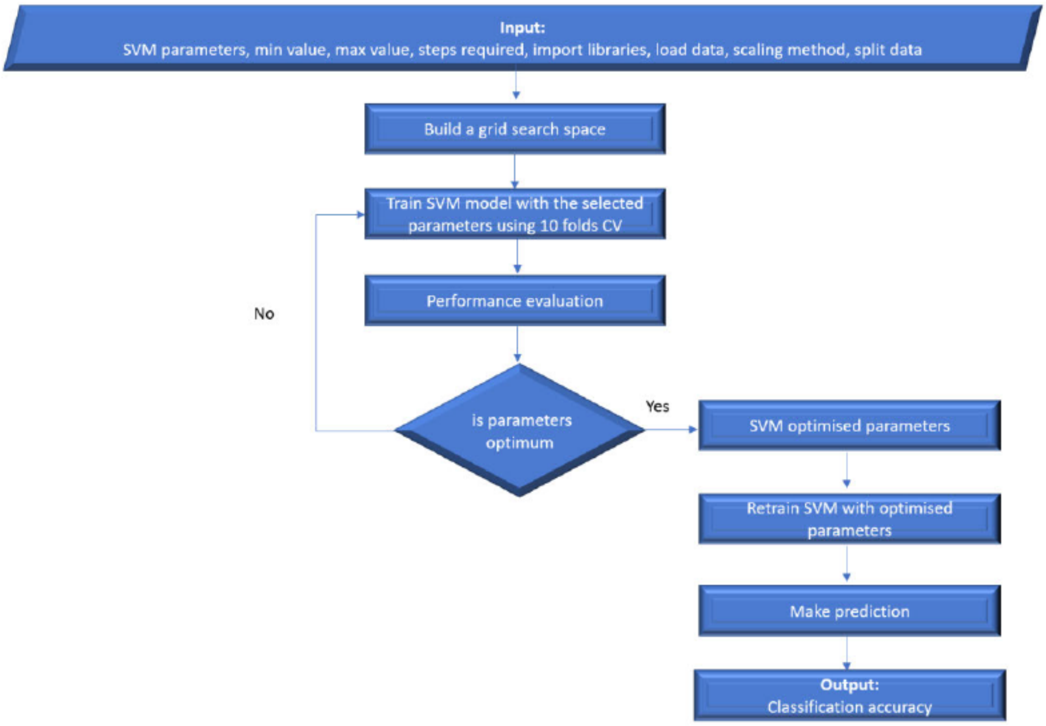


Figure 29. SVM execution flowchart

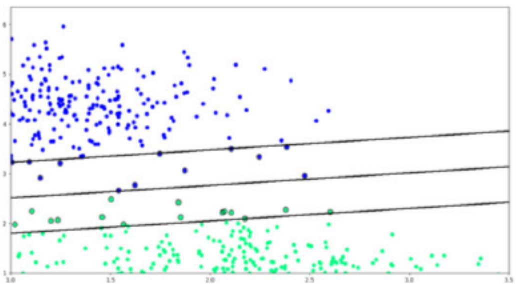
As the first step, the necessary libraries for SVM modelling were imported followed by data loading and scaling. The SVM kernels selection and parameters ranges used for grid search were determined as presented in Table 12 for the experiment on the APS employee learning outcomes.

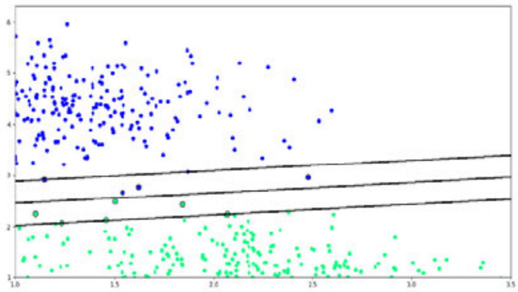
Table 12. SVM kernel selection and parameters ranges used in the exhaustive grid search

Kernels	**linear**	**RFB**	**Sigmoid**
Parameters	*C*	*Gamma*	
Ranges	0.1, 1, 10, 100, 1000		

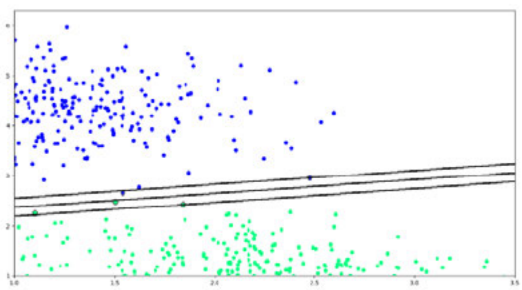
The APS census dataset was then partitioned into train and test data. The grid search space was then built and fitted 10 folds for each of the 75 candidates, totalling 750 fits. The SVM results using the exhaustive grid search based on 10 folds are presented in Appendix 5. The result of the best combination of the hyperparameters was cited as: ‘C’:0.1, ‘gamma’:0.1, ‘kernel’=’linear’. The combinations of hyperparameters are then used to retrain the model and make the prediction. The main consideration in a linear kernel function is the C parameter. When a small C value is used the corresponding margin is narrower. This means the model allows small observations violating the boundary resulting in a highly fitted model but with high variance. Contrarily, a bigger C value will result in higher tolerance whereby more observations violate the boundary rules resulting in a low variance but highly biased model.

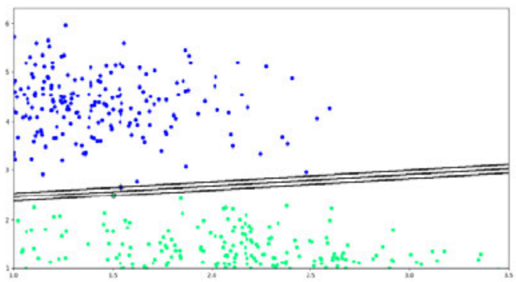
Figure 30 illustrates the linear kernel SVM scatter plot and its corresponding hyperplanes on different C parameters. The nodes or observations that touch the boundary of the hyperplane are the support vectors, the decision boundary is the line in the middle separating the two classes and the distance between the hyperplanes is known as the margin.



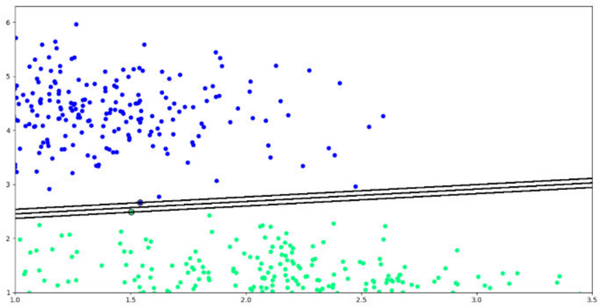


C= 0.1 C= 1





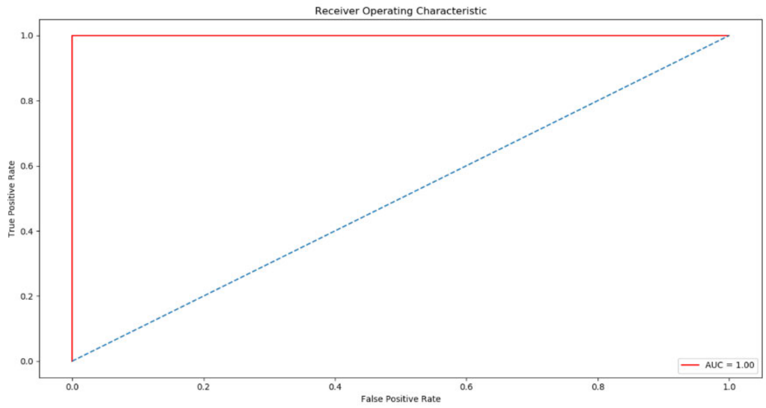
C= 10 C= 100



C= 1000

Figure 30. SVM scatter plot and its corresponding hyperplanes

Figure 31 depicts the effect of different C parameters on the SVM performance. Often the C parameters are sensitive influencers in model performance (Badr et al. 2021; Gu et al. 2021). The receiver operating characteristics (ROC) curve and area under the ROC (AUC) are important metrics providing valuable sights to evaluate the performance of the classifier. An AUC score of 1 represents the perfect classifier (Qutub et al. 2021). In this thesis, assessing the accuracy and the ROC AUC concluded that the C parameters have no significant effect on the model performance. Comparatively to the previous KNN results (Table 11), the major achievement of the proposed SVM model with parameter optimisation is the development of a predictive model with better performance, approximately 18% improvement over the KNN model, attaining 100% accuracy scores when implemented with the 10-folds CV method. Despite performance improvement, a major setback in the proposed SVM model is that it takes a long time to train and this is especially significant when the data sample increases. Although the model accuracy is satisfactory, there is no significant improvement in time performance when compared with the earlier KNN baseline model. As such, to further refine the technique, the ensemble ML was put to test next.



C= 0.1, 1, 10, 100, 1000

Figure 31. Performance of proposed SVM model

5.2.5 Predictive modelling using ensemble machine learning

The objective of ensemble ML is to harness the collective individual ML models to produce an optimal predictive model. Generally, the steps are the same as how individual models are executed (see Figure 26). The exception is the need to apply the ensemble voting function. This is invoked with the EnsembledVoteClassifier function in Python to decide on the classifier with the majority vote that can use to train and make a prediction. The ensemble classifier can be built with multiple different (heterogeneous) or same (homogeneous) classifiers to create a meta-classifier. The advantage here is that a single model can be devised and optimised using grid search to produce maximum accuracy predictive results rather than executing individual classifiers and tuning them separately.

The steps taken to execute the heterogeneous ensemble ML algorithm are presented in Figure 32.

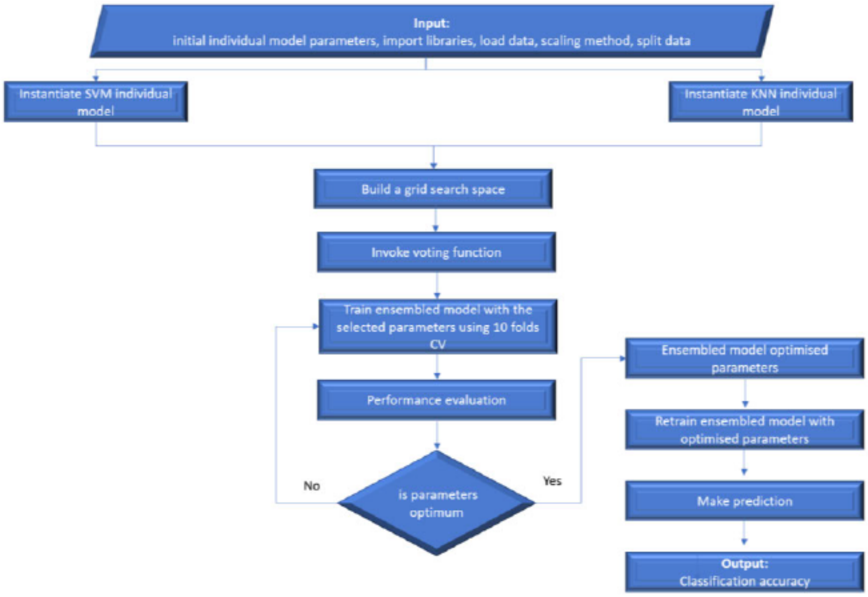


Figure 32. Ensemble ML execution flowchart

Due to an earlier experience working on the hyperparameters and grid search cv function, the construction of the ensemble heterogeneous model in this thesis was based on limited hyperparameters. This is because more hyperparameters introduced more computational complexity into the grid search which regular computers may not be able to comprehend. Therefore, in this thesis experiment, the combinations of two base classifiers were used to construct the heterogeneous ensemble classifiers. The grid search algorithm has been applied to the two base classifiers to obtain the optimum combination of hyperparameters for retraining the ensemble model (see Table 13).

Table 13. Base classifiers and the best combination of main parameters used in building the ensemble model

Base classifiers	Main hyperparameters
SVM	C = 0.1
KNN	Neighbours = 95

The performance result of the heterogeneous ensemble model after the 10-fold CV configured for this thesis can be referred to in Table 21. The ROC AUC performance of the proposed heterogeneous ensemble model is presented in Figure 33.

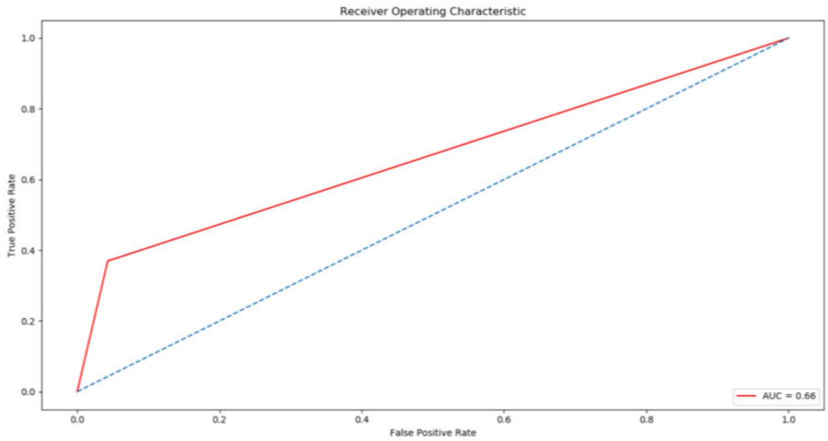


Figure 33. Performance of the proposed heterogeneous ensemble model

Analysing the ROC AUC shows that the heterogeneous ensemble model did not outperform the base classifier which was constructed earlier in the preceding chapter. The accuracy of the model is at 82% and AUC was 66% which is relatively lower than both the based classifiers. Qutub et al. (2021) performed a similar study on employee attrition and found that the performance of the ensemble model was lower than the based classifiers too. Xu, R et al. (2021) reiterated that the combination of the based classifiers influences the performance of the ensemble classifiers. Not all based classifiers when combined would result in a better performance ensemble model. Hence, the result obtained in this experiment is not surprising.

One possible explanation for this is the sample size. Due to the limited APS dataset being used, the performance of the ensemble classifier is also limited. Even though the performance is lower than the based classifiers, the ensemble classifier would be more robust and able to generalise better than the base classifiers (Qutub et al. 2021). Nevertheless, the ensemble model can still be used to automatically learn and classify the APS dataset with a weighted precision of 81%, a weighted recall of 80%, and a weighted F1 score of 80%. The accuracy is not lacking compared with KNN however, the computational time required increased significantly compared with the two based classifiers. Xu, R et al. (2021) suggested to further improve the performance of the ensemble classifiers, other base classifiers should also be examined to discover the best performance base classifiers to configure the best ensemble classifiers.

The technique used to combine the various base classifiers into the ensemble classifier can also be varied. For instance, Pavlyshenko, BM (2019) successfully improve the performance of the sales predictive analytic using the stacking method instead of voting. Therefore, further investigation is needed to evaluate the proposed heterogeneous ensemble model on a real-world dataset that is bigger than the current APS dataset used in this thesis and to also experiment with other base classifiers and ensembling techniques to find the optimum combination.

5.2.6 Predictive modelling using the extreme learning machines

Various ML classifiers were examined in the preceding chapters. Here, the Extreme Learning Machines (ELM) classifier will be evaluated on the APS dataset providing a comparative insight into the search for the best-fit model. ELM is a single-layer feed-forward neural network that distinguishes itself from the earlier presented models for not requiring hyperparameters tuning. Hence, it is deemed to be performing more efficiently than ML and DL methods. The steps taken to execute the ELM are depicted in Figure 34.

Firstly, all the necessary libraries were imported. The APS dataset was loaded, split and scaled accordingly. After which, the random.normal() function was used to draw a random number as weights and biases. The weights are applied to the input passing along together with biases to predict the output. In a single neuron the formula where weight and bias are applied can be written as:

$$y = \sum (\omega * n) + \mathrm{b} \tag{16}$$

Where ω is weight, n is the input feature and b is the bias. Then an activation function was applied to normalise the data and decide which neuron to be activated. Without the activation function, the model could only perform linear regression and would fail in a real-world application. Therefore, the activation function is used to build a more robust model to handle complex learning. Some of the most common activation functions are ReLu, Sigmoid and softmax. Softmax is used for multi-class classification, Sigmoid is for binary classification whereas ReLu is a linear monotonic function that does not react to negative values (Ren et al. 2017). There are advantages and disadvantages associated with each of these activation functions and there is no one perfect activation function. ReLu is commonly applied in ML and DL. It is the standard activation function because it has convergence ability and computational efficiency (Hossain et al. 2021). However, this activation function suffers from dying ReLu (Mastromichalakis 2021). This is because when $x \leq 0$, the derivative of ReLu return 0 whereby it does not react to the negative values. Therefore, the neuron fails to learn at this point and stops. Xu, J et al. (2020)

proposed a variation of the ReLu activation function based on the LeakyReLU to prevent the dying ReLU issue.

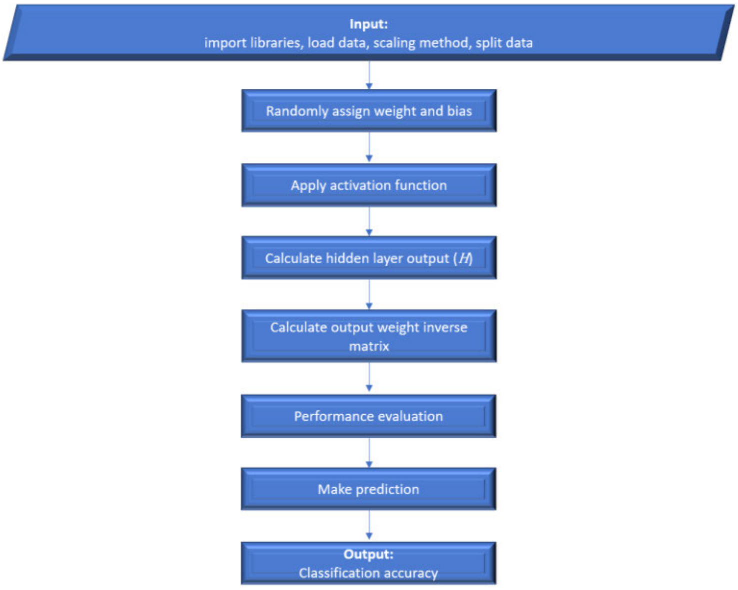


Figure 34. ELM execution flowchart

In this thesis, a robust activation function is proposed optimising the ReLu and Sigmoid functions. According to Banerjee, Mukherjee and Jr (2019), the occurrence of the dying ReLu phenomenon exists but is rare. Therefore, the ReLu activation function is still widely used and has minimum effect on the model. As such, it was chosen to blend with the conventional Sigmoid activation function that has no threshold restriction, unlike the ReLu activation function. The Sigmoid activation function is continuously differentiable (Mishra, Chandra & Ghose 2021) whereby the derivative output can cater to a non-zero value when $x \leq 0$ hence, solving the dying neuron issue. However, the Sigmoid activation function has its pitfalls of vanishing gradient. This is especially significant in the DL network. The deeper the feed-forward network the gradient diminished exponentially when propagating backward through the multi-layer network. Tan and Lim (2019) suggested that the vanishing gradient issue can be mitigated with the ReLu activation function.

Therefore, in this thesis, as part of the ELM algorithm, a blending of Sigmoid and ReLu (BSigReLu) activation functions is proposed to contra the disadvantages of the two selected based activation functions when used alone to achieve a more robust activation function. The blending of the activation functions method has been applied in some recent studies (Manessi & Rozza 2018; Mastromichalakis 2021) but is not extensive in the literature moreover in the context of employee motivation to learn. As with hyperparameter tuning, finding an optimised activation function is still an active area of research (Apicella, Isgrò & Prevete 2019). Given that ELM does not require hyperparameter tuning, then the only concern in building the model is with regards to activating the right activation function to further improve the model performance. The results of 10 iterations of ELM based on the three activation functions (ReLu, Sigmoid and BsigReLu) investigated in this thesis is presented in Appendix 6. Table 14 presents the summary of the average performance of ELM on different activation functions based on Appendix 6.

Table 14. Performance of ELM on different activation functions

Activation	Accuracy	Execution Time
ReLu	100%	1.7s ±0.458
Sigmoid	100%	1.5s ±0.500
BSigReLu	100%	1.7s ±0.458

Results presented in Table 14 confirmed the proposed BSigReLu activation function outperformed the original (ReLu and Sigmoid) activation functions. The accuracy is on par with the original activation functions however in terms of execution time, BsigReLu is better given the complexity involved in computation and the robustness achieved than each of the original activation functions alone. The blending technique was found to be highly effective in DL (Mastromichalakis 2021). As evident in this thesis, the BsigReLu is also highly effective on a single-layer network. However, it is believed there is still room for improvement. According to Afzal, Nair and Asharaf (2021), there are other techniques to enhance the learning power of the ELM and the DL architecture possessed the capability to prevail over contemporary shallow learning. Therefore, the DELM is investigated next using the BSigReLu activation function to confirm its effectivity on DL as claimed by Mastromichalakis (2021).

5.2.7 Predictive modelling using the PCA on DELM with BSigReLu

The differentiation between ELM and DELM is in the number of hidden layers. DELM involves a network of multi-hidden layers whereas ELM is only concerned with a single layer. According to Lu and Lu (2020), the success of DL lies largely in the network topology, the depth of the network allows rigorous learning occurrence to solve a given task. Therefore, the architecture of DELM should be the shallowest possible network topology meeting the desired efficiency performance. The steps taken to execute the DELM are similar to ELM but repeated until the maximum count of the hidden layers set has been reached (Figure 35).

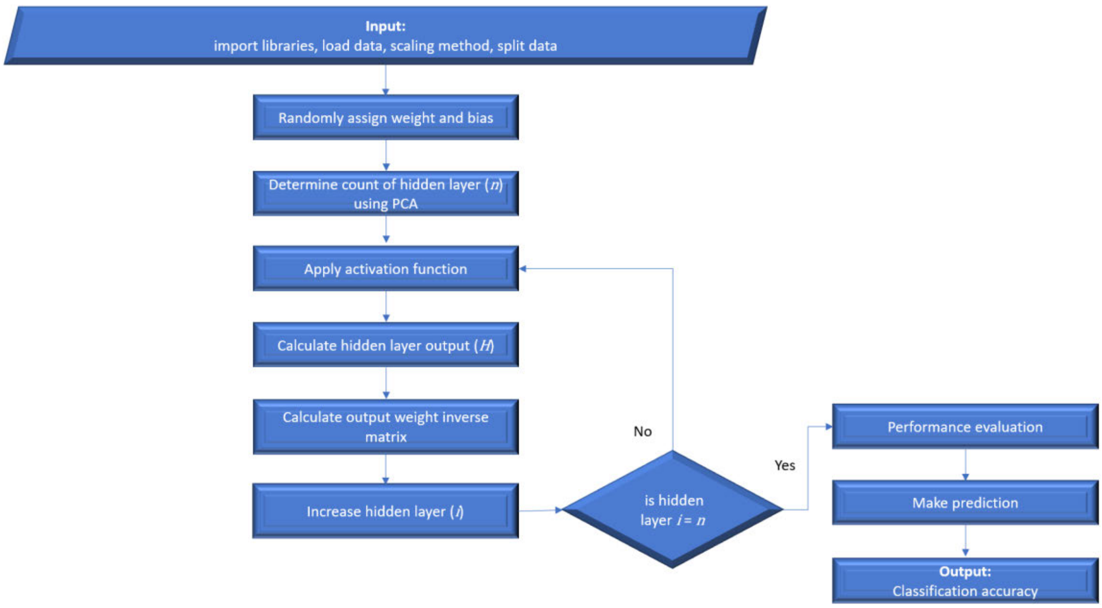


Figure 35. DELM execution flow

One concern is that there is still no universal formula to determine the optimum hidden layers to form the shallowest DL network. What is clear is that the more hidden layers introduced to the model would increase the computational time significantly and might also cause an overfitting issue whereby the training model fits perfectly while the same cannot be achieved with the testing model. On the other hand, using fewer hidden layers might cause an underfitting issue. Muh., Santoso and Surendro (2020) suggested a method to determine the number of hidden layers based on PCA. In the aftermentioned chapter on PCA and Appendix 4, the PCA computed for this thesis is two factors. Hence, a minimum of 2 hidden layers is deemed to be sufficient to build the DL network excluding the output layer. Nevertheless, an experiment is conducted varying between 1 - 3 hidden layers to confirm the optimised number of hidden layers in DELM. Table 15 summarises the DELM architecture trained and the corresponding results.

Table 15. The DELM architecture to be trained and the corresponding results

Architecture	Number of hidden layers	Number of hidden neurons	Epochs	Batch size	Accuracy	Execution time
I.	3	33, 33, 33	8	1	77%	813.5s ± 227
II.	2	50,49	8	1	77%	542.9s ± 29
III.	1	99	8	1	77%	557.4s ± 45
IV.	2	49,50	8	1	77%	567.2s ± 40

Referring to Table 15, taking architecture II, for example, the topology consists of 2 hidden layers. The first hidden layer is with 50 hidden neurons and the 2nd hidden layer is with 49 hidden neurons. Comparing the results of architectures, I - III, it was found that the number of hidden layers did not affect the performance of the model in terms of accuracy scores. It has been consistent across the three experiments however, comparing the time taken architecture II is the optimum model. This also confirmed that the PCA method can be used to determine the appropriate number of hidden layers to be used. Architecture IV is identical to II with a variation of the arrangement of hidden neurons.

Result suggests that having hidden neurons on the left hidden layer smaller than the right hidden layers is not an optimum solution because it is computational costlier. However, comparing the initial ELM model with all the DELM models (I – IV) proposed, the execution time differs significantly. Therefore, the quest for the optimum DELM has not been achieved. Finding the balance between model accuracy and computational performance is vital. To further improve the generalisability of the DELM model using BSigReLu, hyperparameter tuning was done on the number of epochs, batch size and hidden neurons using the exhaustive grid search with 10 folds cv method as introduced earlier in the SVM model hyperparameters tuning.

5.2.8 Predictive modelling using the PCA and exhaustive grid search k-fold CV on DELM with BSigReLu

Figure 36 illustrated the DELM execution process flow with the inclusion of a grid search step to identify the optimum parameters to build the DELM model. Table 16 presents the various parameter ranges used for the exhaustive grid search to find the optimum first layer nodes, epochs and batch sizes.

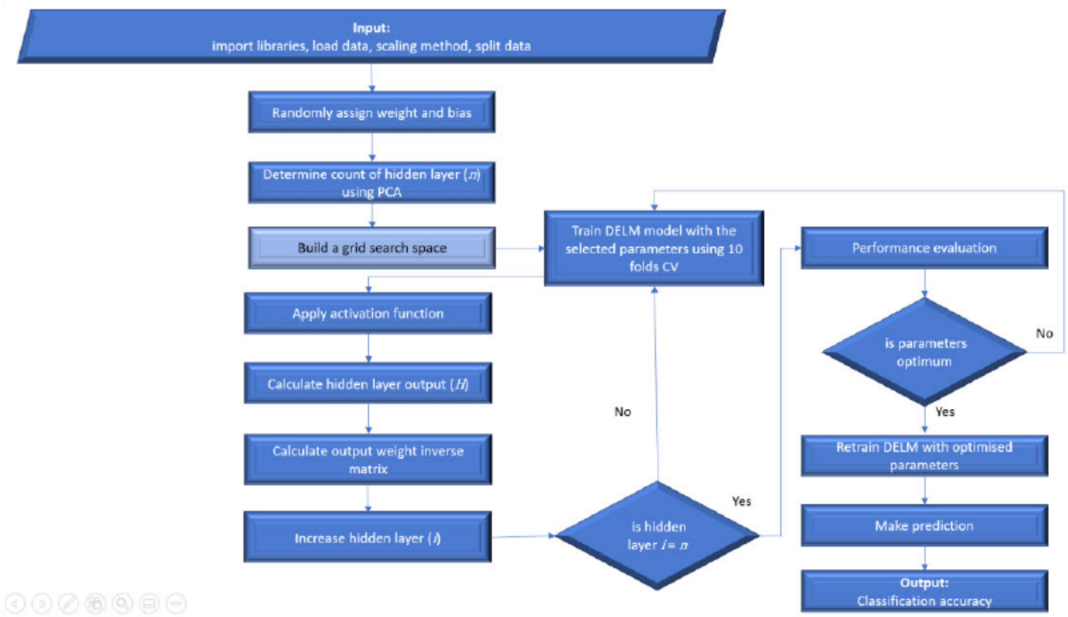


Figure 36. *DELM execution flow with grid search*

Table 16. *Parameter ranges for DELM exhaustive grid search*

First layer nodes	50, 49, **33**
Epochs	20, **60**, 100
Batch sizes	**1000**, 1200

The approach is to train the feedforward network using the parameter ranges identified in Table 16. The combination of best parameters is highlighted in the table (first layer nodes: 33, epochs: 60, batch size: 1000) producing the best accuracy scores that can then be used in model testing. The result after a 10-fold CV configured for this mode is presented in Table 17. Comparing architecture V and II, the accuracy scores improved by 5% that is from 77% to 82% and the execution time reduced significantly from 542.9s to 12.5s.

Table 17. Performance of the optimised DELM with grid search

Architecture	Number of hidden layers	Number of hidden neurons	Epochs	Batch size	Accuracy	Execution time
V.	2	33, 20	60	1000	82.20%	12.5s ± 0.67
VI.	2	33, 20	12	1000	82.29%	3.6s ± 0.49

Despite performance improvement of the optimised DELM with a 10-fold grid search CV, hyperparameter tuning can still be considered limited. One example is that only the first layer of hidden neurons was tuned should the architecture complexity increase the training time would proportionally increase as well. There could be other possibilities of parameters set that can produce an optimum result which may be out of the parameter ranges suggested in Table 16. This is because the grid search technique only searches within the parameter range recommending the nearest optimal parameters' combination within the range. Therefore, the result presented in Table 17 (Architecture V), can be considered suboptimal. Supplementing the exhaustive grid search CV, the early stopping technique was used for fine-tuning the epochs. Figure 37 illustrates the process flow of the inclusion of the early stopping callback function in the DELM model of Figure 36.

Epoch controls the iteration of the complete passes through of the learning algorithm. The result of architecture V was trained with 60 epochs in 1000 batches. This means that 90% of the training dataset (n = 83879) is divided into 83 batches each with 1000 samples. The number of epochs represents the iteration of complete passes through the training dataset (Brownlee 2018). The model weights will only be updated after each batch which consists of 83 updates for each epoch. Architecture V is exposed to 4980 updates for training the entire dataset with 60 epochs. The callbacks.EarlyStopping() function was initialised to monitor the quality of loss values and to halt training when the epochs achieved the least loss.

Sharma (2019) suggested this technique that can overcome the issue of over and underfitting. The underfitting issue is when the model did not achieve the maximum accuracy with a small epoch while the overfitting issue is when the model kept iterating even when the quality plateaued. Based on the count of epochs suggested by grid search CV (epochs = 60), the model was executed to train for 60 epochs.

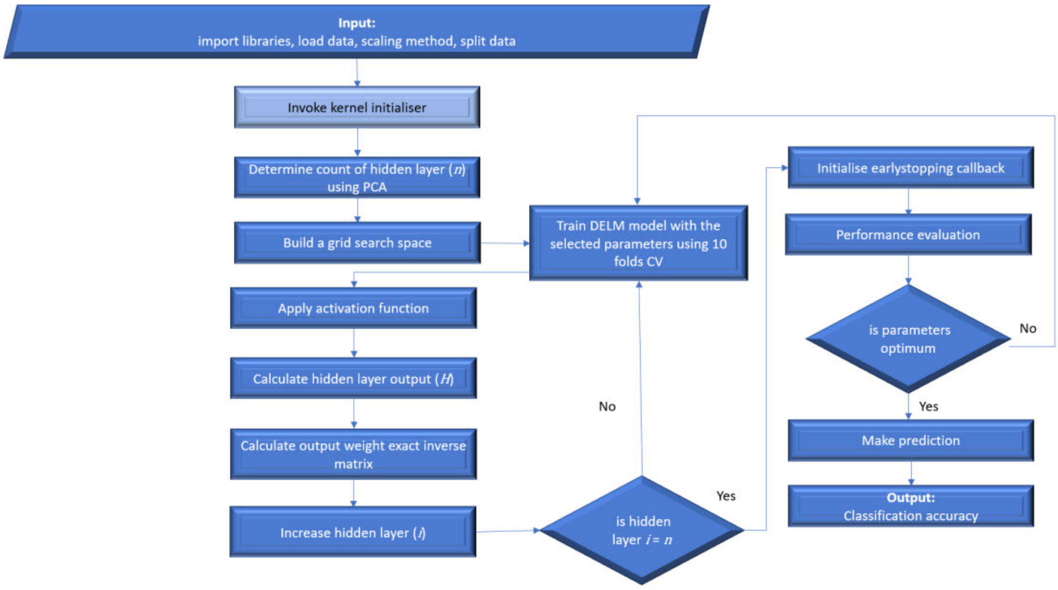


Figure 37. DELM execution flow with grid search and early stopping callback

The training loss and validation loss values are plotted against the number of epochs in the graph as depicted in Figure 38.

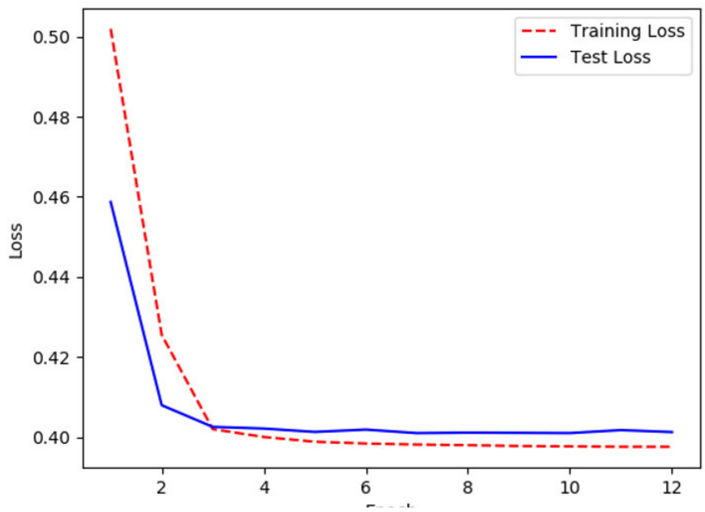


Figure 38. Loss values with early stopping

Observing Figure 38 result with early stop function, the model training stopped at the 12th epoch. That means the model will start overfitting at the 13th epoch. Therefore, the optimum epochs were determined to be 12. Architecture VI was appended to Table 17 showing time efficiency when optimised epochs were used. Architecture V runs for 60 epochs with an accuracy performance of 82.20% while architecture VI runs for 12 epochs to achieve an accuracy performance of 82.29%. Comparing architecture V and VI, 8.9s improvement was observed with 10 iterations. Overall, architecture VI achieved a comparable or equivalent result with a reduction of 80% epochs. However, both architectures still suffer from suboptimal generalisation because of the randomly assigned weights and bias causing non-reproducible results (Appendix 7 and Appendix 8).

Applying the Moore-Penrose generalised output weights inverse to the hidden layer is also computationally expensive because of the storage capacity and time incurred to transform the matrices. In addition to the unavoidable reconstruction errors that get propagated through the architecture (Wong et al. 2018). Only limited hyperparameters are tuned with grid search. There could be other possibilities of parameters paring that can produce an optimum result which has not been investigated yet. Therefore, inspired by the success of the kernel function used in the SVM model earlier, the kernel-based DELM (KDELM) is proposed and discussed next (Afzal, Nair & Asharaf 2021).

5.2.9 Predictive modelling using PCA, exhaustive grid search and early stopping on kernel-based DELM with BSigReLu activation function

The kernel function pride itself on not requiring hyperparameter tuning (Wong et al. 2018). Given i number of hidden layers, often the number of hidden neurons, epochs, batch size, weights and bias are tuned for each i. It is a notorious and daunting task to find the best combination of parameters. Results presented in Appendix 7 and Appendix 8 justified the need to overcome the deficiency of DELM to improve model generalisation by applying the kernel function. It helps to eliminate ambiguity caused by the random initialisation of weights and biases resulting in variance in the output model. The use of conventional Moore-Penrose pseudoinverse solution for matrix transformation in the earlier ELM and DELM is at the cost of reconstruction error and time complexity (Jung & Sael 2020). The proposed kernel transformation matrix in KDELM is a product of an exact inverse for output weights. In another word, it is an invertible kernel transformation matrix that performs a complete feature extraction that reflects the attribute character. As such, the kernel learning is unified into two transformation matrices only (Wong et al. 2018). The resulting KDELM model would have the ability to preserve the advantages of DELM and overcome the issue of local optimal to produce an optimum generalisation that is compact in storage capacity and efficient in execution time. An experiment was conducted to identify the kernel initialiser that is suitable for the proposed BSigReLu activation function. Figure 39 is the accuracy comparison between the six kernel initialisers on the BSigReLu activation function investigated in this thesis.

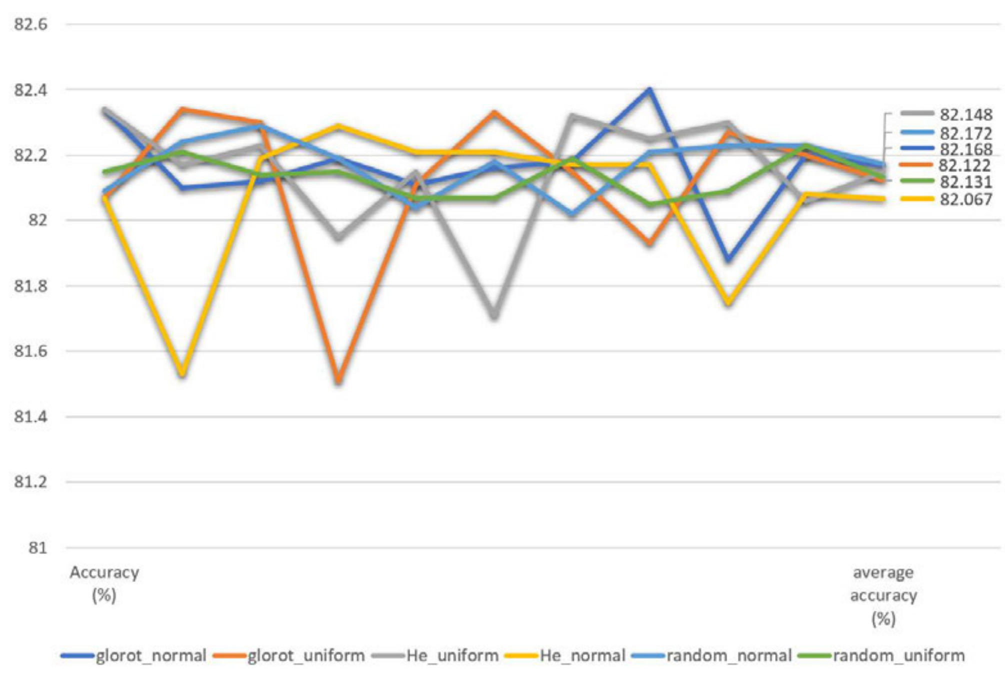


Figure 39. Performance of various kernel initialisers on BSigReLu activation function

As can be observed in Figure 39, the performance of random_normal kernel initialiser results in better performance accuracy than the other kernel initialisers. There is an insignificant difference between glorot_normal and random_normal initialisers despite glorot_normal generally being used in the DL model (Glorot & Bengio 2010; Lee, CS, Baughman & Lee 2017). Ramanujan et al. (2020) affirmed the randomness in the weight's initialisation produces subnetworks that generate impressive performance without needing to explicitly modify the weights but rely on the automatic random with a normal distribution of weights values. Figure 40 depicts the KDELM execution process flow.

Table 18 presents the experimental result using KDELM. The result verified the contributions of the proposed KDELM (Architecture VII). Comparing architecture VII from Table 18 with architecture VI from Table 17, it can be observed that the learning accuracy is comparable however an improvement of 14% in execution time is observed. This finding is consistent with other studies that have employed the DL architecture in the conventional kernel-based ELM (Afzal, Nair & Asharaf 2021). This means the KDELM is fast to learn even when expose to new and unseen datasets.

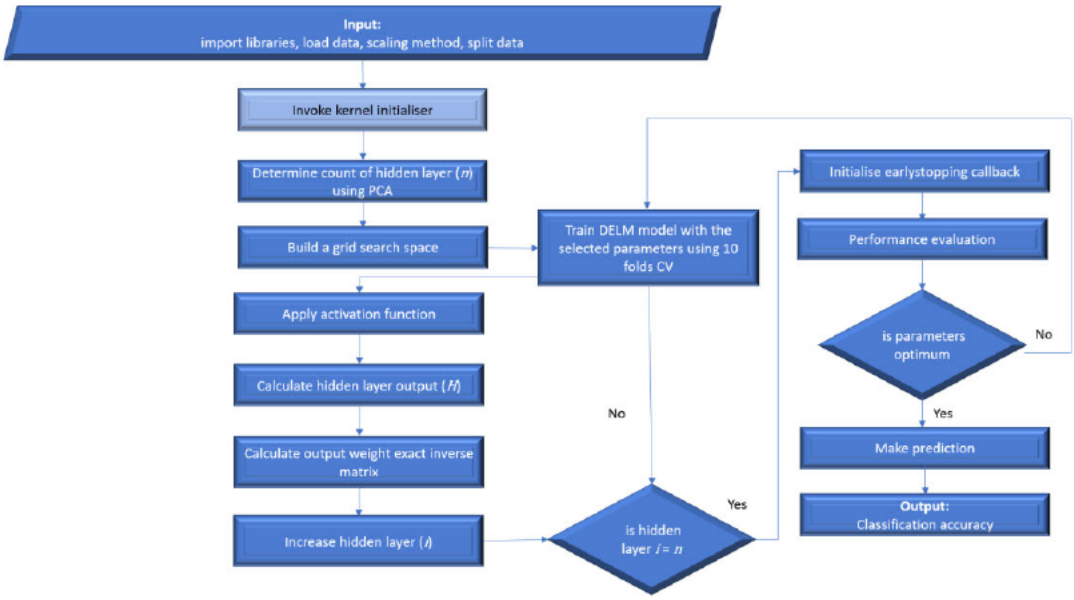


Figure 40. *KDELM execution process flow*

Table 18. *Performance of the KDELM*

Architecture	Number of hidden layers	Number of hidden neurons	Epochs	Batch size	Accuracy	Execution time
VII.	2	33, 20	12	1000	82.23%	3.1s ± 0.3

5.3 Model Testing and evaluation

Following the execution of the KNN, SVM, ensemble ML, DELM, and KDELM algorithms, the performance of these models is evaluated to determine which model is best suited to address the given problem on hand. Generally, accuracy is used to gauge the performance of the model. However, there exist other criteria to assess the model performance and these criteria can be visualised with the confusion matrix (Tharwat 2018). The confusion matrix is a technique to summarise the classification performance. It calculates the ratio of correct and incorrect predictions to the total predictions made. More importantly, interpreting the confusion matrix can determine the type of errors made. In a $M_i \ x \ M_i$ matrix, each row in the matrix represents the instances in an actual class while each column of the matrix represents the instances in a predicted class. In other words, in a confusion matrix of (i, j), the number of samples of class i that were assigned to class j. It follows that the diagonal of the confusion matrix captures the correct classification decisions (*i=j*).

In a two-dimensional confusion matrix as depicted in Table 19, the FN (false negatives), TN (true negatives), FP (false positives), and TP (true positives) are calculated. TP is the count of positive instances that are correctly classified as positive while TN is the count of negative instances that are correctly classified as negative. For a multi-dimensional confusion matrix, the TN of a certain class is the sum of columns and rows excluding the class' column and row. FP is the count of negative instances that are incorrectly classified as positive, and FN refers to the value of positive instances that are misclassified as negative. Figure 41 shows the confusion matrix of the KNN model.

Table 19. Confusion matrix

	Classifier class	
Actual class	C1	C2
C1	TP	FN
C2	FP	TN

$$\begin{bmatrix} 6850 & 415 \\ 1181 & 874 \end{bmatrix}$$

Figure 41. Confusion matrix on the APS employee census dataset using KNN

With reference to Figure 41, TP = 6850, FP = 1181, FN = 415 and TN = 874. The correct values are organised in a diagonal line from top left to bottom-right of the matrix (6850 + 874). More errors were made in predicting employees being highly motivated than unmotivated. Figure 42 shows the confusion matrix for the SVM model.

$$\begin{bmatrix} 4642 & 0 \\ 0 & 4678 \end{bmatrix}$$

Figure 42. Confusion matrix on the APS employee census dataset using SVM

With reference to Figure 42, TP = 4642, FP = 0, FN = 0 and TN = 4678. The correct values are organised in a diagonal line from top left to bottom-right of the matrix (4642 + 4678). No errors were made in the prediction. From the confusion matrix, the precision, recall, F-score, and accuracy can be calculated easily. Accuracy is the calculation of correct classifications divided by the total number of classifications and is denoted as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{17}$$

It is showing the overall correctness of the model. However, apart from accuracy, precision could provide us with some more valuable insights. It is the measure of the accuracy provided that a specific class has been predicted. Precision is the proportion of true positive against all the positive results and is denoted as:

$$Precision = \frac{TP}{TP + FP} \tag{18}$$

where TP and FP are the true positive and false positive predictions for the considered class. A multi-dimensional FP is the sum of values in the corresponding column (excluding the TP). On the other hand, the recall equation:

$$Recall = \frac{TP}{TP + FN} \tag{19}$$

is the ratio of correct positive instances classification to the total number of positive instances. It is also known as sensitivity or the true positive rate of the considered class. When the recall value is high means that a classifier returns most of the relevant results. Apart from the above-mentioned, accuracy, precision, and recall calculations, a more comprehensive measure is the F1 score. It combines precision and recalls computing the weighted average. The F1 score is best when the output is 1 and the worst when it is 0. The F-score is calculated with the following formula:

$$F1\,score = \frac{2 * Precision * Recall}{Precision + Recall} \tag{20}$$

Table 20 presents the F1 scores for the KNN and SVM models evaluated in this thesis.

Table 20. Summary of the weighted performance variation between the base models analysed in this thesis

Classifier	Accuracy	Precision	Recall	F1-score	Execution Time
KNN	82%	81%	82%	81%	1s
SVM	100%	100%	100%	100%	19s

As shown in Table 20, the KNN model achieved 82% accuracy with 81% sensitivity while the SVM model achieved 100% accuracy and sensitivity. Therefore, it can be observed on the dataset, that the performance of the SVM algorithm is better than that of the KNN algorithm in all aspects; accuracy, precision, recall, and F1-score. Apart from accuracy, precision, recall and the F1-score, the performance of the models investigated in this thesis is particularly measured by Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Percentage of Similarity (PS), and Computation Efficiency (CE). This is to provide an unbias analysis of the results from various models experimented with within this thesis. Similarly, these indices are used in the study done by (Khan et al. 2021; Mastromichalakis 2021). The measures are calculated based on the formula below:

$$MSE = \frac{1}{N} \sum_{o=1}^{N} (y_o - \hat{y}_o)^2 \tag{21}$$

$$RMSE = \sqrt{MSE} \tag{22}$$

$$PS = \frac{y - \hat{y}}{||y||.\,||\hat{y}||} \tag{23}$$

$$CE = T_I - T_1 \tag{24}$$

Where y is the observed data, $\hat{y}$ is the predicted value of y, N is the sample size, T_i is the execution end time and T_1 is the execution start time. RMSE can be derived by calculating the square root of MSE. Figure 43 illustrates MSE on a graph whereby y is being represented by the dots and the points on the line are the predicted value ($\hat{y}$). There are numerous lines (A, B, C) that can represent the given dataset. The distance between $\hat{y}$ and the fitted line (B) is known as error. MSE can then be calculated by averaging the sum of squares for all the $\hat{y}$. The best fit model would have high PS with low MSE, RSME and CE. This means high accuracy with low error and fast learning. Table 21 shows the models' performance evaluated on 10 iterations.

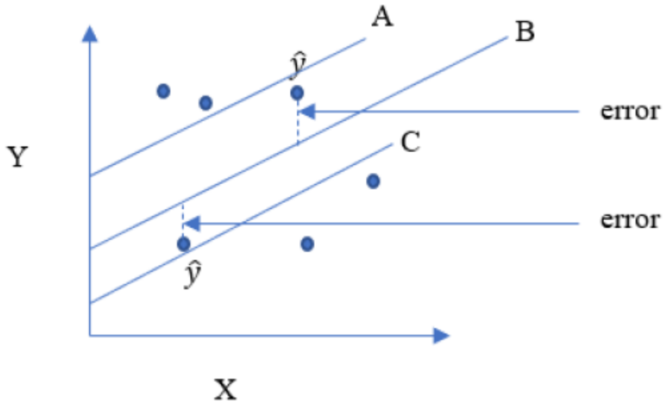


Figure 43. *Mean Squared Error (MSE) representation in graph*

Table 21. *Models performance evaluated on 10 iterations*

Models	Architecture	MSE	RMSE	PS	CE
KNN	-	0.18	0.42	82%	1.6s ± 0.49
SVM	-	0	0	100%	3.4s ± 0.67
EL (KNN + SVM)	-	0.71	0.84	82%	550.2s ± 203.33
ELM with BSigReLu	-	0	0	100%	1.7s ±0.458

Models	Architecture	MSE	RMSE	PS	CE
PCA-DELM with BSigReLu	II	3.68	1.92	77%	542.9s ± 29
PCA and grid search on DELM with BSigReLu	V	0.40	0.63	82%	12.5s ± 0.67
PCA and grid search CV on DELM with BSigReLu	VI	0.13	0.36	82%	3.6s ± 0.49
PCA, grid search CV and KDELM with BSigReLu	VII	0.13	0.36	82%	3.1s ± 0.3

KNN: K-Nearest Neighbour; SVM: Support Vector Machine; EL: Ensemble Learning; ELM: Extreme Learning Machines, DELM: Deep Extreme Learning Machines; KDELM: Kernel-based Deep Extreme Learning Machines; BSigReLu: Blended Sigmoid Rectified Linear activation function, PCA: Principal Component Analysis, CV: Cross-Validation, MSE: Mean Squared Error, RMSE: Root Mean Squared Error, PS: Percentage of Similarity, CE: Computational Efficiency.

The performance of the newly developed model is evaluated through testing the training model on the 9320 identified test datasets. Experimental results have verified the contributions of the proposed KDELM model wherein the proposed model outperforms other models in terms of scalability and efficiency. The KDELM performance in terms of MSE, RSME and PS are comparable with other models examined. This means deploying any one of the models examined in this study is capable to analyse the employee learning motivation signals autonomously and accurately. The KDELM is more efficient with a substantial improvement in execution speed by 419% despite its deep architecture. Comparing KDELM with a conventional model like KNN, KDELM is slower by 1.5s to compute. This is not alarming due to the KDELM model complexity. It is expected that KDELM will be more robust and generalise better than other models in learning high-level features presented in the real-world dataset (Qutub et al. 2021; Tabrizi, Pashazadeh & Javani 2020). The EL model is by far the slowest with the highest MSE and RSME. The result is as expected because when complexity increases, the parameters required for tuning increase as well. Consequently, the time needed to execute the model proportionately increases. However, this preliminary finding will change with further model comparison and selection.

5.4 Model comparison and selection

To select the good-fit model, an unbiased estimate using the 5x2CV paired *t*-test is used for the models' comparison. The 5x2CV paired *t*-test is a 2-folds CV operationalised with 5 iterations (Hamarashid 2021). There exist other validation testing methods such as leave-one-out CV, k-fold CV, Wilcoxon signed-rank test however, the 5x2CV paired *t*-test has been selected because of its statistical soundness and suitability to compare different types of models on the same feature set (Hamarashid 2021). In the 5x2CV paired *t*-test, two operations were performed using the same dataset. Firstly, the dataset is split into the train (90%) and test (10%) datasets. Then the model is trained with the training dataset and tested with the test dataset, called 1st fold. Secondly, the dataset used for training and testing the model is reversed. That is when the model is being trained with the test (10%) dataset and tested with the train (90%) dataset, called the 2nd fold. In both operations, the accuracy of the model is identified. The difference between the error rate is calculated, to get D^1 and D^2. For this first run of CV, the mean and the variance of the differences are estimated (S^2) where:

$$\overline{D} = \frac{D^1 + D^2}{2} \tag{25}$$

$$S^2 = (D^1 - \overline{D})^2 + (D^2 - \overline{D})^2 \tag{26}$$

The variance computed from the 5th run of CV is represented with S_5^2 . The $\tilde{t}$-statistic can be computed with:

$$\tilde{t} = \frac{D_1^1}{\sqrt{\frac{1}{5}\sum_1^5 S^2}} \tag{27}$$

Where D_1^1 is the mean-variance of the first run of the CV. The chosen significance level is $\alpha = 0.05$ (Hamarashid 2021; Talukder & Ahammed 2020). That will give 5 degrees of freedom on the $\tilde{t}$-statistic. Table 22 shows the error rate for each model evaluated on 2-fold CV on 5 iterations.

Table 22. The error rate on each model evaluated on 5x2CV

Model	*t*
KNN	388.9087297
SVM	141.4214
EL	0
ELM	0
DELM	122.4395
KDELM	23.88476

KNN: K-Nearest Neighbour; SVM: Support Vector Machine; EL: Ensemble Learning; ELM: Extreme Learning Machines, DELM: Deep Extreme Learning Machines; KDELM: Kernel-based Deep Extreme Learning Machines.

Each time, two models are being tested. Appendix 9 - Appendix 23 record the 2 folds of each iteration of the pairwise models. Table 23 displays the summary results of the 5 runs of 2-fold CV, and the resulting *t*-statistics and *p*-values from the significance tests.

Table 23. Comparison between models evaluated on 5x2CV

Model	*t*	*p*	*Significance*
KNN vs SVM	61.87184335	0.00000	True
KNN vs EL	2.357022604	0.03250	True
KNN vs ELM	82.49579	0.00000	True
KNN vs DELM (Architecture VI)	0.311313	0.38406	False
KNN vs KDELM (Architecture VII)	0.077364	0.47067	False
SVM vs EL	36.36549	0.00000	True
SVM vs ELM	0	0.50000	False

Model	*t*	*p*	*Significance*
SVM vs DELM (Architecture VI)	83.2399	0.00000	True
SVM vs KDELM (Architecture VII)	6.019713	0.00091	True
EL vs ELM	0	0.50000	False
EL vs DELM (Architecture VI)	1.703773	0.07457	False
EL vs KDELM (Architecture VII)	0.080536	0.46947	False
ELM vs DELM (Architecture VI)	26.24234	0.00000	True
ELM vs KDELM (Architecture VII)	5.154461	0.00180	True
DELM vs KDELM (Architecture VII)	0.035869	0.48639	False

KNN: K-Nearest Neighbour; SVM: Support Vector Machine; EL: Ensemble Learning; ELM: Extreme Learning Machines, DELM: Deep Extreme Learning Machines; KDELM: Kernel-based Deep Extreme Learning Machines.

Given the α of 0.05, a null hypothesis is that the models' performance is the same. The result from Table 23 shows that there is no significant difference in the performance of 7 pairwise models indicated with 'False' in the table (KNN and DELM, KNN and KDELM, SVM and ELM, EL and ELM, EL and DELM, EL and KDELM, DELM and KDELM). This means the null hypothesis is accepted. Whether KNN is better than DELM or DELM is better than KDELM there is no way to determine this as they are equally good. Where else, the null hypothesis on the other 8 pairwise models marked with 'True' are rejected (KNN and SVM, KNN and EL, KNN and ELM, SVM and EL, SVM and DELM, SVM and KDELM, ELM and DELM, ELM and KDELM). That means the data support the notion that there is a significant difference in the performance of the paired models because the significance test results are lesser than the chosen 0.05. This finding is contradictory to the observations from Table 21.

Table 23 provides evidence that some models are performing differently as evident through the 5x2CV statistical test result, even though they have the same error rates. For example, comparing the performance of KNN and EL from Table 21. The error rate is the key determinant to select the best model. Therefore, based on the error ratio presented in Table 22, under 5x2CV, EL and ELM are the best classifiers, KDELM the second-best, DELM the third, SVM the fourth and KNN the worst.

The computational execution cost is calculated under each model pair. Table 24 presents the pairwise model comparison on the computation efficiency evaluated on 5 iterations of 2-fold CV.

Table 24. Computational efficiency comparison between models evaluated on 5x2CV

Model	*t*	*p*	*Significance*
KNN vs SVM	1.316378	0.12258	False
KNN vs EL	1.368988	0.11465	False
KNN vs ELM	0.430331	0.34244	False
KNN vs DELM (Architecture VI)	1.267731	0.13036	False
KNN vs KDELM (Architecture VII)	0	0.5	False
SVM vs EL	1.376869	0.11350	False
SVM vs ELM	1.770716	0.06841	False
SVM vs DELM (Architecture VI)	1.446728	0.10381	False
SVM vs KDELM (Architecture VII)	1.705606	0.07440	False
EL vs ELM	1.390422	0.11156	False
EL vs DELM (Architecture VI)	1.383402	0.11256	False
EL vs KDELM (Architecture VII)	1.393043	0.11119	False
ELM vs DELM (Architecture VI)	5.163978	0.00179	True
ELM vs KDELM (Architecture VII)	2.236068	0.03779	True

Model	*t*	*p*	*Significance*
DELM vs KDELM (Architecture VII)	3.585686	0.00789	True

KNN: K-Nearest Neighbour; SVM: Support Vector Machine; EL: Ensemble Learning; ELM: Extreme Learning Machines, DELM: Deep Extreme Learning Machines; KDELM: Kernel-based Deep Extreme Learning Machines.

Result of Table 24, with all values in seconds. Result suggests that the null hypothesis can be rejected on 3 pairwise models with a *p-value* of 0.00179, 0.03779 and 0.00789, which are lesser than the significance level of 0.05. This means, there is a difference in the CE on these models. Even though the CE is no longer than 5s, it is worth noting that CE could be a concern when working on a complex model. Table 25 shows the CE for each model evaluated on 2-fold CV on 5 iterations.

Table 25. Computational efficiency on each model evaluated on 5x2CV

Model	*t*
KNN	1.088214
SVM	1.974710
EL	1.554351
ELM	4.472136
DELM	9.486833
KDELM	4.743416

KNN: K-Nearest Neighbour; SVM: Support Vector Machine; EL: Ensemble Learning; ELM: Extreme Learning Machines, DELM: Deep Extreme Learning Machines; KDELM: Kernel-based Deep Extreme Learning Machines.

The result in Table 25 suggests that KNN is the fastest followed by EL, SVM, ELM, KDELM and DELM. Therefore, to decide on the good-fit model, the aim of the thesis is to be revisited. That is to find the model that is capable of accurately predicting most cost-effectively. Therefore, for this thesis, KNN is the best-fit model.

5.5 Model deployment and maintenance

The selected model can then be stored using the pickle function and deployed for later use to solve the employee learning motivation problem. A different organisation may have different environments for deploying the model. The selected model is generalisable regardless of whether it is to be deployed on a real-time basis or otherwise via batch processing. The preference lies with the organisation depending on the optimisation of the available resources such as budget, memory, storage capacity, computational cost, and effort required. An integral part of deployment is the periodic model evaluation and auditing to ensure the model is maintaining its accuracy and remained optimal.

5.6 Summary

The overall objective of Chapter 5 was to discuss the use of a machine learning algorithm as the main method for testing the hypothesized model. There were two stages, exploratory data analysis was done to identify the main characteristics of the constructs while the inference measurement model was to find the correlations and prediction. In sum, it has been discovered there is an association between AI support and EOC characteristics with employee learning outcomes and there is no multicollinearity issue among the investigated features. These findings suggest that the models are reliable and can be generalised. The usage of AI support and the investment of EOC is attributable to the employee's learning outcome. Such findings have significant theoretical and practical implications, which are discussed in Chapter 6.

CHAPTER 6 DISCUSSIONS

6.1 Introduction

This chapter presents an outline and the interpretation of the thesis findings. The discussion is focused on the theoretical, practical and methodological implications of these findings as well as the strengths and limitations of the thesis conducted herein. Finally, suggestions for future research examining employee learning outcomes linkages at the employee level are presented.

6.2 Major Findings

- Employee expectations can be obtained via EOC branding which is an explicit motivation that eventually leads to overall job satisfaction, performance, and well-being.
- Employees' self-determination was positively related to basic psychological need satisfaction, which, in turn, positively impacting employees' learning outcomes.
- Partial meditationl was supported providing 95% CI for the indirect effect of AI with 5000 bootstrap on EOC utility perception and self-determination on employee learning outcomes.
- The relationship between perceived EOC utility and self-determination is moderated by the usage of AI

6.2.1 EOC utility perception and learning outcome

Figure 44 presents the correlation heatmap of the EOC utility perception and employee learning outcomes.

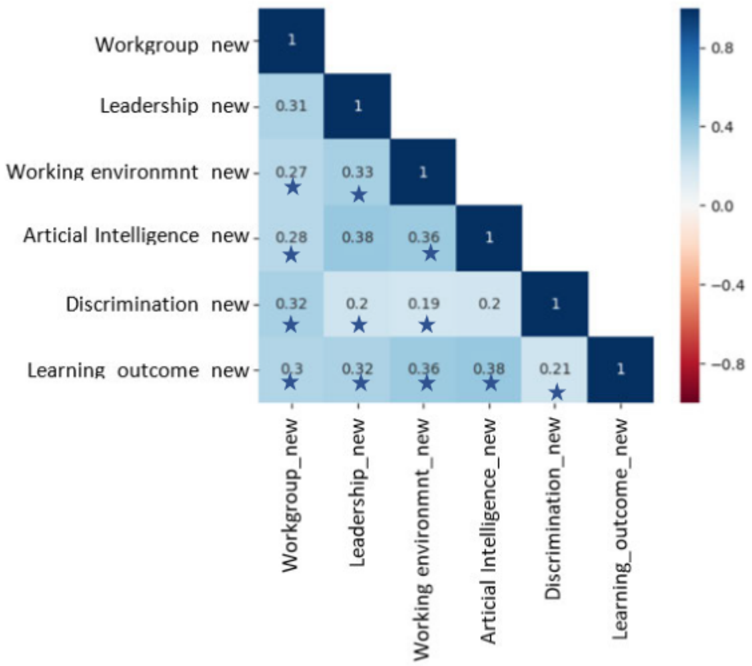


Figure 44. The correlation heatmap of the pairwise correlation of the EOC utility perception and employee learning outcomes

The correlation coefficient ranged from a low of 0.21 to a high of 0.38. Overall, this thesis presents good evidence suggesting EOC utility perception (workgroup, leadership, working environment, AI, and discrimination) is indeed related to the presence of employee learning outcomes (job satisfaction, performance, and well-being). Based on the social exchange theory, employer and employee relationships is an exchange process. This exchange is never meant to be equal. An employer is always trying to maximise its benefits by recruiting employees at minimised costs. Similarly, employees are weighing the benefits they could obtain from the employer and the cost of this social relationship to evaluate if they should continue in the social exchange. When an employee feels that the benefits outweigh the costs, the employee will stay in the relationship and develops a sense of belonging to the organisation. This results in employees feeling obligated to respond positively to favourable offers from the employer as an act of reciprocity. Houben et al. (2021) confirmed the reciprocal relationship between employee learning motivation and employment. The findings further support the arguments from Bock et al. (2005), Smith, Gregory and Cannon (1996) and Zhang, W, Jiang and Zhang (2021) about the association between employee commitment to the organisation and overall job satisfaction. Thus, the cost and benefits analysis in the social exchange process plays a critical role. Potential employees often rely on explicitly available information to establish a comparative level that is mostly influenced by social expectations and experience. Therefore, the results of the present thesis confirmed that employee expectations can be obtained via EOC branding which is an explicit motivation that eventually leads to overall job satisfaction, performance, and well-being.

For the long-term health and success of any organisation, the retention of employees is critical. Specifically, organisations' investment in EOC branding helps to attract and retain the right talents. Leadership, working environment, the general perception of the workgroup, non-discriminant value, and the adoption of AI systems are attributes that link to positive employees' learning behaviour outcomes. As discussed, in Chapter 2, according to the signalling theory, EOC branding signals that the organisation is supportive of employees and is seeking to establish and maintain a mutual employer-employee relationship.

6.2.2 Employees' self-determination and learning outcome

Figure 45 presents the correlation heatmap of the pairwise correlation between employees' self-determination and learning outcomes.

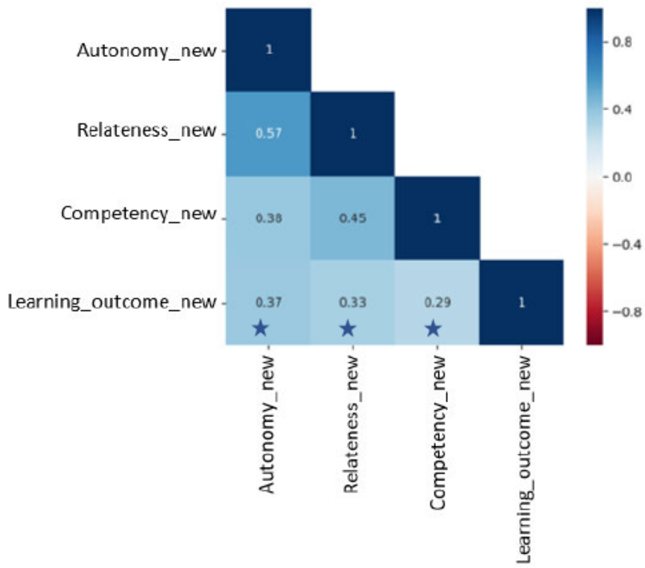


Figure 45. The correlation heatmap of the pairwise correlation between employee self-determination and learning outcomes

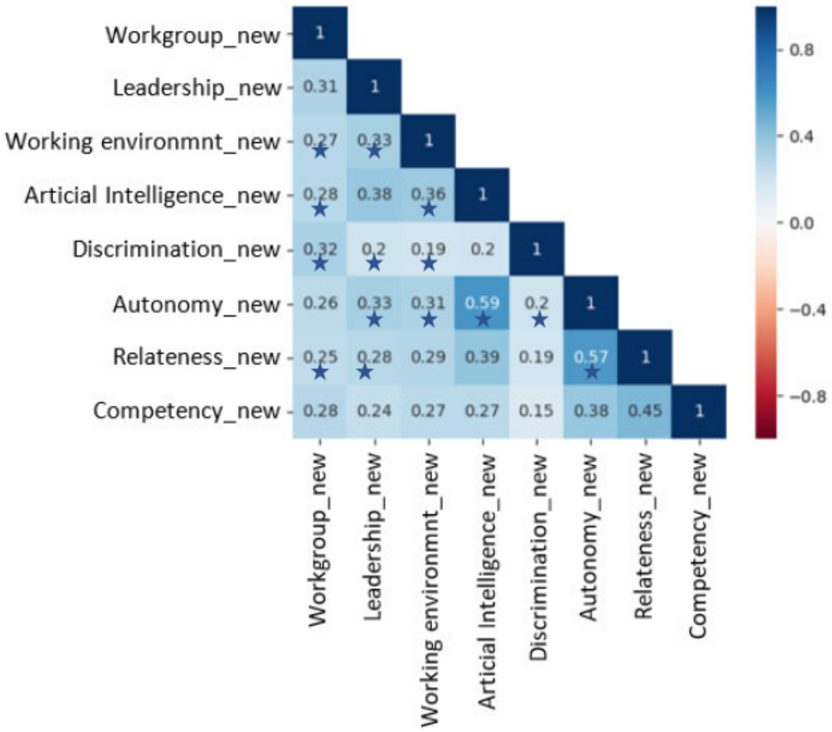
The correlation coefficient ranged from a low of 0.29 to a high of 0.57. The result reaffirmed, that apart from environmental motivation, employees have their own ignited desire (autonomy, competency, relatedness) to learn and master new skills that contribute to a positive employee learning outcome. Consistent with the findings from Broeck et al. (2016), this thesis adds a new dimension with empirical evidence from the APS population showing that employees value autonomy, competence, and relatedness. Irrespective of age or gender everyone has these three needs as posited in the self-determination theory according to Ryan and Deci (2000a). Therefore, it was not surprising employees' self-determination was positively related to basic psychological need satisfaction, which, in turn, positively impacted employees' learning outcomes.

Deci, Edward L., Koestner and Ryan (2001) argued environmental rewards thwart the objective of the intention and undermine attitudinal motivation. That is when the attitudinal value of the task is weakened and the individuals associate their behaviour with the reward. However, it can be argued, that what motivates employees to do what they are doing day-to-day may not necessarily relate to environmental rewards. Doing the task itself can be rewarding for the employee. For example, having the autonomy to choose what to learn and be recognised for solving an optimal challenging learning course is rewarding in itself. This is also evident in the study by Hewett and Conway (2016) that verbal rewards could also influence the employee's day-to-day work behaviour that does not necessarily form part of the organisational policies for monetary rewards. Therefore, it is fair to say that employees are attitudinally motivated and empowered on their own accord to make further advances contributing to their job satisfaction, performance, and well-being.

6.2.3 Employee EOC utility perception and self-determination

Figure 46 depicts the correlation heatmap of the pairwise correlation of the EOC utility perception and self-determination. In other words,

Figure 46 shows the correlation heatmap between attitudinal (self-determination) and environmental (EOC utility perception) motivators. The heatmap shows evidence of the relationship between attitudinal motivators with employee learning outcomes and environmental motivators with employee learning outcomes. It might seem like both environmental and



attitudinal motivation are opposed whereby attitudinal motivation comes from within while environmental motivation comes from external sources. No doubt, employees should be proactive and take ownership of their learnings, but it's also the responsibility of the employer to guide those efforts.

Figure 46. The correlation heatmap of the pairwise correlation of the EOC utility perception and employee self-determination

The correlation coefficient ranged from a low of 0.19 to a high of 0.59. As such, the result strongly supports the third hypothesis, within the limits of the model that both EOC utility perception as the environmental motivator and self-determination as the attitudinal motivator should be mutually complementing contributing to employee learning outcomes. As described in the self-determination theory (Ryan and Deci, 2000a), both attitudinal and environmental motivation are powerful forces in shaping the motivational outcome. At the same time, as postulated in the social exchange theory, employees are constantly evaluating the value of the task and how it aligned with their sense of self hence, employee motivation varies in a continuum ranging from amotivation, and environmentally motivated to attitudinally motivated. Therefore, employees' EOC utility perception and self-determination could be present at the same time resulting in some form of employee learning outcomes.

6.2.4 Testing the mediating effect of AI on EOC utility perception and self-determination on employee learning outcomes

Following the statistical analysis of the correlation coefficient, it is typical in contemporary research to further substantiate the findings with mediation analysis to establish the causal relationship of the variables in the thesis endeavour. A mediation research design has been referred to by Pieters (2017) and Memon et al. (2018) as an indispensable tool to scientifically examine the mechanisms which intervene in the relationship between the dependant and independent variables. In another word, a mediator helps to answer ‘why’ or ‘how’ the independent variable such as EOC utility perception and self-determination affect the dependent variable which is the employee learning outcomes. AI was introduced as a potential mediator which has an influence on either weakening or strengthening the existing correlation between the independent variable (EOC utility perception and self-determination) and the dependent variable (employee learning outcomes). Figure 47 is the submodel to test the role of AI in mediating the relationships between the dimensions of EOC utility perceptions, self-determination, and employee learning outcomes.

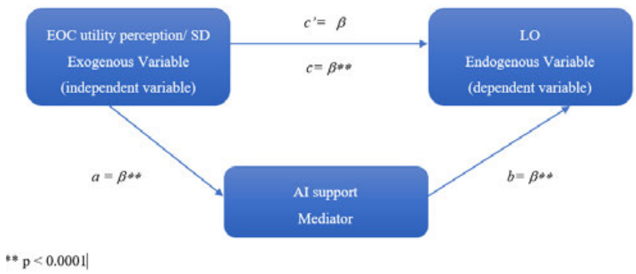


Figure 47. The theoretical model of the role of AI as the mediator in the relationship between dimensions of EOC utility perception, self-determination, and employee learning outcomes

A common approach for testing the mediating effects is following the Baron and Kenny (1986) guidelines, however, Aguinis, Edwards and Bradley (2016) have criticised the causal step approach and encouraged the use of the more current technique for mediation analysis. That is because one of the first conditions in the causal step approach is also its limitation which is testing the significance of the exogenous variable, A with the endogenous variable, $C (A-> C)$. Memon et al. (2018) echoed the testing of $A-> C$ is rather unnecessary for confirming the mediation effect yet hindered the researcher from further investigating the other theoretically driven mediators. As such in this thesis, a contemporary mediation analysis approach was implemented following Hayes' PROCESS macro (Aguinis, Edwards & Bradley 2016). However, PROCESS macro was neither designed for PyCharm nor coded with Python. Fortunately, an open-source PyProcessMacro; a replication based on PROCESS macro was made available by Quentin (2020). Hence, the PyProcessMacro library was used to enable the mediation analysis for this thesis. An important improvement and differentiator in the PyProcessMacro is that the mediation analysis can proceed even when the $A-> C$ is insignificant.

Referring to Figure 24 of Chapter 5.2.3.1, all variables were significant, however, when dealing with smaller datasets even when the result is insignificant using the PROCESS macro approach, the mediation analysis could proceed because the mediation model being tested is aligned with the theory. For simplicity, in this thesis, the mediation analysis was done one at a time using a two-step linear regression approach. Table 26 presents the hypothesised model of the exogenous variable, EOC utility perception, and self-determination, AI support as the mediator variable, and the employee learning outcomes as the endogenous variable.

Table 26. The role of AI support in the relationship between EOC utility perception, self-determination, and employee learning outcomes

	a path	*b* path	*c* path	*c'* path	Effect	Boot SE	Boot Lower CI	Boot Upper CI
1. WG-AI-LO	0.0000 **	0.0000 **	0.0000 **	0.0000 **	0.0774	0.0012	0.0751	0.0798

	a path	*b* path	*c* path	*c'* path	Effect	Boot SE	Boot Lower CI	Boot Upper CI
2. WE-AI-LO	0.0000 **	0.0000 **	0.0000 **	0.0000 **	0.0604	0.0009	0.0588	0.0622
3. Leadership-AI-LO	0.0000 **	0.0000 **	0.0000 **	0.0000 **	0.0626	0.0009	0.0609	0.0644
4. Discrimination-AI-LO	0.0000 **	0.0000 **	0.0000 **	0.0000 **	0.0589	0.0011	0.0568	0.0611
5. Autonomy-AI-LO	0.0000 **	0.0000 **	0.0000 **	0.0000 **	0.0899	0.0015	0.0870	0.0929
6. Relatedness-AI-LO	0.0000 **	0.0000 **	0.0000 **	0.0000 **	0.0761	0.0010	0.0741	0.0781
7. Competency-AI-LO	0.0000 **	0.0000 **	0.0000 **	0.0000 **	0.1000	0.0016	0.0969	0.1032

Confidence Interval (CI); WorkGroup climate (WG); Working Environment (WE), Artificial Intelligence (AI); Learning Outcome (LO); Standard Error (SE). $^{**}p < 0.0001$.

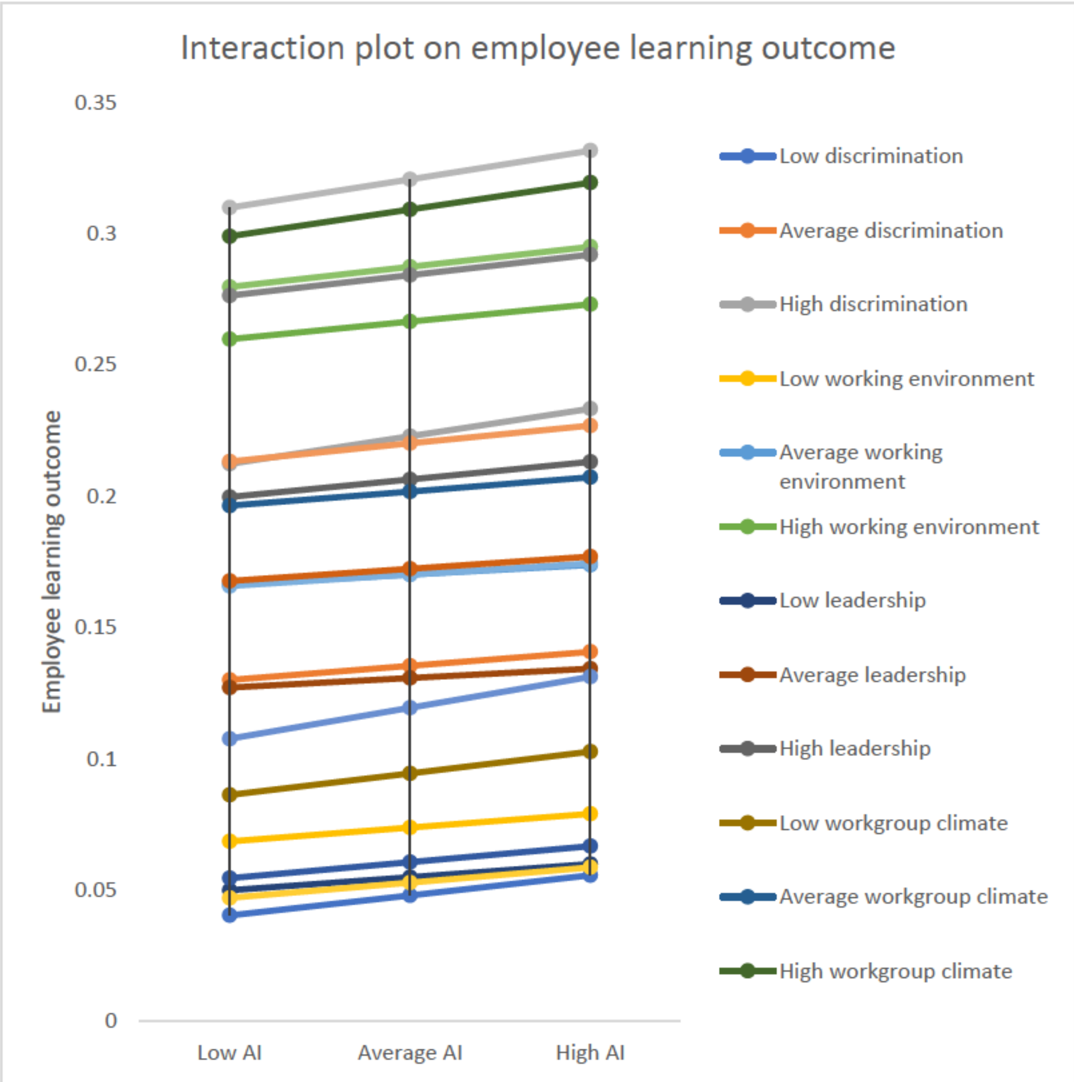
The regression of EOC utility perception (workgroup climate, working environment, leadership climate, non-discrimination), self-determination (autonomy, relatedness, competency) on the mediator, and AI support are significant, however, the test conducted did not find full mediation in the model. That is the significant paths between EOC utility perception (workgroup, work environment, discrimination) and self-determination (autonomy, relatedness, competency) with employee learning outcome did not reduce to non-significant when AI support is included in the predictive model. No doubt, the relationships between workgroup, work environment, discrimination, autonomy, relatedness, and competency as well as employee learning outcome and AI support became less significant, but they remained significant. According to Baron and Kenny (1986), to establish a complete mediation, the effect of EOC utility perception and self-determination over the employee learning outcome while controlling for the mediator, AI support is equivalent to the reduction of significance to a point of no correlation. Thus, full mediation was not fulfilled, and partial mediation was supported providing 95% CI for the indirect effect of AI support with 5000 bootstraps.

6.2.5 Testing the moderating effect of AI on EOC utility perception and self-determination on employee learning outcomes

The preceding mediation analysis examined under which circumstances the AI support effect operates and here the author executes the testing of moderation analysis aiming to statistically investigate the boundary of the AI support effect. According to Baron and Kenny (1986), a moderator variable is a third variable that affects the correlations between two variables. When a third variable is introduced, it changes the interaction effect of the relationship between the predictor and outcome variables. There are three possible outcomes to the interaction effect, which are either increased, decreased or reverse effect between the predictor and outcome. The theoretical model of interest for the present thesis is shown in Figure 9. The moderating hypotheses state that the direct paths between ECO utility perception and self-determination and employee learning outcomes differ (in magnitude and/or direction) across high and low levels of AI support. Therefore, to test the hypothesis that the employee learning outcomes are a function of multiple motivational factors and whether AI support moderates the relationship between EOC utility perception and self-determination, a hierarchical multiple regression analysis was conducted.

In the first step, two variables were included: employee workgroup climate and the usage of AI. These variables accounted for a significant amount of variance in employee learning problems, R^2 = 0.1845, F(2, 93196) = 10545.5317, p < 0.001. To assist with interpretation and avoid potentially model-fitting problems due to high multicollinearity with the interaction term, the variables were standardised and an interaction term between AI and employee workgroup climate was created. Next, the interaction term between employee workgroup climate and AI support was added to the regression model, which accounted for a significant proportion of the variance in employee learning problems, ΔR^2 = 0.0068, ΔF(3, 93195) = 7349.0718, p = 0.000, b = 0.1074, t(93195) = 27.9264, p < 0.01. Examination of the interaction plot showed an enhancing effect that as employee workgroup climate improved and AI support increased, employee learning outcomes increased. At low or poor employee workgroup climate, employee learning outcome was also poor with low AI utilisation. The results show that AI support could have a considerable impact on employee learning outcomes. A similar process was repeated on the rest of the variables.

To assess the moderation effect of AI support on EOC utility perception, self-determination and employee learning outcome, initially, the baseline model was estimated. Then



the interaction effect was added to the baseline model and reestimated. The new model generated was assessed for significant R^2 change and significant effect of the new interaction term. The result of the interaction plot between the EOC utility perception, self-determination and AI support is depicted in Figure 48.

Figure 48. *Interaction plot on employee learning outcome*

Figure 48 shows, the relationship between AI support and employee learning outcome. By plotting the interaction term, it captured the model whereby the relationships change based on the value of another variable. There is a positive relationship between all variables with AI support affecting the employee learning outcome. These results showed that AI support increased employees' sense of autonomy, competence, relatedness, workgroup climate, working environment, leadership climate, and non-discrimination values. The effects are significant; hence support was found for H_7 that the relationship between perceived EOC utility and self-determination is moderated by the usage of AI.

6.3 Hypothesis testing

The main goal of hypothesis testing is to estimate the probability of getting the observed result which is often referred to as the *p*-value of the correlation coefficient. The null hypothesis (H_0) is a statement of no relationship or difference between two variables or factors being tested. Alternatively, the H_1 - H_8 is the hypothesis the author is interested in proving. According to McDonald (2014), the conventional statistically significant value is set at 0.05. The choice of the conventional significance level is rather arbitrarily, it can be set at 0.04,.025 or 0.071 however, in this thesis it has been set at 0.05 as proposed by McDonald (2014) and Taff (2018). This means there is a 5% probability that the alternative hypothesis is accepted while the null hypothesis is true. Table 27 summarises the hypothesis testing result of this thesis.

Table 27. Summary of hypothesis testing result

Hypothesis	Result of hypothesis
H_1: Employee EOC utility perceptions are positively associated with employee learning outcomes.	Accept
H_2: Employee self-determination is positively associated with employee learning outcomes.	Accept
H_3: Employee EOC utility perception is positively associated with employee self-determination.	Accept
H_4: The relationship between EOC utility perception as an environmental motivator and employee learning outcomes is mediated, at least in part, by AI support.	Accept

Hypothesis	Result of hypothesis
H_5: The relationship between self-determination as an attitudinal motivator and employee learning outcomes is mediated, at least in part, by AI support.	Accept
H_6: The relationship between EOC utility perception as an environmental motivator and self-determination as an attitudinal motivator is mediated, at least in part, by AI support.	Accept
H_7: The relationship between perceived EOC utility and self-determination motivation is moderated by AI support. That is, employee learning outcomes will be higher following AI support when EOC utility perceptions are high than when they are low.	Accept
H_8: EOC utility perceptions, self-determination, and AI support significantly predict employee learning outcomes.	Accept

6.4 Implications for Theory, Practice and Methodology

6.4.1 Theoretical implications

This thesis offers multiple implications to the theory and employee learning motivation literature. Firstly, it sheds light on environmental, and attitudinal influences on employee learning behavioural consequences. Learning is mostly associated with student learning in an educational context rather than employee learning in the workplace context. Therefore, the current thesis enriches the learning literature by studying employee learning motivation. This provides insights into the nuances of employee learning.

Secondly, early studies have focused on content (Maslow 1970, 2013) and the process theories of motivation (Porter & Lawler 1968; Vroom 1964); therefore, discussion of dualists theory (Reiss 2012)is rare. The current thesis provides a coherent and comprehensive theoretical framework integrating the SDT and agency theory. SDT is a dualist theory and also a macro-theory of motivation (Adams, Little & Ryan 2017). The agency theory is used to represent the interaction of all agents involved in the learning context. Hence, the extension of SDT with agency theory discloses avenues for future researchers.

Thirdly, apart from SDT and agency theory, employees' decision to learn is guided by decision theory. Before we arrive at a decision, a mental model is created to aid the processing of information. It is a broader concept capturing the essence of a machine learning problem. In machine learning, the output of the model suggests the optimal actions under various conditions. That is as seen before in the trained dataset. Similarly, in an organisational setting, both employers and employees are constantly involved in decision-making processes. Both entities are in a combative environment. Hence, often seen in a dispute as described in the agency theory as the agency-principal problem whereby employers want employees to learn but employees are reluctant to invest time in workplace learning. In this situation, employees' productivity decreases, miscommunication increases and organisational goals derail. In worst situations, organisational growth is stagnant and performance deteriorates.

Employees' decision whether to learn or not is also influenced by their knowledge and experience over time on their learning initiative. Employees have some preconceptions of the employer even before joining the organisation through word-of-mouth, social media publication and employer branding which forms the psychological contract (Bal, Chiaburu & Jansen 2010). The psychological contract theory postulated the existence of employee cognitive structure influencing the level of commitment and the willingness to maintain the employer-employee exchange relationship. The exchange relationship between employer and employees is not limited to the formal employment contract but repeatedly demonstrated by researchers the positive influence of psychological contract on employee engagement subsequently influencing employees' behavioural outcomes (Estreder et al. 2020). Similarly, Kwok, Watabe and Ahmed (2021) found evidence of higher employees' job satisfaction when employees perceive the inducement received is higher than psychologically perceived. When the psychological climate is not well maintained, will evoke a psychological contract breach causing the breakdown of the exchange relationship. Therefore, EOC award citation forms a part of the cognitive evaluation that influenced how the employee feels, think and react to the learning tasks, thus creating a basis for the employer-employee exchange relationship. And these exchanges are well-weighted employer-employee exchanges.

The psychological contract breach can also be explained with the expectation confirmation theory positing that employees' have expectations from the employer and their experience in the organisation confirmed if the employer has met the expectations or not. The expectation confirmation theory looks at both the pre and post-behavioural perspectives. In other words, what is expected and what has been experienced influencing the continual behaviour. Therefore, employees' continual learning depends greatly on the gap between expectation and experience. The narrower the gap between expectation and experience, the higher the employee satisfaction with learning engagement. Rahi et al. (2021) confirmed users' Internet banking adoption and continuance usage behaviour.

Social exchange theory postulates that employees will continue the learning tasks only when the weighted reward (outcome) elicits approval from the employee rather than elicits disapproval. Social presence elements as described in CET (Ryan & Deci 2000b) are an important influence on the adoption of employee learning in general. The results of this thesis suggest that employers who are interested in fostering positive employee learning might find guidance in growing the AI literature. That is, investing in AI systems to enable quality decision-making. Therefore, through AI support, employees should be given options on the learning tasks as well as the form of reward that is acceptable for employees to complete the learning program. Overall, AI helps to indirectly institute a communication mechanism that incorporates employees' decisions and fulfilment of the employer's promise to support employees on their self-determined learning path.

Adopting the decision support system theory, AI systems act as an intervention not to decide for the employees but to provide a systemic approach to support the decision-making process. This can be achieved through the provisioning of options and recommendations of learning based on employees' input and past learning pattern recognition as in how AI could be used in employee selection (Murad et al. 2020). AI too can be used for curriculum selection for employees. Customisation of employee professional development plan could enhance the employee learning outcomes indirectly contributing to motivating employees both attitudinally and environmentally.

6.4.2 Pratical implications

The findings of this thesis provide various practical implications for employees, employers, external agencies and policymakers alike. Firstly, the results of this thesis give a deeper understanding of underpinned factors including leadership climate, workplace environment, workgroup climate, non-discrimination values, autonomy, competence, and relatedness in influencing employees' learning motivation. This will help policymakers, managers, and decision-makers to better design strategies for motivating employees to learn. The result from Figure 48 shows that competency and workgroup climate are the top 2 important factors in determining employee learning behaviour. Therefore, managers and decision-makers must take into consideration both environmental and attitudinal motivators to better motivate employees to learn.

The findings of this thesis suggest that EOC utility perceptions are related, albeit indirectly, to affect employee self-determination, which in turn, was found to be related to a desirable employee learning outcome. Of the EOC features examined in this thesis, evaluations of high workgroup climate were found to be the best predictors of employee learning outcomes. This is not surprising because employees are mostly working in a complex organisation often in a matrix structure whereby the employee does not report into a silo functional group but cross-functionally. As such, relationships among employees become very complicated and prone to rising competition, miscommunication, and frustration. In bigger organisations with a global presence, the issue becomes more pronounced with increased diversity among employees hence, posing a bigger challenge. Therefore, the thesis will benefit workgroup leaders and HR managers in maintaining an effective workgroup climate to enable healthy workgroup development and performance.

The better the collaborations among teams, the more efficient is the team. Allowing employees to contribute to knowledge sharing and learn openly among one another. Besides, according to Dyer, Dyer and Dyer (2013), team building is one of the proven strategies for improving team performance and reducing conflicts. As such, organisations that invest in team-building not only help to strengthen the employees' relationships as a team but also generate a perception of support from the employer cultivating stronger ties between employer-employees relationship. It shows a clear proposition from the management committed to supporting and improve on the workgroup climate. Consequently, this suggests that the EOC citation award, apart from serving as a marketing instrument to attract employees, the EOC characteristics also play an important non-instrumental role in communicating to employees the characteristics that the employer values indirectly communicating to the employees that they are valued and cared for by the organisation.

The advantage of identifying the mediating mechanisms in this thesis is that it can provide evidence of what has been largely a contentious issue in learning. AI has been mediating in almost everything today in the new technological era except learning (Clark 2020). However, this thesis opens the possibility of showing AI as a technological force in supporting employee learning outcomes. AI support had shown significant impact in supporting employee learning and could better align employer-employee objectives. Despite, meta-analysis evidence showing rewards thwart motivation (Deci, Koestner & Ryan 2001), there is no reason for employers to resist using a reward in the workplace. CET suggests rewarding employees with care as a payoff for superior completion of learning tasks could produce an excellent effect. Even for a simple task, verbal rewards tend to be an important component in everyday work (Hewett & Conway 2016). Hence, to enable employers to judge what kind of reward, when to provide reward and how to reward effectively in the workplace AI could come into the picture offering models to activate reward objectively without bias. No doubt, focusing on reward alone is deemed insufficient but it does not deny the fact as demonstrated in this thesis that when an employer improves on its environmental attributes such as workgroup climate, working environment, leadership quality, and non-discrimination value overall affects the employees' perceived EOC utility and indirectly influence the employee self-determination resulting in improvement of employees learning outcome.

Apart from focusing on environmental motivation, it is equally important for employers to focus on how to facilitate attitudinal motivation by initiating the development of the AI system from the employee's perspective. Of all the self-determination attributes, evaluations of high competency were found to be the best predictors of employee learning outcomes. This can be explained, when employees have mastered the current level of competency, they will want to challenge themselves to the next level of competency. As described by Duncan (2018), it is the learning curve that employees are constantly getting into. Therefore, the organisation could benefit from AI support to assist employees to thrive in learning. For example, to include more interesting learning activities such as a combination of online learning and on-job-training to move on to the next level of certification as well as to provide more learning pathways and various learning assessment types such as multiple-choice questions, open-ended questions, interviews, and others.

To establish optimal challenge in the learning tasks to ignite attitudinal motivation. Virtual badges, coins, stars and the like or better known as micro-credentials have gained considerable acknowledgement in gaming to reward players' achievements. The success of this virtual celebratory was seen quickly used by a variety of online platforms including Lazada, Shopee and Huffing Post. Similarly, organisations could consider gamification to increase employees' participation and engagement in workplace learning. Early signs of its effects were tested in educational settings and yielded recognition (Boticki et al. 2016; Denny 2013). Therefore, the gamification concept should be considered in the employee learning context possibly with modifications such as allowing the virtual badges to be exchanged with a monetary reward, time-off and others deemed suitable for employees and the organisation.

Finally, as seen in this thesis, perceived EOC utility combined with self-determination and AI support could bring employee learning outcomes to a greater height and can therefore be used to break the current learning barriers seen in the workplace so that positive outcomes for both employers and employees can be achieved. From an organisational development perspective, EOC award citation is not only a branding to market externally to attract talents but also communication mechanisms internally on the characteristics valued by the employer. Support for professional development should be included as part of the EOC key characteristic award evaluation criteria to align between the organisational need for employees to learn and be supported in learning for employees looking to build their careers.

6.4.3 Methodology implications

As with theoretical and practical implications, this thesis also contributes from the methodological perspective. This thesis has taken the positivism paradigm and carried out with a quantitative approach following the empirical data analysis. The core strength of this thesis is the adoption of recent advances in statistical learning and the convergence of ML and DL algorithms to achieve advanced artificial neural networks. To further optimise the learning model, a customised activation function was introduced resulting in an efficient learning model despite the complex structure of analysing employees' learning motivation. A rigorous analysis was done with multiple iterations of experiments using PyCharm 193.5662.61 built with an Anaconda environment running on a 2.8GHz i7 CPU.

Secondly, the historical dataset gathered from APS employees (n = 93,199) was deemed to be statistically reasonable and can be considered as high. Miočević et al. (2018) suggested that sample sizes of around 500 are optimally required for testing the mediation effect. Therefore, to determine the correct sample size is obtained and to avoid sampling error, Yamane's sample size calculation formula was used (Liu, X & Prompanyo 2021; Yamane 1973) and can be referred to in Chapter 4.6.4. The sample size (n = 93,199) is considered substantial as it is more than the calculated size recommended (n = 398). Due to the substantial sample size, it is predicted that the central relationships analysed within the cohort and factors cited influencing employees' motivations are reliable, valid and enhance the generalisability of the research model.

Finally, even though, the common method bias is largely a theoretical concern than a practical issue (Baumgartner, Weijters & Pieters 2021), to avoid the common method bias, the constructs under study were entered into factor analysis and the PCA was conducted. The correlation heatmap is used to check the multicollinearity assumption (see Figure 24). The result suggests that multicollinearity does not present in this thesis given that the highest correlations between the Autonomy and Artificial Intelligence constructs are 0.59 which is significantly lesser than the 0.85 ratios proposed by (Kline 2015). Thus, multicollinearity has not been violated. Further, the Varimax rotation PCA was conducted yielding 2 factors with eigenvalues > 1 (Figure 25). Labelled as PCA1 (relatedness, competency, autonomy) and PCA2 (workgroup climate, leadership, non-discrimination values, working environment) that explained 39.62% and 14.69% variances of the dataset respectively. Given that a single factor did not emerge, and the overall factor did not account for most of the variances, the common method bias is not considered a major problem in this thesis (see Appendix 4). The dimensionality reduction using PCA enriches the reliability and validity of the data set and contributed to the efficiency of the various models presented in this thesis.

6.5 Limitations of the thesis and recommendations for further research

It is contended that the census data obtained is from an ethical and reliable source and that the analysis techniques employed were appropriate. This has enabled the author to unpack the relationships between the variables in the framework and provide predictions that can be revealed with machine learning algorithms. Nevertheless, this thesis has some limitations and one of them is the use of secondary data. As the author has no control over the data collection process it was assumed that the data collected is of high validity and reliability. Besides, the hypothesis testing was done involving a single source which is employees. Accordingly, the observed relationships are exposed to common method bias that is tending to be influenced by employees' self-deception. Any negative experience from the employee would have skewed the overall ratings. However, the utilisation of census data represents an appropriate mechanism for the risk identified that can be mitigated in future research by using triangulation. According to Denzin (2017), there are four types of triangulations namely, data, investigator, theory and method. Instead of relying on data from a single source, method triangulation can be used in future research to investigate the relationships between variables presented in this thesis. It has been noted that the data obtained from multiple sources provide more richness and produce more vigorous findings. Therefore, apart from census data from employees, a targeted interview can be conducted, or a focus group can be organised to gather the required data from multiple sources so that good coverage of multiple points of view can be obtained. Specifically, future research must include employers' perspectives.

Besides, there is a likelihood of sample data being exposed to fatigue. That is for a period when the respondents are repeatedly exposed to the research instrument, the respondent will be worn out by skipping some questions or not motivated to continue the survey (Hart, Rennison & Gibson 2005). Census is usually time-consuming. As the census is targeted for planning and initiating improvements in APS hence, the questions are not targeted for this thesis purpose. There were 95 questions in total however only a handful was repurposed and used in this thesis. Therefore, it is not surprised due to many questions to be answered especially towards the end of the census respondents are exposed to stimuli problems, losing interest and impact on the overall census result. In this thesis, to overcome this issue the dataset was reengineered, firstly by removing incomplete census data. Secondly, the data sample was randomly selected. Thirdly, splitting the data into train and test data to execute the ML and DL algorithms. Fourthly, bootstrapping was used to resample the data for ML analysis. Finally, hyperparameter tuning and model validation was also done to ensure the optimised model was selected.

Another possible limitation of this thesis is that it is not longitudinal but cross-sectional research. Despite the evidence of relationships presented in the previous chapter, the correlations research design, inferences regarding the nature of the interrelationships among the variables are restricted because there is no direction of the causality could be determined. For example, the relationship found between EOC utility perception and self-determination toward employee learning outcome could be because of reverse causality. That is due to the employee's self-determination in learning the employee could have perceived the EOC utility fulfilment. Preferably a longitudinal study is to be conducted to determine the causal effect among variables. Nevertheless, the findings from this thesis will still be beneficial for organisations and management literature.

A further limitation of this thesis is that the sample is a representation of the APS organisations. Therefore, it could restrict the generalisability of this study and the result should be cautiously used to generalise beyond the APS organisations or other geographical locations. Nevertheless, when organisations share similarities with APS organisations, then the result of this thesis could be useful. Findings from this thesis act as a springboard to suggest future researchers look at different populations given the evidence from this thesis. Employees of diverse backgrounds may have different needs and expectations thus, as done in this thesis, further research needs to be conducted capturing a vast employee demographic composition apart from gender and age such as employment status whether full-time or part-time employees to better understand their point of view on EOC utility, self-determination and employee learning outcome. Ideally, similar research could be conducted in different work contexts covering a wider population to test and ensure the validity of the instrument as a measure of employee learning across a range of industries. Apart, a comprehensive list of variables that characterise EOC utility was not used in this thesis. Hence, further research using additional variables, continuing to explore the new dataset, using other DL methods operationalising EOC utility fulfilment is needed and a comparative study to better generalise the findings.

Finally, while this thesis proposed that AI support is one primary means having its indirect effects, there are certainly other variables that could potentially mediate the relationship between EOC utility perception and self-determination with employee learning outcomes and this should be remedied by future research. Another possible methodological study is to do a comparative study of the traditional and machine learning methods for hypothesis testing. The traditional statistical and machine learning methods are largely regarded as two separate streams of study and rarely been compared with each other. Future research may also want to investigate whether there is a significant difference in employee learning motivation between urban and rural employees or between bigger and smaller cities so that targetted intervention can be provided to address the unmotivated employees in learning in the specific cohort.

6.6 Summary

The overall objective of Chapter 6 was to determine whether there was support for the hypothesized model by testing it and answering the thesis questions. In sum, all hypotheses are accepted, and the findings give a deeper understanding of underpinned factors influencing employees' learning motivation. Multiple theoretical, methodological, and practical implications are discussed. The limitation of the existing thesis and future research directions are highlighted. The next chapter presents the newly developed framework and provides the concluding remarks for this thesis.

CHAPTER 7 CONCLUSIONS

Motivations and learning are broad concepts of both unique challenges and opportunities faced by organisations and workforces. The initial chapter of this thesis provided an overview and evidence of the phenomena of unmotivated employees in learning. The current intense period of emerging technology reveals a widespread need for reorientation of the agenda and policy of EOC utility and learning at national and international levels. However, at present, the organisational behaviour literature provides an inadequate understanding of the linkages between environmental and attitudinal motivation in the employee learning context. The inadequacy of research addressing the contemporary issue in the digital era has been highlighted by numerous scholars (Sitzmann & Ely 2011; Verma, Ahuja & Hermon 2019) and practitioners (Busby 2018). Echoing them, a paradigm shift is needed to address the issue of unmotivated employees in learning. An employee-centric analysis is needed for proactive intervention.

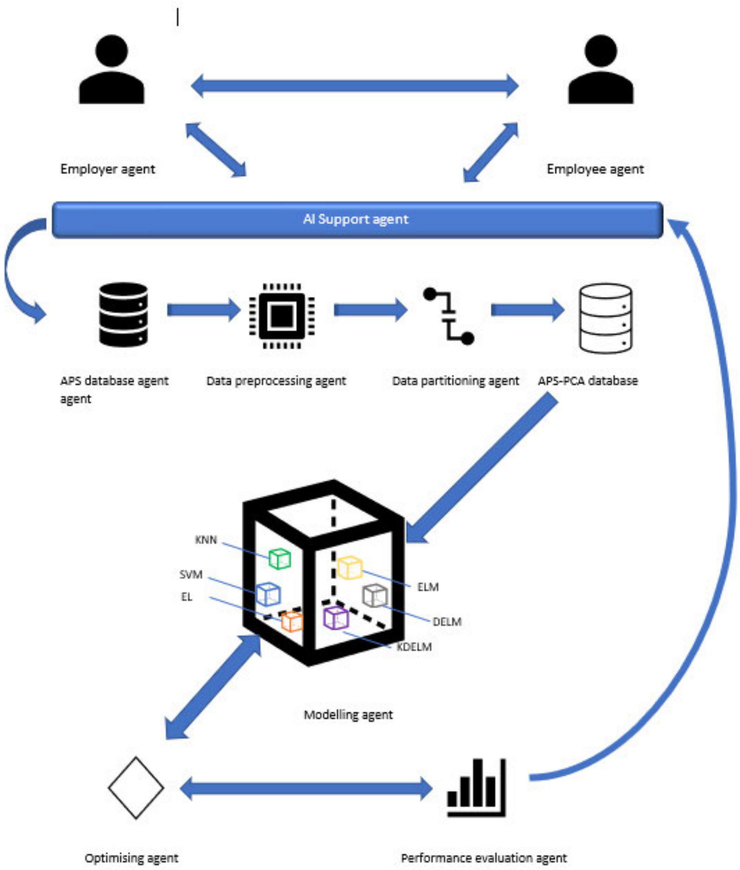
Furthermore, the role of EOC utility perception and AI support in the environment-attitude-behaviour relationships has remained unknown in the literature and there is very little understanding of how investing in EOC citation could exert influence on employee learning and contribute to organisational outcomes. The focus of organisations was on attracting talent through EOC award citations, but little is done to retain and develop talent hence, organisations are not reaping the true benefits of the award recognition.

In the new knowledge economy, employees need to be reflexive; ready to upskill to keep pace with the rapidly changing and technologically complex society. Motivation needs to come into the picture to complete the scene. However, research has not been as extensive in examining the two types of motivations as proposed in SDT (Ryan & Deci 2000a) in fostering employee learning nor proposing a suggestion for AI-driven practical implications. This shows that the quest for interventions that will lead to sustainable workforce engagement in learning that will contribute to employer competitiveness and employees' work satisfaction, performance and well-being is not accomplished. SDT has suggested that employees have a basic need to learn, and learning takes place throughout the lifecycle of learners. Therefore, the provisioning of learning opportunities across employment is one way by which employees can satisfy these basic needs.

This is an opportunity for people to bring their knowledge up to date for personal and professional reasons. It is no longer an option but an absolute necessity in this digital age.

The goal of the present research began with the investigation of employees' motivation to learn through the statistical analysis of relationships between employees' perceived EOC utility and self-determination that influenced employee learning outcomes. Subsequently, how these relationships are affected by the influence of AI support. This thesis has validated EOC utility and SDT in the employee learning context and provided a further understanding of the employees' possible perceptions about the EOC utility and self-determination in achieving a favourable outcome of employee learning with AI support.

The newly developed framework of the self-motivated employee learning model is presented in Figure 49.



KNN: K-Nearest Neighbour; SVM: Support Vector Machine; EL: Ensemble Learning; APS: Australian Public Service; PCA: Principal Component Analysis; ELM: Extreme Learning Machines; DELM: Deep Extreme Learning Machines; KDELM: Kernel-based Deep Extreme Learning Machines.

Figure 49. A self-motivated employee learning model

The features are extracted from the secondary data and used for training the classifiers. Instead of relying on the traditional dataset, the new source of historical data fulfils the big data revolution of having a huge and near-complete dataset. Feature engineering was applied to remove any outliers before training. The general quantitative analysis methods such as descriptive analysis, factor analysis, Kaiser-Meyer-Olkin (KMO) and Bartlett's test of sphericity and Principal Component Analysis (PCA) are applied to the dataset. The KNN and SVM were used as classifiers and a DT was used to evaluate the performance of the classifiers which can yield an unbiased estimation of classification methods. Comparing SVM and KNN performance in every measuring metric, SVM outperforms KNN.

Both KNN and SVM are ensembled to create a meta-learning model named EL. Next, the DELM with a customised activation function was constructed and a variation to DELM is introduced using the kernel function. The result shows that the base models are superior to EL in terms of MSE, RSME and CE, but the state-of-art models are not superior to KDELM. The DELM and KDELM performance in terms of MSE, RSME and PS are identical, but the proposed KDELM outperformed by achieving the same result as DELM within a distinctively faster learning speed. The innovative combination of kernel-based DELM with BSigReLu activation function contributed to and confirmed the efficiency of the model. It is expected that the KDELM with BSigReLu model can be further optimised with various kernel optimisers and a lower generalisation error could be achieved by sampling other real-world datasets. Consequently, all models presented in this thesis can ultimately be used to capture the dataset pattern automatically and effectively to predict future occurrences.

To select the good-fit model, the error rate for each model is evaluated on a 2-fold CV on 5 iterations. It was found that there is no significant difference in the performance of KNN and DELM, KNN and KDELM, SVM and ELM, EL and ELM, EL and DELM, EL and KDELM, DELM and KDELM. There is a significant difference in the performance of KNN and SVM, KNN and EL, KNN and ELM, SVM and EL, SVM and DELM, SVM and KDELM, ELM and DELM, ELM and KDELM. The same 2-fold CV on 5 iterations was repeated to analyse the CE for each model. KNN is the fastest followed by EL, SVM, ELM, KDELM and DELM. In this thesis, the aim is to find the model that could autonomously and economically predict employee learning motivation outcomes. Hence, it can be concluded that the KNN is the good-fit model to resolve the issue highlighted in this thesis. Therefore, it maintained that the choice of machine learning techniques highly depends on the jurisdiction of the analyst or the researcher to select one that best produces a predictive model for the given task or addresses the given problem.

This research added to the body of knowledge in the field of AI, data science, and organisational behaviour by suggesting the EOC utility perception as an environmental motivator plays an important role in influencing employee self-determination to learn and AI support plays an important mediating role in the relationship between environmental, attitudinal motivation and employee outcomes. Based on the results of this investigation it was proposed to assess better the EOC utility and to consider possible improvements as well as the investment of AI systems in supporting organisation decision-makers to plan, evaluate and implement AI-driven employee learning tools. While the importance of learning curriculum and the level of employee autonomy in choosing courses may continue to prevail, the reality is superficial. Social elements have a great influence on employees' decision to learn as described in the social exchange theory and AI plays an influential role in motivating employees to learn.

Since we have limited knowledge of the environment-attitude-behaviour relationships in the employee learning context, the use of a machine learning model helps to drive insights for decision making which is very empowering for organisations even with an incomplete dataset. The model proposed is capable to learn the pattern and generalising for other organisations. AI systems are geared toward solving tasks from a vast scope of disciplines while at the same time having their intellectual challenges with the techniques available today. As such collaborative intelligence is necessary to optimise human-machine interaction and collaboration (Wilson & Daugherty 2018). It is essential to make it clear for both employers and employees through this thesis so that all parties involved could have near-complete information in implementing collaborative intelligence employee learning strategies.

From a signalling theory perspective, the employer and employees are in a non-cooperative system. That means information from both employers and employees is asymmetrical. The information available from the employer provides reasoning for wanting the employees to learn. However, this information may not be well communicated or available to the employees. In a non-cooperative signalling theory, both employers and employees are formulating a different strategy based on the incomplete information available to them. A tailored professional development plan would be beneficial to establishing an equilibrium signal between employer and employees. Employees provide information about their desire to learn to advance in the chosen career path while employers provide the necessary learning curriculum and resources available to support the employees learning journey aligning with business requirements. Following the completion of the learning curriculum, the employers would be able to gain valuable resources to achieve their business goals while employees can progress in their careers.

Finally, research on the learning realm has benefited from SRT and SDT but still needs to draw on findings from other fields. In the study of motivation, findings by Barrow and Ambler (2016) in human resource management and marketing as well as evidence from Murad et al. (2020) and Pandey and Chermack (2008) on how AI is used to support decision-making must not be overlooked to reshape the employee learning framework. Clark's observations on how AI can motivate employees to learn to achieve the organisation's goals are timeless, and they were remarkably prescient (Clark 2020). The trend observation of the advances of AI technology in various disciplines is justifiable to believe that AI will continue to be impactful and disruptive to deliver its value across all industries. Much is known about it, but much more remains to be learnt. This thesis continues to fuel the academic debate on the topic of AI, motivation, and employee learning. Therefore, further development of the theories is expected and continue in future research to create a more comprehensive problem-solving model for EOC utility, self-determination, AI support, employee job satisfaction, well-being, and performance.

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APPENDICES

Appendix 1. Item included in the measurement of constructs investigated in this thesis

Factor	Variable	Item
Employee	Gender	What is your gender?
	Age	How old were you on your last birthday?
Employer of choice	Leadership	My immediate Senior Executive Service (SES) Line/Branch/Group manager or equivalent is of high quality
	Working environment	I feel a strong personal attachment to my agency
	Workgroup climate	The people in my workgroup behave acceptably towards people from diverse backgrounds
	Supervisor	My immediate supervisor treats people with respect
	Non-discrimination	Do colleagues in your immediate workgroup act following the APS Values in their everyday work?
Self-determination	Autonomy	I can access learning and development solutions to meet my needs.
	Competency	I seek out opportunities to apply what I learn in my day-to-day work.
	Relatedness	I have a clear understanding of my development needs.
Employee learning	Job satisfaction	My job gives me a feeling of personal accomplishment.
	Well-being	Considering your work and life priorities, how satisfied are you with the work-life balance in your current job?
	Performance	The work processes we have in place allow me to be as productive as possible
Artificial Intelligence	AI	My workplace provides access to effective learning and development

Appendix 2. Critical appraisal of the appropriateness of using secondary data

Steps for doing secondary research	Current research evaluation
1. Develop your research question	1) What are the relationships between EOC utility perceptions as an environmental motivator and self-determination as an attitudinal motivator in the context of employee learning and the motivational features that affect employee learning outcomes? 2) What are the mechanisms through which these effects manifest themselves or to what extent AI support mediates the relationship between employee motivation (EOC utility perception and self-determination) and employee learning outcomes? 3) How does AI interact with EOC utility perceptions, self-determination, and employee learning, or does AI support moderate the relationship between EOC utility perception, self-determination, and employee learning?
2. Identify a secondary dataset	2018 APS census and this data can be reused
3. Evaluate a secondary dataset	
a. What was the aim of the original study?	The census conducted aims to look at the current state of the APS to strengthen the culture and the capability of the APS. The data was used by the Australian Public Service Commission and agencies to inform planning and initiatives.
b. Who has collected the data?	Australian government (professional source)
c. Which measures were employed?	Demographic characteristics (gender, age) and well-being, performance. Reliable and valid source.
d. When was the data collected?	June 2018

Steps for doing secondary research	Current research evaluation
e. What methodology was used to collect the data?	The sample was representative of APS employees from different backgrounds; large sample size (N = 103137); a low number of missing values
f. Making a final evaluation	Sufficiently developed dataset
4. Prepare and analyse secondary data	Outline all variables of interest and transfer data to a new .csv file; Remove missing data; Recode variables; Calculate final scores; Analyse the data using Python.

Source: Adapted from O'Leary (2020)

Appendix 3. *Data coding*

Data codinFactor	Factor Code	Variable Code	Variable	Variable options	Definition
Employee characteristics	F1	V1	Gender	Female	1
				Male	2
				Indeterminate/Intersex/Unspecified	3
				Prefer not to say	4
		V2	Age	Under 40 years	1
				40 to 54 years	2
				55 years or older	3
Employer of choice	F2	V11	Leadership	Strongly disagree	1
				Disagree	2
				Neither agree nor disagree	3
				Agree	4
				Strongly agree	5
		V12	Working environment	Strongly disagree	1
				Disagree	2
				Neither agree nor disagree	3
				Agree	4
				Strongly agree	5
		V13	Workgroup climate	Strongly disagree	1
				Disagree	2
				Neither agree nor disagree	3
				Agree	4
				Strongly agree	5
		V14	Supervisor	Strongly disagree	1
				Disagree	2
				Neither agree nor disagree	3
				Agree	4
				Strongly agree	5
		V15	Non-Discrimination	Not sure	1
				Never	2
				Rarely	3
				Sometimes	4
				Often	5

Data codinFactor	Factor Code	Variable Code	Variable	Variable options	Definition
				Always	6
Self-determination	F3	V17	Autonomy	Strongly disagree	1
				Disagree	2
				Neither agree nor disagree	3
				Agree	4
				Strongly agree	5
		V18	Competency	Strongly disagree	1
				Disagree	2
				Neither agree nor disagree	3
				Agree	4
				Strongly agree	5
		V19	Relatedness	Strongly disagree	1
				Disagree	2
				Neither agree nor disagree	3
				Agree	4
				Strongly agree	5
Employee learning	F4	V20	Job satisfaction	Strongly disagree	1
				Disagree	2
				Neither agree nor disagree	3
				Agree	4
				Strongly agree	5
		V21	Well-being	Very dissatisfied	1
				Dissatisfied	2
				Neither satisfied nor dissatisfied	3
				Satisfied	4
				Very satisfied	5
		V23	Performance	Strongly disagree	1
				Disagree	2
				Neither agree nor disagree	3
				Agree	4
				Strongly agree	5
Artificial Intelligence	F5	V24	Artificial Intelligence	Strongly disagree	1
				Disagree	2
				Neither agree nor disagree	3
				Agree	4

Data codinFactor	Factor Code	Variable Code	Variable	Variable options	Definition
				Strongly agree	5

Appendix 4. Factor Analysis Results with Varimax Rotation of EOC utility and SD

	Factor loadings	
	PCA1	PCA2
Factor 1: Workgroup climate • The people in my workgroup behave acceptably towards people from diverse backgrounds	0.16700189	**0.62431456**
Factor 2: Leadership • My immediate Senior Executive Service (SES) Line/Branch/Group manager or equivalent is of high quality	0.28241009	**0.44892264**
Factor 3: Working environment • I feel a strong personal attachment to my agency	0.30232582	**0.40418073**
Factor 4: Autonomy • I can access learning and development solutions to meet my needs.	**0.6531512**	0.27565727
Factor 5: Relatedness • I have a clear understanding of my development needs.	**0.79578605**	0.17669502
Factor 6: Competency • I seek out opportunities to apply what I learn in my day-to-day work.	**0.4898788**	0.26926258
Factor 7: Non-Discrimination • Do colleagues in your immediate workgroup act following the APS Values in their everyday work?	0.11825633	**0.43316176**
% variance explained	39.62	14.69
% cumulative variance	39.62	54.32
Cronbach's α	0.72	0.59
Number of items (Total = 7)	3	4

Appendix 5. SVM hyperparameters optimisation outcome using 10-fold CV

#	Parameters		Kernel function		
	C	*gamma*	Linear	RBF	Sigmoid
			Average scores (%)		
1	0.1	0.1	**100**	99.89	89.67
2	0.1	1	**100**	**100**	56.44
3	0.1	10	**100**	**100**	51.67
4	0.1	100	**100**	67.34	51.56
5	0.1	1000	**100**	46.01	50.56
6	1	0.1	**100**	99.78	81.33
7	1	1	**100**	**100**	51.00
8	1	10	**100**	**100**	52.45
9	1	100	**100**	98.24	54.46
10	1	1000	**100**	81.88	55.01
11	10	0.1	**100**	**100**	79.67
12	10	1	**100**	**100**	62.78
13	10	10	**100**	**100**	55.45
14	10	100	**100**	98.24	54.46
15	10	1000	**100**	82.55	57.57
16	100	0.1	99.89	**100**	79.56
17	100	1	98.90	98.90	62.67
18	100	10	98.90	**100**	75.78
19	100	100	**98.90**	98.24	54.46
20	100	1000	**98.90**	82.55	57.57
21	1000	0.1	**98.90**	**98.90**	79.56
22	1000	1	**98.90**	**98.90**	62.56
23	1000	10	98.90	**100**	77.56
24	1000	100	**98.90**	98.24	54.35

25	1000	1000	**98.90**	82.55	57.57

Appendix 6. Result of 10 iterations of ELM based on different AF investigated

Count of iteration	Activation functions execution time		
	ReLu	Sigmoid	BSigReLu
1	2s	2s	2s
2	2s	2s	2s
3	2s	1s	2s
4	1s	1s	1s
5	1s	2s	1s
6	1s	1s	1s
7	2s	1s	2s
8	2s	2s	2s
9	2s	1s	2s
10	2s	2s	2s

Appendix 7. Result of 10 iterations of DELM with optimised parameters

Iteration	Accuracy	Execution time
1	82.17%	12s
2	82.10%	12s
3	82.12%	13s
4	82.14%	12s
5	82.09%	14s
6	82.16%	12s
7	82.18%	12s
8	82.00%	13s
9	82.83%	13s
10	82.17%	12s

Appendix 8. Result of 10 iterations of DELM with optimised epochs

Iteration	Accuracy	Execution time
1	82.19%	3s
2	82.27%	4s
3	82.25%	3s
4	82.35%	4s
5	82.25%	4s
6	82.33%	3s
7	82.21%	4s
8	82.19%	3s
9	82.14%	4s
10	82.29%	4s

Appendix 9. Results of 5x2CV on KNN vs SVM

Iteration	Fold	Model	Accuracy	CE	Accuracy Difference	CE Difference
1	1	KNN	82.5%	3s	0.175	12
		SVM	100.0%	15s		
	2	KNN	82.2%	4s	0.171	1
		SVM	99.3%	5s		
2	1	KNN	82.5%	1s	0.175	18
		SVM	100.0%	19s		
	2	KNN	82.2%	5s	0.171	0
		SVM	99.3%	5s		
3	1	KNN	82.5%	2s	0.175	12
		SVM	100.0%	14s		
	2	KNN	82.2%	5s	0.171	0
		SVM	99.3%	5s		
4	1	KNN	82.5%	1s	0.175	13
		SVM	100.0%	14s		
	2	KNN	82.2%	6s	0.171	2
		SVM	99.3%	4s		
5	1	KNN	82.5%	1s	0.175	13
		SVM	100.0%	14s		
	2	KNN	82.2%	6s	0.171	2
		SVM	99.3%	4s		

Appendix 10. Results of 5x2CV on KNN vs EL

Iteration	Fold	Model	Accuracy	CE	Accuracy Difference	CE Difference
1	1	KNN	82.5%	3s	0.5	316
		EL	82.0%	319s		
	2	KNN	82.2%	4s	0.2	6
		EL	82.0%	10s		
2	1	KNN	82.5%	1s	0.5	324
		EL	82.0%	325s		
	2	KNN	82.2%	5s	0.2	4
		EL	82.0%	9s		
3	1	KNN	82.5%	2s	0.5	338
		EL	82.0%	340s		
	2	KNN	82.2%	5s	0.2	4
		EL	82.0%	9s		
4	1	KNN	82.5%	1s	0.5	349
		EL	82.0%	350s		
	2	KNN	82.2%	6s	0.2	3
		EL	82.0%	9s		
5	1	KNN	82.5%	1s	0.5	324
		EL	82.0%	325s		
	2	KNN	82.2%	6s	0.2	3
		EL	82.0%	9s		

Appendix 11. Results of 5x2CV on KNN vs ELM

Iteration	Fold	Model	Accuracy	CE	Accuracy Difference	CE Difference
1	1	KNN	82.5%	3s	0.175	1
		ELM	100%	2s		
	2	KNN	82.2%	4s	0.178	3
		ELM	100%	1s		
2	1	KNN	82.5%	1s	0.175	0
		ELM	100%	1s		
	2	KNN	82.2%	5s	0.178	4
		ELM	100%	1s		
3	1	KNN	82.5%	2s	0.175	1
		ELM	100%	1s		
	2	KNN	82.2%	5s	0.178	4
		ELM	100%	1s		
4	1	KNN	82.5%	1s	0.175	1
		ELM	100%	2s		
	2	KNN	82.2%	6s	0.178	4
		ELM	100%	2s		
5	1	KNN	82.5%	1s	0.175	1
		ELM	100%	2s		
	2	KNN	82.2%	6s	0.178	5
		ELM	100%	1s		

Appendix 12. Results of 5x2CV on KNN vs DELM

Iteration	Fold	Model	Accuracy	CE	Accuracy Difference	CE Difference
1	1	KNN	82.5%	3s	0.15	3
		DELM	82.35%	6s		
	2	KNN	82.2%	4s	0.79	1
		DELM	81.41%	5s		
2	1	KNN	82.5%	1s	0.13	5
		DELM	82.37%	6s		
	2	KNN	82.2%	5s	0.51	1
		DELM	81.69%	6s		
3	1	KNN	82.5%	2s	0.15	3
		DELM	82.35%	5s		
	2	KNN	82.2%	5s	1.01	1
		DELM	81.19%	6s		
4	1	KNN	82.5%	1s	0.19	4
		DELM	82.31%	5s		
	2	KNN	82.2%	6s	0.65	0
		DELM	81.55%	6s		
5	1	KNN	82.5%	1s	0.12	4
		DELM	82.38%	5s		
	2	KNN	82.2%	6s	0.94	0
		DELM	81.26%	6s		

Appendix 13. Results of 5x2CV on KNN vs KDELM

Iteration	Fold	Model	Accuracy	CE	Accuracy Difference	CE Difference
1	1	KNN	82.5%	3s	0.25	0
		KDELM	82.25%	3s		
	2	KNN	82.2%	4s	4.83	2
		KDELM	77.37%	2s		
2	1	KNN	82.5%	1s	0.26	2
		KDELM	82.24%	3s		
	2	KNN	82.2%	5s	4.83	3
		KDELM	77.37%	2s		
3	1	KNN	82.5%	2s	0.25	1
		KDELM	82.25%	3s		
	2	KNN	82.2%	5s	4.83	3
		KDELM	77.37%	2s		
4	1	KNN	82.5%	1s	0.26	2
		KDELM	82.24%	3s		
	2	KNN	82.2%	6s	4.83	3
		KDELM	77.37%	3s		
5	1	KNN	82.5%	1s	0.28	3
		KDELM	82.22%	4s		
	2	KNN	82.2%	6s	4.83	3
		KDELM	77.37%	3s		

Appendix 14. Results of 5x2CV on SVM vs EL

Iteration	Fold	Model	Accuracy	CE	Accuracy Difference	CE Difference
1	1	SVM	100.0%	15s	0.18	304
		EL	82.0%	319s		
	2	SVM	99.3%	5s	0.173	5
		EL	82.0%	10s		
2	1	SVM	100.0%	19s	0.18	306
		EL	82.0%	325s		
	2	SVM	99.3%	5s	0.173	4
		EL	82.0%	9s		
3	1	SVM	100.0%	14s	0.18	326
		EL	82.0%	340s		
	2	SVM	99.3%	5s	0.173	4
		EL	82.0%	9s		
4	1	SVM	100.0%	14s	0.18	336
		EL	82.0%	350s		
	2	SVM	99.3%	4s	0.173	5
		EL	82.0%	9s		
5	1	SVM	100.0%	14s	0.18	311
		EL	82.0%	325s		
	2	SVM	99.3%	4s	0.173	5
		EL	82.0%	9s		

Appendix 15. Results of 5x2CV on SVM vs ELM

Iteration	Fold	Model	Accuracy	CE	Accuracy Difference	CE Difference
1	1	SVM	100.0%	15s	0	13
		ELM	100%	2s		
	2	SVM	99.3%	5s	0.7	4
		ELM	100%	1s		
2	1	SVM	100.0%	19s	0	18
		ELM	100%	1s		
	2	SVM	99.3%	5s	0.7	4
		ELM	100%	1s		
3	1	SVM	100.0%	14s	0	13
		ELM	100%	1s		
	2	SVM	99.3%	5s	0.7	4
		ELM	100%	1s		
4	1	SVM	100.0%	14s	0	12
		ELM	100%	2s		
	2	SVM	99.3%	4s	0.7	2
		ELM	100%	2s		
5	1	SVM	100.0%	14s	0	12
		ELM	100%	2s		
	2	SVM	99.3%	4s	0.7	3
		ELM	100%	1s		

Appendix 16. Results of 5x2CV on SVM vs DELM

Iteration	Fold	Model	Accuracy	CE	Accuracy Difference	CE Difference
1	1	SVM	100.0%	15s	17.65	9
		DELM	82.35%	6s		
	2	SVM	99.3%	5s	17.89	0
		DELM	81.41%	5s		
2	1	SVM	100.0%	19s	17.63	13
		DELM	82.37%	6s		
	2	SVM	99.3%	5s	17.61	1
		DELM	81.69%	6s		
3	1	SVM	100.0%	14s	17.65	9
		DELM	82.35%	5s		
	2	SVM	99.3%	5s	18.11	1
		DELM	81.19%	6s		
4	1	SVM	100.0%	14s	17.69	9
		DELM	82.31%	5s		
	2	SVM	99.3%	4s	17.75	2
		DELM	81.55%	6s		
5	1	SVM	100.0%	14s	17.62	9
		DELM	82.38%	5s		
	2	SVM	99.3%	4s	18.04	2
		DELM	81.26%	6s		

Appendix 17. Results of 5x2CV on SVM vs KDELM

Iteration	Fold	Model	Accuracy	CE	Accuracy Difference	CE Difference
1	1	SVM	100.0%	15s	17.75	12
		KDELM	82.25%	3s		
	2	SVM	99.3%	5s	21.93	3
		KDELM	77.37%	2s		
2	1	SVM	100.0%	19s	17.76	16
		KDELM	82.24%	3s		
	2	SVM	99.3%	5s	21.93	3
		KDELM	77.37%	2s		
3	1	SVM	100.0%	14s	17.75	11
		KDELM	82.25%	3s		
	2	SVM	99.3%	5s	21.93	3
		KDELM	77.37%	2s		
4	1	SVM	100.0%	14s	17.76	11
		KDELM	82.24%	3s		
	2	SVM	99.3%	4s	21.93	1
		KDELM	77.37%	3s		
5	1	SVM	100.0%	14s	17.78	10
		KDELM	82.22%	4s		
	2	SVM	99.3%	4s	21.93	1
		KDELM	77.37%	3s		

Appendix 18. Results of 5x2CV on EL vs ELM

Iteration	Fold	Model	Accuracy	CE	Accuracy Difference	CE Difference
1	1	EL	82%	319s	0.18	317
		ELM	100%	2s		
	2	EL	82%	10s	0.18	9
		ELM	100%	1s		
2	1	EL	82%	325s	0.18	324
		ELM	100%	1s		
	2	EL	82%	9s	0.18	8
		ELM	100%	1s		
3	1	EL	82%	340s	0.18	339
		ELM	100%	1s		
	2	EL	82%	9s	0.18	8
		ELM	100%	1s		
4	1	EL	82%	350s	0.18	348
		ELM	100%	2s		
	2	EL	82%	9s	0.18	7
		ELM	100%	2s		
5	1	EL	82%	325s	0.18	323
		ELM	100%	2s		
	2	EL	82%	9s	0.18	8
		ELM	100%	1s		

Appendix 19. Results of 5x2CV on EL vs DELM

Iteration	Fold	Model	Accuracy	CE	Accuracy Difference	CE Difference
1	1	EL	82%	319s	0.35	313
		DELM	82.35%	6s		
	2	EL	82%	10s	0.59	5
		DELM	81.41%	5s		
2	1	EL	82%	325s	0.37	319
		DELM	82.37%	6s		
	2	EL	82%	9s	0.31	3
		DELM	81.69%	6s		
3	1	EL	82%	340s	0.35	335
		DELM	82.35%	5s		
	2	EL	82%	9s	0.81	3
		DELM	81.19%	6s		
4	1	EL	82%	350s	0.31	345
		DELM	82.31%	5s		
	2	EL	82%	9s	0.45	3
		DELM	81.55%	6s		
5	1	EL	82%	325s	0.38	320
		DELM	82.38%	5s		
	2	EL	82%	9s	0.74	3
		DELM	81.26%	6s		

Appendix 20. Results of 5x2CV on EL vs KDELM

Iteration	Fold	Model	Accuracy	CE	Accuracy Difference	CE Difference
1	1	EL	82%	319s	0.25	316
		KDELM	82.25%	3s		
	2	EL	82%	10s	4.63	8
		KDELM	77.37%	2s		
2	1	EL	82%	325s	0.24	322
		KDELM	82.24%	3s		
	2	EL	82%	9s	4.63	7
		KDELM	77.37%	2s		
3	1	EL	82%	340s	0.25	337
		KDELM	82.25%	3s		
	2	EL	82%	9s	4.63	7
		KDELM	77.37%	2s		
4	1	EL	82%	350s	0.24	347
		KDELM	82.24%	3s		
	2	EL	82%	9s	4.63	6
		KDELM	77.37%	3s		
5	1	EL	82%	325s	0.22	321
		KDELM	82.22%	4s		
	2	EL	82%	9s	4.63	6
		KDELM	77.37%	3s		

Appendix 21. Results of 5x2CV on ELM vs DELM

Iteration	Fold	Model	Accuracy	CE	Accuracy Difference	CE Difference
1	1	ELM	100%	2s	17.65	4
		DELM	82.35%	6s		
	2	ELM	100%	1s	18.59	4
		DELM	81.41%	5s		
2	1	ELM	100%	1s	17.63	5
		DELM	82.37%	6s		
	2	ELM	100%	1s	18.31	5
		DELM	81.69%	6s		
3	1	ELM	100%	1s	17.65	4
		DELM	82.35%	5s		
	2	ELM	100%	1s	18.81	5
		DELM	81.19%	6s		
4	1	ELM	100%	2s	17.69	3
		DELM	82.31%	5s		
	2	ELM	100%	2s	18.45	4
		DELM	81.55%	6s		
5	1	ELM	100%	2s	17.62	3
		DELM	82.38%	5s		
	2	ELM	100%	1s	18.74	5
		DELM	81.26%	6s		

Appendix 22. Results of 5x2CV on ELM vs KDELM

Iteration	Fold	Model	Accuracy	CE	Accuracy Difference	CE Difference
1	1	ELM	100%	2s	17.75	1
		KDELM	82.25%	3s		
	2	ELM	100%	1s	22.63	1
		KDELM	77.37%	2s		
2	1	ELM	100%	1s	17.76	2
		KDELM	82.24%	3s		
	2	ELM	100%	1s	22.63	1
		KDELM	77.37%	2s		
3	1	ELM	100%	1s	17.75	2
		KDELM	82.25%	3s		
	2	ELM	100%	1s	22.63	1
		KDELM	77.37%	2s		
4	1	ELM	100%	2s	17.76	1
		KDELM	82.24%	3s		
	2	ELM	100%	2s	22.63	1
		KDELM	77.37%	3s		
5	1	ELM	100%	2s	17.78	2
		KDELM	82.22%	4s		
	2	ELM	100%	1s	22.63	2
		KDELM	77.37%	3s		

Appendix 23. Results of 5x2CV on DELM vs KDELM

Iteration	Fold	Model	Accuracy	CE	Accuracy Difference	CE Difference
1	1	DELM	82.35%	6s	0.1	3
		KDELM	82.25%	3s		
	2	DELM	81.41%	5s	4.04	3
		KDELM	77.37%	2s		
2	1	DELM	82.37%	6s	0.13	3
		KDELM	82.24%	3s		
	2	DELM	81.69%	6s	4.32	4
		KDELM	77.37%	2s		
3	1	DELM	82.35%	5s	0.1	2
		KDELM	82.25%	3s		
	2	DELM	81.19%	6s	3.82	4
		KDELM	77.37%	2s		
4	1	DELM	82.31%	5s	0.07	2
		KDELM	82.24%	3s		
	2	DELM	81.55%	6s	4.18	3
		KDELM	77.37%	3s		
5	1	DELM	82.38%	5s	0.16	1
		KDELM	82.22%	4s		
	2	DELM	81.26%	6s	3.89	3
		KDELM	77.37%	3s		

Appendix 24. KNN source codes

```python
#import libraries
import time
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import sklearn
from sklearn.metrics import accuracy_score
from sklearn.metrics import classification_report
from sklearn.metrics import mean_squared_error
from sklearn.neighbors import KNeighborsClassifier
from sklearn.preprocessing import StandardScaler
from sklearn.externals import joblib

start_time = int(time.time())
#load data
data = pd.read_csv("DEMOFinal.csv")

#identify input and output data
data = data[['PCA1','PCA2','LO','AI']]
predict = "LO"

x = np.array(data.drop(predict,axis=1))
y = np.array(data[predict])

#split data into training data and test data
x_train, x_test, y_train, y_test =sklearn.model_selection.train_test_split(x,y,test_size=0.1,random_state=42)

#standardise the dataset
sc_X = StandardScaler()
x_train = sc_X.fit_transform(x_train)
x_test = sc_X.fit_transform(x_test)

#apply KNN classifier
classifier = KNeighborsClassifier(n_neighbors=95, p = 2, metric='euclidean')
classifier.fit(x_train,y_train)

y_pred = classifier.predict(x_test)

#display result
print(accuracy_score(y_test,y_pred))
print(classification_report(y_test,y_pred))
end_time = int(time.time())
diff = end_time - start_time
print("--- %s seconds ---" % (diff))

scores = []

for k in [5,15,45,95,105,155]:
    knn = KNeighborsClassifier(n_neighbors=k)
    knn.fit(x_train, y_train)
    y_pred = knn.predict(x_test)
    scores.append(accuracy_score(y_test, y_pred))

print(scores)
print("MSE : %.2f" % mean_squared_error(y_test,y_pred))
plt.plot([5,15,45,95,105,155], scores)
plt.xlabel('Value of K for KNN')
plt.ylabel('Testing Accuracy')
plt.show()
```

Appendix 25. SVM source codes

```
# import libraries
import pandas as pd
import numpy as np
import sklearn
from matplotlib.pyplot import xlim
from matplotlib.pyplot import ylim
from sklearn.svm import SVC
from sklearn.datasets.samples_generator import make_blobs
from matplotlib import pyplot as plt
from sklearn.metrics import classification_report, confusion_matrix
from sklearn.model_selection import KFold
import time
from sklearn.metrics import roc_curve, auc, roc_auc_score
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import mean_squared_error

start_time = int(time.time())

#load data
data = pd.read_csv("DEMOFinal.csv")

#identify input and output data
data = data[['PCA1','PCA2','LO','AI']]
predict = "LO"

x = np.array(data.drop(predict,axis=1))
y = np.array(data[predict])

# show unclassified data
#make 250 blobs
x, y = make_blobs(n_samples=1000, centers=2,
                  random_state=0, cluster_std=0.60)
```

```
#classify into 1 and -1
y[y == 0] = -1
tmp = np.ones(len(x))
y = tmp * y

#display scatter plots
plt.scatter(x[:, 0], x[:, 1], c=y, cmap='winter')
plt.show()

#split the data into training data and test data
x_train, x_test, y_train, y_test = sklearn.model_selection.train_test_split(x,y,test_size=0.1, random_state=42)

#standardize the dataset
svm = SVC()
svm.fit(x_train, y_train)
print('Accuracy of SVM classifier on training set: {:.2f}'
      .format(svm.score(x_train, y_train)))
print('Accuracy of SVM classifier on test set: {:.2f}'
      .format(svm.score(x_test, y_test)))

# defining parameter range
param_grid = {'C': [0.1, 1, 10, 100, 1000],
              'gamma' : [0.1, 1, 10, 100, 1000],
              'kernel': ['linear','rbf', 'sigmoid']}

#define cross-validation method to use
cv = KFold(n_splits=10, random_state=42, shuffle=True)

grid = GridSearchCV(SVC(), param_grid, refit=True, verbose=3, cv = cv)
```

```
# fitting the model for grid search
grid.fit(x_train, y_train)

# print best parameter after tuning
print(grid.best_params_)


# print how our model looks after hyper-parameter tuning
print(grid.best_estimator_)

#grid_predictions = grid.predict(x_test)
#print(classification_report(y_test, grid_predictions))

clf = SVC(kernel='linear', C=0.1, decision_function_shape="ovo")
clf.fit(x_train, y_train)
plt.scatter(x_train[:, 0], x_train[:, 1], c=y_train, s = 30, cmap='winter')
plt.xlim(-1,3.5)


def plot_svc_decision_function(clf, ax=None, plot_support=True):
    if ax is None:
        ax = plt.gca()
        xlim = ax.get_xlim()
        ylim = ax.get_ylim()


# create grid to evaluate model
xx = np.linspace(xlim(0), xlim(1), 30)
yy = np.linspace(ylim(0), ylim(1), 30)
YY, XX = np.meshgrid(yy, xx)
xy = np.vstack([XX.ravel(), YY.ravel()]).T
Z = clf.decision_function(xy).reshape(XX.shape)
```

```
# plot decision boundary and margins
plt.contour(XX, YY, Z, colors='k', levels=[-1, 0, 1], alpha=0.5, linestyles=['--', '-', '--'])
# plot support vectors
plt.scatter(clf.support_vectors_[:, 0], clf.support_vectors_[:, 1], s=70, linewidth=1, facecolors='none', edgecolors='k')



#display result
plt.show()
print("Support vectors:" % (clf.support_vectors_))
grid_predictions = grid.predict(x_test)
print(confusion_matrix(y_test,grid_predictions))
print(classification_report(y_test, grid_predictions))

#y_pred = clf.predict(x_test)
#print(confusion_matrix(y_test,y_pred))
#print(classification_report(y_test,y_pred))
end_time = int(time.time())
diff = end_time - start_time
print("--- %s seconds ---" % (diff))

auc_roc=classification_report(y_test,grid_predictions)
#auc_roc=classification_report(y_test,y_pred)
print (auc_roc)
```

```
#auc_roc=roc_auc_score(y_test,y_pred)
auc_roc=roc_auc_score(y_test,grid_predictions)
print (auc_roc)

false_positive_rate, true_positive_rate, thresholds = roc_curve(y_test, grid_predictions)
#false_positive_rate, true_positive_rate, thresholds = roc_curve(y_test, y_pred)
roc_auc = auc(false_positive_rate, true_positive_rate)
print (roc_auc)


plt.figure(figsize=(10,10))
plt.title('Receiver Operating Characteristic')
plt.plot(false_positive_rate,true_positive_rate, color='red',label = 'AUC = %0.2f' % roc_auc)
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],linestyle='--')
plt.axis('tight')
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```

Appendix 26. EL source codes

```
import pandas as pd
import numpy as np
import time
import sklearn
from sklearn.neighbors import KNeighborsClassifier
from mlxtend.classifier import EnsembleVoteClassifier
from sklearn.metrics import classification_report
from sklearn.metrics import accuracy_score
from matplotlib import pyplot as plt
from sklearn.metrics import roc_curve, auc, roc_auc_score
from sklearn.svm import SVC
from sklearn.metrics import mean_squared_error


start_time = int(time.time())

#load data
data = pd.read_csv("DEMOFinal.csv")

#identify input and output data
data = data[['PCA1','PCA2','LO','AI']]
predict = "LO"

x = np.array(data.drop(predict,axis=1))
y = np.array(data[predict])

#classify into 1 and -1
y[y == 0] = -1
tmp = np.ones(len(x))
y = tmp * y
```

```
#split the data into training data and test data
x_train, x_test, y_train, y_test = sklearn.model_selection.train_test_split(x,y,test_size=0.9, random_state=42)

svmclf = SVC(kernel='linear', C=0.1, decision_function_shape="ovo",probability=True)

knnclf=KNeighborsClassifier(n_neighbors=95,p=2,metric='euclidean')


classifiers = [svmclf,knnclf]
mv_clf = EnsembleVoteClassifier(clfs=classifiers, weights=[1.5, 1], voting ='soft')
mv_clf.fit(x_train,y_train)

y_pred=mv_clf.predict(x_test)
print(accuracy_score(y_test,y_pred))
print(pd.crosstab(y_test,y_pred))
print(classification_report(y_test,y_pred))
print("MSE : %.2f" % mean_squared_error(y_test,y_pred))
end_time = int(time.time())
diff = end_time - start_time
print("--- %s seconds ---" % (diff))

#auc_roc=classification_report(y_test,grid_predictions)
auc_roc=classification_report(y_test,y_pred)
print (auc_roc)

auc_roc=roc_auc_score(y_test,y_pred)
#auc_roc=roc_auc_score(y_test,grid_predictions)
print (auc_roc)
```

```
#false_positive_rate, true_positive_rate, thresholds = roc_curve(y_test, grid_predictions)
false_positive_rate, true_positive_rate, thresholds = roc_curve(y_test, y_pred)
roc_auc = auc(false_positive_rate, true_positive_rate)
print (roc_auc)


plt.figure(figsize=(10,10))
plt.title('Receiver Operating Characteristic')
plt.plot(false_positive_rate,true_positive_rate, color='red',label = 'AUC = %0.2f' % roc_auc)
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],linestyle='--')
plt.axis('tight')
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```

Appendix 27. ELM source codes

```python
import tensorflow as tf
from keras.models import Sequential
import pandas as pd
from keras.layers import Dense
import numpy as np
import sklearn
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler


#load data
data = pd.read_csv("DEMOFinal.csv")

#identify input and output data
data = data[['PCA1','PCA2','LO','AI']]
predict = "LO"

x = np.array(data.drop(predict,axis=1))
y = np.array(data[predict])

#classify into 1 and -1
y[y == 0] = -1
tmp = np.ones(len(x))
y = tmp * y

#split the data into training data and test data
x_train, x_test, y_train, y_test = sklearn.model_selection.train_test_split(x,y,test_size=0.1, random_state=42)

scaler = StandardScaler().fit(x_train)

x_train = scaler.transform(x_train)

x_test = scaler.transform(x_test)

model = Sequential()

model.add(Dense(8, activation='relu', input_shape=(3,)))

model.add(Dense(8, activation='sigmoid'))

model.add(Dense(1, activation='relu'))

model.compile(loss='binary_crossentropy',
              optimizer='sgd',
              metrics=['accuracy'])

model.fit(x_train, y_train, epochs=8, batch_size=1, verbose=1)

y_pred = model.predict(x_test)

score = model.evaluate(x_test, y_test,verbose=1)

print(score)
```

Appendix 28. DELM source codes

```python
import numpy as np
import pandas as pd
import sklearn
import time
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import OneHotEncoder
from sklearn.preprocessing import MinMaxScaler
import time
from sklearn.metrics import roc_curve, auc, roc_auc_score
from sklearn.metrics import classification_report, confusion_matrix
from sklearn.metrics import precision_recall_curve
from sklearn.metrics import f1_score, precision_score, recall_score
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import StandardScaler
from sklearn import metrics
import tensorflow as tf
from tensorflow.keras.utils import get_custom_objects
from keras.layers import activations
from keras.models import Sequential
from keras.layers import Dense
from matplotlib import pyplot as plt
from keras.layers import Activation
from keras import backend as K
from keras.utils.generic_utils import get_custom_objects

from keras import callbacks


import elm
params = ["linear", 5, []]
elmk = elm.ELMKernel(params)

start_time = int(time.time())
```

```python
#load data
data = pd.read_csv("DEMOFinal.csv")

data = data.astype(float)

#identify input and output data
data = data[['PCA1','PCA2','LO','AI']]
predict = "LO"

x = np.array(data.drop(predict,axis=1))
y = np.array(data[predict])

#split the data into training data and test data
x_train, x_test, y_train, y_test = sklearn.model_selection.train_test_split(x,y,test_size=0.9, random_state=42)

def sigmoidrelu(x):
    return K.maximum(tf.keras.activations.relu(x), tf.keras.activations.sigmoid(x))

get_custom_objects().update({'sigmoidrelu': tf.keras.layers.Activation(sigmoidrelu)})

scaler = StandardScaler().fit(x_train)

x_train = scaler.transform(x_train)

x_test = scaler.transform(x_test)

model = Sequential()

model.add(Dense(33, activation ='sigmoidrelu', input_shape=(3,)))

model.add(Dense(20, activation='sigmoidrelu'))
```

```
#model.add(Dense(33, activation='sigmoidrelu'))

model.add(Dense(1, activation='sigmoidrelu'))

model.compile(loss='binary_crossentropy',
              optimizer='adam',
              metrics=['accuracy'])

y_pred = model.predict(x_test)

score = model.evaluate(x_test, y_test,verbose=1)



earlystopping = callbacks.EarlyStopping(monitor="val_loss",
                                        mode="min", patience=5,
                                        restore_best_weights=True)


history = model.fit(x_train, y_train, epochs=12, batch_size=1000, verbose=1,  validation_data=(x_test, y_test),callbacks=[earlystopping])



# Get training and test loss histories
training_loss = history.history['loss']
test_loss = history.history['val_loss']

# Create count of the number of epochs
epoch_count = range(1, len(training_loss) + 1)
```

```
# Visualize loss history
plt.plot(epoch_count, training_loss, 'r--')
plt.plot(epoch_count, test_loss, 'b-')
plt.legend(['Training Loss', 'Test Loss'])
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.show();

print(score)
end_time = int(time.time())

diff = end_time - start_time
print("--- %s seconds ---" % (diff))

```

Appendix 29. KDELM source codes

```
import numpy as np
import pandas as pd
import sklearn
import sklearn.model_selection
import time
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import r2_score
import tensorflow as tf
from keras.models import Sequential
from keras.layers import Dense
from keras import regularizers
from keras import backend as K
from keras.utils.generic_utils import get_custom_objects


start_time = int(time.time())

#load data
data = pd.read_csv("DEMOFinal.csv")

data = data.astype(float)

#identify input and output data
data = data[['PCA1','PCA2','LO','AI']]
predict = "LO"

x = np.array(data.drop(predict,axis=1))
y = np.array(data[predict])

#split the data into training data and test data
x_train, x_test, y_train, y_test = sklearn.model_selection.train_test_split(x,y,test_size=0.9, random_state=42)

```

```
def sigmoidrelu(x):
  return K.maximum(tf.keras.activations.relu(x), tf.keras.activations.sigmoid(x))
get_custom_objects().update({'sigmoidrelu': tf.keras.layers.Activation(sigmoidrelu)})
scaler = StandardScaler().fit(x_train)
x_train = scaler.transform(x_train)
x_test = scaler.transform(x_test)

model = Sequential()
#mo# del.add(Dense(33, kernel_initializer='random_uniform', activation='sigmoidrelu', activity_regularizer=regularizers.l1(10e-5), input_shape=(3,)))
model.add(Dense(33, kernel_initializer='random_uniform', kernel_regularizer=regularizers.l2(0.0001), activation='sigmoidrelu', input_shape=(3,)))
model.add(Dense(20, kernel_initializer='random_uniform', activation='sigmoidrelu'))
model.add(Dense(1, kernel_initializer='random_uniform', activation='sigmoidrelu'))
model.compile(loss='mean_squared_error',
              optimizer='adam',
              metrics=['accuracy', 'mean_squared_error'])

model.fit(x_train, y_train, epochs=12, batch_size=1000,verbose=1,)

y_pred = model.predict_proba(x_test)
score = model.evaluate(x_test, y_test,verbose=1)
print(model.metrics_names)
print(score)
print("R2 score : %.2f" % r2_score(y_test,y_pred))
end_time = int(time.time())
diff = end_time - start_time
print("--- %s seconds ---" % (diff))
```

Appendix 30. List of variables and APS data mapping

Factor	Variable	Variable options	Coding	APS Reference Question
Employee characteristics	Gender	Female	1	1. What is your gender?
		Male	2	
		Indeterminate/Intersex/Unspecified	3	
		Prefer not to say	4	
	Age	Under 40 years	1	2. How old are you at your last birthday?
		40 to 54 years	2	
		55 years or older	3	
Perceived EOC utility	Leadership	Strongly disagree	1	Rate your level of agreement with the following statements regarding your immediate Senior Executive Service (SES) Line/Branch/Group manager or equivalent. 29a. My SES manager is of a high quality?
		Disagree	2	
		Neither agree nor disagree	3	
		Agree	4	
		Strongly agree	5	
	Working environment	Strongly disagree	1	Rate your level of agreement with the following statements regarding

Factor	Variable	Variable options	Coding	APS Reference Question
		Disagree	2	aspects of your agency's working environment. 32a. I feel a strong personal attachment to my agency.
		Neither agree nor disagree	3	
		Agree	4	
		Strongly agree	5	
	Workgroup	Strongly disagree	1	Rate your level of agreement with the following statements regarding your workgroup and/or team; people you currently work with on a daily basis. 25e. The people in my workgroup behave in an accepting manner towards people from diverse backgrounds?
		Disagree	2	
		Neither agree nor disagree	3	
		Agree	4	
		Strongly agree	5	
	Non-discrimination	Not sure	1	Based on your experience in the workplace, how frequently: 81a. Do colleagues in your immediate workgroup act in accordance with the APS Values in their everyday work?
		Never	2	
		Rarely	3	
		Sometimes	4	
		Often	5	
		Always	6	

Factor	Variable	Variable options	Coding	APS Reference Question
Self-determination	Autonomy	Strongly disagree	1	Please rate your level of agreement with the following statements. 64a. I am able to access learning and development solutions to meet my needs
		Disagree	2	
		Neither agree nor disagree	3	
		Agree	4	
		Strongly agree	5	
	Competency	Strongly disagree	1	64d. I seek out opportunities to apply what I learn in my day-to-day work
		Disagree	2	
		Neither agree nor disagree	3	
		Agree	4	
		Strongly agree	5	
	Relatedness	Strongly disagree	1	64b. I have a clear understanding of my development needs
		Disagree	2	
		Neither agree nor disagree	3	

Factor	Variable	Variable options	Coding	APS Reference Question
		Agree	4	
		Strongly agree	5	
Employee learning outcomes	Job satisfaction	Strongly disagree	1	Please rate your level of agreement with the following statements regarding your current job: 24b. My job gives me a feeling of personal accomplishment
		Disagree	2	
		Neither agree nor disagree	3	
		Agree	4	
		Strongly agree	5	
	Well-being	Very dissatisfied	1	33. Considering your work and life priorities, how satisfied are you with the work-life balance in your current job?
		Dissatisfied	2	
		Neither satisfied nor dissatisfied	3	
		Satisfied	4	
		Very satisfied	5	
	Performance	Strongly disagree	1	Please rate your level of agreement with the following statements:
		Disagree	2	

Factor	Variable	Variable options	Coding	APS Reference Question
		Neither agree nor disagree	3	77c. The work processes we have in place allow me to be as productive as possible.
		Agree	4	
		Strongly agree	5	
AI support	Artificial Intelligence	Strongly disagree	1	Please rate your level of agreement with the following statements regarding aspects of your agency's working environment: 32e. My workplace provides access to effective learning and development (e.g. formal training, learning on the job, e-learning, secondments).
		Disagree	2	
		Neither agree nor disagree	3	
		Agree	4	
		Strongly agree	5	