A FRAMEWORK TO SUPPORT ENGINEERING STUDENTS LEARNING FOR INDUSTRY 4.0

By

SIN YING TAN

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DECLARATION

I declare that:

· I have written this thesis by myself.

· The thesis has not been submitted to other universities before.

· During the thesis preparation, some parts of the thesis that were also my own work were transferred to posters and papers. These are listed in Appendix 1.

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ABSTRACT

Industry has been undergoing intensive technological developments, such as sensors, autonomous robots and intelligent networks, at an unprecedented pace over the last few decades. This rapidly changing world requires higher education institutions and industrial organisations to adapt. Considering this challenge, this thesis highlighted a mismatch between industry's expectations, Engineering students' expectations and graduates' readiness in the United Kingdom. The current technological landscape has made student readiness a critical issue, prompting an investigation into the factors that contributed to the readiness of Engineering students for industry 4.0. The research methodology used to guide the research is Design Science Research. This research used pragmatic approach and mixed-method research to find out the different criteria that contribute to the readiness of students for industry 4.0. This study introduced "ASK SUMA" as a novel learning framework designed to facilitate integration with industry 4.0 by focusing on learning processes. Specifically, ASK SUMA used self-directed learning, a key pillar of active learning, to support students in analysing their needs and monitoring their progress through self-review. This framework also assessed technical skills and attitude using maturity levels. The research found out that readiness of Engineering students for industry 4.0 could be enhanced if students had high level of skills and positive learning attitude. The findings were then translated into a framework and data on skill levels were collected before and after implementing the framework. Findings revealed that the proposed framework supported individual learners by focusing on their self-directed learning and awareness. In addition, the proposed learning process was essential for students' development as future graduates, supporting them to emerge as flexible, proactive, and adaptive professionals in a workplace defined by constant change. Future work will involve implementing the ASK SUMA framework with lecturers and will also investigate integrating this framework with artificial intelligence.

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ABBREVIATIONS

AI	**Artificial Intelligence**
AR	**Augmented Reality**
AVE	**Average Variance Extracted**
CPS	**Cyberphysical Systems**
DSR	**Design Science Research**
DL	**Deep Learning**
IBM	**International Business Management**
IET	**Institution of Engineering and Technology**
IoT	**Internet of Things**
IT	**Information Technology**
LAs	**Learning Analytics**
LMS	**Learning Management System**
ML	**Machine Learning**
PLC	**Programmable Logic Controller**
SCT	**Social Constructivism Theory**
SDLC	**Self-Directed Learning Cycle**
SDT	**Self- Determination Theory**
TPB	**Theory of Planned Behaviour**
TSS	**Technological Soft Skills**
UAE	**United Arab Emirates**
UK	**United Kingdom**
VLE	**Virtual Learning Environment**
WEF	**World Economic Forum**

CHAPTER 1: INTRODUCTION

1.1 Overview

Industry 4.0 is the fourth industrial revolution sweeping through the technology world. Rapid technological advances have been increasing the need for specific skills, and employers have been raising the issue of a lack of desired skills among current graduates and employees. Different parts of the world have already started taking the initiative to close the gap between employers' needs and graduates' skills by providing collaborative training programs across industries, universities, and regulatory organisations (Tay et al., 2018). According to the Institution of Engineering and Technology (IET) (2023), employers strongly demand new knowledge and skills such as cloud computing.

Universities play a vital role in equipping future employees with industrial relevant practical knowledge. However, the changing trends in artificial intelligence (AI), machine learning (ML), deep learning (DL), cloud computing and blockchain technology have transformed at a faster pace than education systems (Benešová and Tupa, 2017). The rapid advance in this respect was beyond the universities capabilities in terms of adapting the traditional education system to fulfil the aforementioned technologies. Recent studies have supported this assumption by proving that employers often found that graduates had not been fully equipped with what they were looking for (IET, 2023; Goulart et al., 2022; Félix-Herrán, Rendon-Nava and Nieto Jalil, 2021; Azmi et al., 2018). The literature also confirmed that a large proportion of graduates left their first job because they had not been well-prepared for the working world (Lee et al., 2023).

This was partly because university did not emphasise positive learning attitude and independent learning throughout projects and coursework despite including skills in project and assessments. Positive attitude was important part of the learning process. Fostering adaptability and flexibility in graduates was crucial to equip them for the challenges of industry 4.0. Therefore, the question that emerged in this research was: "Were universities preparing the right future workforce to fulfil the needs of industry?" The research aimed to develop a framework to support students in the learning process for preparation to meet the needs of industry 4.0. An investigation was conducted to examine factors that affected students' readiness for industry 4.0. Such factors included gamification on students' engagement and personal development skills (Sclater, Peasgood, and Mullan, 2016; Huberth et al., 2015; Arnold and Pistilli 2012).

1.2 Motivation for the Research

1.2.1 Academic Justification

The rapid progression of industrial revolution highlighted the need for education to accelerate its adaptation to rapid technological advancements. Industry 4.0 has undergone a digital transformation process, exposing higher education to challenges and opportunities in meeting the needs of the fast-growing sector. Peck (2024) and UNICEF (2019) noted that the gap between industrial development needs and educational learning levels has been growing. Therefore, addressing this gap was important. This research was essential to identify the critical issues in preparing students for industry 4.0.

Industry 4.0 has driven the world into an automated and flexible environment, resulting in a global competition for jobs requiring specialised skills to interact with advanced technologies such as robotics and AI (Motyl et al., 2017; Kergroach, 2017; Richert et al., 2016). Robotics and AI, alongside big datasets, have advanced industry 4.0 massively beyond the preceding three industrial revolutions. Industry 4.0 integration in this sense placed special focus on the quality of organisations' skills and qualifications that played a prominent role in driving organisations' innovation and competitiveness (Benešová and Tupa, 2017). Thus, lack of skills negatively impacted organisations (Schallock et al., 2018).

Having skills in industry 4.0 offered opportunities for quality and productive employment; yet, potentially resulted in unemployment due to automation of manual and repetitive jobs. The way to mitigate this unemployment was by upskilling graduates in technology, automation, and AI. However, many countries have been facing serious shortage of professionals equipped with industry 4.0 skills (Pradhan and Agwa-Ejon, 2018). This urged the need for investigating key requirements for skills in digital economy and determining how these skills could be developed and incorporated into existing educational structures.

Goulart et al. (2022) and Shvetsova and Kuzmina (2018) pointed out an existing gap in the industry 4.0 era between the skills required and those being developed emphasising the need for a clear understanding of the skills that met industry 4.0 requirements. Tortorella et al. (2022) also stressed that developing countries struggled to keep up with technological advances to gain competitiveness, while developed countries such as Germany and the United States integrated industry 4.0 into their manufacturing sectors. However, developed countries had several limitations in their efforts to achieve this (Cezarino et al., 2019; Dalenogare et al., 2018). These limitations included:

- historical focus of developed countries' economies on commodities;
- technological gaps between companies in developed and developing countries;
- infrastructure for information and communication technologies;
- instability in economy and politics;
- differences in educational levels between developed and developing countries (Dalenogare et al., 2018).

Horváth and Szabó (2019) highlighted that industry 4.0 required changes in educational systems, where partnerships between universities and companies were necessary for the success of industry 4.0. Therefore, the issue to be addressed in this research was how to effectively prepare undergraduate students to work in this reality. Upon graduation, students must have mastered communication, leadership, teamwork, creativity, and problem-solving skills needed in the working world. As such, industry 4.0 required technical knowledge alongside soft skills that depended on individuals as well as organisations (Jagannathan et al., 2019; Liboni et al., 2019; Teng et al., 2019).

1.2.2 Industry Practice Justification

The technological era promoted innovations that led to industry 4.0. Inventions of new technologies, including mobile computing, cloud and fog computing, and the Internet, have greatly influenced different sectors of the world economy. The digital technology sector in the UK has contributed significantly to the economy and grown tremendously despite the economic crisis in 2008 (Alkaraan et al., 2023). However, the UK government has identified an urgent need to intensify efforts to boost the number of skilled workers to meet the growing demand. The growth of the digital economy and the emergence of new technologies have led to skills shortages and increased demand for graduates with the right qualifications (British Chambers of Commerce, 2023). Rapid advances in AI, robotics, and other emerging technologies changed the nature of jobs and skills needed to carry out these jobs (World Economic Forum, 2023).

These advancements prompted educational institutions to change curricula to prepare students to work in industry 4.0 post-graduation. The contributions from educational institutions and industries (e.g. Siemens, Cisco, PWC, and Deloitte) have given rise to questions regarding the status of industry 4.0. These questions were also raised by the UK government in Made Smarter Review. The results of the latter review agreed with another study that reported 57% of manufacturing leaders felt their organisation lacks skilled workers to support smart manufacturing and digitalisation (Stamford, 2021). These driving forces made the fourth industrial revolution one of the most frequently discussed topics of many manufacturing conferences, forums, and exhibitions in the past few years. This confirmed that it was vital to investigate industry 4.0 skills requirements and development.

1.3 Novelty and Summary of Contributions

The thesis's novelty comprised developing ASK SUMA framework that integrated Self-Directed Learning Cycle (SDLC) with social constructivism theory, (SDC) specifically tailoring a student-centred approach to developing critical industry 4.0 skills. It also used a maturity model to monitor technical skills, personal development skills, and attitude. This research extended beyond a theoretical framework by using the maturity model that is usually used to assess an organisation's readiness for assessing students' readiness for the rapidly evolving demands of industry 4.0, thus bridging a crucial gap between academic training and industrial needs. Additionally, the study provided unique insights by investigating the perspectives of university students, educators and industrial managers, contributing to a deeper understanding of the alignment—or misalignment—between educational outcomes and the competencies required in industry 4.0. By linking theory to practice, this research advanced knowledge in both educational strategies and industrial workforce preparedness.

This research specifically extended the existing knowledge regarding skills in industry 4.0 in four main ways by:

- identifying skills required in the Engineering sector;
- developing a novel industry 4.0 learning evaluation framework that used the maturity model from the student's perspective;
- empowering Engineering students to assess their technical and personal development skills and attitude;

- identifying the importance of personal development skills in preparing students for industry 4.0.

The latter four ways impacted major stakeholders including:

- **Students** who were exposed to self-directing and self-reflecting opportunities that focused on improvements in skills required in future workplaces;
- **New graduates** who were exposed to the practising and evidencing of skills that prepared them for work-related challenges;
- **Academic tutors** that had tools emphasising technical and personal development skills for implementing student-centred approach to learning;
- **Employers** that met the demand for skills required in the workforce (IET, 2023);
- **Higher Education Institutions and policymakers** who understood the readiness of students for industry 4.0 and kept up with technological developments.

1.4 Research Scope

This thesis involved two main elements. The first element entailed the analysis of literature regarding industry 4.0 skills and existing skills frameworks. The second element involved the design and development of a framework that could support students working in industry 4.0. More specifically, the research focused on developing and validating ASK SUMA framework that bridged the gap between industry 4.0 skills and the readiness of graduates entering the workforce.

The following areas defined the scope:

1. Target Audience:

The research specifically addressed university students at the School of Engineering. It focused on their readiness for industry 4.0 by developing technical and personal development skills.

2. Geographical Context:

The research only focused on students in the UK as the report conducted by IET (2023) stated that UK was the only country where most employers think the education system did not prepare graduates well for industry 4.0.

3. Industry 4.0 Focus:

The research focused on identifying and cultivating the essential skills and knowledge required for industry 4.0. It explored technical skills, personal development skills and continuous learning that future graduates needed to succeed in an environment defined by constant technological advancements.

4. Theoretical Foundation:

ASK SUMA was grounded in the SDLC and SCT. The research investigated how these learning approaches could be applied to develop student-centred strategies that fostered life-long learning and preparedness for the evolving demands of industry 4.0. The maturity model was used to assess and monitor the skills.

5. Research Methodology:

The study used Design Science Research (DSR) to develop and validate the ASK SUMA framework. It employed literature analysis, surveys and interviews to assess students' readiness to industry 4.0 and to different frameworks' effectiveness in improving their industry 4.0 skills.

6. Educational Impact:

Beyond theoretical development, this research offered practical contributions by providing a framework that could be implemented in educational institutions. The scope included future work involving integrating ASK SUMA with AI to enhance personalised learning experiences for students.

1.5 Research Questions

The research explored the appropriate model for preparing students for existing and future industries. The research questions were:

1. What are the key skillsets required for the future workforce to be ready for industry 4.0?
2. How do pedagogical interventions aim at facilitating students' learning process to prepare and support them?
3. How does the proposed framework contribute to supporting students to embrace industry 4.0?

1.6 Research Aim and Objectives

This study proposed a framework to support students' learning process, which placed more emphasis on self-management skills to help prepare them to face industry 4.0 needs.

The aim was addressed by the following objectives (Table 1.1):

i) identify and evaluate the key skills required by industry 4.0 and their role in preparing students for industry 4.0;

ii) develop and implement an assessment model that enables students to measure their skill level;

iii) test and evaluate the effectiveness of ASK SUMA framework in supporting the learning process and preparing students for the needs of industry 4.0.

Table 1.1: Summary of Research Questions, Methodology, Aim and Methods

Research Questions	Corresponding Aim	Methodology	Method
Phase One	**Need Assessment/Investigation**		
What are the key skillsets required by the future workforce to be ready for industry 4.0?	To identify and evaluate the key skills required by industry 4.0 and their role in preparing students for industry 4.0.	Quantitative and Qualitative	Review academic journals and evaluate research study. Semi-structured Interviews. Questionnaires.
Phase Two	**Development of the Framework**		
How do pedagogical interventions aim at facilitating students'	To develop and implement an assessment model that enables students to measure their skill level.	Framework design and development.	Review different models and learning theories

learning process to prepare and support them?			Assessment model structure and criteria.
Phase Three	**Validation of Framework**		
How does the proposed framework contribute to supporting students to embrace industry 4.0?	To test and evaluate the effectiveness of the framework in supporting the learning process and preparing students for the needs of industry 4.0.	Quantitative	Investigate the acceptance of the model-based on questionnaire's results.

1.7 Thesis Structure

The structure of the thesis was as follows:

Chapter 1 - Introduction: This chapter provided the research motivation, research novelty and contributions, research scope, research questions, aim, objectives and thesis structures.

Chapter 2 - Background: Review of background of industry 4.0 and its nine pillars, which included examples and applications of industry 4.0 and its status. This chapter also mapped the evolution of education with the four industrial revolutions. Further information can be found in Appendix 10 which highlighted the forgotten industry (industry 0.0) where the algorithms were first discovered at the House of Wisdom in Baghdad.

Chapter 3 - Literature Review: A critical review of the different types of analytics used in education, including the definition of big data analytics, academic analytics and learning analytics, the processes, existing framework and discussion. Knowledge-sharing theory is also discussed.

Chapter 4 - Methodology: Described the detail of the methodology, including research design, methodology used and participants.

Chapter 5 - Investigated the readiness level of students for industry 4.0 (phase 2): This chapter determined the important attributes that contributed to students' readiness for industry 4.0. First, the quantitative studies' findings were presented to validate the literature review. The findings of the first study were then used to design the interview research questions of the second study. The second study encompassed qualitative semi-structured interviews to which thematic analysis was applied.

Chapter 6 - Development and validation of industry 4.0 learning framework (phase 3): The results from chapter 5 were employed to create and develop a learning framework to monitor the learning process and prepare students for industry 4.0. This chapter presented the outcomes of each stage of the ASK SUMA framework.

Chapter 7 - Conclusion: The overall findings of the research and critical discussion were presented in this chapter. Moreover, this chapter comprised a critical discussion that highlighted the limitations of the research and recommended future work.

References

Appendices

1.8 Chapter Summary

Chapter 1 provided an overview of the research topic, which focused on developing a learning framework to enhance students' readiness to meet the demands of industry 4.0. This chapter outlined the rapid technological advancements that constituted the fourth industrial revolution and highlighted the widening gap between the skills required by employers and those possessed by new graduates. The motivation of the research was examined in this chapter from both academic and industrial perspectives. The chapter also presented the novelty and contributions of the research which was a tailored student-centred approach to developing and monitor the technical skills (knowledge needed to accomplish certain tasks), personal development skills and attitude, followed by the research scope. Informed by the literature review, three key research questions were formulated for the study and the primary aim of the research was to propose a framework supporting students' learning process, emphasising self-management skills to prepare them for industry 4.0 and future industrial needs. Therefore, to achieve the aim of the study, three key research objectives were planned around identifying and evaluating skills required for industry

4.0 and developing and testing of the proposed framework. The chapter addressed a critical need in the higher education and workforce development by proposing a framework to assess and develop skills and attitude required for industry 4.0. ASK SUMA framework intended to bridge the gap between academic training and industrial needs. The subsequent chapters will present background information underpinning this thesis.

CHAPTER 2: BACKGROUND

2.1 Introduction

This chapter presented the background of the study. Section 2.2 reviewed industry 4.0 and its nine pillars. The different stages of industrial revolutions were explained in Section 2.3. In Section 2.4, the evolution of education was studied, followed by a discussion on mapping education with industries in Section 2.5.

2.2 Industry 4.0 and Its Nine Pillars

Industry 4.0 was introduced and enhanced by Germany in 2011, using the concept to integrate information and communication technologies with industrial technology. National initiatives like "Industria Conectada 4.0" (European Commission,2017), or "Factory of the Future, (FoF)", and "Go Forth" were then taken by other countries in Europe, such as Spain, Italy, France, and the UK, to transform the idea into reality.

The aim of this concept was to create a highly flexible production model of personalised and digital products and services which encourages real-time interaction between people, products and devices during production processes (K. Zhou, Liu, and L. Zhou, 2015). Industry 4.0 combines Big Data, Internet of Things (IoT), and advanced analytics to provide industries with insights into manufacturing performance, customer behaviour and new product development. Germany launched the national programs of the "organised" digital economy by adopting "industry 4.0" concept in 2012. To date, such strategies have been adopted and provided with regulatory documents in almost two dozen countries, from the local "Smart Nation" in Singapore (2015) to the global Chinese concept "Internet +" (2015) and the launch of the Russian digital economy program (2016). The EU has introduced a wide array of financial instruments to support the innovative activity of enterprises over the years from 2021 to 2027 (Wyrwa, 2020). The UK government adapted this initiative which was known as AI match-fit with a £118 million skills package to put AI to work improving every element of Britain's lives (Department for Science, 2023).

2.2.1 Nine Pillars of Industry 4.0

Industry 4.0 seeks to digitise industry and physical devices and facilitate communication between devices via the Internet. Industry 4.0 pillars are referred to as Key Enabling Technologies of industry 4.0. Industry 4.0 nine pillars include autonomous robots, simulation, Internet of Things (IoT), cybersecurity, cloud computing, 3D-printing, augmented reality (AR), big data and data analytics.

The first pillar is autonomous robots that interact with one another and work safely together alongside humans. AI allows these robots themselves to start learning from humans so that they can undertake repetitive work more efficiently. The second pillar of industry 4.0 is simulation. Simulation is used to speed up the development of products and materials and the production process. Simulation allows factory operators to test and optimise the machine settings in a virtual model for the next product, even before the production starts, which in turn saves time and improves quality. The third pillar comprises horizontal and vertical system integration that helps to connect companies with suppliers and customers. This pillar is also known as IoT that connects great numbers of products by means of sensors and the Internet.

The fourth pillar encompasses cybersecurity which protects information systems and manufacturing lines from cybercrimes. This is applied by using sophisticated identity and machine access management systems that in turn provide secure and reliable communication. The fifth pillar includes cloud computing that plays an important role in achieving response times in milliseconds for data sharing. The sixth pillar is 3D printing technology that is also known as additive manufacturing. 3D-printing is popular in industry 4.0 due to its high performance in producing small batches of customised products. The seventh pillar is AR that provides operators with real-time information that is needed for faster decision-making and improving work processes.

The final two pillars are big data and data analytics. Analytics and decision-making processes are decentralised in industry 4.0 and that enables real-time responses. As industry 4.0 interconnects people, data, and entities, the ability to analyse the enormous data comprises the strength of industry 4.0. Data analysis provides insights in processes, which are useful in optimising production quality, saving energy, and improving services. Big data transforms every sector in the industry 4.0 as each organisation has data. Thus, big data facilitates real-time data analysis and predictive maintenance (Jagatheesaperumal et al., 2021).

2.2.2 Applications of Industry 4.0

A common research question that is frequently asked is whether industry 4.0 is only a concept or reality. Based on the research report written by The Manufacturer and Oracle (2019), Worcester Bosch, the UK gas boiler manufacturing arm of German industrial giant Bosch, has announced a boiler add-on, developed in conjunction with British Gas, through which consumers' boilers will automatically summon a maintenance engineer in the event of a malfunction. Aero-engine manufacturer Rolls-Royce, has been capturing half a terabyte of manufacturing data on each individual engine fan blade that it manufactures, analysing it with its clusters of high-power supercomputers to seek improvements to quality levels and product performance. The 'Smart factory' is also another example of this new industry era, which is based on Cyber Physical Systems (CPS) environments (Ryalat et al., 2023).

2.2.3 Current Status of Industry 4.0

The literature reported many industrial research studies regarding industry 4.0 that had been delivered by Siemens, Cisco, PWC, Deloitte, and others. Looking at all of these contributions from academia and industry and the broad range of different interests that they encompass, a question arises on the current status of industry 4.0. The UK government has also conducted the Made Smarter Review about the potential of industry 4.0. Based on this review, the UK's International Technology Strategy was developed.

In addition, various academic research studies have assessed the readiness of the UK to embrace the concept of industry 4.0. Research reports also showed that 67% of manufacturers recognised the potential of industry 4.0 (Annual Manufacturing Report, 2017) but only 12% have undertaken strategies to move into the new era. These driving forces have made the fourth industrial revolution one of the most frequently discussed topics of manufacturing conferences, forums and exhibitions over the past few years. In October 2021, Russia and the World Economic Forum (WEF) announced the Centre for the Fourth Industrial Revolution Russia to work across the global network to maximise the benefits of industry 4.0 technologies (World Economic Forum, 2021).

2.3 Industrial Revolution

In this section, a brief overview of each of the four stages of the industrial revolution was provided, focusing on the historical background of the evolution of industrial innovations and crucial changes they introduced.

2.3.1 First Industrial Revolution (Industry 1.0)

Before the first industrial Revolution, most people worked in the agricultural sector to support their daily lives. Most people grew just enough crops for their families while only a few produced enough crops to trade. Changes were seen in this period of mechanical refinement, where devices and machines were invented to make lives better and easier. In 1712, Thomas Newcomen, who played an important role in Industry 1.0, invented a steam engine that could assist in the process of removing water from the bottom of mines and allow miners to dig deeper. In 1784, Cort introduced his puddling and rolling technique for making wrought iron, which was one of the most important products during that time (Greenwood, 1997).

These production facilities led to industry 1.0, which started at the end of the 18th century. This is the time when the agricultural age was transformed into the industrial age, where individual cottage owners who were used to taking care of their own needs, grew into organisations and thereby to businesses.

This also marked the beginning of the textile industry. While the textile machinery was developing, James Watt discovered the inefficiency of the steam engine invented by Newcomen and made some improvements (Deane, 1979). Deane argued that the development of industry started when coal was used to replace wood because the coal and iron industries became the first users of the steam engines (Wrigley, 2004). At the same time, the demand for products increased. Hence, the steam engine was then used to assist in transporting goods and people. Railways first started in England during industry 1.0.

In summary, industry 1.0 involved the transition from hand production methods to the use of machines, which developed rapidly during this time; new production processes for iron, growth of the textile industry, and increasing use of steam power (Crafts, 2004). Industry 1.0 marked great progress in the manufacturing industries and started the cycle of mechanisation.

2.3.2 Second Industrial Revolution (Industry 2.0)

During the first industrial revolution (industry 1.0), the machines were simple, and many inventions were made. As the era of mechanisation continued to grow, Michael Faraday discovered that electricity could be produced mechanically which actually led to the transition from industry 1.0 to industry 2.0. Soon after that, his method was applied to machinery and transportation. In the 19th century, the era of mass production began when the first electricity-powered assembly line was built in slaughterhouses in 1870 (Victor, 2008).

Industry 2.0 began with the electrification cycle, when electricity became the primary source of power in the 20th century (Hughes, 1993). This enabled businesses to use power sources to operate machines, making them more portable and easier to use compared to their operation by water and steam. Electric power was then used to replace steam power in factories as it was found to be more cost-efficient (Victor, 2008; Hughes, 1993). It was also during this period that the famous mechanical engineer, Frederick Taylor introduced workplace methods to increase productivity and optimise work. Henry Ford then further refined the way in which manufacturing companies could improve their quality and output by applying just-in-time and lean manufacturing principles (Giedion, 1948).

2.3.3 Third Industrial Revolution (Industry 3.0)

Industry 3.0 is also known as the information revolution or the digital revolution. This was the era of production automation, when there was an increasing use of electronics in industrial processes and commerce, and computer-programmed electronic devices replaced the electricity-based production machines (Khan, 1987). In the last few decades of the 20th century, electronic devices such as transistor and integrated circuit chips were invented and manufactured, making it possible to fully automate individual machines to supplement or replace operators (Khan, 1987; Jensen, 1999). As a result, the costs were reduced by moving component and assembly operations to low-cost countries, which leads to the concept of supply chain management.

During this period, there was also growing application of electronics and Information Technology (IT) to automate the production processes. Enterprise resource planning tools were also created in order to help humans in planning, scheduling, and tracking product flows through the factory. Apple Computers, Commodore, and International Business Machines (IBM) entered the microcomputer market, as the use of computers in business became economically feasible (Khan, 1987). Furthermore, telecommunication systems also contributed to industry 3.0 (Fitzsimmons, 1994). During this time, the telecommunication industries underwent some changes when copper wire cables were changed to optical fibre technology, which increased the efficiency of the systems.

Industry 3.0 era was known as the digital age due to the use of digital technology. Space satellites were used in communication, acting as an alternative to land-based or undersea cables, which performed slower in terms of data transmission. The field of robotics also commenced in the time of industry 3.0 (Khan, 1987). For example, motor manufacturers such as Nissan in Japan started to automate their manufacturing processes during this industry.

2.3.4 Fourth Industrial Revolution (Industry 4.0)

In 2011, Germany officially initiated a future project, which was known as industry 4.0. There were many organisations and industrial associations focusing on this project and they made numerous investments in various areas. Such areas included additive manufacturing, robotics, AI and other cognitive technologies, advanced materials, and AR (Maier, 2017). Big data environment emphasised the importance of achieving self-aware and self-learning techniques (Lee, Kao, and Yang, 2014). Similarly, health management algorithms were created to efficiently implement current data management technologies.

Industry 4.0 has been happening since then through the use of CPS, which feature real-time responsiveness, replacing Programmable Logic Controller (PLC). This also meant that machines and robotics were controlled by automation systems equipped with machine learning (ML) algorithms (Lasi et al., 2014). During the later stages of the 20th century, some manufacturing systems lacked the technology needed to make their complete implementation possible. Hence, IoT was created to connect with manufacturing techniques to enable integrated systems to share information, analyse it and use it to guide intelligent actions. This also meant that sensors were used to sense the surrounding environment and to collect data, so that decision-making algorithms could be applied to improve the performance of the systems.

Table 2.1 summarises the different industrial revolutions.

2.4 Education Evolution

In a similar way to the four industrial revolutions, education has undergone an evolutionary process. However, the pace of change, the adoption of new technologies in education, and the transformation of learning frameworks was not rapid. Despite the slow pace of change in education, “version” tags were added so that the stages of education revolution could be easily understood (Table 2.2).

Table 2.1: Summary of the Stages of the Industrial Revolution

Industry Version	**1.0**	**2.0**	**3.0**	**4.0**
Focus	Mechanisation/Steam	Electricity/Mass Production	Automation (IT)/Electronics	Smart Automation
Examples	Steam engines Steam factories Iron production Textile Industry Mining and Metallurgy Machine Tools	Mass Production Globalisation Engines/ Turbines Broad adoption of telegraph, gas, water supply	Computer/Internet PLC/Robotics Digital Manufacturing and Digitisation Automation Electronic/Digital Networks Digital Machines	Autonomous Machine Advanced robotics Big Data/Analytics and Cloud Management IoT Machine Learning and AI Cyber Physical

Table 2.2: Education Evolution Chart based on Leapfrog Principles (Harkins, 2008; Demartini and Benussi, 2017).

Attributes	Education 1.0	Education 2.0	Education 3.0	Education 4.0
Time	18^{th} -Early 20^{th} Century	Late 20^{th} Century	21^{st} Century	From 2020 and beyond
Model	"Download" education	"Open Access" Education	"Knowledge Producing" Education.	"Innovation producing" education.
Approach and Focus	Instructivist 3R's (receive, respond and regurgitate)	Constructivist 4C's (Communicating, contributing, collaborating, and co-creating)	Connectivist 3C's (Connecting, collectives, and curating)	Adaptive learning driven by AI portal Learning process will be based on real-time student profiles. Built through selective individual and team-driven embodiments in practice by focusing on innovation.
Educator	Knowledge source	Facilitator who team with students and others to create more interesting class experiences.	Learning designers, leader of collaborative knowledge creation.	Supported by an AI learning portal.

Students	Passive learners	Active learners	Co-developers and co-researchers. Authors, drivers and assessors of learning experiences.	Self-governed learning (autonomous). counsellors and AI help co-develop education plans, continuously updated by AI models. Input of learners as a major source of technology evolution in the service of innovation production.
Technology	Distance Courses. Purchased at great cost but was not really used widely.	E-Learning collaboration involving other institutions, mainly within the borders of a single learning management system. Open source and available at lower costs.	Low-cost digital mobile. Web driven technologies. Used purposively for the selective production of knowledge.	Personalised intelligent models, IoT. Web driven e-learning.

2.4.1 Education 1.0

The trend of educational thinking and practice began to change in the industrial age when factory-based production started expanding. Before the industrial age, the family was the focal point in education, and children could perceive and participate in almost all productive activities (Dewey,1902).

Education 1.0 focused on the instructivist approach (Petrina, 1998; Gerstein, 2014). It involved 3Rs, meaning “Receiving”, “Responding,” and “Regurgitating”. Students “receive” (learn) by listening to the teacher, “respond” by taking notes, reading text and doing repetitive worksheets, and lastly, “regurgitate” by doing similar assessments, which were used to measure their learning performance. This was called “one-size-fits-all education” because all learners were viewed as the same. It only involved a “one-way” learning process where students were passive and they were instilled with the most essential, or basic, academic knowledge and skills and character development.

In addition to the categories of teaching pedagogies (*sage*, *guide* and *meddler*) proposed by McWilliam (Salmon, 2014), Education 1.0 was categorised as “sage on the stage”, which meant students learn passively by receiving the knowledge and information transferred by the teacher. Standardised learning materials were used to support the pre-determined syllabus containing specific knowledge and opportunities for skill development. The students were also expected to learn as fast and as much as they could and their learning progress was pre-determined by the intended learning outcomes. There was also little room for students to develop their creativity in education 1.0 as learners only do what the teachers want them to do and the assessments ensure students focus on certain requirements, rather than engaging in an open-ended learning process (Gerstein, 2014).

During this era, digital tools, such as e-books and websites, were created to support students’ learning processes. Yet, students did not interact sufficiently with e-books and websites. The Learning Management System (LMS), which was also known as a Virtual Learning Environment (VLE), was introduced and educators enhanced face-to-face learning combined with web-access, which reflected the “knowledge transmission” paradigm of teaching. However, this system was very limited in every single institution (Demartini and Benussi, 2017). Therefore, within education 1.0, besides libraries and news outlets, the educator was the students’ knowledge source and the venue of learning would be the traditional classroom.

2.4.2 Education 2.0

As the world was filled with ambiguity and uncertainties and there was rarely a single answer to a single problem, teachers realised that the instructivist approach had not effective (Gerstein, 2014). Thus, they sought ways to improve learning processes and found that students learnt best by gaining real-world experience. In response, teachers promoted interactivity by encouraging students to interact with their peers and co-create knowledge. This approach was aligned with the teaching pedagogy proposed by McWilliams (2009), which was a “guide on the side” where the educators acted as facilitators and team with students to create more interesting class experiences.

Unlike education 1.0, the constructivist approach was applied during education 2.0, where students were active learners and gained knowledge by formulating and solving their problems. Education 2.0 involved interaction between users and activities (Gerstein, 2014), and this meant that it consisted of 4Cs. 4Cs included communicating, contributing, collaborating, and co-creating. Thus, students learnt through activities like projects and research by exploring the problems, interacting with each other, searching for resources, and discovering possible solutions. This approach of training students to discover possible solutions was used to prepare them for their future careers.

Technologies in education 2.0 enhanced traditional approaches to education during this era. This resulted in open educational resources and open access distributed content platforms like Wikis, personal websites, blogs, and social media platforms. This latter content boosted collaboration, social learning, co-creation of knowledge and artefacts, personal reflection, sharing of personalised learning, and curation of knowledge (Gerstein, 2014). This complied with the learning structure, which applied the principles of active, experiential, authentic, relevant, and socially networked learning experiences (Gerstein, 2014). This model was related to providing procedures and resources for helping learners to acquire new information and skills. The flipped classroom was a good example of education 2.0, which involved transmitting data outside of the lecture room, and was often used for students to access and work on learning materials themselves (Salmon, 2014).

2.4.3 Education 3.0

The emergence of the Internet caused a major shift in education. Unlike education 1.0 and 2.0, education 3.0 showed a substantial change compared to previous educational eras. In education 3.0, a technological platform was created and the role of the teacher was changed to a facilitator. With the presence of online platforms, students self-determined what they want to learn and decide on their own learning objectives, with the guidance of their teachers. Students utilised the expertise of teachers and share knowledge with members of other learning communities to introduce content-related resources.

Education 3.0 focused on learning by connecting individuals who were interested in sharing their knowledge to co-create new knowledge (Gerstein, 2014). This type of education focused on 3Cs being connecting, collectives, and curating. This meant that the environment of learning was collective, where people with various skills and levels of knowledge gather and interact to gain new knowledge. In other words, students played vital roles as creators of knowledge artefacts that were shared and social networking and social benefits played a strong role in learning. The research also added that the learning process comprised of deciding what to learn and maintaining connections to facilitate continual learning (Siemens, 2005). In education 3.0, students took learning initiative due to academic curiosity and not for the purpose of formal recognition.

In the 20th century, interactive whiteboards replaced traditional chalkboards. This era depicted the digital age, where students started using computers to learn. Technologies such as LMS were developed to help students in learning virtually. There was no clear boundary between space and time. Students could learn anywhere and anytime they want. Students were also actively engaged in the process of learning..

2.4.4 Education 4.0

Education 4.0 emerged because of the changing skills requirements from industry. It was the vision of the future of education, which responds to the needs of industry 4.0. Education 4.0 was known as innovation-producing because students designed their learning path. This latter approach allowed students to co-create knowledge in a meaningful and innovative way (Harkins, 2008).

In education 4.0, the student or learner was responsible for defining their own educational path, which also led to the concept of personalised learning. The learning process was aided by using AI. The input of learners has become the source of technological evolution in the service of innovative production. Algorithms were applied to real-time student profiles on the AI portal to improve adaptive learning performance and to develop education plans updated by AI models (Thompson, 2017).

As education 4.0 is still emerging, current models are still in the process of development and research, as part of which Learning Analytics (LAs) have been introduced. Siemens first defined LAs in his 2011 blog post as the use of intelligent data, learner-produced data and analysis models to discover information and social connections and to predict and advise on learning (cited in Ferguson, 2012). LAs actually allow personalised learning experience in education, as learners can reflect on their achievements, trends and progress in relation to their own goals (European Commission, 2016). For instance, the SmartGPA system, which uses sensors to collect data from students' smartphones, was created to understand the individual behavioural differences between strong and weak performers during a single 10-week term and to predict their academic performance (Wang et al., 2015).

2.5 Discussion: Mapping Education with Industrial Revolution

The evolution of industry 1.0 to 4.0 is an indication that education should also be developed. Yet this is not the case in education 4.0 that is still behind the industrial revolutions. Industry 4.0 advanced digital transformation which exposed education to challenges and opportunities in meeting the needs of this fast-growing industry. Thus, implementing industry 4.0 pillars required advanced skillsets that cannot be offered by education 4.0 nowadays. Therefore, the current and future education structure should not only focus on training knowledge-based skilled labour but also emphasise the cultivation of innovative talent to meet the current demands of industry.

Before the industrial revolutions, education focused only on teaching the elite classes that were mainly of male gender. Education was taught informally before it was transformed by focusing on scientific research. Most education started with the dominance of religion. The industrial revolution caused widespread change in all aspects of society. Therefore, motivated individuals could easily take advantage of the economic opportunities that became available. Research studies also contributed, in that modern economic growth depends on the growth of useful knowledge (Tang and Werner, 2017). This emphasised the importance of gaining knowledge through education. Industry 1.0 marked the beginning of industrialisation, which led to the demand for mass education - education for ordinary people, especially from the lower classes. This was the time when there was a demand for a workforce fit for the industrial sector. More schools were built and the new concept, "free education" was introduced at the same time (Robinson, 2011).

During the second industrial revolution (industry 2.0) where there was hardly a proper educational system in place, students were viewed as ill-prepared assembly line workers as the invention of machines helped in mass production. However, skill undoubtedly played an important role in technological innovation and adoption

(Greenwood, 1997). People did not know how to work efficiently until Frederick Taylor and Henry Ford proposed workplace methods and applied some of the just in time and lean manufacturing principles to optimise the workforce and improve their quality and output (Gieldon, 1948).

The third industrial revolution (industry 3.0) initiated the telecommunication industry and this meant that, as communication became easier, people could access and create content anywhere, any time. Although some countries were still applying the approach used in education 1.0 and 2.0, while other countries have started developing new education models that enable increasingly flexible, experimental and fairer learning environments which lead to the introduction of the new era, Education 3.0. Students started sharing their knowledge with peers who have different skills and levels of knowledge to co-create new knowledge. This shows that technology is used to assist students' learning process and help them in shaping the content, location and ways in which they learn.

In the new industry era, technology is growing rapidly and there are many new inventions. However, Lortie (2002) argued that at the beginning of the 21st century, the education does not change at a rapid pace, as the structures of education are still the same as the 20th century. The existence of sensors and IoT can actually indicate an early sign of the use of wearable devices to assist teaching, learning and training.

Recently, a limited number of research studies have used smartphones and sensors to study the factors that affect students' academic performance. However, there are many other factors that affect students' performance and this leads to complexity in research. As education 4.0, the world is complex: the standardisation approach that was applied during education 1.0 era has to be eradicated. Furthermore, standardised learning methods cannot deliver what current and future education needs when it comes to coping with complexity (Wallner, 2012). Everyone is different, and therefore, the standardisation approach is no longer helpful. In addition, one can perform well if they can discover their own suitable method of effective learning. This can be done with the assistance of current technologies invented in industry 4.0. LAs were developed as a significant tool to cope with the demands of industry 4.0, and it is symbolic that the notion of industry 4.0 appeared in the same year – 2011 – as the definition of LAs (Ferguson, 2012). It was also developed to respond to the challenges of the industrial revolution, and the core principle of LAs comes from the fourth industrial revolution.

In addition, the Talent Shortage Survey has clearly shown that we are still not ready yet to answer the question, “With our current approach, are our students prepared to face rapidly changing industry?” (Manpower, 2015). In addition, the UK is also facing a critical level in terms of skills shortages, putting the country’s growth at risk (The Telegraph, 2018). Moreover, in the most recent WEF, Jack Ma, the founder of the Alibaba Group, mentioned that the knowledge-based approach of 200 years ago would cause our kids to fail; they would never be able to compete with machines, and they should be taught soft skills like independent thinking, values and team-work, which can be tackled by first understanding their behaviour and attitudes towards learning (World Economic Forum, 2021). At the same Forum, Justin Trudeau also spoke about the importance of education in equipping his country for industry 4.0.

Table 2.3 summarises the comparison between the industrial revolution and the evolution of education. It shows that the gap between industry and education must be addressed as soon as possible, so that the supply of skills and talents can be matched with the demands of industry.

Table 2.3: Summary of Comparison between Industrial Revolution and Education Evolution

Types of Revolution (Age)	**Before 18th Century (Agricultural Age)**	**18th Century (Industrial Age)**	**19th Century (Knowledge Age)**	**20th Century (Digital Age)**	**21st Century (Connected World)**
Industry	Before Industry 1.0	1.0 (Mechanisation)	2.0 (Electrification Cycle)	3.0 (Automation)	4.0 (Smart Automation)
The Views of Industry on graduates	(Industrial age has not started yet)	Assembly line workers	As ill-prepared assembly line workers	As co-workers	Lack of required skills and talents (Talent Shortage Survey)
Education	1.0	1.0 2.0 (ideally)	1.0 2.0 3.0 (ideally)	1.0 2.0 3.0 4.0 (ideally)	1.0 2.0 3.0 4.0 (ideally but already emerging in some countries)

Implication	-	There is a gap between each education era and technology era. Education moves slower than industry. It has to move faster in order to catch up with the fast-growing demands and, in fact, it should be faster than the industry so that the supply of skills and talents can match the demands of industry.

2.6 Theoretical Framework

A theoretical framework provides a foundation for the research by underlying and defining the key theories behind the choice of a specific research approach (Creswell, 2014; Bryman, 2015; Merriam and Tisdell, 2016; Grant and Osanloo, 2021). It also helps the researchers to identify research questions, hypotheses and data collection methods by providing a clear structure and a set of theories. Highlighting the importance of a theoretical framework, Sarter (2005) and Imenda (2014) contended that a study without a justifiable theoretical framework would produce research that lacks useful findings and conclusions and lack accurate direction in the search for appropriate literature. The theoretical framework guides the researcher throughout the entire research process from identifying the research questions to final interpretation of the research findings. Akintoye (2015) further implied that the proper selection of a theoretical framework convinces scholars in the field that the research study is not based on personal instincts of the researcher but deeply rooted in an established theory selected through a thorough literature search. The selection of a theoretical framework requires a thorough understanding of the research problem, purpose, significance and research questions so that the right research methods can be chosen to tackle the research problem.

2.7 Theoretical Paradigms

Methodology summarises the research process and deciding on a methodology starts with the choice of research paradigm that informs the study. Lincoln and Guba (1985) stated that the four pillars of research paradigms are epistemology, ontology, methodology and axiology. It is vital to understand these four elements as each comprises its own basic assumptions, beliefs, norms and values. Epistemology is defined as the study of the nature of knowledge and justification (Schwandt, 1997; Cooksey and McDonald, 2011). Ontology is the philosophical study of the nature of existence or reality, while methodology is the broad term used for the research design, approaches and procedures used in a research study (Keeves,1997). Axiology refers to the ethical issues considered when planning a research study (Finnis, 1980). Putting the information about these four pillars together informs the purpose of the research paradigm. In other words, the research paradigm establishes the structure of the research. There are different types of theoretical paradigms which will be discussed.

One of the major research paradigms is positivism, which was first introduced by Comte (1856). The research process for positivist paradigm studies often begins with the formulation of an empirical hypothesis, which is subsequently supported or rejected by data gathering and analysis. Positivists believe that theories are only authentic if they can be verified through observations and measurements (Fadhel, 2002). This view was expanded by Durkheim (1964) who elaborated that social scientists should study social phenomena like other scientists. Positivists approach research objectively and advocate quantitative data collection rather than looking for qualitative explanations for those patterns.

Pragmatism is a paradigm where pragmatists argue that it is impossible to access the truth by a single scientific method advocated by the positivist paradigm and they think that reality is always changing in the midst of ever-changing conditions. As a result, rather than employing a single research paradigm, they combine the positivism and interpretivism approaches to apply the framework best suited to the research topic under consideration (Alise and Teddlie, 2010). Pragmatists argue that the optimal research method is the one that addresses the research issue most effectively.

Constructivists believe in several realities rather than one reality. According to the constructivist paradigm, understanding of the world is developed through interaction and reflecting on it (Punch, 2005). The constructivist study aims to comprehend the interpretations that people place on their experiences. As a result, qualitative techniques like interviews and case studies are commonly employed. Constructivists aim to understand the reasons that lead to events.

Interpretivism refers to a philosophy where the social world cannot be investigated from an objective view of the researcher and all observation is based on theory and values (Leitch, Hill and Harrison, 2009). This means that the interpretivist philosophy seeks to understand and interpret the meanings of the participants' experiences (Spiggle, 1994). Hence, interpretivism is understood as a philosophy that seeks an explanation from the view of participants based on their own experiences. Therefore, it also means that every participant will have different interpretations of their world. According to Klein and Myers (1999), theory is essential to interpretive research in information systems. Theory is employed as a "sensitising tool" to create a particular worldview. Observations can be connected to abstract categories, ideas and concepts that can be used in a variety of contexts, suggesting some degree of generalisability.

According to Creswell (2013), the transformative worldview "holds that research inquiry needs to be intertwined with politics and a political change agenda to confront social oppression at whatever levels it occurs". Those who take this view reject both positivism and interpretivism and believe that both frameworks do not adequately represent the realities of marginalised communities. Transformative researchers typically employ both qualitative and quantitative methods to better identify inequities in community interactions, promote social justice and ultimately achieve transformative change (Greene, 2007). Table 2.4 shows the characteristics of major research paradigms.

According to Ponelis (2015), interpretivism is characterised by a need to understand reality according to its particular context. In addition, Carson et al. (2001) noted that the findings of interpretivist research are only relevant and valid in the specific context of that research. Since the objective of this research is to understand more about industry 4.0 and education that can help to fulfil its needs and to find out how to minimise the gap between the industry's expectations and academic production, an interpretivist philosophy is thus adopted in this current study. The findings of this research will be used to understand context-specific conditions and interpret data from the participants' perspectives. The pragmatic approach is the approach used in study as it involves mixed-method research, and it emphasises on practical considerations that theoretical ones. It combines different approaches to gain broader understanding (Mangava and Kabanda, 2023).

Table 2.4 Characteristics of Major Research Paradigms

	Positivism	**Pragmatism**	**Constructivism**	**Interpretivism**	**Transformative**
Epistemology	Knowledge is real and objective.	Obtained by doing and acting	Knowledge as human construction-engage in building and sharing	Understood through perceived knowledge.	Knowledge is socially and historically located.
Methodology	Surveys, experiment and statistical analysis	Mixed-methods research, action research, design science	Qualitative	Primarily non-quantitative	Qualitative/ quantitative/ mixed methods
Ontology	Realist	Objective/Subjective	Multiple realities	Subjective	Issues of power and

					critical interrogation of multiple realities
Purpose	Prediction/ control/ explanation	Consequences of actions	Understanding	Understanding	Political

2.8 Chapter Summary

Chapter 2 covered the background of the study, focusing on both industrial revolution and education evolution. It highlighted the role of education in knowledge transfer and its influence on shaping the future industries. Chapter 2 also examined these revolutions from two perspectives. The first perspective addressed the necessity for education to meet the demands of industry 4.0. The second perspective explored how technologies invented in industry 4.0 could be used to assist the learning processes in education 4.0. This analysis underscored the mutual support between the industrial and educational sectors through their evolution. Furthermore, the chapter traced the evolution of industrial revolutions, arguing that each stage was critical as they brought significant technological and societal changes. It highlighted that the current industry 4.0 demanded a workforce with a new set of skills and competencies. In parallel, the chapter examined the evolution of education and argued that educational paradigms have not been able to keep up with the pace with industrial advancements. This chapter contended that there was a significant gap between the skills demanded by industry 4.0 and those provided by the current educational systems. The next chapter will present the literature review on readiness for industry 4.0.

CHAPTER 3: LITERATURE REVIEW

3.1 Introduction

This chapter provides the literature review of the study. Students' readiness for industry 4.0 is reviewed in Section 3.2. Domains of learning attitude and different types of skills will be examined in Section 3.3. Section 3.4 explains the overview of learning process. Section 3.5 discusses the different learning frameworks for industry 4.0. Section 3.6 discussed the research gap and identified the preliminary framework in Section 3.7.

3.2 Readiness for Industry 4.0

Readiness refers to the capacity of individuals to adjust and flourish in environments shaped by advanced technologies. Students' preparedness for industry 4.0 is defined as their ability to meet the changing requirements of the contemporary workforce, which are marked by advanced technologies and innovative practices. Universities need to evaluate the readiness levels of students if they wish to guide them towards a comprehension of industry 4.0 and its applications, as this assessment allows these institutions to initiate and develop educational programs and training initiatives (Oke and Fernandes, 2020). Several studies have investigated students' preparedness for industry 4.0 in universities across developing nations such as South Africa, Malaysia, Thailand, Oman, and Brazil, as well as in developed regions like Japan, Korea, and Italy.

For instance, in South Africa, a study investigating the awareness and readiness of 24 students from three universities in Namibia, using a quantitative method, revealed that students understood industry 4.0 (Ujakpa et al., 2020). However, it recommended further education on its application to prepare students for industry roles. Moreover, the study indicated that while most students were familiar with and capable of using the technologies, they had not been directly exposed to relevant education. Additionally, Kayembe and Nel (2019) noted that the education sector faces numerous hurdles in adapting to industry 4.0, such as the need for pedagogical adjustments, teacher development, inadequate funding and infrastructure, and skills necessary to equip graduates for the rapidly evolving technological landscape.

Research on students' readiness for industry 4.0 has been extensively conducted in Malaysia. Findings indicated that a majority of the studies were equipped to implement the technical skills necessary for industry 4.0 and were willing to acquire new knowledge and adjust to changes (Ahmad et al., 2019). The students highlighted the importance of enhancing their problem-solving abilities independently, despite asserting that they possessed the soft skills required for industry 4.0. Furthermore, another study conducted in 2019 revealed that students felt ill-prepared to enter the industry 4.0 workforce and conveyed a lack of clarity regarding industry 4.0 itself. In Thailand, Puriwat and Tripopsakul (2020) evaluated the readiness levels of 132 graduates embracing industry 4.0 and discovered deficiencies in the digital and information skills they needed, signalling the necessity for reform in Thailand's education system to better prepare them for the industry. They recommended implementing initiatives to elevate students' comprehension of industry 4.0 and its practical applications. In Oman, researchers explored students' readiness levels for industry 4.0 and identified that characteristics of students, familiarity with industry 4.0 technologies, and organisational factors significantly affect their preparedness (Al-Maskari, Al Riyami and Ghnimi, 2022).

Dos Santos et al. (2018) found that chemical engineering students encountered challenges necessitating a blend of their expertise with programming knowledge in their coursework. The researchers presented a successful strategy in Brazil to integrate industry 4.0 competencies, engaging chemical engineering students in applying industry 4.0-related programming skills in their curricula by establishing practical training that enhanced their preparedness for industry 4.0. Similarly, Watanabe, R., Watanabe T. and Skitmore (2023) investigated integrating construction information technology in education, focusing on students' acceptance and readiness for industry 4.0. They found out that their perception of the usefulness of construction information technology in future employment is a more influential factor in their willingness or readiness to accept and participate in the courses compared to its perceived importance for industry development. The researchers recommended an effort between the industry and the university to bridge the gap between academic and industry needs, create job opportunities for students, and nurture talent. Hizam (2020) proposed six dimensions (Technology, People, Strategy, Leadership, Process and Innovation) that can be considered as the most important dimensions for organisations.

Tinmaz and Jin (2019) conducted research with 129 undergraduate students at a private university in South Korea to assess their knowledge of the industry 4.0 concept. The findings indicated that they were unclear about its practical uses despite being aware of the term. The students acknowledged that although industry 4.0 is widely discussed, they did not possess a good foundation of its principles, and there was insufficient training and specialised programs focused on industry 4.0 in South Korean higher education. Likewise, Motyl et al. (2017) assessed the readiness for industry 4.0 among 463 undergraduate students across three universities in Italy and highlighted that it is necessary for a comprehensive educational framework to deliver more structured knowledge to students. Most studies indicated that students felt inadequately prepared to enter the industry 4.0 workforce, emphasising the need for universities to enhance their efforts in equipping them for this new era. The previous studies also showed that many factors contributed to student's readiness for industry 4.0 in universities. The industry 4.0 readiness was explored from two perspectives, organisation and students. Although they were examined in different contexts, they were interconnected. For example, technology dimension in the organisational context was aligned with the knowledge in industry 4.0 in terms of students' context. The people aspect in the organisational context corresponded to the students' characteristics. Consequently, it is worth further investigating the factors that contributed to the readiness of students for industry 4.0 in the UK.

3.3 Domains of Learning

According to Lizzio and Wilson (2004), competency comprises three key constituents: knowledge, skills, and attitudes. Eraut (1994) and Kaslow et al. (2007) also stressed that competence development theories emphasised that learners must not only acquire but also integrate knowledge, skills and attitude to achieve competence. Baartman and Brujin (2011) suggested that the integration of these three components should be evaluated as part of the learning process. As this research investigated the framework in supporting students' learning process, it was important to understand these three domains of learning; attitude (affective), skills (psychomotor) and knowledge (cognitive).

3.3.1 Attitudes

Attitude was one of the primary domains of learning that impact human behaviour, yet no universally agreed definition exists for what an attitude entails. Psychologists could not decide whether attitude should be understood as one single phenomenon or several phenomena simultaneously. This research investigated various theoretical frameworks and empirical studies on attitudes as a domain of learning.

Attitudes were defined by Robbins and Judge (2007) as evaluations of various objects, people, or events, and that which directs "a person's aspirations and ambitions" (Collins and Sikes, 2003, p. 32). Wood (2000) and Bruvold (1980), on the other hand, defined attitude as a positive or negative reaction towards the experience that influences a person's response to people, objects, and situations. The authors also implied that attitudes are learned, organised, and closely related to a person's personality, which serves as the emotional foundation for our social interactions and sense of belonging.

Research has shown that attitudes could have a significant impact on behaviour, with positive attitudes leading to positive behaviours and negative attitudes leading to negative behaviours (Ajzen and Fishbein, 1980). A positive attitude was critical in learning and personal development, particularly in the technology industry, which is continuously evolving. Employers value a positive attitude when recruiting in the technology industry because it would indicate the potential employee behaviours at work and are frequently associated with positive outcomes within the organisation (Newstrom and Davis, 1993). For example, leading technology companies, such as Google, Apple and Amazon, value their employees' positive attitudes toward learning and innovation and consequently, this has resulted in the development of game-changing technologies which form part of the industry 4.0 including AI, VR, and cloud computing (Munir et al., 2022).

Positive attitudes could take many forms, including a growth mindset, adaptability and a willingness to learn. A growth mindset was characterised by a belief in one's ability to learn and improve, whereas adaptability was defined as the ability to adapt to changing circumstances (Ng, 2018). According to Nja (2022), a positive attitude enhanced students' academic performance, motivation, engagement, and creativity. In conclusion, positive attitudes towards learning were important for students to be industry 4.0 ready and educators played an important role in this.

3.3.2 Skills

Skills were an essential component of personal and professional development. Skills comprised "the abilities, knowledge and expertise that are necessary to perform a task or function effectively," (Klein et al., 1999). According to Noe, Hollenbeck and Gerhart (2015), skills comprised the capacity to perform a job well and were categorised into technical and behavioural groups.

Rainsbury et al. (2002) defined hard skills as the technical skills needed to carry out a variety of job-related tasks, most of which were cognitive in nature and influenced by intelligent quotient (Kenayathulla, Ahmad, and Idris, 2019). Skills were often referred to as knowledge received in educational institutions. Lombardi (2019) asserted that technical skills could be created, recorded, and transferred between educational units with the support of education systems and cultures. Technical skills were observable behaviours and abilities that produced immediate results and could be evaluated through assessments. According to a report by the World Economic Forum (2023), there was an increasing demand for skills related to AI, cloud computing, and data analysis in the technology industry. The report suggested that individuals must acquire these skills to remain competitive in the job market and contribute to the growth of the industry. Li et al. (2021) indicated that there was a significant shortage of professionals who combined robust data science skills with deep industry 4.0 knowledge. They also identified that the top technical skills and knowledge in the domain in the Big Data field were Java, Python Programming, R Programming, Statistics, and ML. The progress of industry 4.0 necessitated those skills required in many technical domains to be re-examined. In addition, Kesavan (2025) also emphasised that cloud computing skills must be prioritised due to its role in facilitating data analysis. ML was essential for extracting insights from data as ML represented core components of the Big Data and AI landscape within industry 4.0 (Mohamad et al., 2019). In order for one to master ML, a solid foundation in mathematics like calculus, linear algebra, and statistics was necessary in the field of AI and big data. Velten et al. (2024) stated that mathematical principles provided necessary tools for data modelling while data analysis required one to be proficient in Java, Python and R (Yusof et al., 2020). Yudiono (2021) also added that these languages were crucial to enhance the students' readiness for technical roles in industry 4.0. As noted by Akyazi et al. (2020), familiarity with technologies and mentioned programming languages were critical skill set for students to work in industry 4.0. One of the technologies would be IoT that facilitates connectivity among devices and systems. Therefore, mastering IoT was increasingly recognised in literature. Signal processing played a pivotal role in the context of industry 4.0, particularly in the analysis and interpretation of data generated by smart devices and sensors. In their research, Okoye and Edokpolor (2021) emphasised the importance of technical skills for students entering technology-driven industries. According to the literature, technical skills that were mentioned were critical in this rapidly evolving industrial landscape. Students would need to ensure that they possess these skills before entering the workforce. However, Mwita (2024) argued that universities should not only emphasise on technical skills but also consider the importance of soft skills too.

Soft skills are attributes that cannot be transformed easily into technical skills (Zhang et al., 2015). Soft skills are defined as transversal skills which differ from basic skills and personal traits that relate to involvement, attitude and compatibility with other people during interaction. Soft skills are equally important as technical skills and one needs both to keep their job and reach professional development in industry 4.0 (Cotet et al., 2017; Chaka, 2020).

Rapid technological advancement signals that in-demand soft skills will change over the next five years or longer; therefore, skill gaps will continue to be significant. Table 3.1 shows the review of World Economic Forum reports on top 10 skills on reskilling and upskilling future-ready workforce (Whiting, 2020). From the table, skills in self-management such as active learning, resilience, stress tolerance and flexibility emerged as the important skills to have for future. Judgment and decision-making skill did not make the cut into the top 10 skills in 2025 as AI and ML are expected to support organisations in providing decision support information.

Table 3.1 Top 10 Skills Based on Future of Jobs Reports (Whiting, 2023)

2020	2025	On the Rise (2023-2027)
Complex problem solving	Analytical thinking and innovation	Creative Thinking
Critical thinking	Active learning and learning strategies	Analytical thinking
Creativity	Complex problem solving	Technological literacy
People management	Critical thinking and analysis	Curiosity and Lifelong learning
Coordinating with others	Creativity, originality and initiative	Resilience, flexibility and agility
Emotional intelligence	Leadership and social influence	Systems thinking
Judgment and decision making	Technology use, monitoring and control	AI and Big Data

Service orientation	Technology design and programming	Motivation and self-awareness
Negotiation	Resilience, stress tolerance and flexibility	Talent Management
Cognitive Flexibility	Reasoning, problem solving	Service Orientation and Customer Service

Prifti et al. (2017) pointed out that students will require a certain level of Engineering related training to develop skills for industry 4.0 and will require a certain level of Engineering professional training. They also explained that the skills requirements for industry 4.0 differ from previous developments in the industry because, beyond domain knowledge, personal skills prove to play a vital role, and the interaction between the technologies and their virtual nature creates something conceptual. Behavioural competencies were identified and categorised in the framework developed by Prifti, et al. (2017). However, the comprehensive work does not include each professional level while on the other hand, Cotet et al. (2017) identified soft skills and technical skills in comparison with behavioural skills and domain skills respectively and soft skills are found to be contributing significantly to the success and development of the employee in the industry 4.0 era. According to Cotet et al. (2017), creativity, emotional intelligence and proactive thinking are known to be the top three skills in assisting employees to adapt easily to the incremental changes. Adolph et al. (2014) also discussed skills like agility in problem-solving, the ability to reshape processes, flexibility, and self-learning are important traits to have in industry 4.0.

In conclusion, skills are a critical aspect of personal and professional development. The acquisition of skills can be through education, training and experience, and is essential for addressing social and economic challenges.

3.3.3 Knowledge

Knowledge is known as cognitive skills that are taught and applied to process and understand facts and to create and present new ideas and solutions. Nonaka (1994) defined knowledge as "a fluid blend of experience, values, contextual information and expert insight that serves as a framework for evaluating and incorporating new experiences and information".

There are two types of knowledge which are declarative and procedural knowledge. Anderson and Schunn (2000) defined declarative knowledge as factual information that an individual was aware of and might report on whereas procedural knowledge refers to knowledge that cannot be conveyed. According to Miller (1990), ‘knowing that’ refers to knowledge about facts, concepts, and definitions and ‘knowing how’ refers to knowing how to do something without any actions. Knowing how can refer to both declarative and procedural knowledge as a person can report on how to do something but not doing any actual actions. Explicit knowledge is a type of knowledge that is recorded in sources like textbooks, manuals, and databases and is easily transmitted to others via formal education and training programs. In the context of this research, the university’s education system focuses on explicit knowledge.

Tacit knowledge refers to personal, subjective knowledge that is difficult to be documented and expressed De Jong and Ferguson-Hessler, (1996). Personal experience, observation and socialisation are frequently used to acquire this type of knowledge. Knowledge that is embedded in products, processes and routines is referred to as embedded knowledge. This type of knowledge is frequently hidden and implicit, and it can only be acquired through practice and experimentation.

In the context of this study, the industry 4.0 era demands a transformation in the higher education system as the existing one is not focusing much on tacit knowledge and embedded knowledge. The future workforce must have a diverse set of knowledge to remain competitive and adaptable in current industry era. Therefore, the best way to learn is through socialisation and immersion in a community of practice, where individuals learn from one another through observation and collaboration (Brown and Duguid, 2001).

3.4 Overview of the Learning Process

Understanding the learning process within industry 4.0 becomes crucial for preparing students to embrace industry. To understand the learning process, it is important to know the definition of learning. Learning is defined as the process of acquiring knowledge, skills and attitude (Brockbank and McGill, 2007). Learning is also taken to mean “a relatively permanent change in behavioural potentiality that occurs as a result of reinforced practice” (Kimble, 1961). In addition, it is an integrated and ongoing process that allows students to meet individual goals. Human learning is a complex process as theorists find it difficult to conclusively define it. Therefore, it is vital to have a better understanding of the different learning theories.

3.4.1 Theories of Learning

Learning theories are a set of principles explaining the process of an individual's acquisition of skills and knowledge. There are different learning theories; namely, behaviourism, cognitivism and constructivism.

Behaviourism is a learning theory that focuses on observable behaviour and posits that it is shaped by environmental factors rather than cognitive processes (Pavlov, 2010). Behaviourists believe that by understanding and altering the environmental factors, they can change or modify behaviour in predictable ways. Watson stated that thoughts and feelings should be ignored when analysing a behaviour while Skinner argued that internal processes should be included, and this is known as radical behaviourism. Skinner believed that successful learning is through showing and positive reinforcement (O. Omomia and T. Omomia, 2014). According to Marton and Booth (1997), learning process in behaviourism is viewed as a passive activity and it is a result of a direct experience or practice. Learning outcome is measured based on observation of behaviours. For instance, students are given knowledge and asked to reproduce what they have learnt to teacher.

Cognitivism usually relates to the role of information processing in different aspects like memory, organisation and neurological connections. Observable behaviour is used as an indication for deducing what is going on in the person's mind (Gage and Berliner, 1979). They emphasise on the mental processing which refer to different cognitive processes. Cognitivism is different from behaviourism in terms of learning processes but both theories tend to agree that knowledge is given. However, Reid (2005) stated that learner's role in cognitivism is an active and creative activity rather than a passive one.

Constructivism is a learning or meaning-making theory (Richardson, 2005) that is actively constructed in the mind of learners. According to Bruning et al., (1999), each learner generates their own mental model through experiences and reflections on those experiences. To further explain this theory, this principle is where learners start with a complex problem and work out to discover the fundamental skills required to solve it. Constructivism in education involves a process of self-knowledge of the problems where learners create their own new understandings by constructing and reconstructing meaning of their experience, and they learn and develop, personally and professionally.

From the constructivist perspective, learning is an active process (Bruner, 1966; Piaget, 1977) and this happens in the social interaction (Vygotsky and Cole, 1978).

Vygotsky and Cole (1978) stated that the social constructivism theory encourages learning environments that place collaboration at the centre of the learning environment. Thus, developing formal or informal mentoring relationships will shape a reciprocal learning environment for the people involved, where they will benefit from these relationships and construct critical- reflecting meaning-making exchange (Greyling & Du Toit, 2008).

3.4.2 Active Learning Methodology

Active learning is defined as a process where students use opportunities to decide about the aspects of the learning process and put in efforts to actively create their knowledge (Brame, 2016). Active learning is closely related to making decision about learning and active use of thinking. Active learning is more attractive than passive learning as students are usually more motivated and interested to make decisions about their own learning when they are mentally challenged. In exploring different things independently, they discover their own interests and motivation in developing more skills that are required to be part of the future workforce (Van Hout-Wolters et al., 2000).

Self-directed learning refers to number and types of decisions that are made by the students themselves with or without the support of a mentor or teacher. In this case, they plan their own time and goals and activities and then evaluate by themselves. The study of this theory explored mainly from process and personal attributes. Brookfield (1984) argued that self-directed learning is less focused in a specific context. Personal attributes refer to the motivations and capability for learners to play their role in their own learning (Garrison, 1997). Personal attributes can also be their prior knowledge or experience. The second element of self-directed learning is process. It refers to the autonomous learning process. This means learners oversee their own planning, monitoring and evaluation of the learning process (Moore, 1972). Context focuses on environmental factors and how do those factors affect the learner. This can be closely related to support in the learning context. Therefore, it can be peer support or mentor's feedback.

There are different models of self-directed learning. Song and Hill (2007) had introduced a conceptual model for understanding self-directed learning which integrates the three main elements; personal attributes, process, and context as they believe that level of self-direction needed would change based on contexts. The three main elements are also applied in the context. Garrison's model of self-directed learning included personal attributes as part of the learning process (Garrison, 1997).

He focuses more on the use of resources and explained that when learners control, it does not mean independence but rather a collaboration with other people. In contrast to Song and Hill (2007), Knowles (1975) actually acknowledged that there were situations where learner's experience contributed little value especially when they have no previous experience. Candy (1991) concluded that there are four dimensions in the theory; self-direction as a personal attribute, the willingness and capacity to manage own education, ability to organise instruction in formal settings and lastly as the individual of learning opportunities. However, this model did not look at how it is relevant in different learning environments like online learning or classroom learning.

3.4.3 Self-Directed Learning and Social Constructivism

Morris (2019) highlights the significance of self-directed learning (SDL) as an essential skill for adults in managing the complexities of contemporary life. The research contends that SDL cultivates adaptability, empowering individuals to take control of their educational journeys and effectively respond to evolving situations. Morris identifies crucial methods for fostering SDL, such as establishing personal learning objectives, seeking out resources, and reflecting on one's learning experiences. The results indicate that nurturing a culture of SDL can enhance lifelong education and equip adults with the abilities needed to flourish in an unpredictable world. Simons (2020) examined the theoretical foundations of self-directed learning through a constructivist perspective. The research asserts that learning is an active, constructive process where learners develop knowledge based on their experiences and interactions. Simons advocates for incorporating constructivist principles into SDL frameworks, underscoring the importance of social interactions and collaborative learning in enriching self-directed learning experiences. The study underscores the necessity for educational practices that empower learners to take responsibility for their education while engaging with peers and mentors. The research explores the connection between self-directed learning readiness, Internet self-efficacy, and preferences for constructivist online learning environments among older adults. The results show that higher levels of self-directed learning readiness are positively linked to Internet self-efficacy, indicating that individuals confident in their online abilities are more likely to participate in self-directed learning. Furthermore, the study indicates that older adults prefer constructivist learning settings that encourage interaction and collaboration, in line with the principles of SDL. This research highlights the importance of aiding older learners in developing self-directed learning skills and digital proficiencies. Chuang examines how constructivist and social learning theories can be utilized to promote ongoing growth in adults. The study underscores the importance of social interactions and collaborative learning experiences in facilitating knowledge construction and skill acquisition. Chuang contends that incorporating these theories into adult education practices can boost engagement and motivation, ultimately resulting in more effective learning outcomes. The research stresses the necessity for educational programs that cultivate a supportive learning community, allowing adults to benefit from each other's insights and apply their knowledge in real-life situations. The collective studies emphasise the importance of self-directed learning and constructivist principles in the realm of adult education. They call attention to the need for educational frameworks that encourage adaptability, collaboration, and continuous growth, especially within the context of a rapidly changing world. By advancing self-directed learning readiness and integrating constructivist methodologies, educators can more effectively prepare adults with the skills required to navigate the complexities of modern life and enhance their lifelong learning experiences.

While Simons' study proposes a theoretical framework that combines constructivism and self-directed learning, there is a need for empirical research that tests this integration in diverse educational contexts and to explore how these frameworks can be effectively combined to enhance learning outcomes. Morris emphasises the importance of adaptability through self-directed learning, but there is a lack of longitudinal studies that examine how SDL impacts individuals' adaptability over time. Research that tracks the long-term effects of self-directed learning on adaptability in various contexts would provide valuable insights. The studies primarily focus on specific populations, such as adults in general or older adults in Chu and Tsai's research (2009).

There is a need for more research that examines self-directed learning and social constructivism across diverse demographic groups, including different age ranges, cultural backgrounds, and educational levels. Although the studies discuss theoretical frameworks and concepts, there is a gap in practical applications and strategies for educators to implement self-directed learning and social constructivism in their teaching practices. Research that provides concrete examples and best practices would be beneficial for educators seeking to apply these theories in their classrooms. In conclusion, while the literature on self-directed learning and social constructivism provides valuable insights into their interplay, addressing the identified gaps will contribute to a more comprehensive understanding of how these concepts can be effectively integrated into educational practices.

3.5 Learning Frameworks and Models for Industry 4.0

The emergence and adoption of a new wave of technologies has resulted in a significant shift in the nature of work and employment (Ackerman and Kanfer, 2020). As a result, it is necessary to identify the skills required to meet the present and upcoming organisational challenges to developing the workforce for industry 4.0.

Over the past decade, numerous efforts have been undertaken to identify learning frameworks required for meeting current and future societal and work challenges in the 21st century, both by scholars as well as labour stakeholders (Kanfer and Blivin 2019). Numerous countries and international organisations have investigated the skill requirements for occupations, roles and sectors using national or international taxonomies and databases. Table 3.2 provides an overview of some of the world's most frequently utilised and representative skill taxonomies that are used to identify specific skill gaps or identify new market trends at a macro-level (national/regional levels). According to Whiting (2020), 2025 will demand skills such as (1) analytical thinking and innovation, (2) active learning strategies, (3) complex problem-solving, (4) critical thinking analysis, (5) creativity, (6) originality, (7) initiative, (8) leadership, (9) social influence, (10) technology use, (11) resilience, (12) stress tolerance, (13) reasoning, (14) problem-solving and (15) ideation skills.

Table 3.2 lists the reviews that have already been undertaken on skill frameworks for the digital age, where various complementary approaches and disciplines offer insightful findings on the subject. While some (such as Chaka, 2020; Prifti, Knigge, Kienegger, and Krcmar, 2017) suggested a revised version of the Great Competencies Model (Bartram, 2005) by adding/relating new dimensions, others (such as Silva, Kovaleski, and Pagani, 2019) present specific competencies for professions in the industry 4.0. In a different review, key knowledge and skills are presented alongside enabling technologies in a bibliometric analysis that focuses on a scientific mapping of skills in industry 4.0 (Kipper et al., 2021). More recently, van Laar et al. (2020) developed the 21st century digital skills framework, and even though this proposition focuses on ICT and digital-related skills, the skills presented can be considered to be related to the basic technological aspects (e.g., ICT, Internet, computer) of industry 4.0. More recently, van Laar et al. (2020) developed the 21st century digital skills framework.

The DigComp Framework is a framework that consists of five dimensions: (1) competence areas, (2) competences, (3) proficiency level, (4) examples of knowledge skills and attitudes and (5) examples of applicability to purpose (Ferrari, 2013). The competence areas, which include information, communication, content creation, safety and problem-solving, are the main components of this framework (Vourikari et al., 2016). This framework is being applied in the education sector and has proven to be helpful in investigating healthcare students' digital attitudes, skills and development needs (Evangelinos and Holley, 2016). In addition, this framework is used to examine factors predicting lower secondary school students' digital competence (Hatelvik et al., 2015). This framework also covers three different proficiency levels and specified indicators for the development of each digital competence.

Similar to the DigComp framework, the EntreComp framework is also developed by the European Commission to establish a bridge between the world of education and employment and to be used as a reference by any initiative which aims to encourage entrepreneurial learning. Like the DigComp Framework, EntreComp specifies competence areas, i.e., ideas and opportunities, resources and putting strategies into action. Each area includes five competences, which makes a total of 15 competencies along an eight-level progression model (Bacigalupo et al., 2016).

Several concerns should be taken into consideration when it comes to designing LAs. Researchers will also need to investigate problems learners face in different environments, and what success looks like from the learners' perspective (Ferguson, 2012). The analytics process should be transparent so that the learners can respond with feedback that can be used to refine the model and to be able to see how their data are used. Other researchers added that LAs can be effective if the outcome can generate insights into the pedagogical consequences for both learning and teaching practice (Ferguson, 2012; Van Den Bogaard and De Vries, 2017). LAs should be designed based on theoretical models, and the needs of students should be well understood. Feedback from LAs is essential for learning, and it is important to identify which kind of feedback is suitable for each student.

Feedback from LAs leads to the question of the quality assurance of LAs. The quality assurance of LAs' services is questioned as they might only meet the expectations of specific stakeholders (e.g., managers) whilst overlooking those who are the most important (e.g., students) (Liñán, L.C. and Pérez, 2015). This shows that type of feedback is important.

Although the DigComp framework is being widely used for strategic support for policymaking by European Union members, none has displayed strategies that can be used with different stakeholders to develop digital competence, especially from the point of view of problem-solving (Balula, 2016). Balula also said that it's vital to highlight that the DigComp framework is descriptive, rather than prescriptive; therefore, this framework is always subject to revision and updating. Each update takes a long time as it involves many stakeholders to reach a consensus. The EntreComp framework has not yet been adapted to or tested in real-world settings, and it is a result of a robust research methodology which involves experts' consultation and input. Therefore, it will also take time for the framework to be updated. A framework that suits education and industry needs should be updated quickly to suit those needs, as the evolution of education has been slow, while technology is growing rapidly.

On the other hand, the TEFFIC framework by Christiansen (2022) had been tested across Europe in 14 pilot studies. This model distinguished itself from other educational design frameworks by combining the concept of authentic task design with an interactive approach towards problem solving. All the mentioned learning frameworks are emphasising more on the curriculum, the teaching material and content rather than the importance of the students' role in their own development. In addition, Acerbi et al. (2022) identified skills required in manufacturing industry and developed an assessment model based on industry 4.0 readiness.

Table 3.2 Comparison of Different Frameworks for Industry 4.0

Framework	Authors	Focus
DigComp	European Commission (2022)	Investigate the digital attitudes, skills and development needs of students and examine factors predicting digital competence
TEFFIC Framework	Christiansen et al. (2022)	Proposed educational framework for educators to create educational content targeting future industries. It combines an interactive approach towards problem solving with the concept of authentic task design as the main elements of the framework.
Assessment Model for Industry 4.0	Acerbi et al. (2022)	Identified soft skills and hard skills required in manufacturing industry and integrated it with maturity model.

Science map of Industry 4.0 Aspects	Kipper et al. (2021)	According to the findings, the following skills are regarded as being essential for industry 4.0: leadership, strategic knowledge view, self-organisation, giving and receiving feedback, proactivity, creativity, problem-solving, interdisciplinary, teamwork, collaborative work, initiative, communication, innovation, adaptability, flexibility, and self-management. Additionally, the authors advise having knowledge of general systems theory, software development and security, automation, sustainable development methods, and information and communication technology.
Reviewed Framework of Great Eight Competencies Model	Chaka (2020)	Specifically included three new clusters: competencies of mastering and displaying language-specific skills/competencies, displaying inter-/cross-disciplinary skills/literacies, and displaying job-related skills/competencies.
Two-Skills Framework	Maisiri et al. (2020)	Technical skills (i.e., technological, programming, and digital) and non-technical skills/soft skills (i.e., thinking, social, and personal) are divided into two categories in the two-skills framework. The various skill sub-categories that make up both skill categories present a comprehensive list of 39 skill descriptors.
21st Century Digital Skills Framework	Van Laar et al. (2020)	Made up of both core skills (such as technical, information management, communication, collaboration, creativity, critical thinking, and problem-solving) and contextual skills (such as ethical awareness, cultural awareness, flexibility, self-direction, and lifelong learning).

Specific Competencies Related to the Main Ten Professions in Industry 4.0	Silva et al. (2019)	The authors outlined specific competencies related to the top ten industry 4.0 professions. A project manager, for instance, would require the following skills: environmental responsibility, perspectives and future vision, ability to track changes globally, entrepreneurial thought, creativity, innovation, global communication, leadership, ease of conflict resolution, prompt responses to organisational problems, critical thinking, analytical skill, and knowledge.
Great Eight Competencies Model (Bartram, 2005), relating three variants of competencies: Information Systems, Computer Science and Engineering competencies	Prifti et al., (2017)	Related three different types of competencies: Information Systems, Computer Science, and Engineering. 68 competencies are listed in detail as being important personal resources for industry 4.0.
EntreComp	European Commission (2017)	Used as a reference by any initiative which aims to encourage entrepreneurial learning
European Skill/Competence Qualifications and Occupations	European Commission (2013)	Identified and categorised professionals on the labour market in the European Union by evaluating skills, knowledge, attitudes, and values as well as knowledge and language. This skills classification, which is available in 27 languages, includes more than 2900 occupations and 13,000 skills.

These frameworks identified skills required for students to be ready for industry 4.0. It is crucial to recognise that these skills need to be assessed. Nonetheless, research on assessing readiness for industry 4.0 was quite limited. Maturity model was used by Acerbi et al. (2022) to assess the levels of skills, and this model will serve as a reference in this thesis to evaluate students' willingness to learn, particularly in terms of their attitude.

3.6 Research Gaps

Building on the preliminary gaps identified in the student readiness for industry 4.0 in Section 3.2, research gaps are refined with respect to the extended review of adjacent research fields. By complementing skill gaps through insights into learning theory, the following overarching research gap around readiness of Engineering students for industry 4.0. More specifically, research gaps emerged as shown in Figure 3.2:

- Lacking understanding of maturity model and active learning methodology to investigate readiness for industry 4.0 from an individual perspective;
- Lacking empirical evidence on the effectiveness of assessment framework in developing skills and positive learning attitude;
- Uncertainty about the suitability of existing training evaluation approaches for skill framework.

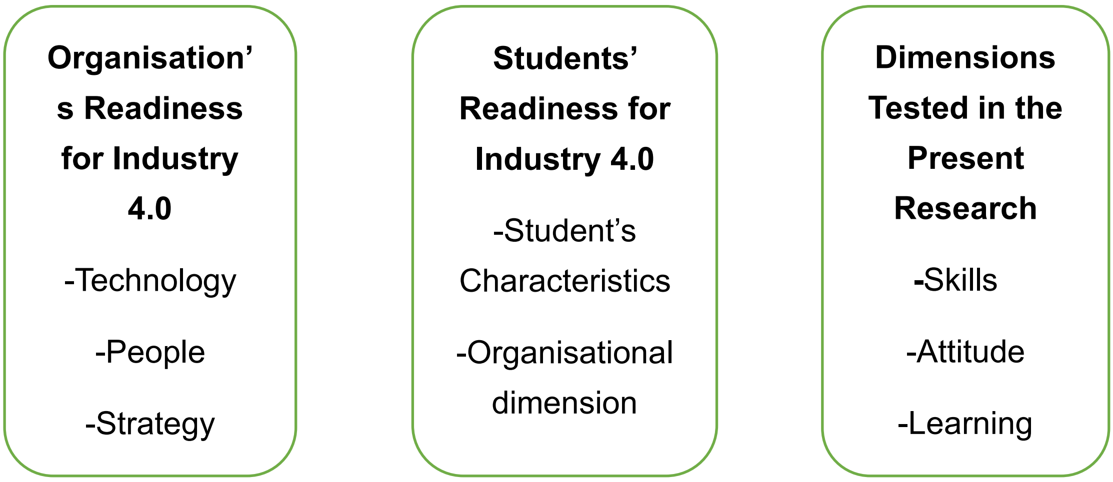


Figure 3.1 Research Gap

3.7 Chapter Summary

Chapter 3 provided an overview of the literature and set the foundation for the research by defining the readiness for industry 4.0. After looking at different research studies on students' readiness, this chapter highlighted that the readiness of the educational sector for industry 4.0 was crucial and needed evaluation by universities worldwide. The lack of readiness for industry 4.0 in universities was mainly found due to traditional educational models that focus on knowledge rather than skills. Knowledge in this case included underlying theoretical knowledge and basic technical skills such as those related to software use. On the other hand, soft skills such as problem solving and attention to detail are not core in university curricula. These two skills, alongside other soft skills, might be linked to certain courses taught at universities, but these skills are not taught as separate courses.

The issues of integrating hard and soft skills in different curricula was not limited to one country; but occurred globally across many educational systems. The main barrier to integration was not related to educational institutions' resources, nor to the educators' skills; but rather to these students' readiness for industry 4.0. Studies from Asia, Europe, South Africa and South America have reported challenges in implementing industry 4.0 technologies in education due to lack of students' readiness. These countries included Brazil, Italy, Japan, Korea, Malaysia, Oman, South Africa and Thailand.

Factors that hindered implementation of industry 4.0 technologies in education were related to the different domains of learning, the learning processes, and the different theories of learning. Different domains of learning encompassed knowledge, technical skills and soft skills. Knowledge was the key domain taught in all universities globally in different fields within and beyond engineering. Categories of the knowledge identified in literature review were subject-specific knowledge, procedural knowledge, explicit knowledge, implicit knowledge and factual knowledge. It is worth mentioning these are not the only types of knowledge that vary between different classification and over time. For instance, embedded knowledge is one type of knowledge used by AI models in integrating information from multiple sources. However, knowledge generated by AI still have many issues related to ethics, data breach and accuracy of the generated information. This could be contributing factor to the lack of implementation of AI in academic institutions.

As such, learning processes in academic institutions comprised predominantly of traditional pedagogical models where the teacher transferred the knowledge to students. Modern interactive learning such as flipped classrooms, authentic learning and augmented learning are still underused and limited to case studies. The latter challenge is mainly related to students' resistance to engaging with other tools in an educational context. Students might use interactive technologies in their social lives but not in an educational context where the knowledge transfer relied heavily on the teacher. This could be related to the expectations placed on universities, students and teachers.

Henceforth, passive learning theory was more prevalent in universities rather than the active learning theory which could be found more in online platforms such as Coursera. The active learning methodology is based primarily on self-directed learning where students were to design their own goals and undertake evaluations independent of teachers. Despite the advantage, still active learning theory are implemented in private education providers and professional companies but not in the universities. Yet the universities utilised professional companies for training their staff on soft skills. For example, KnowBe4 is professional company that British universities used to train their staff on soft skills. Nevertheless, this model is not adopted for all university students because of the resistance of using technological models by students in favour of university real-life experience.

While missing on novel approaches to education, students often miss on skills and thereby readiness for industry 4.0. Industry 4.0 skills had been reported in various framework as essential especially adaptability (resilience), creativity, digital skills, problem solving and self-management. These skills have been identified in key framework such as; The EU DigComp, the EU EntreComp, the EU Skill/Competence Qualifications and Occupation, TEFFIC, Science Map of Industry 4.0 Aspects, Framework of Great Eight Competencies Model, Two Skills Framework, 21st Century Digital Skills framework, Specific Competencies Related to the Main Ten Professions in Industry 4.0, and Great Eight Competencies Model. Among these frameworks, most commonly used was the Great Eight Competencies Model that became more popular than other frameworks including the EU multiple frameworks. This was because the Great Eight Model displayed competencies relating to jobs that are beneficial to users' careers and futures.

Despite the presence of multiple frameworks, there was a lack of skills specifically tailored for engineering students and most studies focused on few hard/soft skills while neglecting self-management skills. Common hard/soft skills in studies within the educational context included; software knowledge, problem solving, creativity, communication and teamwork. Nonetheless, there is no framework to date that focused on all three elements of skills, attitude and knowledge. Key frameworks were published over three periods being: 2013, 2017-2019, and 2020 onwards. The focus in 2013 was on knowledge, and attitude to knowledge (European Commission, 2013). While 2017-2019 and 2020 onwards, the focus changed to business and technological skills respectively. Thus, the first framework was launched in 2013 and focused on knowledge and attitudes to knowledge. It is interesting to mention that this framework was published in 27 languages. Moreover, between 2017 and 2019, frameworks focused on entrepreneurial learning (European Commission, 2017); project management (Silva et al., 2019) and using information systems (Prifti et al., 2017). From 2020 onwards, skills focused on industry 4.0 tasks related to technology and digital skills only (European Commission, 2022); approach to working including problem solving and interaction (Christiansen et al., 2022) or attitude to work.

In summary, this chapter acknowledged several research gaps including a lack of understanding of maturity models and active learning methodologies for investigating individual readiness for industry 4.0 in education. There was insufficient empirical evidence on the effectiveness of assessment framework in developing skills and positive learning attitude. Based on these gaps, the chapter implicitly argued for the need to develop a new framework that can address the identified shortcomings and better prepare students for industry 4.0. This framework should be adaptable, focus on individual readiness, and incorporate active learning methodologies.

CHAPTER 4: RESEARCH DESIGN AND METHODOLOGY

This chapter presents the research design of the thesis. It then discusses the methods used to explore and analyse factors that contribute to students' readiness for industry 4.0. Mixed-method approach and that was composed of quantitative questionnaire and qualitative interviews. The quantitative questionnaire determined the components for the proposed framework; whereas, the qualitative semi-structured interviews provided in-depth understanding of individual participants' perspectives. Participants, population, and sampling methods are discussed in this chapter, followed by data analysis and ethical considerations.

4.1 Research Design

Design Science Research (DSR) is a research methodology primarily used in the fields of Engineering, computer science and information systems. DSR is a powerful tool used for improving methods in Engineering educational research (Carstensen and Bernhard, 2018). There were six steps in DSR that include: scope, design, population, testing, deployment and maintenance (Figure 4.1).

The first step in DSR identified the relevant research problem that was the readiness of students to industry 4.0. The second step comprised identifying and evaluating the skills required for industry 4.0 using mixed-method research. After skills were identified, ASK SUMA framework was developed and tested. The design process involved iterative cycles of prototyping and refinement. This involved testing the performance of the prototype in a case study, simulation and/or a real-world application. The prototype and refinement phase was followed by the evaluation phase that tested the framework's effectiveness.

The evaluation phase, in turn, was applied using a mixed-method approach that gathered feedback from users and stakeholders. In this case, pre-test and post-test data were collected. Evaluation was critical to determine whether the framework met its objectives and provided value. Finally, the results of the DSR process, including the artefact and its evaluation, were communicated to relevant stakeholders and the broader research community. This step ensured that the knowledge gained from the research was disseminated and could inform future work. The communication of findings was essential for advancing the field and contributing to theoretical knowledge (Vaishnavi & Kuechler, 2022).

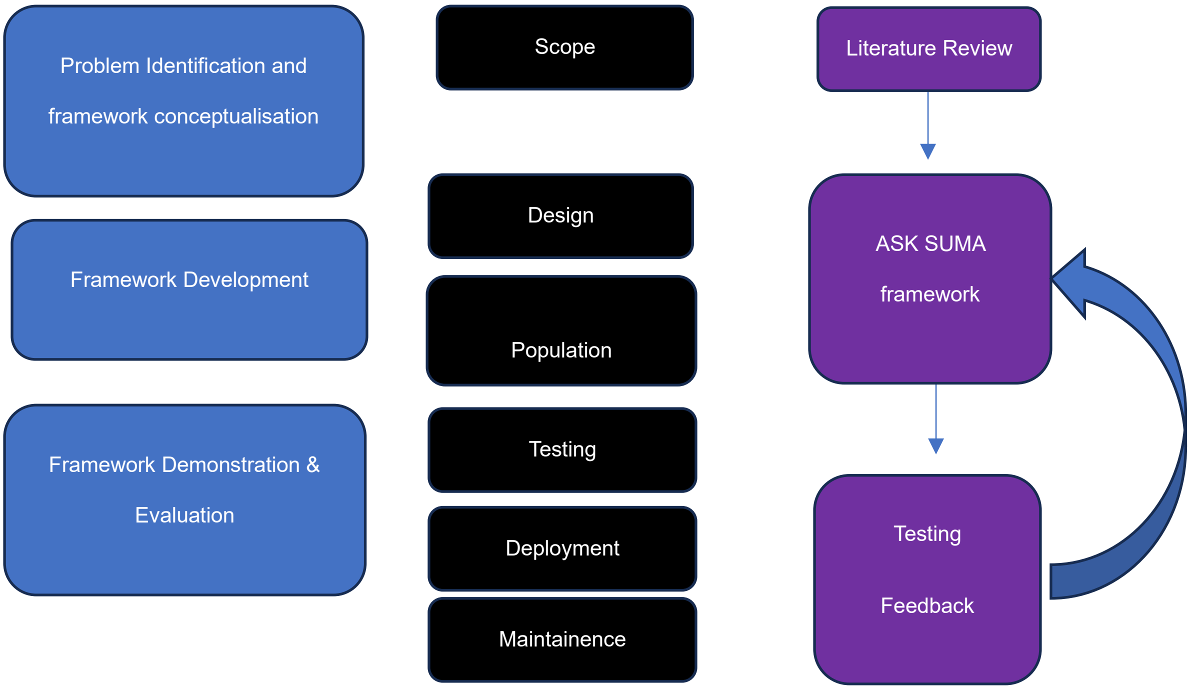


Figure 4.1 The Complete Design Science Research Cycle

The present contribution to theoretical knowledge intended to develop a holistic and prescriptive framework that had an assessment model which supported students in the Engineering courses in evaluating their skills . To address this goal, this research employed DSR method. This has been done with the goal to develop an objective and customisable maturity model for the assessment. The first phase was the scope that defined the extent of the problem to be addressed and developed the solutions effectively. It is worth mentioning that the research problem in this thesis was the readiness of the students for industry 4.0. Furthermore, the objective of the solution was to create a framework to support learning process by using a maturity model to ascertain the level of students in their technical skills and personal development skills.

Based on these key elements, it has been set on the ground to design and populate the model, reflecting the “development” phase of the DSR. These phases have been addressed mainly through three separate research areas: 1) the readiness of students for industry 4.0, 2) the learning process, and 3) frameworks and models for industry 4.0 (Figure 4.2). The latter three areas were explored using the questionnaire survey and semi-structured interviews respectively. The survey was showed the factors that contributed to the readiness of students for industry 4.0, while the semi-structured interview determined the different perspectives of different stakeholders towards industry 4.0. The research was conducted from 15 April 2024 to

31 May 2024. The questionnaires were analysed using SPSS V.29 and R Project for Statistical Computing whereas the interview data was analysed using thematic analysis. The analysis method will be further discussed in the next chapter, along with the chapter's findings.

Based on this knowledge, entering phase 2, a proposed framework was developed by incorporating SDLC and assessment model that used maturity levels that were objective and customisable facilitating the definition of improvement plan. Literature review was done on exploring different concepts and frameworks around learning and industry 4.0 readiness.

The third phase comprised a framework evaluation, which has been conducted based on the interaction with the target audience of the framework, which were students. The framework was tested on 151 students from different Engineering courses at different universities. In this phase, a survey was conducted to evaluate the effectiveness of the framework by looking at the pre-test rating for skills and post-test rating for skills to determine whether there was any improvement. This framework was tested for three months during summer break (1^{st} June 2024 to 15^{th} September 2024). The choice of the summertime frame was because students had summer internships during this time and it fitted the research's sampling criteria.

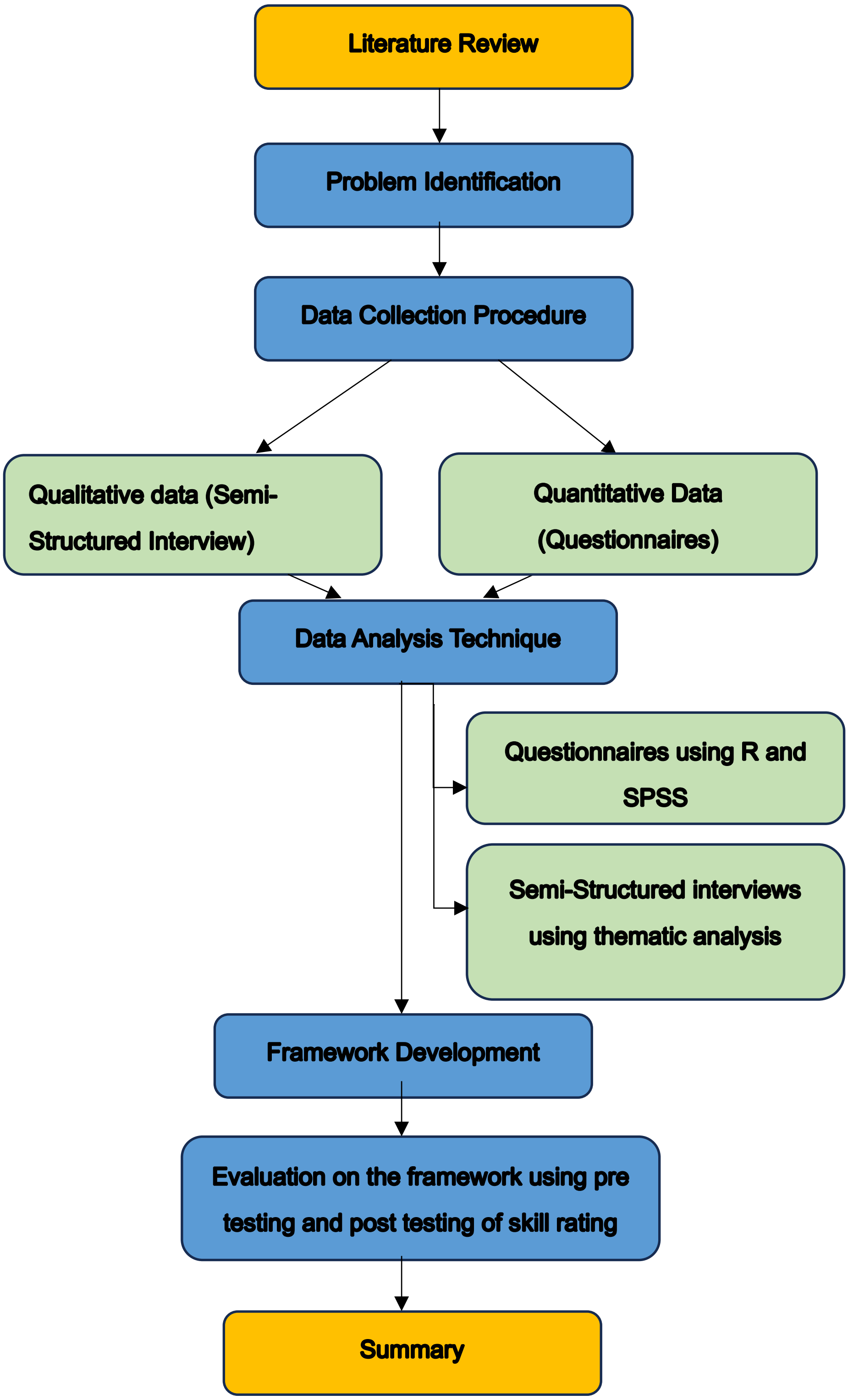


Figure 4.2 The Stages of Research Design

4.2 Mixed-Method Research

Mixed-method research was chosen to provide a broader perspective on the topic investigated in this research. Mixed-method research integrated both qualitative and quantitative data collection and analysis techniques within a single study. This approach allowed to leverage the strengths of both methodologies, providing a richer and more nuanced understanding of the research question. According to Smajic et al. (2022), mixed-method research often results in broader perspectives.

There are several design frameworks within mixed-method research. Explanatory Sequential Design begins with quantitative data collection and analysis, followed by qualitative data collection to explain or elaborate on the quantitative findings. Smajic et al. (2022) utilised this design to assess organisational cybersecurity readiness, demonstrating how qualitative insights can enhance the understanding of quantitative results (Kunzmann and Hamacher, 2018). Exploratory study is an approach where qualitative data is collected first to explore a phenomenon, followed by quantitative data collection to test or generalise the qualitative findings. This design is particularly useful in developing new theories or instruments. Convergent Parallel Design involves collecting qualitative and quantitative data simultaneously but analysing them separately before merging the results to draw conclusions. This approach allows for triangulation, enhancing the validity of the findings.

Mixed-method research poses challenges, especially regarding the complexity of design and data integration. Wang et al. (2021) observed that while some standards exist for qualitative and quantitative research, specific reporting standards for mixed methods research are still evolving (Kettunen et al., 2022). Additionally, researchers must carefully consider the balance between qualitative and quantitative components to ensure both contribute significantly to the overall findings.

4.2.1 Quantitative Approach

Quantitative approach in research has been widely used in many different disciplines such as health, psychology and computer science (Creswell, 2013). This approach is defined as asking voluntary participants specific and tailored questions to obtain specific answers. Mujis (2010) described the quantitative approach as a mathematically based method that is used to examine collected numerical information to explain a scenario or situation.

Additionally, the quantitative approach offers several advantages for researchers undertaking scientific studies (Mujis, 2010). One of these benefits is that it allows them to involve more subjects enhancing the generalisability of their research results. It also allows them to summarise vast sources of information and help ensure the accuracy of their research results.

This study used the quantitative approach to investigate the performance of the proposed framework that had been created to prepare students for industry 4.0. The quantitative approach employed a questionnaire that was distributed to students who were involved in experiments relating to using the proposed framework. The findings of the quantitative approach were complemented by a qualitative study approach that comprised interviews about participants' attitudes, feelings, and behaviours in greater detail. The latter details were used for evaluating the performance of the proposed framework.

4.2.2 Qualitative approach

The qualitative approach is exploratory research that determines new insights into phenomena; understanding the different perspectives around the phenomena (Saunders, Lewis and Thornhill, 2009). Hence, the qualitative method enables a researcher to understand the real views and experience of participants regarding a certain topic. While qualitative data provides valuable insights, it raises concerns regarding reliability. According to Saunders, Lewis, and Thornhill (2009), reliability in this context often relates to potential biases from the researcher and respondents. However, Stenbacka (2001) contends that reliability is not applicable to qualitative research, as its primary goal is understanding rather than measurement. Instead, she argues that qualitative studies should be evaluated using criteria tailored to their unique nature.

As this study investigated academics' and employers' understanding of industry 4.0, a qualitative approach was adopted. The qualitative approach allowed the researcher to gain new insights into the relationship between understanding of the concept of industry 4.0 and expectations towards industry 4.0 future. This in turn will help identify trends in future industries beyond industry 4.0. As such, some of the interviews in this research were conducted with industrial experts to understand the needs of employers, being the end-user on the recruitment side. Yet the interviews were not only limited to employers but also involved academics who train students in knowledge and skills preparing them for industry 4.0. In summary, the research mixed-method research brought many advantages to this study by diversifying the approaches, data collected, and analysis (Smajic et al.,2022.). This increased validity, while also ensuring that the combined use of both methods yielded a more comprehensive understanding of the research issue than a single approach alone.

4.3 Participants, Population and Sampling

This research consisted of two main studies. The first study determined the factors that contributed to the readiness for industry 4.0. The second one evaluated the effectiveness of the proposed framework. Mixed-method approach was used in both studies and involved questionnaires and semi-structured interviews.

Sampling for this study involved Engineering students from different UK universities. Inclusion criteria were students in their final year to ensure they had undertaken sufficient learning related to industry 4.0 throughout the degree. Students from all engineering disciplines were considered including, Aerospace, Architectural, Chemical, Civil, Electrical, Manufacture, Mechanical, Product Design, Software Engineering. A total of 428 final year Engineering students were recruited via purposive and snowball sampling (Creswell, 2015). Table 4.1 shows that Software Engineering was slightly overrepresented while Aerospace Engineering was slightly underrepresented. Overall, the distribution across most disciplines indicated a balanced representation.

Table 4.1 Demographic Profile of Participants

Discipline	Percentage	Representation
Software Engineering	12.4%	1.12
Chemical Engineering	12.1%	1.09
Manufacture Engineering	12.1%	1.09
Electrical Engineering	11.9%	1.07
Civil Engineering	11.0%	0.99

Product Design	10.7%	0.96
Architectural	10.5%	0.95
Mechanical Engineering	10.3%	0.93
Aerospace	9.1%	0.82

The representation value was calculated by comparing the actual percentage of responses for each discipline to the percentage expected if all disciplines were equally represented which in this case is 11.1%. As it was not evenly distributed, there would be potential bias in the research. To overcome it, Cochran's formula was used to calculate the sample size to ensure that the sample size was substantial enough to provide meaningful insights across all disciplines.

Cochran's formula as shown in Equation 4.1 was used to determine the sample size as the population was unknown (Shariatzadeh & Bijani, 2022; Cochran, 1977). It was used to ensure that the research produced accurate and reliable data (Equation 4.1):

$$n_0 = \left(Z^2 * p * (1 - p)\right) / e^2 \tag{4.1}$$

Where,

p is the fraction of the population (as percentage) that displays the attribute

e is desired level of precision, the margin of error

z is the z-value, corresponding to the desired confidence level

So, *p* = 0.5. 95% is the desired confidence level and at least 5 percent—plus or minus—precision. A 95 % confidence level gives us Z values of 1.96, per the normal tables.

$$n_0 = \left(1.96^2 * 0.5 * (1 - 0.5)\right) / 0.05^2 = 384.16 = 385 \tag{4.2}$$

Therefore, the sample size for the survey on students' readiness for industry 4.0 was at least 385 as shown in Equation 4.2 to ensure the reliability of data. To gain more insights that offered as much reasoning as possible on industry 4.0 and its implementation, interviews were conducted with UK-based industrial experts and academics. Both cases, included participants who had more than 12 years of experience. Details of industrial experts and academics are shown in Table 4.2.

Table 4.2 Details for Qualitative Interview with the Industry

Position	Industry	Years of Experience
Chairman	Consulting	30
Director of IT	Tele-Communications	17
Director of IT	Manufacturing	20
Director of IT	Consulting	18
Manager	Manufacturing	12
Manager	Manufacturing	11
Consultant	Manufacturing	12
Consultant	Software	12

Prior to participants' recruitment, a message was sent to them and that explained the purpose of the interviews. The message also included the researcher's background details, the main supervisor's details, and a request for consent. Bryman (2008) stated that it was essential for researchers to build a good relationship with interviewees to produce a successful interview session. Therefore, the researcher would send individual emails to participants. As Arksey and Knight (1999) suggested that being friendly and open helps to foster a good rapport in the interviews, the researcher introduced themselves in the email. Before each interview, participant information sheets were sent to participants electronically to help them understand the purpose of this research. A consent request was also sent to participants in a written form at the beginning of the interview session. Participants were made aware that they could withdraw from the interview anytime they wanted.

On the other hand, the questionnaire was distributed online through snowballing method. The total sample size of the questionnaire was 428. The data involved in this research was anonymised to present the students' privacy and confidentiality. To get new findings, participants were probed to express their own specific situations and experiences. Mason (2002) stated that by asking different questions to different participants, situated knowledge could be generated. Therefore, in this study, an interview schedule was produced as shown in Appendix 2 to guide the researcher so that she could probe the participants accordingly.

The proposed research model was tested with final year undergraduate Engineering students in the UK. Due to various reasons, it is seldom possible to study the whole population. Only participants who gave informed consent to participate in a study could be studied. The sample consisted of all students who were willing to become involved in the first part of the research and who signed the consent form. As a variety of statistical methods for testing, the ASK SUMA framework was used, and the effect was predicted as medium.

4.4 Data Analysis

In this research, methods used to analyse the data were of both qualitative and quantitative in nature. Quantitative data analysis was conducted using IBM SPSS Statistics 29 and the R Project for Statistical Computing to help determine the important elements needed in industry 4.0. Qualitative data analysis was conducted using thematic analysis as keywords were identified to explore relationships between identified concepts (Devi, 2009). In this research, relational analysis was employed to obtain meaningful information from the data.

4.4.1 Stages of Qualitative Data Analysis

Open coding is an approach where underlying meaning and key patterns in and across data are identified (Fathurrahman, et. al., 2024). Open coding was conducted in this study through categorisation of information. In this respect, contents of posts were read, and reread prior to patterns' identification and constructions of codes. Once a list of categories was identified, the categories were grouped together using higher-order headings. The reason behind creation of headings was to reduce the number of categories by collapsing similar ones into a broader category (Haatainen, et. al., 2024).

In practice, for this initial coding phase, the content of transcripts was analysed line-by-line, applying a code that briefly describes what was interpreted in transcripts. Unexpected patterns were also identified to generate new findings. The process was iterative, where the first list of codes was produced after analysing the first interview transcript. Then by slowly building up the list of codes through the remaining transcripts, the coding list was expanded. Codes were then grouped together into categories, and the researcher considered any “other” codes that did not easily fit with the existing categories. Coloured highlight pens were used to distinguish between each category, and a table was created to include different categories and references to interesting verbatim quotations. Though the themes reduced the amount of data, the original meaning of respondents was retained.

From this initial stage of analysis, the researcher could identify relationships between codes. Characteristics and differences of codes were identified, and connections were mapped between categories to explore relationships. The relationships between codes were created by focusing on the aim of the research and the usefulness of the data to this research. Once the relationship between the codes was identified, key themes were then interpreted.

4.4.2 Stages of Quantitative Data Analysis

Data collected by quantitative means is typically analysed using statistics that fall into either interval estimation or hypothesis tests. Interval estimation entails the analysis of a parameter from a sample of data. The parameter value used for all possible data is referred to as the population/true-value parameter. Statistics use sample data called the point-of-estimate to estimate this population/true-value parameter. Measures that assess quantitative data from this point-of-estimate are values such as the mean, standard deviation, variance, mode and median. These values are also often termed descriptive statistics because they describe the basic features of the data.

In terms of quantitative data analysis, there are a lot of statistical methods that can be used. In this study, standardised coefficients were used in regression analysis to measure the strength of the relationship between independent and dependent variables. Nieminen et al. (2022) discussed the application of standardised regression coefficients as effect size indices in epidemiological studies, emphasising their utility in summarising findings from multivariable analyses. In this research, independent variables were technical skills, personal development skills and self-efficacy and attitude. P value was also a fundamental statistic method that helps to determine the significance of results. It indicated the probability of observing the data assuming that null hypothesis was true. Pearson Correlation was also a widely used method for measuring the strength of the linear relationship between two continuous variables. Park and Kim (2018) used Pearson and Kendall correlation coefficients in their study highlighting the importance of using appropriate correlation methods to assess relationships in data. To help in visualisation of data, scatter plot is a tool to allow researchers to visualise the relationship between two quantitative variables while box plot was used to provide insights into data distribution of data points including medians and quartiles (Mugo, 2023). Path analysis was a specialised form of regression analysis that allowed researchers to examine the direct and indirect relationships between variables. It is particularly useful in complex models where multiple variables interact.

Under the hypothesis-testing group, data for uncertainty values was obtained. Hypothesis testing further informed about the validity of a certain statement. Examples of hypothesis testing included measures such as population mean and standard deviation. In statistics, this was often termed univariate analysis, where data analysis involves the examination of cases across variables.

The univariate analysis focuses on three primary characteristics of the variable that are typically examined: (1) the distribution; (2) the central tendency; and (3) the dispersion. Distribution is related to descriptive measures, as this summarises the frequency of the values or ranges for each variable, such as percentages, and frequency distribution. The central tendency estimates the centre of the distribution and is associated with the mean, mode and median. Lastly, dispersion embraces measures that estimate the spread of data values and includes measures such as standard deviation and variance.

4.5 Ethical Considerations

Ethical considerations were accommodated in this research and ethical approval was granted by LJMU. Therefore, the task requiring ethical approval was planned in the early stages of the proposed research and approval was obtained before commencing any research activity with the respondents. This was obligatory as this research experiment involved human participants. The questionnaire and interview questions were reviewed by LJMU Ethics Research Degree Committee. Haatainen, et. al., (2024) and Saunders (2012) stressed that the ethical dimension is vital in the data collection stage. The criteria stipulated involved amendment to the cover letter that accompanied the questionnaire, as follows: it had to be clearly stated that participants had the right to withdraw their participation at any point; it had to be clearly stated that any responses given would be treated with confidentiality throughout the research process and following it; the ethics committee emphasised that the researcher had to provide participants with information about the nature and purpose of the study; and, finally, before the participation of a respondent, the researcher had to obtain the consent of the interview participant in either written or oral form.

4.6 Chapter Summary

This chapter outlined the research design and methodology used to investigate the students' readiness for industry 4.0 and to develop an assessment framework. DSR methodology was deployed to guide the research as it was argued that this methodology is well-suited to be used to develop an educational framework and it allows for the creation of effective solution to a real-world problem (Table 4.3). It comprised of six stages including problem identification, objective of a solution, design and development, demonstration, evaluation, communication and iteration. These steps were carried out in three phases that comprised of problem identification and framework conceptualisation, framework development and framework demonstration and evaluation.

This chapter emphasised the limitations of single methodology approach as there would be potential blind spots or biases in research process. Therefore, mixed-method research was employed combining semi-structured interviews and quantitative surveys. Mixed-method research was used as it leveraged the use of both approaches providing a richer and better understanding of the students' readiness and allowed the researcher to be able to investigate the factors in terms of technical skills, personal skills, self-efficacy (confidence) and attitude of students. It combined statistical data with rich contextual insights and enhanced the validity and reliability of the research findings. For the problem identification and framework conceptualisation, qualitative data was collected from semi-structured interviews with students, lecturers and industry professionals while quantitative data was collected using questionnaires from 428 final year engineering students. Cochran's formula was used to determine the sample size for this study.

To test the framework developed through the data analysis, 151 final year students were invited to evaluate the reliability and validity of the framework. Due to time constraint, power analysis was done to determine the sample size for the second study is sufficient to produce reliable finding. Data analysis involved using SPSS and R for statistical analysis of quantitative data while qualitative data was examined through thematic content analysis of interview questions. The methodology addressed ethical considerations including confidentiality and informed consent. The next chapter would represent the findings and discussion of the research.

Table 4.3 Methodology Matrix for this Research (Author's Own Representation)

Research Questions	Type of Variable	Indicators	Measurement of Scales	Data Collection Method	Instrument/Data Collection Tools	Data Analysis Technique
What are the key skills sets required by the future workforce to be ready for Industry 4.0?	Independent Variable Dependent variable	Technical Skills Personal Skills (Soft Skills) Self-Efficacy Attitude Readiness	Ordinal	Semi-structured Interview Survey	Interview guide Questionnaire	Statistical Analysis- Mean, Cronbach alpha Thematic Analysis
How do pedagogical interventions aim at facilitating students' learning process to prepare and support them?	Independent variable	Effectiveness of the learning method	Likert Scale	Survey	Questionnaire	Thematic analysis and statistical analysis

How does the proposed framework contribute to supporting students to embrace Industry 4.0?	Dependent variable	Improvement in post-test rating from pre-test rating	Ordinal	Open ended survey	Questionnaire	Thematic analysis

CHAPTER 5: INVESTIGATING THE READINESS OF STUDENTS FOR INDUSTRY 4.0 (PHASE 2)

5.1 Introduction

This research was guided by DSR which included mixed-method research to develop and validate the proposed learning framework. This chapter presented specific research methods, settings and participants, proposed sampling, instrument development and validation, and resources that were required.

5.2 Study aim

The focus of this chapter was to identify the main aspects to be considered in the proposed framework to support students' learning process to prepare them for industry 4.0. It was important to know and understand the current industry's expectations and needs so that an appropriate framework could be designed to focus on students.

5.3 Objectives

The objectives of this chapter were to explore the views and perceptions of industry 4.0 held by industrial experts, academics and students from Engineering disciplines.

The two key objectives were:

1. To identify skills required by students to prepare them for industry 4.0.
2. To investigate stakeholders' perceptions towards preparing students for industry 4.0.

5.4 Findings

5.4.1 Interview Analysis

5.4.1.1 Perception on Skills Required by Industry 4.0

The top 10 skills identified by the World Economic Forum (2023) were: complex problem-solving, critical thinking, creativity, people management, coordinating with others, emotional intelligence, judgement and decision making, negotiation, service orientation and cognitive flexibility (skills 4.0). These skills had been provided to participants prior to semi-structured interviews. Then, semi-structured interviews were conducted around these skills and responses were evaluated qualitatively.

The findings implied that different academics had different views on skills 4.0. Some agreed that the list was sufficient, but others thought that some of the listed skills were too general and not specific to industry 4.0. They latter group of people added another skill to the list: independent learning. An academic participant reported:

> “I don’t like service orientation very much as it depends on the field. Negotiation skills too- these skills are not generalised requirements for everyone. I think I would add another one which is independent learners who can easily adapt to any environment.” [A2]

Another participant, who was also an academic, thought that some of the listed skills overlapped with each other. This participant also commented on the order of the skills and compared the list to the business field. The latter participant said:

> “So, what I think about the list, emotional intelligence and cognitive flexibility overlap is very much embedded in having EQ. Research in terms of business management, EQ is something which is crucial in future in gaining prominence, so you know gaining more support. It’s interesting that creativity comes up as high as it does. Business research is more focused on people management. It’s interesting to see that as in my perception it should be further down in the list. Top 4 skills (complex problem solving, critical thinking, creativity and people management) are clear categories. In fact, from 5 to 10, there is a real overlap of these skills. In automation, much more emphasis on communication skills, EQ and people skills. If you like- in the future, there is an arising importance.” [A4]

These findings showed that there were certain skills in the list that were specific to industry 4.0. Moreover, there were skills which were more generalised and depended on which area of Engineering the students were going to work in.

5.4.1.2 Perceptions on ASK

When asked about perceptions of the three important elements of the proposed framework, which are Attitude, Knowledge and Skills (ASK), the academics claimed that it was very difficult to rank them as they were all important. While most believed that attitude was the most essential quality students needed for the workforce, one academic disagreed. Reported opinions were:

> “I think attitude is the key. It’s difficult to rank them in the order. I think it’s attitude, knowledge and then skills. You build your skills on knowledge. In software

engineering, a software engineer needs the knowledge to build the application." [A2]

"First will be attitude. Second knowledge and then skills. Knowledge will help you to use the skills." [A3]

"First will be knowledge. I have positive attitude. It doesn't matter if I have positive attitude and I don't know what I'm talking about." [A4]

"Attitude to skills to knowledge. Knowledge is something you accumulate. For example, I haven't written any line in a game. Graphics programming almost zero. If you give me a week, I have the skills to teach myself and adapt to the new environment. Universities are designed to teach yourself. By level 6 and 7, you should learn by yourself. If you don't bother to work in a group or you're grumpy, the company would not want you." [A1]

Once again, the academics highlighted the importance of independent learning and the ability to adapt to new environments, as reflected in one respondent's comments. This reinforced their consensus that tertiary education was designed to foster independent learning, with the expectation that students would readily adjust to unfamiliar settings. However, these skills were not formally evaluated.

"It's more likely to be knowledge and skills. Attitude is not directly assessed. In the development of modules, we expect them to accomplish their modules based on learning outcomes. The learning outcomes demonstrate that the students can do that. We assess the degree in that they can demonstrate them in terms of marks." [A1]

"Value of each part of coursework- they need the knowledge to demonstrate the skills." [A2]

"You can't assess attitude. It's not easy to be assessed. So, in terms of how knowledge and skills can be developed? Knowledge, through coursework, and skills through placement." [A3]

"In terms of 5th to 10th skills, 9th, we don't teach those skills because they're difficult to teach in academic environment. Our assessments are more focused on logical - how they coordinate with others. We are not assessing 9th. Because the curriculum is set in such an academic way. Although we tried, we don't assign grade. Anything that's not grade-bearing that they don't engage as much. We do a lot of added support around this but it's optional." [A4]

The university encouraged students to enhance their skills through optional support workshops, but since participation was neither compulsory nor graded, engagement remained low. Academics noted the difficulty in evaluating attitude, as it could not be measured directly. Additionally, while the grading system underscored the value of academic knowledge, students appeared to overlook the other two key aspects (skills and attitude).

The majority of academics felt their students lacked readiness for the workforce, citing a need for more hands-on experience and practical training. All agreed that industry exposure was essential in preparing students for employment, yet they expressed concern over the declining number of students undertaking placements. This trend underscored the importance of students proactively seeking industrial placements, especially given the rapid evolution of the technology sector, to better equip themselves for professional demands.

> "Rather depends. All students sign up for our sandwich program. Some go directly through final year. Industrial placements are much better placed unless the direct final year students have experience prior to studying at the university. Exposure to industry is vital in terms of preparing students and this can be done through internships and work placements. The university encourages them to take a sandwich year to work but there are circumstances." [A2]

> "No, they need more practical. That's why placement is very important. Lots of my placement students – they won't be ready for work. There will be lots of training." [A3]

> "No, because we have a reducing number of students doing placement and it sometimes is a shock that they don't go out into industry. Industry is increasingly difficult and challenging. Technology is changing so much more to learn." [A4]

Thus, the responses clearly showed that academics believed that industry played an important role in helping students. It was also up to students whether they wanted to take a year out to earn industry exposure. Therefore, students also played their role in getting themselves ready for work.

In addition, this interview finding also revealed that good students who were more engaged in their studies will be able to do well because of their attitude towards learning and not because of the contents of the course. Students' attitude towards learning was important too as it affected their willingness to learn new skills and, hence, it had a great impact on their readiness to work.

> "I think the good ones are. Courses are fine. If the students engage properly. The lazy students ended up in 2:2, I don't worry about good students. If I'm going to employ among the 211 students, it might only be 11 students." [A1]

5.4.1.3 Expectations of Different Roles Played at the Tertiary Education Level

In this research study, it was found that different stakeholders played important roles in preparing students to work in industry 4.0. The research also showed that everyone had different expectations of each other's roles.

All academics that were interviewed agreed that they could teach the same material more frequently to students if related to knowledge. This was because the industry changed more frequently but academic institutions only updated their contents and syllabuses once every five years. However, academics believed that, although whatever they taught might be indirect to what was needed in the industry, the approach was related. Even though the students did not learn exactly the same thing, they did learn concepts which they could use in various areas of their work. They also thought that their role was to teach students basic things that they need to know to build a strong foundation in the area. Then students had to be independent learners to teach themselves the specific skills they needed to portray in the working world. It is also vital to stress that different students of the same course were interested in different areas. Nonetheless, academics could not predict where their students ended up. Academics thought they could teach students basic knowledge, and students were expected to self-learn to further develop their knowledge. In this respect, academics reported:

> "Database system - some students do use it at work, but some students do not. Two issues of this – so what? We can't teach everything that leads to jobs. Something you learn might not be related but the approach can influence it. For example, we have modules like z notation. I have never used z. The concept of z is taught subconsciously and is with me and I can use the same concept to run

some code in a new state: it's been useful. I don't consider this an issue. We are doing this because everyone thinks it's worthwhile doing." [A2]

"I think it's quite difficult. In some respect, we can't predict where our students will end up in. For example, we can't cover all the software. The material that they learn won't be used but are vital. We taught about different areas of programs to turn students into self-learners to teach themselves the critical skills. The pace of change in our industry is enormous. It changes every month. It's certainly evident you'll expect to pick up your new skills based on your knowledge." [A1]

"That's normal. We are building the foundation and the whole concept." [A3]

"The only thing I think that is we taught software development cycle into industry more agile approach. Students complain that they don't want programming – want to do analyst. You need to know the core to understand to do your job. These are building blocks that you have to have basic knowledge. They need the basic building block. Technology's constantly changing. We try our best but we have to catch up!" [A4]

5.4.1.4 The Importance of Employers' Role in Preparing Students for Work

Sandwich year aims to give opportunities to studies for an extended period of work experience at an approved partner that will complement their programme of study at LJMU. This will allow students to develop professional skills relevant to their programme of study, It also allows students to develop their attitudes and behaviours necessary for employment in a diverse and changing environment. The university also works with partners and employers' panel to evaluate the modules in these courses. In this research, industrial experts discussed the technology to be incorporated in curricula:

"Seven to eight CEOs comment twice a year to talk about what trends" [A1]

"I would personally say our courses are informed by the employer panel…They talk regarding the technology out there to incorporate into our curriculum." [A4]

Employers often sought proficiency in specific programming languages and expected universities to fully equip graduates with these exact skills. However, many viewed academic curricula as misaligned with industry needs, which created a significant expectation gap. While educators focused on teaching fundamental, transferable principles, employers demanded job-ready technical expertise—highlighting a persistent disconnect between academic preparation and workplace requirements.

> "It's ongoing - in terms of computer languages, industrial advisors will mention the specific language that they want. We teach the principles that are easily transferrable." [A2]

> "They think that what we teach is irrelevant. Each topic should be something that relates to what they do. Companies' apprentices go for a lot of training… There's a big gap between what they expect and what we contribute. We are academic, we are not training." [A3]

The university received feedback from students and companies regarding what should be incorporated into curricula. Students worked with companies on some research projects that helped them to understand more about industrial trends. The university kept in touch with the students' and employers' panel to see whether they had matched the expectations of students and employers. This was demonstrated in responses from participants that had stated that academics do 'very little' and below the expectations of employers and students. Academics thought employers played important roles in giving training to students to enhance their specific skills through placement opportunities.

> "Erm…, goes back to employer panel. To tell us what skills they want. The destination statistics where our students go and what they're doing. Our lecturers keep in touch with the students till they get their graduate jobs. We did ask them anything you wish that we taught we don't. The students would say "You don't teach us the practical hands on. We don't have facilities that they are expecting and the students have to understand that we need to make the most effective use of our resources. What we can do is just limited- what do we think that we can offer up to our standard. They expected it to be more specialised course. We haven't used particular software. We can't do every software. It's not feasible. That's why there is placement for. You know the application of things that you learnt at university." [A4]

5.4.1.5 Awareness and Perception of Industry 4.0 and its Pillars

Industry 4.0 has been mentioned multiple times in universities but it was surprising to find out that academics rarely used the term industry 4.0. Yet, universities' curricula also covered some of the pillars of industry 4.0. It was also found that different academics had different views on the industry.

> "I don't really know much about industry 4.0. There are points of connection to what we deliver but can't really say that whether we incorporate them in the curriculum. Don't think that there are physical visibilities in the university. If you go to our staff, I don't think 18 of them will know about industry 4.0." [A2]

> "The name is silly as it doesn't mean anything. In terms of technology roles like IoT, I will argue that point of sales systems have been around. Online shopping - e-buyer automated has been progressing and I don't think we are in industry 4.0. It's still a continuation of a trend and it's just a slow evolution." [A1]

> "IoT is Data Science analysis on data. It's something great. In Data Science there is more use and it is something very forward. It will continue next 10 years as well as machine learning. If you look at the topic of research, data science is there too." [A3]

> "It's exciting. The potential advances that may bring to the society. I think they support Big Data Analytics because we have programs on that. For VR, we have VR lab downstairs. IoT is included in the curriculum in a few of our programs. In terms of cloud, we have modules on that. We have programs on security. To sum, we do have those subjects in our curriculum-in our courses but not sure how much internal work will link to." [A4]

Academics did cover some of the pillars of industry 4.0 but they were not sure how much of it was relevant to the needs of industry 4.0. The research finding also revealed that most students who worked in technology-related industry had yet to hear of industry 4.0 and needed to learn more about its pillars. They were aware of some of industry 4.0 pillars but did not really know much.

> "I've never heard of industry 4.0… I heard of cloud, it's like the future" [AS1]

> "No until I Google about industry 4.0… I did hear about autonomous robots, IoT, cyber security, cloud, Augmented reality, Big data." [AS2]

> "No, I've never heard of industry 4.0…I heard of cyber security, cloud, big data, simulation maybe, yeah that's it." [AS3]

“No never heard of industry 4.0. Cyber security, cloud, big data” [AS4]

“I have heard the name.” [AS5]

“I don’t know much – I know a bit about it- a smart technology that connects together.” [AS9]

5.4.1.6 Discussion

The investigation of readiness of students indicated that there was a notable gap between industry and academic’s understanding of industry 4.0. It was shown that students showed limited awareness of their own role in preparing themselves for industry 4.0. Academics acknowledged integration challenges as it was not easy to incorporate all demanded skills (skills 4.0) in the curricula.

One interesting finding from quantitative analysis was that students with positive learning attitude tend to do well in technical skills. This supported the study conducted by Korkmaz (2018) that reported 19 skills categorised into six clusters. From the research study, it was found that in order for graduates to keep pace and ensure that they stay relevant to the industrial needs, it was important for them to continuously learn. From the interviews, it was also found that self-directed learning was crucial, as the lecturers would only be able to teach the basics. Therefore, to keep pace and stay relevant with recent technological trends, the key was to learn, unlearn and re-learn and the approach to do it was active learning.

All three stakeholders consistently emphasized the importance of attitude and self-management skills. Upskilling was seen as the critical approach to navigating the fast-changing technology landscape. To keep pace and remain relevant, universities needed to prioritize cultivating lifelong, self-directed learners capable of independently managing their skill development. The interviews revealed that the university’s curriculum could not keep up with the rapid advancement of technology, as updating it required a lengthy process. Given this challenge, it became imperative to implement a learning tool to help students—future graduates—stay ahead of industry changes and their impact on jobs. Study results indicated that there was a rift in the expectations of industries and universities. These differences in expectation were achieved despite sharing a common interest which was the competent labour force. Students and new graduates were considered viable candidates for intern or junior positions in IT companies. Yet, stakeholders had different understandings of what was expected from students. Universities thought that their graduates should be able to apply their knowledge in practice and contribute at the workplace. However, from industry's point of view, in general they still lacked some skills required to perform at the needed level. The varying levels of understanding and awareness of industry 4.0 indicate a need for better education and communication.

Due to the rapid changes emerging in the transition to industry 4.0, there was an increasing need to involve IT specialists in other industry areas, which required them to be able to adapt to the needs of these areas and apply their knowledge in entirely new contexts which were not taught in the university. Companies have been embracing new technologies but face challenges in skill shortages and workforce upskilling. This was where flexibility and adaptability skills proved very important. Hence, students needed to adapt to any new unfamiliar environment by upskilling themselves.

Participants of the study indicated that it might not be reasonable to try aligning courses or curricula to very specific needs. For example, when it comes to the newest trends in technology, universities should spend time creating a designated subject, training existing or find new lecturers with the required competency, create study materials, and go through the necessary bureaucracy. Even if this is done in a short time, the technology may still need to be updated by the time the students graduate and continue to the labour market. "We will always teach in the past," one participant from the university stated, "the first and second-year students will emerge to the labour market with a delay".

A similar situation was also noted from the business side. There were cases where recruitment of a candidate has had to be stopped mid-way because the specific technical skill required for the job was no longer needed. These advocates are against trying to include novel, so-called "bleeding-edge" technologies or competencies in courses and curricula, even though they may be prospering at the time.

Both academic and industrial participants reflected that understanding the underlying principles was more important than knowing specific technologies. In an ideal, work-integrated learning situation, the university would be responsible for teaching these principles while the student chooses the technologies based on the needs of the partnering business organisations. Adaptability had become essential, particularly for individuals working on services provided to other industries. A university representative noted that completing a subject did not mean a student could stop practicing. On the contrary, this marked the point where the student became prepared to independently enhance their skills as methods evolved, improved, expanded, and in the case of technical competencies, were eventually replaced by entirely new approaches.

It is important for students to also understand to what extent they were predicted to be disrupted and what technological trends they could expect. Maintaining balance between skills required to get a job and beginning to develop new skills that will be necessary for a step-change in future were critical. Therefore, a shift towards this new breed of learner should be produced by universities or students themselves who should be aware of their own needs. They should become increasingly autonomous, supreme multitaskers, expecting feedback and service to be immediate and want learning to be on-demand and just in time.

The interview analysis revealed a lack of tools to promote positive learning attitudes, despite the transformative potential of unlimited learning access in such an environment. Before students could fully benefit from unrestricted learning at either an organizational or individual level, they first needed to develop self-directedness and be empowered to do so. Building a learning-fit organization required individuals to identify which skills they needed to develop, assess their own learning gaps independently, and measure their personal progress. However, the analysis found no existing tool that fostered independent learning, even though lecturers expected students to take initiative in this area. Meanwhile, student responses indicated they felt insufficiently supported by the university in preparing for their future careers. With the rise of Industry 4.0, students must become more self-aware and proactively adapt to necessary changes. Additionally, the emphasis on attitude over knowledge and skills suggests that companies increasingly value adaptability and a willingness to learn.

5.4.2 Analysis of Questionnaires

To further clarify the validity of the interview data, questionnaires were carried out to collect data on the level of readiness and confidence of students in meeting the needs of industry 4.0. The variables are categorised as shown in Appendix 3 (Table A3.1).

Discriminant Validity

Before conducting any data analysis, validity and reliability tests were conducted on the dataset. The discriminant validity value can be seen from the Average Variance

Extracted (AVE) value (Table 5.1). A variable is considered to have a good degree of validity if it has an AVE value of ≥ 0.50 (Hair et al., 2021).

Table 5.1 Average Variance Extracted for Each Skill

Variables	Average Variance Extracted (AVE)
Technical Skills	0.620
Personal Skills	0.789
Self-Efficacy (Confidence)	0.541
Attitude	0.787

AVE ≥ 0.5: Good convergent validity

The results showed that the average variance extracted (AVE) value of each variable is above 0.50, so it can be concluded that all variables in this study are valid.

Reliability Test

As explained in chapter 4, Cronbach's alpha test was used to measure the internal consistency of the items. The vital step in quantitative analysis was to conduct a model reliability test to ensure there were no measurement-related concerns. Indicators of Composite Reliability and Cronbach's Alpha are utilised to conduct reliability tests (Table 5.2). The Composite Reliability and Cronbach's Alpha tests were used to assess the reliability of research instruments. A Composite Reliability or Cronbach's Alpha of 0.70 (Dash & Paul, 2021; Hair et al., 2021) for all latent variable values showed that the construct was of high quality or that the questionnaire used in this study was reliable or consistent. These values indicate very high reliability for all three scales, well above the conventional threshold of 0.7 for acceptable reliability.

Table 5.2 Cronbach's Alpha and Composite Reliability

Variable	Cronbach's alpha	Composite Reliability	Information
Technical Skills	0.939	0.940	Excellently Reliable
Personal Skills	0.974	0.974	Excellently Reliable
Self-Efficacy (Confidence)	0.920	0.921	Excellently Reliable
Attitude	0.914	0.917	Excellently Reliable

CR ≥ 0.7: Good reliability

All Cronbach's Alpha values were above 0.9 which indicated excellent internal consistency. The Composite reliability values were all above 0.9, which indicate excellent composite reliability. So, these results suggested that the measurement scales for the data were reliable and valid and could be confidently used for further analysis or decision-making related to these constructs.

Path Analysis

This research aimed to identify which independent variables/factors affected readiness. Therefore, it was important to understand the definition of the *p*-value in Pearson correlation, which was used to determine whether the correlation coefficient was statistically significant. A path analysis model was employed to examine the effects of learning attitude, technical skills, and personal development skills on the readiness of engineering students for Industry 4.0. It was worth noting that technical skills had a significant direct effect on readiness, with a standardized coefficient of 0.416 (*p* < 0.001). This indicated that students with higher ratings in technical skills were more likely to be prepared, underscoring the importance of technical competencies in achieving readiness.

The total effects referred to the overall impact of learning attitude towards readiness combining both direct and indirect pathways, which summed up to 0.17. This effect demonstrated that even though attitude did not directly affect readiness, it still played an important role in helping students get ready for industry 4.0.

Indirect effect analysis of learning attitude on readiness through personal development skills could be explained through two pathways. First path was learning attitude towards personal development skills and the path coefficient is 0.397 ($p<0.001$) (Figure 5.1). This positive coefficient indicated that a standard deviation had increased in learning attitude, 0.397 standard deviation would increase in the personal development skills. Second path would be personal development skills towards readiness and surprisingly, the result suggested that it was a negative coefficient of -0.163 ($p<0.05$) which implied that one standard deviation increase in core was associated with a decrease in readiness. While learning attitude positively influenced personal development skills, the relationship between personal development skills and readiness was negative. The total effect, which included all direct and indirect pathways, still remained a positive value at 0.17, which indicated that better learning attitudes were associated with higher readiness levels.

To understand the relationships between key variables, a correlation heat map was generated. From the figure, the strength and direction of the correlation between variables were visually represented. The darker the shade was, the stronger the relationship. The relationship between personal development skills and technical skills, appeared to be very strong with a value of 0.83. this in turn suggested that students who had strong personal development skills would tend to do very well in their technical skills, too. Moreover, it could be seen that learning attitude showed a moderate positive correlation with both personal development skills at a value of 0.40 and core skills at 0.48, which indicated that a positive learning attitude was associated with high skill levels.

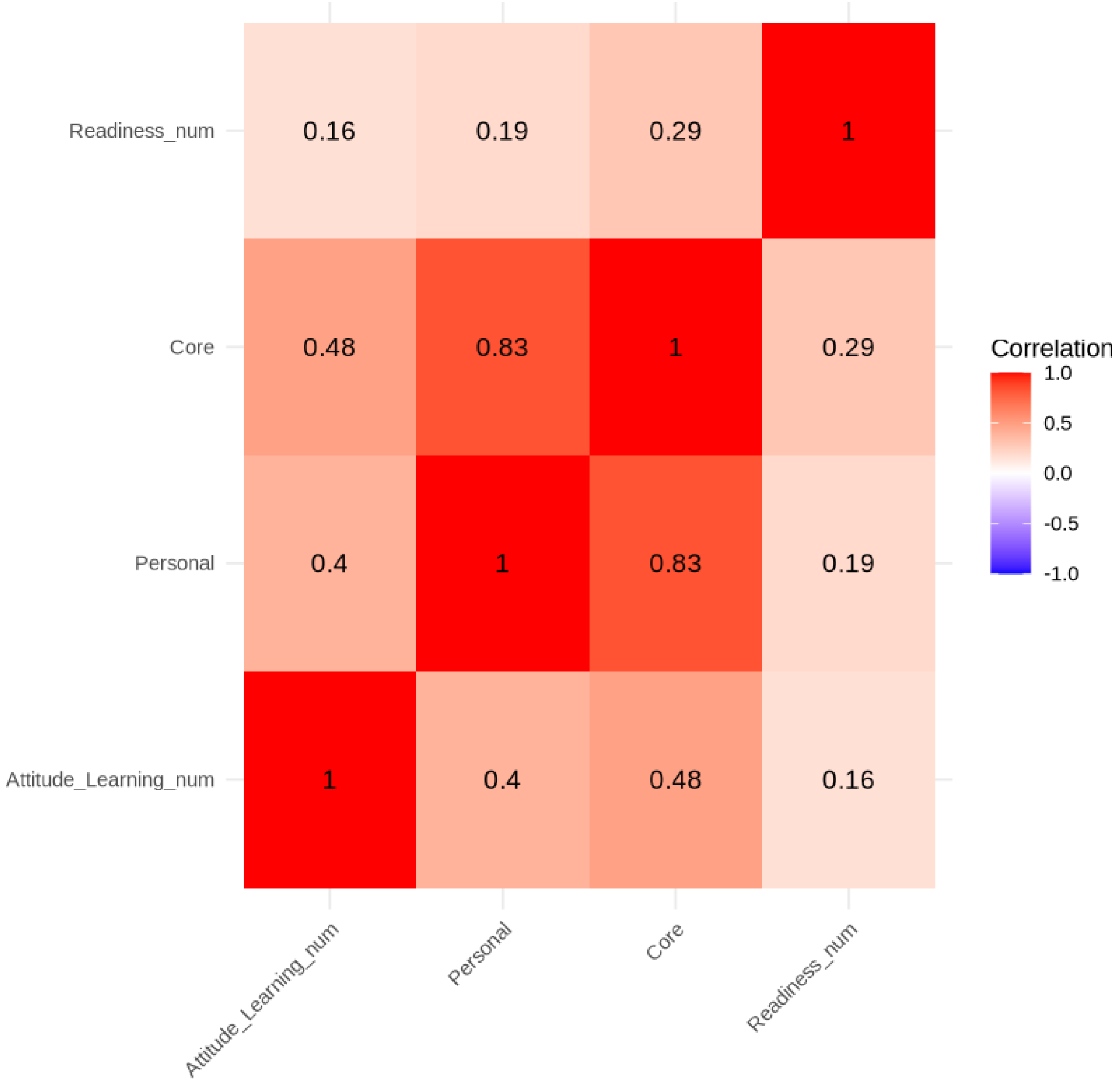


Figure 5.1 Correlation Heat map

To further explore the pairwise relationships between the variables, a scatter plot matrix was created (Figure 5.2). The purpose of a scatter plot matrix was to provide a comprehensive way of viewing data distribution and potential linear relationships. It could be clearly seen that when both the technical and personal development skills levels were higher, the readiness was increased. The correlation between personal development skills and technical skills was significant and this relationship might suggest that the students' personal development skills helped to them to learn and apply technical skills effectively.

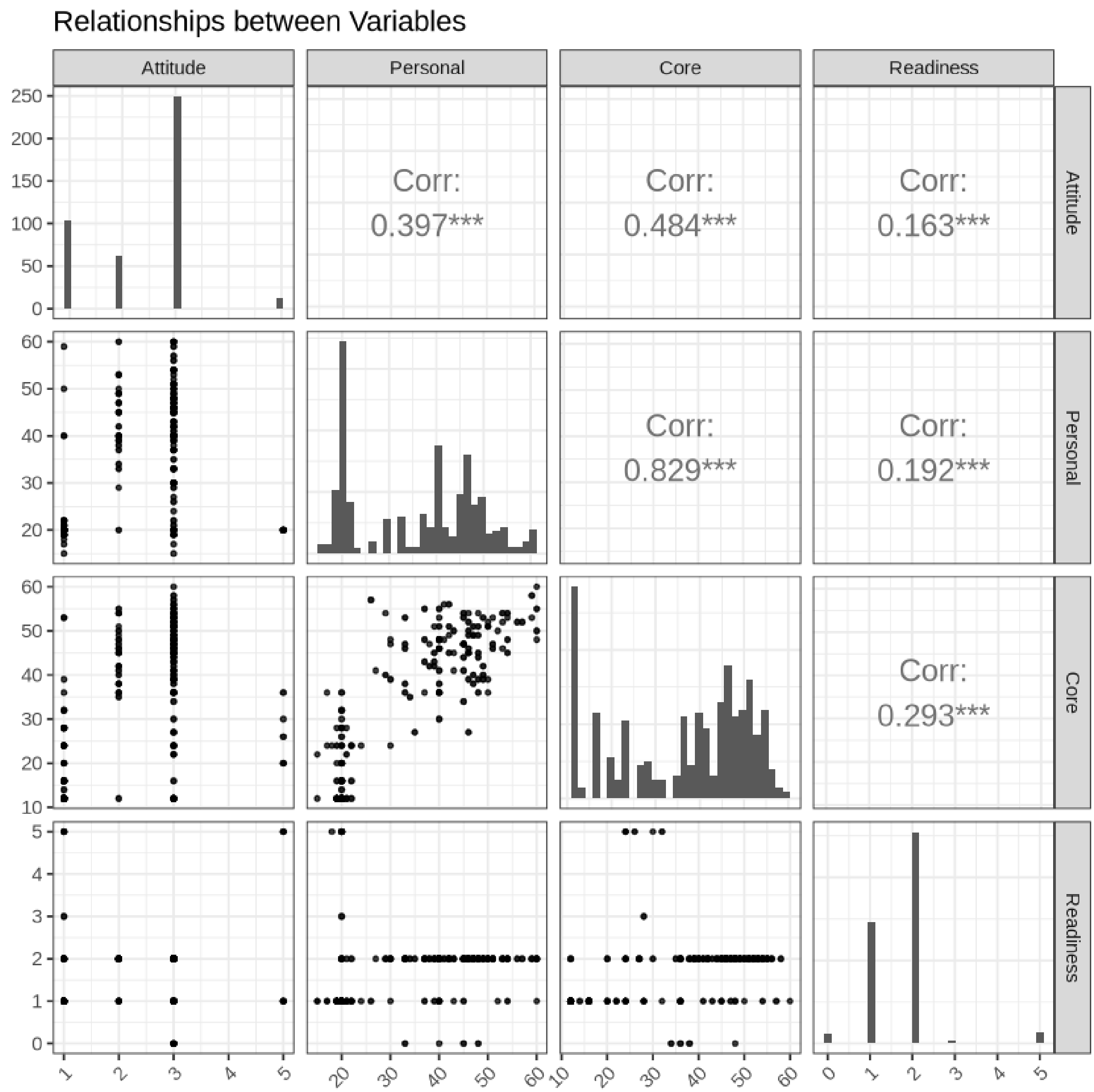


Figure 5.2 Scatter Plot Matrix

The scatter plot showed that there was a moderate positive correlation between attitude with personal development skills. The scatter points showed an upward trend but with more variation and this suggested that students tend had better personal skills if they had positive learning attitudes. The moderate correlation indicated that other factors could play the important role in improving personal development skills.

There was a stronger correlation between attitude and technical skills compared to personal ones. The scatter points demonstrated a clearer upward trend and this suggested that students were more likely to develop stronger technical skills if they possessed positive learning attitude. Students with positive learning attitude would be more persistent in learning especially when it came to the rapid changing era.

Skills' clusters

There were so many technical skills to focus on. Therefore, skills were categorised using correlation (Figure 5.3). Signal processing, cloud computing, and ML were categorised as the advanced technical skills with the average correlation of 0.831. These skills formed the tightest group with consistently high correlations. The second cluster showed the following skills: programming and mathematics which consists of Python programming, R programming, linear algebra/calculus/statistics, with the average correlation of 0.602. The cluster formed a coherent group with moderately strong relationship. The third cluster for technical skills was known as systems and infrastructure which comprised Java, Big Data technologies and IoT with the average correlation of 0.669. This cluster reflected consistent moderate-to-strong correlations, indicating these skills were often developed together but with less interdependence compared to the other clusters. Data visualisation stood out as an outlier, exhibiting generally low correlations (0.21 to 0.38) with all other skills, which implied it was a separate skill that progressed independently from other skills. Therefore, data visualisation was not part of the proposed framework. This information could inform curriculum design, recruitment strategies, and individual skill enhancement by highlighting the interrelationship of certain skills and the autonomy of others.

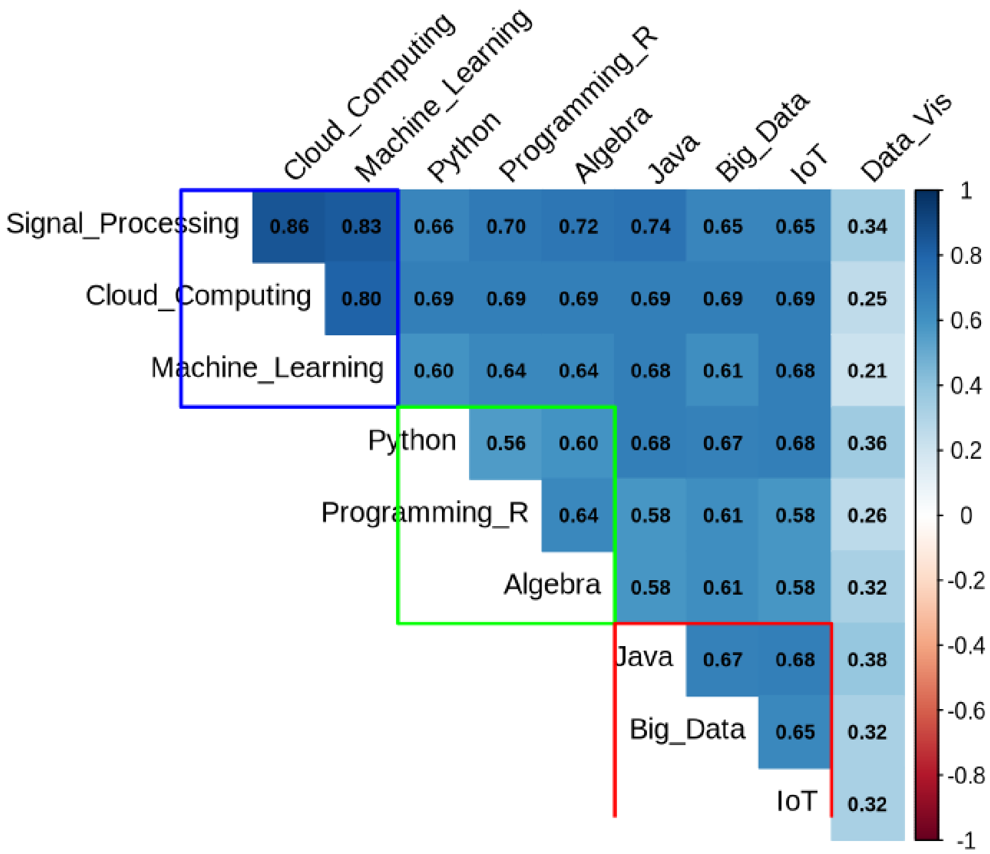


Figure 5.3 Correlation Matrix for Technical Skills

On the other contrary, a correlation matrix was computed for personal development skills. Groups of skills are were identified where the average correlation among the group members was high. The first group was the analytical thinking cluster which included problem solving, critical thinking and analytical thinking with the average correlation of 0.812 (Figure 5.4). This also indicated that the skills in this group had a strong mutual association that shared a common cognitive base, where reasoning, problem-solving capabilities, and analysis were interdependent. The second group was self-development cluster that included motivation and self-awareness, curiosity, lifelong learning and resilience, flexibility and agility with an average correlation of 0.831. This also indicated that individuals who scored high in one of these self-development related skills tended to score high in the others, indicating strong intrinsic links related to personal growth and adaptability. This also reflected that traits such as curiosity and resilience often supported each other in personal development. The adaptability cluster comprised system thinking, service orientation, talent management and creativity with the value of 0.802 which indicated a robust relationship among these skills, suggesting that they were functionally related to adapting to new challenges, managing change, and understanding complex systems.

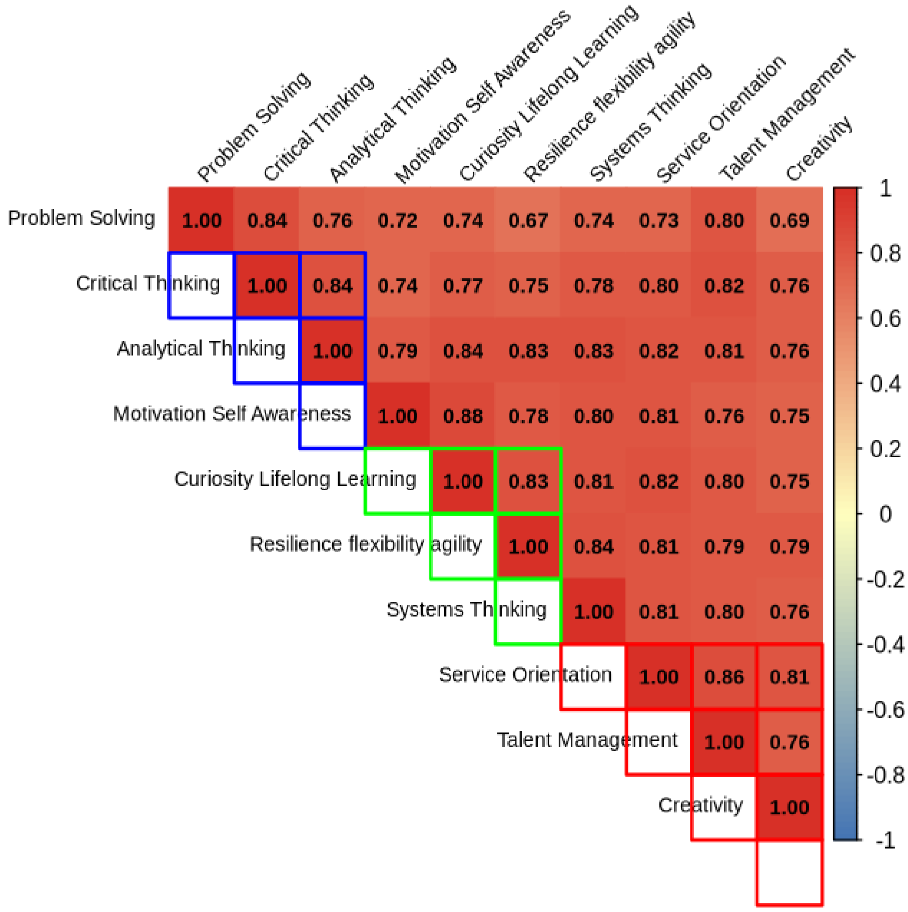


Figure 5.4 Correlation Matrix for Personal Development Skills

5.5 Chapter Summary

Chapter 5 presented research finding aimed at students' readiness for industry 4.0, using a mixed-method approach combining quantitative and qualitative data collection. The chapter determined skills required for industry 4.0 and uncovered stakeholders' perceptions about preparing students for this industry. The key findings from the interviews with academics were that they had different views on the top 10 skills listed by the World Economic Forum as important for the industry 4.0. Some felt that the list was sufficient while others thought some skills were too general or some even overlapped. From the qualitative study, attitude was seen as the most important element for students to possess, followed by knowledge and skills. However, attitude was difficult to directly assess in academic settings. Most academics believed that students were not well equipped for work and needed more practical experience, but they needed to be proactive in this aspect. All academics were aligned with the role where they agreed that their responsibility was to only teach foundational knowledge and concepts expecting students to proactively and independently develop more specific skills needed for work. Given the rapid industry shifts and limited curriculum updates, there was a gap between employer expectations and what academics could realistically teach. Awareness and understanding of industry 4.0 varied among academics. While some pillars were covered in curricula, it was unclear how relevant this was to industry needs.

The findings from students' questionnaires have shown that the technical skills had a significant direct effect on student readiness for industry 4.0. The learning attitude had an indirect positive effect on readiness through its impact on development of skills. There was a strong correlation between personal development skills and technical skills. It was also found out that students with positive learning attitude tended to have better personal and technical skills. There were various personal and technical skills and therefore, the skills were clustered into three main groups respectively. Personal skills such as problem solving, critical thinking, analytical thinking, motivation and self-awareness, curiosity and lifelong learning, resilience, flexibility and agility, systems thinking, service orientation, talent management and creativity were clustered into three main groups: analytical thinking, self-management and adaptability. Technical skills which were mainly focused on the big data and AI comprised of signal processing, cloud computing, machine learning/neural network, Python, R, linear algebra/ calculus/ statistics, Java, Big Data technologies and IoT were categorised into advanced technical skills, programming and mathematics and systems and infrastructure.

The research finding implied that a systematic approach is needed to prepare students for industry 4.0, focusing on technical skills, personal development and positive learning attitudes. Universities should provide more exposure and activities to enhance student awareness and dedication. Self-directed, lifelong learning is crucial for students to keep pace with rapid technological changes. There is a need to bridge gaps between industry expectations and university curricula. Flexibility and adaptability are important skills as graduates may need to apply knowledge in new contexts. Universities should focus on teaching underlying principles rather than specific technologies that may quickly become outdated. Students need support in developing self-directed learning and ability to identify and address their own learning gaps. Companies value adaptability and willingness to learn over specific knowledge.

In conclusion, preparing students for industry 4.0 required a multifaceted approach focusing a combination of technical skills, personal skills development and fostering positive learning attitudes. All stakeholders including universities, students and employers have vital roles to play in this process. Continuous learning and adaptability are the key attributes for students to stay relevant in the industry 4.0. Chapter 5 opened up new opportunities for the researcher to develop and validate a learning framework discussed in Chapter 6 to enhance the industry 4.0 requirements of students for the future workforce.

CHAPTER 6: DEVELOPMENT AND VALIDATION OF INDUSTRY 4.0 LEARNING FRAMEWORK

6.1 Introduction

A learning framework was developed considering the needs of the two stakeholder groups evaluated in this thesis being students and employers. This was applied after collating the findings of the literature review (chapter 2) and the quantitative and qualitative studies (chapters 4 and 5). From the aforementioned three chapters, a framework was developed which covered the different areas that had been identified by the stakeholders. Moreover, the framework addressed and built on the limitations of other published learning frameworks.

6.2 Framework Development

The preliminary investigation identified gaps in research regarding the factors that led to readiness of students for industry 4.0. As such, the developed framework in this chapter addressed the identified gaps by following a systematic and methodological process.

First, the literature review found that dimensions of industry 4.0 for students' readiness were rarely investigated, and only technical and soft skills had been considered in previous research studies. Henceforth, most research studies had focused on industrial readiness rather than the students' readiness. These studies ignored that students were the future workforce and their attitude is very important in education and employment contexts. Even though numerous general studies often claimed that attitude was important, attitude had hardly been mentioned in studies related to industry 4.0. The findings from chapter 5 showed that students' readiness for industry 4.0 was influenced indirectly by their learning attitude. Based on the literature review, it was found that there was no research on industry 4.0 related learning processes from students' perspective. Literature studies missed many skills related to students e.g. self-management skills. The lack and under-reporting of such skills was also found upon the qualitative study analysis. The outcomes of the qualitative interviews showed that active learning was the most important skill for all students.

Subsequently, this research focused on self-management and self-development where the change should start from students themselves especially in a rapidly changing environment such as industry 4.0. A positive learning attitude in such cases allows students to adapt quickly to innovative environments such that industry 4.0. These finds were confirmed in both the questionnaire and interviews (chapter 5).

Second, the review showed the presence of problems of assessing skills and attitude of students to industry 4.0. To the researchers' knowledge, studies that focused on methods to measure attitude always ended up in a long questionnaire. This could be addressed through the development of an assessment model structure that, measured skills and attitude using maturity levels. Maturity levels were adapted from the maturity level model to assess organisations' readiness for industry 4.0. Many studies have not focused on self-management skills. Yet recently, the research conducted by World Economic Forum has listed motivation and self-awareness as important skills for industry between 2023 to 2027. This latter aspect fulfilled the SDLC theory that was integrated in the proposed framework.

To enhance the novelty of the research, Big Data and AI were considered especially that the UK government emphasised the need for everyone to be technologically skilled. This could be seen through the UK government initiative to push for students to take AI and data science courses when they announced a £118 million AI skills fund. The fund has been used to fund a range of developments, including the creation of a £1 million “AI Future Grants Scheme” to support top AI researchers and Engineers from across the globe to work with UK universities and businesses. In addition, the Future Job Report by the World Economic Forum has also listed that AI and Big Data were some of the skills that have been in demand until today.

Consequently, the proposed framework, ASK SUMA, adapted different pedagogies to be comprehensive in supporting students’ learning process to get them ready for industry 4.0. ASK SUMA consisted of four stages and encouraged students to be more proactive in their learning considering the continuous rapid technological changes. Another contribution of the ASK SUMA framework was monitoring the framework’s theoretical aspects. The theoretical aspects of the ASK SUMA framework were self-directed (active) learning and social constructivism. The framework clarified for students what position they were into by evaluating their skills and attitudes towards industry 4.0.

The model developed in this contribution was adapted from the assessment model structure proposed by Acerbi, Assiani and Taisch (2019a). In the latter study, the authors reduced the six levels proposed by Russo (2016) to five levels so that it was easier to analyse the skills. One component that was not being assessed in this model was attitude. So, a new component of attitude was added to this model, with five levels to measure the attitude. Willingness to learn was the attitude that was going to be the main focus as this was the early stage of research in assessing attitude rather than using questionnaires. It emphasised reflection, which was also part of the self-directed learning cycle. The assessment model structure was presented in the following Table 6.1.

Table 6.1 Assessment Model Structure

Adapted from Acerbi et., al. (2022) and Trisca (2024)

Maturity Levels	Definition for Skills (Technical and personal Development Skills)	Attitude (Willingness to learn)
Basic	I do not know of the existence of this skill, and I do not possess them.	Demonstrates openness to new ideas
Aware	I know of the existence of this skill, but I do not possess it. I am therefore inclined to apply myself to improve.	Actively seeks learning opportunities and new information.
Practiced	I know this skill exists, and I have it in a basic way, sometimes needing an external supervisor. I work hard to improve myself.	Continuously upskills with in-demand trends/technologies and is an asset for any new project.
Competent	I possess this skill and master it almost automatically. I can manage complex and unforeseen activities in an innovation-oriented way, even in contexts other than the everyday.	Shares knowledge and experience proactively within the team

Proficient	I possess this skill and I master it almost automatically. In an innovation-oriented way, I can manage complex and unforeseen activities, even in contexts different from the everyday, and I can teach it to my colleagues.	Acts as a thought leader and stays committed to constant upskilling, and spreads knowledge and expertise.

6.3 Proposed "ASK SUMA" Framework

The review of the literature revealed that existing frameworks offered limited guidelines on what students needed to do to develop the required skill when integrating technologies. Most existing research around learning concentrated on technical skills and non-self-management skills, the curriculum content and the role of academics but did not address the needs that were uncovered by the analysis of the data acquired in this study.

The results of the data analysis provided several key elements which needed to be available for strategy to be implemented. These elements were, however, interrelated and could not be implemented in isolation. Therefore, the proposed framework was developed using a relationship diagram that connects all the necessary elements in the order in which they would need to be implemented. In order to be able to distinguish each of the needs and their attributes, the framework was based on three components (Figure 6.1):

(1) Theories: Self-Directed Learning and Social Constructivism, Maturity model
(2) Attributes of needs: Assessment and Development of Technical, Personal Development Skills and Attitude
(3) Stakeholder: Students

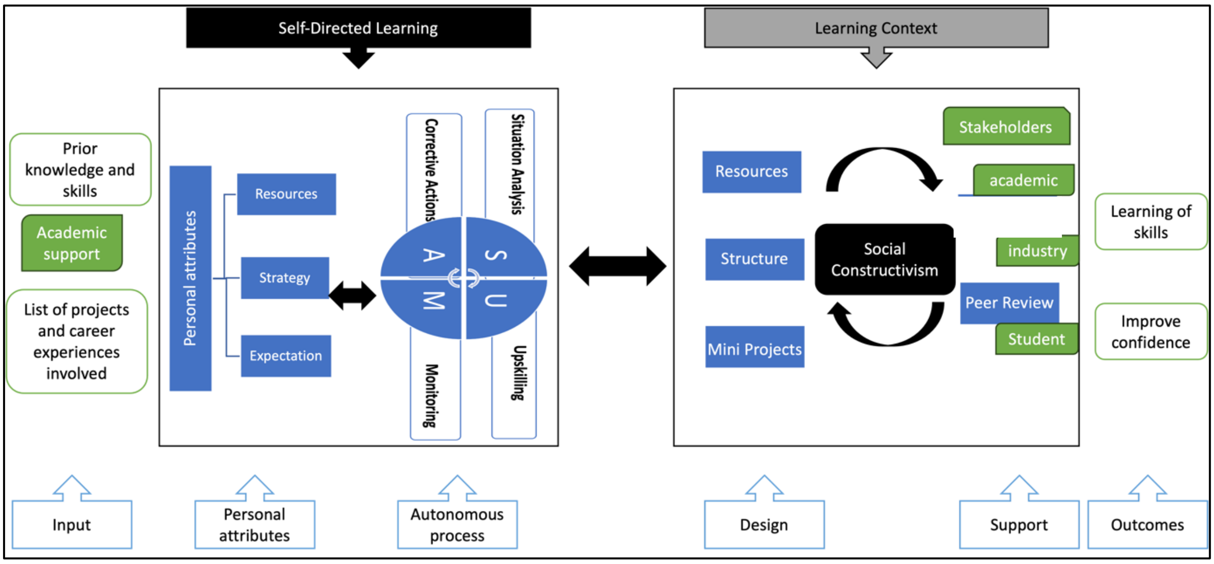


Figure 6.1 Complete integration of ASK SUMA with Self-Directed Learning Model

In this context of research, the prior knowledge or skills were the characteristics of students in terms of personal attributes. Morris and Rohs (2021) stated that higher level of personal attributes would contribute to an enthusiastic learning climate, which allowed the students to perform desirable technological soft skills (TSS).

In this framework, the process focused on the students' autonomous learning process. During this process, students developed their own situation analysis to create a plan by identifying goals and resources. Detailed information is explained in Section 6.3.1. Students undertook evaluation and reflection processes during the phase of monitoring and corrective action phase in ASK SUMA framework. Through the four stages of learning processes, students would be more creative in developing solutions to their problems or projects (Yeh and Lin, 2015). Learning context referred to resources and tasks or projects that allowed students to develop self-management skills which would result in other important soft skills like communication, problem solving, and creativity skills. The self-directed learning cycle developed by Hill and Song (2007) and Knowles (1975) was adopted with some adaptations in this proposed framework as shown in Table 6.2.

Table 6.2: Adaptation of Hill and Song (2007)'s Self Directed Learning in Proposed Framework

Self-Directed Learning Cycle	Proposed framework to fit the context of Industry 4.0
Diagnosing learning needs	**Stage 1:** Situation Analysis
Formulating learning needs	
Identifying human material sources for learning	**Stage 2:** Upskilling
Choosing and implementing appropriate learning strategies	
Evaluating learning	**Stage 3:** Monitor
	Stage 4: Action Plan

6.3.1 Stages in ASK SUMA framework

"ASK SUMA" was integrated with the self-directed learning cycle and consists of four stages; Situation Analysis, Upskilling, Monitoring and Actions as shown in Figure 6.1. ASK stands for attitude, knowledge and skills.

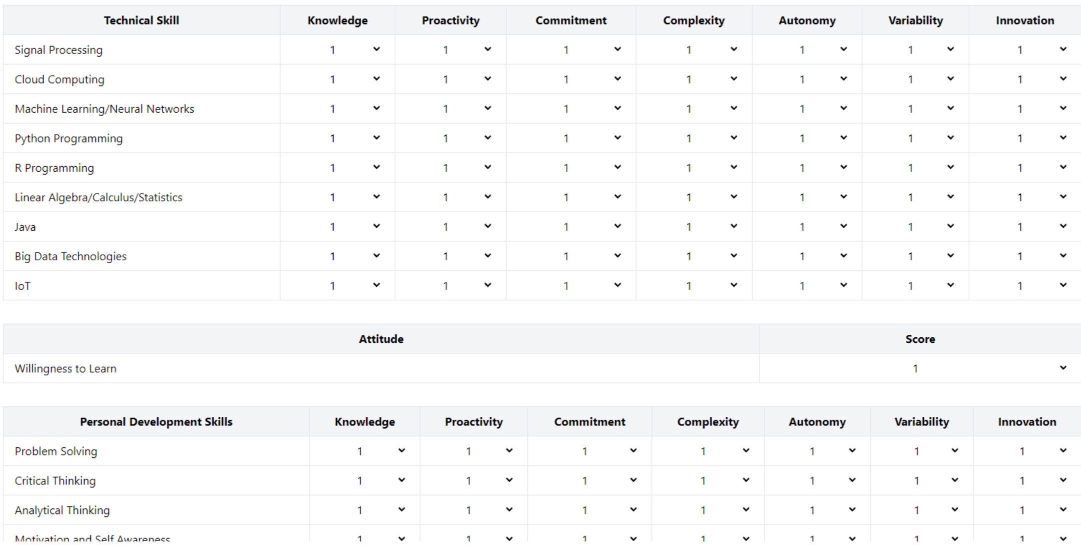
First, it was important to understand the current situation of the student in terms of background knowledge, skills and mindset in embracing the challenges of future industry. The table below shows the main components of the ASK SUMA Framework and the figures below showed that students can have self-review and peer-review on skills (Table 6.3). An online platform was created to conduct the research to help students visualise how the framework was supposed to be used as shown in Figure 6.2-6.4.

Table 6.3 Main Components of the ASK SUMA Framework

Aspects	Justification for inclusion	Details
Technical Skills	From literature and questionnaire and interview.	**Knowledge- Big Data and AI** **Cluster 1: Advanced Technical Skills** Signal Processing, Cloud Computing, Machine Learning/Neural Networks **Cluster 2 - Programming and Mathematics** Python Programming, R Programming, Linear Algebra/Calculus/Statistics **Cluster 3 - Systems and Infrastructure** Java, Big Data Technologies, IoT
Personal development skills	From questionnaire statistical analysis in Section 5.4.1 and literature.	**Cluster 1: Analytical Thinking** Problem Solving Critical Thinking Analytical Thinking **Cluster 2: Self-Management** Motivation and Self-Awareness Curiosity and Lifelong Learning Resilience, flexibility and agility **Cluster 3: Adaptability** Systems Thinking Service Orientation Talent Management Creativity

Attitude	From interview and finding from survey	**Willingness to Learn**

The students could use maturity model proposed in Table 6.1 to self-rate their skills and attitude as shown on Figure 6.3. Once they have rated their skills, feedback would be given to them through the platform as shown in Figure 6.4. Then the students could start making their own plan.



Technical Skill	Knowledge	Proactivity	Commitment	Complexity	Autonomy	Variability	Innovation
Signal Processing	1	1	1	1	1	1	1
Cloud Computing	1	1	1	1	1	1	1
Machine Learning/Neural Networks	1	1	1	1	1	1	1
Python Programming	1	1	1	1	1	1	1
R Programming	1	1	1	1	1	1	1
Linear Algebra/Calculus/Statistics	1	1	1	1	1	1	1
Java	1	1	1	1	1	1	1
Big Data Technologies	1	1	1	1	1	1	1
IoT	1	1	1	1	1	1	1

Attitude	Score
Willingness to Learn	1

Personal Development Skills	Knowledge	Proactivity	Commitment	Complexity	Autonomy	Variability	Innovation
Problem Solving	1	1	1	1	1	1	1
Critical Thinking	1	1	1	1	1	1	1
Analytical Thinking	1	1	1	1	1	1	1
Motivation and Self Awareness	1	1	1	1	1	1	1

Figure 6.2 Skill Categorisation

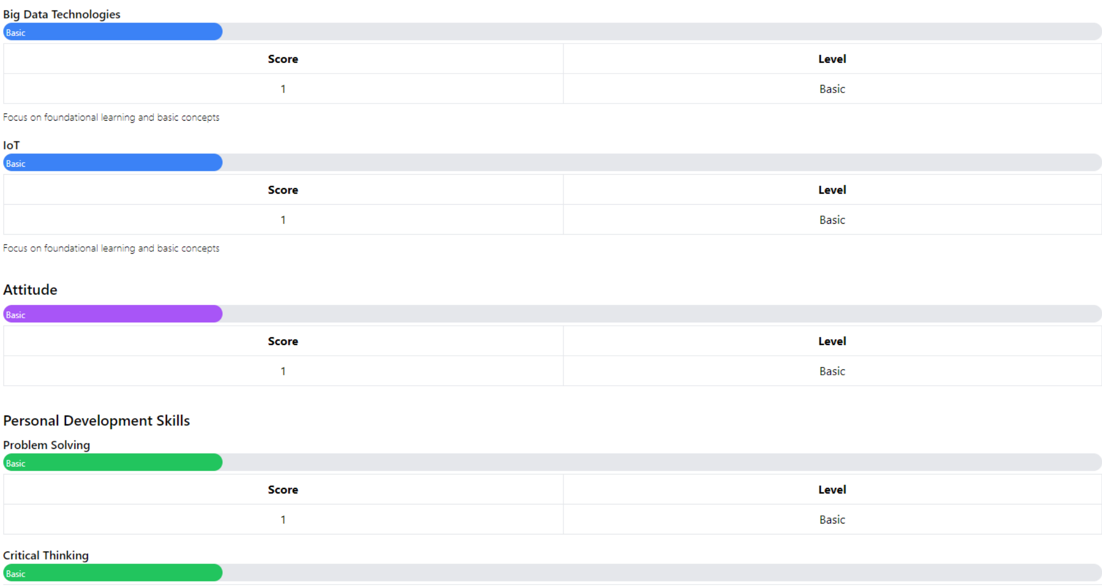


Figure 6.3 Skill Self- Assessment

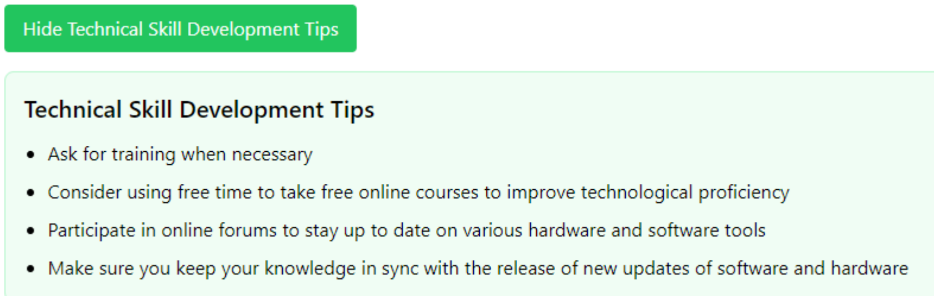


Figure 6.4 Recommendation or Tips on Skill Improvement

The next stage would be upskilling which entailed developing methods to address the issues highlighted in the first stage. In the context of research, students could consult the companies that they were doing their summer internships with to assist their development and enhance what they needed. In this phase, students may prefer mentored instruction over independent learning as according to Dickinson's (1987) definition, self-directed learners could differ in the degree to which the implementation of their learning activities, as determined during the planning process, is considered autonomous.

The third stage would be monitoring. The students could continue to use the online platform. Students could continue seeking feedback from their peers, colleagues or supervisors. Feedback should be used as an ongoing process to monitor the performance of the key actions carried out by the students.

Last stage would be corrective actions. After reviewing the strategies planned, corrective actions were taken and situation of student would be reanalysed. All these are done by students themselves as this framework was encouraging students to self-manage themselves.

6.4 Evaluation and Validation of Framework

6.4.1 Evaluation of the Effectiveness of the Framework in Supporting the Students for Industry 4.0

The final step in the development of the learning framework was validation. The purpose of this study was to explore a framework in supporting higher education students in meeting the needs of industry 4.0 and future industry. Therefore, Engineering students from various universities in the UK were invited to participate to evaluate the effectiveness of ASK SUMA framework. The framework was tested on 151 students from different Engineering courses at different universities. In this phase, a survey was conducted to evaluate the effectiveness of the framework by looking at the pre-test rating for skills and post-test rating for skills to determine whether there was any improvement. This framework was tested for three months during summer break (1st June 2024 to 15th September 2024). The choice of the summertime frame was because students had summer internships during this time, and it fitted the research's sampling criteria.

Due to time constraints, only self-assessment could be done to evaluate the effectiveness of the framework, It was important to note that self-reported data risked over underestimation of skills and attitude. Therefore, results might not reflect the level of skills and attitude. To mitigate this limitation, calibration exercise was done to make sure participants were clear with how they mitigate. It was done online as participants came from different universities. High Cronbach's α of 0.82 was proven as evidence of internal consistency and used to overcome this limitation.

To test the effectiveness of the framework, data on initial levels of skills were collected before and after using the framework and the improvement percentages was then calculated. The data analysis plan involved the calculation of internal consistency, pre and post comparison of maturity levels of skills and attitude in terms of success rate, paired t-tests, effect sizes using Cohen's d, McNemar and K-Fold Cross-Validation tests.

The improvement values were calculated by using the differences in initial and subsequent data. The differences were then quantified using mean difference values.

These mean differences provide a quantitative measure of improvement, representing the change in skills before and after the use of the ASK SUMA framework. To further support the validity of these metrics, statistical tests such as paired t-tests were employed to assess whether the changes observed in the mean values were statistically significant. Box plots were also used to give a visual representation of the data summary. In addition, Cohen's d effect sizes were calculated to indicate the magnitude of improvements. To further strengthen the evaluation, k-fold and McNemar's test were used to provide a more comprehensive evaluation which gave a detailed understanding of the effectiveness of the framework in enhancing student readiness for Industry 4.0 Table 6.4

To give a better visualisation of improvement in skills, percentage was used to show the improvement of the clusters after using the ASK SUMA framework as shown in Table 6.4. The formula used is shown in Equation 6.1.

$$\frac{(Mean\ After\ -\ Mean\ Before)}{Mean\ Before} \times 100 \tag{6.1}$$

The results showed significant improvements across all skills after using the framework. Largest improvements could be seen especially in self-management cluster of skills as the mean difference value is 0.536, followed by an increase of 0.457 in adaptability. Improvement could be seen in the six clusters of skills. The calculation of mean and mean-difference values could be seen in Table 6.4. Moderate improvements could be seen in advanced technical skills, systems and infrastructure and programming skills. All improvements were statistically significant ($p < 0.05$).

Table 6.4 Mean and P-Value of Data

Measures	Before_Mean	After_Mean	Mean_Difference	Percentage_Improvement
Learning Attitude (Willingness to Learn)	2.338	3.060	0.722	30.88%
Analytical Thinking	2.384	2.854	0.417	19.72%
Self-Management	2.821	3.358	0.536	19.01%
Adaptability	3.325	3.781	0.457	13.74%
Advanced Technical	3.265	3.464	0.199	6.09%
Programming and Mathematics	2.219	2.384	0.166	7.48%

Systems and Infrastructure	3.735	3.907	0.172	4.61%

In order to show significant improvement through data analysis, paired t-tests were used and the results indicated statistically significant improvements across all skills, with p-values less than 0.05.

The effect sizes, measured by Cohen's d as shown in figure below, suggested that large effects for analytic and self-management skills, indicating substantial improvements (Figure 6.5). This bar chart illustrates the effect sizes (Cohen's d) associated with each skill. The dashed lines denoted the benchmarks for small, medium, and large effects. Skills with bars that surpassed these lines indicated the degree of improvement, with taller bars reflecting more significant effects. Medium effects for adaptability, advanced, programming, and system skills, suggested moderate improvements.

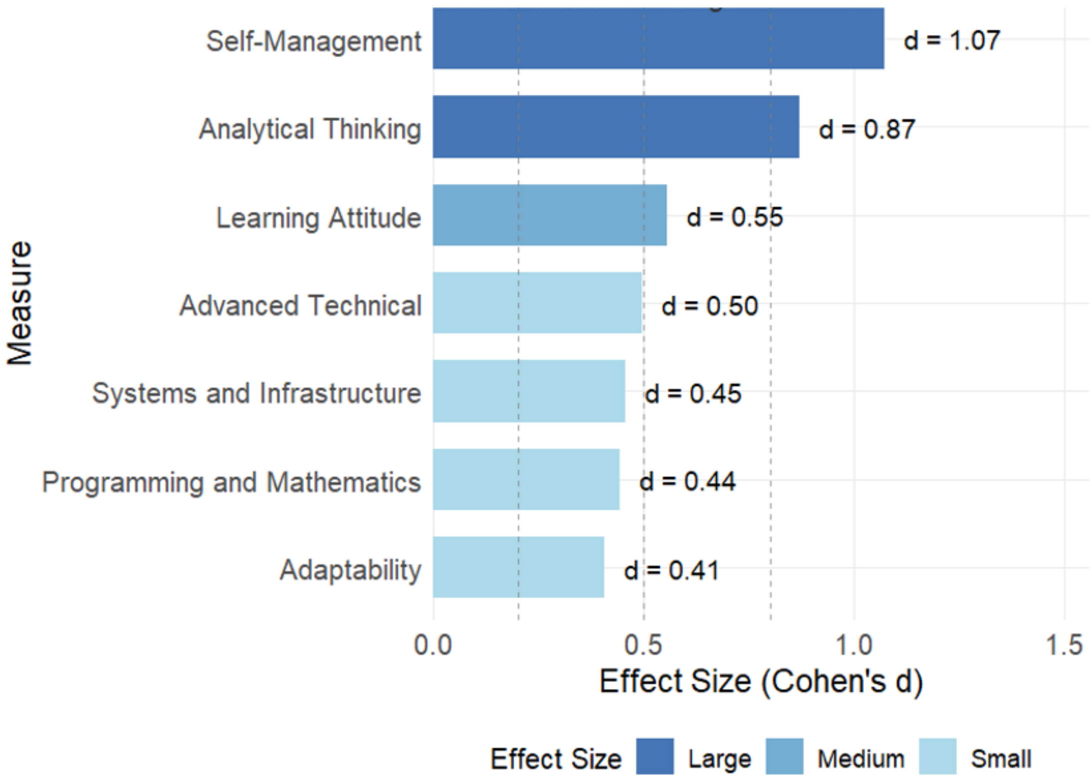


Figure 6.5 Cohen's D (Effect Size by Measure)

The box plot in Figure 6.6. showed each measure in terms of analytical thinking, self-management, adaptability, programming and mathematics, advanced technical skills and systems and infrastructure. The box plot overlaid the distribution of before against after levels of measurement. Red boxes showed that the level of these measures became more consistent after using the framework.

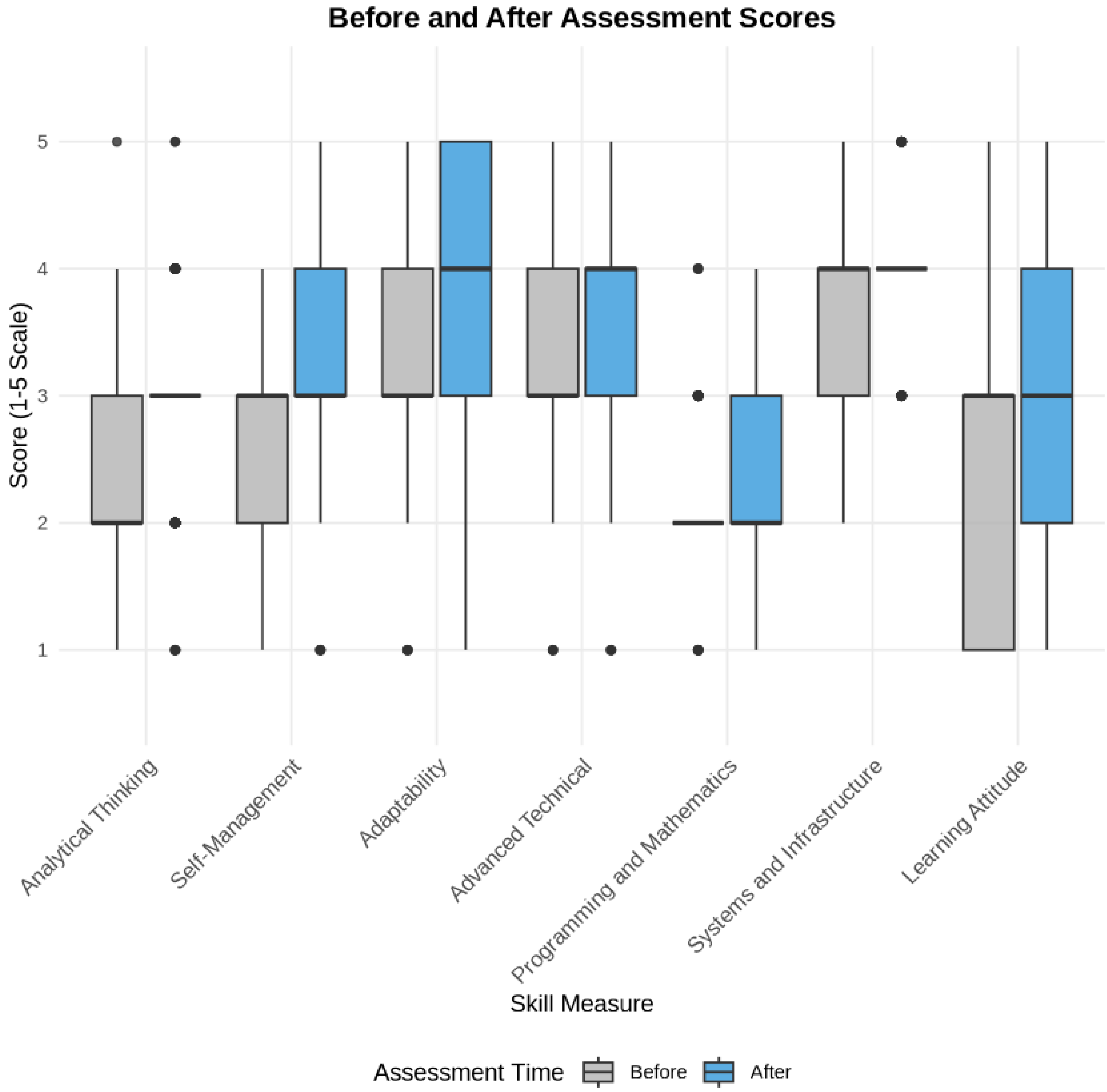


Figure 6.6 Box Plot for Skills and Attitude

Success rate was also calculated as shown in Table 6.5. to show how many individuals actually improved. The area of self-management demonstrated the greatest rate of improvement, with 53.64% of participants showing progress. Analytical thinking skills ranked second in terms of improvement rate, with 41.72% of participants demonstrating growth. Adaptability exhibited notable improvement at 49.01%, although a small percentage of participants (11.92%) experienced a decline. Programming, advanced technical skills, and systems and infrastructure displayed strong stability, with 80-83% of individuals maintaining their performance level. These domains also experienced minor yet steady improvement rates, ranging from 16% to 20%. In terms of reliability, the majority of skills showed no signs of regression, with 0% deterioration. Only adaptability indicated some decline (11.92%), suggesting that this area may require further enhancement within the framework. The distribution of total personal development illustrates the ways in which participants enhanced their abilities in all areas.

Table 6.5 Success Rate Table

Measure	Improved Count	Success Rate (%)
Learning Attitude (Willingness to Learn)	91	60.26
Self-Management	81	53.64
Adaptability	74	49.01
Analytical Thinking	68	45.00
Advanced Technical	30	19.87
System and Infrastructure	26	17.22
Programming and Mathematics	25	16.56

To further enhance the robustness of the study's evaluation process, t-test, k-fold validation, and McNemar's tests were conducted. These three tests were selected as they were used to compare the self-review score before and after using the proposed framework.

Paired T-Tests were performed each cluster of the skill. This test compared the means of the measurements from before and after using the framework by examining the differences for each cluster of skills. The objective of paired t-test was to detect whether the average change of measurements is significantly different from zero. T statistic and p-value were computed by using the sample mean difference, standard error, and degrees of freedom. A small p-value indicated that the change was statistically significant which suggested that there was a positive shift in the skill performance. A positive mean difference means an overall improvement of skills from before to after using the framework, while a negative value implies a deterioration in skills. In all instances of this research, the p-values were extreme low which indicated that the differences between the pre- and post-measurements for each skill were statistically significant.

McNemar’s Test was used to provide statistical evidence that the changes observed were not just random fluctuation. The question answered by this test was whether the participants were different after using the proposed framework. The formula used is shown in Equation 6.2.

$$\chi^2 = \frac{(b-c)^2}{(b+c)} \tag{6.2}$$

Where,

b is the number of people who improved (went from low to high)

c is the number of people who declined (went from high to low)

The McNemar's test shows significant changes ($p < 0.05$) for most skills (Table 6.6):

Table 6.6 McNemar's Test Results

Skills	p-value
Self-Development	1.52×10^{-12}
Analytical Thinking	0.0077
Adaptability	0.00087
Programming and Mathematics	0.1336
Advanced Technical	9.44×10^{-7}
Systems and Infrastructure	2.15×10^{-5}
Attitude	1.24×10^{-10}

In Table 6.6, it could be seen that all attributes tested showed significant change from before to after ($p<.05$). except for Programming. Attitude shifts were highly significant as well as the self-management skill too. This indicated that participants not only felt more capable but also more positively motivated by the framework. The framework's emphasis on systems and infrastructure skills and technical advanced skills were validated by the significant change. However, the framework showed that students might need to focus more on programming. In summary, these tests confirmed that most aspects of the framework drove significant change especially in attitude.

On the other hand, the k-fold cross-validation showed that the self-development skill had the highest improvement (Table 6.7). Analytical thinking and adaptability demonstrated moderate improvements whereas programming and mathematics, advanced technical skills and systems and infrastructure skills had smaller but consistent improvements.

Table 6.7 K-Fold Cross-Validation Results

Skills	Mean Improvement	Standard Deviation
Self-Development	0.538	0.142
Analytical Thinking	0.470	0.149
Adaptability	0.455	0.2531
Programming and Mathematics	0.166	0.073
Advanced Technical Skills	0.199	0.099
Systems and Infrastructure	0.213	0.108
Attitude	0.7229	0.315

From Table 6.7, a higher mean showed larger average gains from before using the framework to after using the framework. A lower standard deviation meant that the estimated gain was consistent across different splits. In this research, 10-fold Cross-

Validation method was used to reduce bias. 10% of participants were repeatedly held out fitted the model on the remaining 90%. Averaging across folds yielded the mean values and standard deviation reflected how much they fold-level mean fluctuated. Attitude and self-management skills showed the largest improvements while the improvements for Systems and Infrastructure skills showed the most consistent improvement. It was important to compare the effect size and reliability. Self-management skills and attitude were variable across samples although showing larger effects. As for Programming, it did not show any large effect or high reliability.

The McNemar's test indicated significant changes in all skills except Programming and Mathematics as the participants did not get worse or better. The k-fold cross-validation confirmed these improvements and provides estimates of their magnitude. The confidence intervals from the k-fold validation did not contain zero, suggesting consistent improvements across different subsets of the data. The results were robust across both testing methods, strengthening the conclusion that the interventions were effective for most skills.

6.5 Chapter Summary

Chapter 6 presented the development of the framework, structure and validation of a novel learning framework known as ASK SUMA, designed to prepare Engineering students for coping with the demands of industry 4.0. This framework was developed by integrating insights from a comprehensive literature review and data collected through mixed-method approach. The chapter reinforced the significance of addressing both employers' and students' needs and revealed critical gaps in existing frameworks, particularly those relating to students' attitudes and self-management skills.

The initial section of the chapter defined the justification for the proposed framework. Most studies focused on firms' readiness for industry 4.0 compared to students who would be the future workforce. While technical and soft skills were often discussed, students' attitude especially their willingness to learn were often neglected. The research findings indicated that a positive learning attitude contributed to students' readiness for industry 4.0. Furthermore, the literature lacked emphasis on self-management and active learning from the students' perspective. The chapter indicated that self-development should be the central focus as the dynamic nature of industry 4.0 required students to continuously adapt and learn.

In the direction of addressing the challenges of assessing skills and attitudes, the framework incorporated a maturity model adapted from the assessments of organisational readiness for industry 4.0. This model included five levels which consisted of basic, aware, practiced, competent, and proficient which were used to assess skills and attitudes. The novel component of this framework was the willingness to learn, and it highlighted openness to new ideas, proactive learning, and knowledge sharing with peers. This more structured approach allowed for a better evaluation of student readiness moving beyond binary assessments to a more detailed understanding of each student's capability.

ASK SUMA framework was developed based on three theoretical components which were Self-Directed Learning (SDL), Social Constructivism and Maturity Model. These three theories were used as they supported the focus of this study which was continuous improvement of skills, independent learning and collaborative knowledge. The framework is comprised of four stages: situation analysis, upskilling, monitoring and action planning. These stages aligned with the SDL cycle proposed by Hill and Song (2007) and Knowles (1975) adapted to the context of industry 4.0 and Big Data field.

The framework categorises essential attributes of readiness for industry 4.0 into three main areas: technical skills, personal development skills, and attitude. Both technical skills and personal development skills were further divided into three clusters. Attitude was represented by the level of willingness to learn which was assessed through the maturity model.

In addition, it was important to evaluate and validate framework proposed in this thesis. A quantitative study involving Engineering students from various universities was conducted to collect baseline data on students' skills and attitudes before implementing the framework, and follow-up data was gathered afterwards. The results showed statistically significant improvements across all skills' clusters, with the most substantial gains in self-management (19%), analytical thinking (17.49%), and adaptability (13.74%). Technical skills also improved, though to a lesser extent: programming and mathematics (7.48%), advanced technical skills (6.09%), and systems and infrastructure (4.61%).

Paired t-tests and Cohen's d effect sizes confirmed the significance and magnitude of improvements in the skills. The research indicated substantial gains which were observed in the large effect sizes in self-management and analytical thinking. Box plots and bar charts illustrated the distribution and consistency of improvements while success rate showed that most students either improved or maintained their performance across all skill areas. However, adaptability showed some decline in a small percentage of participants which suggested a need for further advancement in the framework.

To further enhance robustness of this framework, additional statistical tests such as k-fold cross-validation and McNemar’s test were conducted. These tests were crucial as they validated the consistency of the improvements across data and confirmed the reliability of the framework’s impacts. The use of multiple validation methods strengthened the credibility of the findings and supported the framework’s effectiveness in preparing students for industry 4.0.

The ASK SUMA framework represented a significant advancement in preparing students for the evolving demands of industry 4.0. The framework addressed critical gaps in existing educational approaches. The positive evaluation results suggested that ASK SUMA could effectively support students in developing the technical, personal, and attitudes needed for future industrial challenges by emphasising the importance of self-directed learning, proactive attitude, and continuous development of skills.

CHAPTER 7: CONCLUSION

7.1 Introduction

This chapter concludes the thesis by discussing its contributions to theory and practical implications as well as its limitations. Future research directions are suggested. The discussion is structured based on research questions and objectives.

7.2 Critical Discussion

The study sought to develop a framework to support students' learning processes and equip them with the skills required for industry 4.0. This was accomplished through an investigation of the current gaps between university curricula and the skills expected by the industry. The framework addressed the disconnect between industry's and universities' expectations, supporting the assessment of skills through an extended industry 4.0 assessment model structure.

Research Question 1:

What are the key skills sets required by the future workforce to be ready for industry 4.0?

The findings from quantitative research indicated that technical and personal development skills are equally critical for industry 4.0 readiness while attitude indirectly contribute to the readiness through both type of skills. Technical skills include signal processing, cloud computing, machine learning and neural networks, Python programming, R programming, linear algebra, calculus and statistics, Java, Big Data Technologies, and IoT. Personal development skills include problem solving, critical thinking, analytical thinking, motivation and self-awareness, curiosity and lifelong learning, resilience, flexibility and agility, systems thinking, service orientation and customer service, talent management and creativity. Both types of skills were further grouped into three clusters each so that the students could choose which one to focus first. One of the clusters is known as self-management skills that is made up of motivation and self-awareness, curiosity and lifelong learning, resilience, flexibility and agility. According to Aljohani (2022), self-management skills, although highly valued by employers, have been neglected in academic settings. So, this framework addressed the gap. It was hypothesised that the lack of an adequately skilled workforce was an existing or emerging barrier to the digital transformation of companies (Galanti et al., 2023).

In addition, the highly demanded skills that are discovered through extant literature are actually promoted through the use of the framework. This supported the framework as it emphasises the balance between these skills by incorporating a self-directed learning cycle that promotes adaptability, critical thinking, and resilience. These findings support previous literature (e.g., Prifti et al., 2017) highlighting the need for workers who can think critically and manage rapid technological changes in industry 4.0. By aligning with the demanded skill sets, the framework provided a systematic approach for students to gradually build these skills, progressing with maturity levels from basic to proficient skills.

This skill and attitude focus not only aligns with workforce demands in industry 4.0 but also provides insights into how educational institutions can prepare students to be agile and responsive to evolving technological era. Adding Big Data and Analytics to the framework further broadens students' technical capacities, equipping them for the uprising sector.

Research Question 2 (RQ2):

How do pedagogical interventions aim at facilitating students' learning process to prepare and support them?

The objective of RQ2 was to design a learning methodology that supports skill acquisition. According to the responses to RQ2, it was vital to find the right methodology to support students in their learning process. Based on the analysis of the needs assessment, it was found that the students need to be independent in learning and also to be able to adapt to any environment by applying the foundation that the university has laid for them. In order to support the students, a self-directed learning cycle was used to integrate with the theory of social constructivism which encourages knowledge sharing and the affective aspect of the learning domain to help encourage students to share knowledge with each other.

The pedagogical strategies included within the framework, such as self-directed learning, principles of social constructivism, and assessments of maturity levels, significantly contributed to the improvement of student engagement and skill development. The self-directed learning cycle enabled students to assume control over their educational journey, promoting a natural drive to continually enhance their skills. This is in line with Bandura's (1986) self-efficacy theory, which posits that students are more likely to acquire enduring skills when they are given the power to guide their own learning. This approach supports students in developing personal development skills like curiosity and lifelong learning, adaptability in a context that simulates the collaborative nature of industry 4.0 work environments. Additionally, maturity levels allow students to see clear progress, helping them identify areas for improvement and build confidence in their abilities. Thus, the pedagogical components not only enhance learning but also bridge the gap between theoretical knowledge and practical application in an industry 4.0 context.

Research Question 3 (RQ3):

How does the proposed framework contribute to supporting students to embrace industry 4.0?

The objective related to RQ3 was to test and evaluate the effectiveness of the framework in supporting the learning process and preparing students for the needs of industry 4.0. Through the application of the ASK SUMA framework in educational environments, students were shown to increase their confidence and engage more deeply with the latest technological trends. Companies found the framework beneficial for assessing and developing skills, which aligns with their needs for industry 4.0. The framework created a dynamic, student-centred learning environment that encouraged continuous improvement.

In discussing RQ3, it is important to apply best practices alongside other market participants to evaluate and cultivate the necessary skills, as individuals will continue to play a crucial role. The ASK SUMA framework was demonstrated to effectively assist students in their preparation for industry 4.0; data from questionnaires indicated that it enhanced students' confidence levels and enabled industries to share updates on recent technological trends, ensuring students remain informed about the latest advancements. Furthermore, it fostered an enthusiastic learning environment, as it was devised based on a self-directed learning cycle that empowers students to learn continuously and independently. Additionally, the research sought to outline the elements of a framework that would improve students' learning experiences in industry 4.0. To promote self-awareness and autonomy in learning, a framework was created.

The framework's systematic approach, which encompasses skill evaluations, the pillars of industry 4.0, and self-directed learning, presents a comprehensive method for preparing students to meet the challenges of contemporary industries. By incorporating maturity levels to assess progress in both technical and personal development skills, the framework provides a clear pathway for skill development, motivating students to attain the proficiency levels sought by employers. What distinguishes the framework is it’s the emphasis of learning attitude that has to be focused on to help improve technical skills and personal development skills and indirectly contribute to the readiness for industry 4.0 as that was proven in the quantitative analysis.

7.3 Theoretical Implications

The ASK SUMA framework contributed to existing learning theory by combining self-directed learning and social constructivism with maturity model. These theories were selected because of their potential to enhance the development of self-management skills, which are among the top skills projected to be necessary for 2025 and it encourages students to develop their technical skills (Whiting, 2020). While these theories have been extensively applied in organisational contexts and adult learning, their use in universities have been limited. Although the studies discuss theoretical frameworks and concepts, there is a gap in practical applications and strategies for educators to implement self-directed learning and social constructivism in their teaching practices. The framework demonstrates how these learning theories can be applied in higher education to foster industry 4.0-relevant skills.

The findings support and extend the conceptual model of students’ readiness for industry 4.0 by identifying two more dimensions which are attitude and learning process, particularly emphasising the integration of technical and personal development skills in tandem. Traditional competency frameworks often view skills in isolated categories, but the findings suggest a more interconnected approach where technical skills (e.g., Python, Java, IoT understanding) and soft skills (e.g., adaptability, resilience, and self-management) are equally critical and mutually reinforcing in industry 4.0 contexts.

By integrating positive learning attitude, technical skills, and personal development skills into an educational framework, this research contributes to theories on workforce readiness and suggests that future competency models for industry 4.0 should emphasise adaptability, continuous learning, and interdisciplinary skill development as foundational aspects of education. Moreover, the application of a self-directed learning cycle highlights the need for educational environments that foster autonomy and self-motivation, particularly in contexts where adaptability and self-sufficiency are crucial.

The findings suggest that educational frameworks aiming to prepare students for industry 4.0 should not only align with workforce competency demands but also evolve to include systems thinking and interdisciplinary integration—concepts supported by systems theory. In an industry 4.0 setting, technical and personal development skills are part of a larger system of interconnected competencies where understanding data flows, digital interdependencies, and systems integration are essential. The framework, by incorporating elements of Big Data and Analytics and assessing students' adaptability, effectively prepares them for these interconnected systems, thereby reinforcing the relevance of systems theory to educational design.

7.4 Practical Implications

This study helped identify factors that affected the readiness of students for industry 4.0. The results of the study and the review of the literature on frameworks guided the design of a comprehensive framework that met the needs of employers and represented a specific set of categories that need to be taken into consideration, and in the proper order of implementation, in order for students to prepare for industry 4.0.

The practical implications of identifying essential skills for industry 4.0 involve designing curricula and learning experiences that prioritise these skills in educational settings. By understanding the skills that industry 4.0 demands in terms of Big Data, educators would be aware of the requirements and support students accordingly. This new knowledge would also contribute to assessment methods for attitudes and skills. The framework contributed by providing maturity levels to structure the progression of skill development, ensuring a clear path for students from beginner to professional levels in both technical and personal development skills. This framework can help students to gauge their readiness and identify areas for improvement before entering the workforce. Industry-relevant skills are now known through this framework can be incorporated into the activities and universities can encourage students to develop themselves more through this framework that encourages self-directed learning. It also empowers students to actively engage in their learning and become adaptive problem-solver.

This proposed framework is a basis for companies and education stakeholders to understand the importance of shaping a positive learning attitude, which is an important attribute to have to face industry 4.0 and the future needs of the industry. This framework also helps to direct their focus on what is most needed to assess, develop and acquire the right attributes to transform their organisations through industry 4.0 technologies (Whysall et al., 2019). In this case, this research proposed the important skills required by companies to face the upcoming industry. Although the analysis was not role-specific, it provided educational institutions and employers with general insights and guidance into preparing the right talent for the industry. From this perspective, the study contributed to improving the student's learning process and showed the importance of industry 4.0 needs and enabling the creation of appropriate talents to embrace challenges of industry 4.0.

The recent COVID-19 disruption has also proven the importance of developing self-management skills as everyone needed to quickly find ways to adapt to the new environment and new ways of working and studying. COVID-19 has also changed the working environment and so people must learn to be adaptable, flexible and have the willingness to learn new things. Students were also more confident and felt more supported by the proposed framework as it enabled them to get an overview of their skill levels to help them with self-reflection.

This model is often used to evaluate training program for organisations and firms. This time it is used to test the effectiveness of framework on students. This has contributed practically as this model can be used at the universities in the UK as an evaluation model to assess students too not just employees. Reflection mechanism allows students to reflect on the skills that they would like to improve on. This empowers students to identify weaknesses and help them to increase self-awareness and improve skills which in turn would help them prepare themselves to be future workforce.

7.5 Limitation

Although I believe that this study makes an important contribution, it has some limitations. The main limitation was that there may be hidden biases in the study due to the non-random selection of research participants (Etikan, 2016). The use of purposive and snowball sampling methods could introduce bias into the results of the research despite being effective in gathering insights from specific groups. As these techniques heavily relied on specific criteria and recommendation, it could lead to a non-random sample. The findings might not be representative of the entire population of Engineering students.

Although the researcher had put effort in balancing out the diversity of disciplines as Engineering covers a large number of disciplines, there might still be some bias in the result. The reliance on purposive and snowball sampling might result in disproportionate representation although the overall distribution was fairly even. Certain disciplines might be more prevalent in the sample due to networks of initial participants which could lead to under-representation and over representation of certain disciplines. The imbalance could lead to findings that are more relevant to certain discipline while overlooking the challenges unique to others. The sample might not represent the overall population of Engineering students as there are many more interdisciplinary courses within the faculty.

Due to time constraint, it was also important to note that as the time was a factor, there was not enough time for employer evaluations to triangulate the self-reports. Therefore, follow up research is proposed to have collaboration with employers. As the evaluation stage only involved quantitative study, it lacked quality insights into why students progressed. So, there was a missed opportunity to refine the usability of framework. At the same time, based on the researcher's knowledge the search was limited to literature published in English. Finally, it is also worth mentioning that, demands for skills could change from time to time so this framework needs to be revisited from time to time to keep it up to date. The proposed framework was only tested on Engineering students, and it might not be representative of students from other courses.

7.6 Recommendations for Future Research

In future research, it is very important to check what is missing in this source, starting by analysing other languages, and examining the competencies in industry 4.0 in other databases to determine which articles may have been overlooked in this study. In addition, it is important to capture the new literature published after this research. There should be several follow-up studies to supplement the research as demand for skills are always changing according to the pace of the industry. Organisational changes, such as changes in bureaucracy and processes, as well as cultural changes, including changes in expectations towards and communication with other stakeholders, will be required to achieve the critical mass of users and information for launching the proposed transformation. Furthermore, to mitigate the possibility of hidden biases, the study should be complemented by a quantitative study of random samplings.

The context of additional framework stakeholders could be explored by including representatives of awarding bodies and qualifications authorities, as well as lecturers, as they play important roles in creating potential talents. On the other hand, digital skills requirements should be addressed, as they are becoming more and more important every day, regardless of the industry or any particular role. This framework should fit into any industry with minor tweaks, as self-management skills are important in developing these technical skills. In addition, to gain the most benefit from the transformation involved in industry 4.0, the competency analysis should be conducted continuously (Jerman et al., 2020).

Working together with the researchers who are developing the TEFFIC framework would be a great improvement for both of our research as this study is focusing on the students while theirs were focusing on the teaching materials (Christiansen, et. al., 2022) and some similarities could be seen in terms of the learning outcomes. It would be a complete framework if both research studies are combined. Therefore, the next step would be looking into the opportunity of working with that research team to further develop the research.

Lastly, the framework should combine elements of AI to increase the effectiveness of the approach with the support of automated data collection and visualisation models with statistics. With AI, it is hoped that the framework will be able to support students with automated feedback and recommendations.

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APPENDICES

Appendix 1 List of Publications

- Poster presentation titled “A Perspective on Education to Support Industry 4.0: A Case Study on Analysis of Computer Science Related Degrees at a UK University”. The poster was published in the Faculty Research Week on 14-18 May 2019
- The poster presentation titled “An Investigation into the Development of An Intelligent Framework to Support the Learning Process for Preparation to Meet the Needs of Industry 4.0”. The poster was published in the Faculty Research Week on 14-18 May 2018
- Tan, S.Y., Al-Jumeily, D., Mustafina, J., Hussain, A., Broderick, A. and Forsyth, H., 2018. Rethinking Our Education to Face The New Industry Era. In *Proceedings of EDULEARN18 Conference 2nd-4th July 2018, Palma, Mallorca, Spain* (pp. 6562-6571).
- Tan, S.Y., Hussain, A., Mustafina, J., Aljaaf, A.J. and Alloghani, M., 2019, October. A Perspective on Education to Support Industry 4.0: A Qualitative Case Study in the UK. In *2019 12th International Conference on Developments in eSystems Engineering (DeSE)* (pp. 215-220). IEEE.
- Tan S.Y., Al-Jumeily D., Mustafina J., Hussain A., Shen Y. (2020) Design Framework for Learning to Support Industry 4.0. In: Lee N. (eds) *Encyclopedia of Computer Graphics and Games. Springer, Cham*

Appendix 2 Interview Schedule

Interview Schedule

Interview with Academics

Hi, I'm Sin Ying Tan from the Computer Science Department and I'm looking to understand your perspective towards industry 4.0 and the challenges faced by the industry. The interview will last between 15-20 minutes, and this will be anonymous and the information will be confidential. You have the right not to answer any questions that you do not wish to, and to withdraw from the interview at any time. Thank you so much for your support.

Section 1: Perspective towards Industry 4.0

Questions	**Probes**
1. Have you ever heard of industry 4.0?	- If not, let me modify the question now. Have you ever heard of big data and analytics, cloud computing, augmented reality, 3D printing ? - What do you think about these areas?
2. How do you think these technologies will affect your company?	- In the industry that your company is involved in, do you mind telling me about the adjustments that you have made to your company in order to match the current trend and needs?

Section 2: Important Attributes of Students for Industry 4.0

Questions	**Probes**
1. If you were to rank the importance among knowledge, attitude and skills, which one will be the most important and least important quality that you are looking for in an employee? in order of most important to least	- Can you explain your reason for the ranking? - How do you assess attitude, skills and knowledge?
2. Look at the list of skills. What do you think about the list? i. Complex problem solving. ii. Critical thinking. iii. Creativity. iv. People management. v. Coordinating with others. vi. Emotional intelligence. vii. Judgement and decision making. viii. Negotiation. ix. Service orientation. x. Cognitive flexibility	- Is there anything that is not in the list?

Section 3: Challenges faced by Industries

Questions	**Probes**
1. We often hear complaints from employers that there is a skill shortage. Do you agree and why?	- Do you think it's easy to recruit the people that you need? Can you explain a little bit further?

2. What do you think the education institution can do to help your industry/company? (What do you expect universities to do?)	- Do you know what might be the future needs of the industry and where do you think your industry is heading to?

Appendix 3 Data Categorisation

Table A3.1 Categorisation of Data

Variable	Type	Description
Course_Type	Nominal	Types of courses taken by the students
Personal_Problem_Solving	Interval	Own self-report of problem solving skills
Personal_Critical_Thinking_Level	Interval	Own self-report of critical thinking skills
Personal_Creativity	Interval	Own self-report of creativity
Personal_People_Management	Interval	Own self-report of people management skills
Personal_Coordinating	Interval	Own self-report of coordinating skills
Personal_EQ	Interval	Own self-report of level of emotional intelligence
Personal_Judgement	Interval	Own self- report of judgement skills
Personal_Negotiation	Interval	Own self-report of negotiation skills
Personal_Service	Interval	Own self-report of service skills
Personal_Cognitive_Flexibility	Interval	Own self-report of cognitive flexibility
Core_Industry	Ordinal	Familiarity of industry 4.0
Core _VR	Ordinal	Familiarity with Virtual reality
Core _AR	Ordinal	Familiarity with AR
Core _SmartFactory	Ordinal	Familiarity with smart factory

Awareness _Robot	Ordinal	Familiarity with autonomous robots
Awareness_System	Ordinal	Familiarity with horizontal and vertical system integration
Awareness _Security	Ordinal	Familiarity with cybersecuriy
Awareness _BigData	Ordinal	Familiarity with big data and analytics
Awareness _Simulation	Ordinal	Familiarity with simulation
Awareness _AdditiveManufacturing	Ordinal	Familiarity with additive manufacturing
Awareness _Cloud	Ordinal	Familiarity with cloud computing
Awareness _IoT	Ordinal	Familiarity with IOT
Attitude_in_Learning	Nominal	Attitude in Learning
Attitude_In_Career	Nominal	Attitude towards future career
Confidence_Virtual	Interval	Confidence in virtual reality
Confidence_AR	Interval	Confidence in AR
Confidence_Robot	Interval	Confidence in autonomous robots
Confidence_System	Interval	Confidence in system integration
Confidence _Security	Interval	Confidence in cybersecurity
Confidence_BigData	Interval	Confidence in big data
Confidence _Simulation	Interval	Confidence in simulation
Confidence_AdditiveManufacturing	Interval	Confidence in additive manufacturing
Confidence_Cloud	Interval	Confidence in cloud computing
Confidence_IoT	Interval	Confidence in IoT

Appendix 4 Data Summary for McNemar's and K-Fold

Summary of contingency table

McNemar's Test Results for Self-Development

Contingency Table:

	after_binary	
before_binary	0	1
0	22	21
1	0	108

Chi-squared: 19.048

p-value: 0.0000127

McNemar's Test Results for Analytical Thinking

Contingency Table:

	after_binary	
before_binary	0	1
0	12	0
1	31	108

Chi-squared: 29.032

p-value: 0.0000000712

McNemar's Test Results for Adaptability

Contingency Table:

after_binary

before_binary 0 1

0 7 17

1 52 75

Chi-squared: 16.754

p-value: 0.0000426

McNemar's Test Results for Programming and Mathematics

Contingency Table:

after_binary

before_binary 0 1

0 6 1

1 0 144

Chi-squared: 0

p-value: 1

McNemar's Test Results for Advanced Technical Skills

Contingency Table:

after_binary

before_binary 0 1

0 20 0

1 48 83

Chi-squared: 46.021

p-value: 0.0000000000117

McNemar's Test Results for Systems and Infrastructure

Contingency Table:

	after_binary	
before_binary	0	1
0	31	20
1	0	100

Chi-squared: 18.05

p-value: 0.0000215

K-Fold Cross-Validation

K-Fold Cross Validation Results for Self

Number of folds: 5

Mean improvement: 0.538

Standard deviation: 0.114

95% CI: 0.396 to 0.679

K-Fold Cross Validation Results for Analytic

Number of folds: 5

Mean improvement: 0.417

Standard deviation: 0.088

95% CI: 0.308 to 0.527

K-Fold Cross Validation Results for Adaptability

Number of folds: 5

Mean improvement: 0.458

Standard deviation: 0.124

95% CI: 0.304 to 0.612

K-Fold Cross Validation Results for Programming

Number of folds: 5

Mean improvement: 0.166

Standard deviation: 0.075

95% CI: 0.073 to 0.26

K-Fold Cross Validation Results for Advanced

Number of folds: 5

Mean improvement: 0.198

Standard deviation: 0.052

95% CI: 0.134 to 0.263

K-Fold Cross Validation Results for System

Number of folds: 5

Mean improvement: 0.172

Standard deviation: 0.064

95% CI: 0.093 to 0.251

K-Fold Cross Validation (10-Fold)

Fold	Item	Mean_Improvement
1	Analytic	0.533333333
1	Self	0.533333333
1	Adaptability	0
1	Advanced	0.066666667
1	Programming	0.266666667
1	System	0.066666667
1	Attitude	0.333333333
2	Analytic	0.2
2	Self	0.6
2	Adaptability	0.666666667
2	Advanced	0.066666667
2	Programming	0.133333333
2	System	0.2
2	Attitude	0.866666667
3	Analytic	0.4375
3	Self	0.3125
3	Adaptability	0.75
3	Advanced	0.1875
3	Programming	0.0625
3	System	0.3125
3	Attitude	0.5625
4	Analytic	0.533333333
4	Self	0.4
4	Adaptability	0.733333333
4	Advanced	0.266666667
4	Programming	0.133333333
4	System	0.066666667
4	Attitude	0.933333333
5	Analytic	0.266666667
5	Self	0.6
5	Adaptability	0.266666667
5	Advanced	0.066666667
5	Programming	0.2
5	System	0.266666667
5	Attitude	1.133333333
6	Analytic	0.533333333
6	Self	0.6
6	Adaptability	0.4

6	Advanced	0.333333333
6	Programming	0.266666667
6	System	0.333333333
6	Attitude	0.733333333
7	Analytic	0.733333333
7	Self	0.466666667
7	Adaptability	0.666666667
7	Advanced	0.266666667
7	Programming	0.133333333
7	System	0.133333333
7	Attitude	0.333333333
8	Analytic	0.533333333
8	Self	0.4
8	Adaptability	0.266666667
8	Advanced	0.266666667
8	Programming	0.066666667
8	System	0.066666667
8	Attitude	0.733333333
9	Analytic	0.466666667
9	Self	0.733333333
9	Adaptability	0.266666667
9	Advanced	0.266666667
9	Programming	0.2
9	System	0.066666667
9	Attitude	0.4
10	Analytic	0.466666667
10	Self	0.733333333
10	Adaptability	0.533333333
10	Advanced	0.2
10	Programming	0.2
10	System	0.2
10	Attitude	1.2

Appendix 5 Template For Participant Recruitment

Template to be Used to Track Participant Recruitment for Round 1 & Round 2

Participant	Date of Emails Sent	Date of follow-up emails	Date of Responses were received	Date of Transcribed Interviews
E1				
E2				
E3				
E4				
E5				
E6				
E7				
E8				

Appendix 6 Delphi Method

Queries for Round 1

Missing Components	
Input	- Encourage students to reflect on the projects or tasks they have been involved and write them down - It's more about self-reporting and it might not be the exact skill or knowledge level that the students have -involve university this exploring stage to help identify the knowledge level and skills level
Personal Attributes	- Even though this is a self-directed learning framework, as an employer I need to know what resources are available for the students so that we know what we could do to be able to support them - Finding out what motivates students in learning is important.
Process	- In the monitoring process, encourage students to list out what they have learnt, what they have applied and what are their reviews on their learning process. We did this for our performance review.
Tasks	- Rather than putting the word "tasks", it should be mini projects (voluntary). -Categorise the tasks. It's too broad.
Strategy	- Add role-playing/simulation-based learning into the framework.
Stakeholders	- Include university as stakeholders

	- Students need academic mentors too besides industry mentors. - We as employers would like to work with academic staff to make sure what’s being taught is relevant to our industry needs.

Appendix 7 Questionnaires (Delphi)

Do you agree that this framework would be effective in supporting you in these three aspects:

A. Effective learning of emerging industry trends
B. Creating an enthusiastic learning climate where students are proactive in learning.
C. Developing TSS and self-management skills

Likert Scale

- Strongly Agree
- Agree
- Neither
- Disagree
- Strongly Disagree

Appendix 8 Participant Consent Form

LIVERPOOL JOHN MOORES UNIVERSITY

PARTICIPANT CONSENT FORM [*University Academics]*

Project title: ***AN INVESTIGATION INTO THE DEVELOPMENT OF A FRAMEWORK TO SUPPORT THE LEARNING PROCESS FOR PREPARATION TO MEET THE NEEDS OF INDUSTRY 4.0***

Research Ethics Committee Reference Number: 24/CMP/002

Principal Investigator: Sin Ying Tan
LJMU postgraduate research student
LJMU Email address: s.y.tan@2013.ljmu.ac.uk
LJMU School/Faculty: Computer Science
LJMU Central telephone number: 0151 231 2121
Supervisor Name: Dhiya Al-Jumeily
Supervisor's LJMU Email address: d.aljumeily@ljmu.ac.uk

If you are happy to participate, please complete and sign the consent form below

		Please initial
1.	I confirm that I have read the information sheet dated................... (version............) for the above project, or it has been read to me. I have had the opportunity to consider the information, ask questions and have had these answered satisfactorily.	
2.	I understand what taking part in the project involves	
3.	I consent voluntarily to be a participant in this project and understand that I can refuse to answer questions I can withdraw from the project	

	at any time, without giving a reason and without penalty or my legal rights being affected.		
4.	I understand that the investigator will be unable to guarantee control of access to authorised viewing of the [audio recordings] taken of me during the project and I am happy to proceed.		
5.	I understand that the project involves taking [audio recordings] of me and I am happy to proceed. I understand that I will not be able to participate in the project if I later decide not to be [audio recorded]	YES	NO
6.	I understand who will have access to personal data provided, how the data will be stored and what will happen to the data at the end of the project.		
7.	I understand that my information may be subject to review by responsible individuals from Liverpool John Moores University for monitoring and audit purposes		
8.	I agree for my contact details to be stored for the purpose of contacting me about future studies and I understand that agreeing to be contacted does not oblige me to participate in any further studies	YES	NO
9.	I understand that personal data will remain confidential and that all efforts will be made to ensure I cannot be identified in reports or any further outputs	YES	NO

10	I understand that parts of our conversation will be used verbatim in future publications or presentations and that all efforts will be made to ensure I cannot be identified in reports or any further outputs.	YES NO
11	I understand that even though all efforts will be made to ensure I cannot be identified, I may be indirectly identifiable when the project findings are disseminated. If the investigators think this may be the case, they will seek explicit consent from me ahead of any publication	
12	I understand the potential risks of being identifiable in reports and any future outputs when the findings of the project are disseminated	
13	I understand that there may be instances where information is revealed which means that the investigators will be obliged to break confidentiality and this has been explained in more detail in the information sheet.	
14	I agree to take part in this project	

Data Protection. Any personal information we collect and use to conduct this project will be processed in accordance with data protection law as explained in the Participant Information Sheet and the LJMU Privacy Notice for Research Participants (https://www.ljmu.ac.uk/legal/privacy-notice-and-cookies/external-stakeholders-privacy-policy/research-participants-privacy-notice)

Name of Participant Date Signature

I have witnessed the accurate reading of the consent form with the potential participant and the individual has had the opportunity to ask questions. I confirm that the individual has given consent freely

Name of Investigator Date Signature

Name of Person taking consent Date Signature

(if different from investigator)

Appendix 9 Data Summary

Variable	Mean	SD	Min	Q1	Median	Q3	Max
University	4.8	2.58	1	3	5	7	9
Course	4.8	2.58	1	3	5	7	9
Personal_Problem_Solving	3.6	1.33	1	2	4	5	6
Personal_Critical_Thinking	3.69	1.43	1	2	4	5	6
Personal_Creativity	3.64	1.47	1	2	4	5	6
Personal_Motivation_Self_Awareness	3.46	1.4	1	2	4	5	6
Personal_Curiosity_Lifelong_Learning	3.67	1.52	1	2	4	5	6
Personal_Resilience_flexibility_agility	3.66	1.56	1	2	4	5	6
Personal_Analytical_Thinking	3.66	1.44	1	2	4	5	6
Personal_Systems_Thinking	3.43	1.43	1	2	3	5	6
Personal_Service_Orientation	3.5	1.44	1	2	4	5	6
Personal_Talent_Management	3.63	1.45	1	2	4	5	6
Readiness_Industry	2.22	1.4	1	1	2	3	5
Core_Signal_Processing_Technique	3.54	1.73	1	1	4	5	5

Core_Programming_Python	3.25	1.62	1	1	4	5	5
Core_Programming_R	3.13	1.62	1	1	4	5	5
Core_Data_Visualisation	2.23	1.4	1	1	2	3	5
Core_Machine_Learning_Neural_Network	3.48	1.68	1	1	4	5	5
Core_Big_Data_Technologies	3.45	1.66	1	1	4	5	5
Core_Java	3.14	1.69	1	1	4	5	5
Core_Linear_Algebra_Calculus_Statistics	3.33	1.62	1	1	4	5	5
Core_Cloud_Computing	3.45	1.73	1	1	4	5	5
Core_IoT	3.13	1.69	1	1	4	5	5
Attitude_Learning	2.43	0.96	1	2	3	3	5
Readiness	1.71	0.8	0	1	2	2	5
Confidence_Signal_Processing_Technique	2.56	1.21	1	2	2	3	5
Confidence_Programming_Python	2.34	1.06	1	2	2	3	5
Confidence_Programming_R	2.41	1.11	1	2	2	3	5
Confidence_Data_Visualisation	2.18	1.06	1	1	2	3	5
Confidence_Machine_Learning_Neural_Network	2.73	1.19	1	2	2	4	5

Confidence_Big_Data_Technologies	2.99	1.16	1	2	3	4	5
Confidence_Java	2.47	1.19	1	2	2	3	5
Confidence_Linear_Algebra_Calculus_Statistics	2.54	1.13	1	2	2	3	5
Confidence_Cloud_Computing	2.89	1.3	1	2	3	4	5
Confidence_IoT	2.81	1.16	1	2	2	4	5

Table A9.1 Questionnaire Survey Section

Self-Assessment Survey

Maturity Level-Rubrics

Maturity Levels	Definition for Skills (Technical and personal Development Skills)	Attitude (Willingness to learn)
Basic	I do not know of the existence of this skill, and I do not possess them.	Demonstrates openness to new ideas
Aware	I know of the existence of this skill, but I do not possess it. I am therefore inclined to apply myself to improve.	Actively seeks learning opportunities and new information.
Practiced	I know this skill exists, and I have it in a basic way, sometimes needing an external supervisor. I work hard to improve myself.	Continuously upskills with in-demand trends/technologies and is an asset for any new project.
Competent	I possess this skill and master it almost automatically. I can manage complex and unforeseen activities in an innovation-oriented way, even in contexts other than the everyday.	Shares knowledge and experience proactively within the team
Proficient	I possess this skill and I master it almost automatically. In an innovation-oriented way, I can manage complex and	Acts as a thought leader and stays committed to constant upskilling, and spreads knowledge and expertise.

	unforeseen activities, even in contexts different from the everyday, and I can teach it to my peers.	

Aspects	Justification for inclusion	Details
Technical Skills	From literature and questionnaire and interview.	**Knowledge- Big Data and AI** **Cluster 1: Advanced Technical Skills** Signal Processing, Cloud Computing, Machine Learning/Neural Networks **Cluster 2 - Programming and Mathematics** Python Programming, R Programming, Linear Algebra/Calculus/Statistics **Cluster 3 - Systems and Infrastructure** Java, Big Data Technologies, IoT
Personal development skills	From questionnaire statistical analysis in Section 5.4.1 and literature.	**Cluster 1: Analytical Thinking** Problem Solving Critical Thinking Analytical Thinking **Cluster 2: Self Management** Motivation and Self-Awareness Curiosity and Lifelong Learning Resilience, flexibility and agility **Cluster 3: Adaptability**

		Systems Thinking
		Service Orientation
		Talent Management
		Creativity
Attitude	From interview and finding from survey	**Willingness to Learn**

Survey Skills Rating

For each skill/ attitude, please select your current maturity level (1-5) based om the definitions above.

Skill/Attitude	**Basic**	**Aware**	**Practiced**	**Competent**	**Proficient**
Advanced Technical					
Programming/Mathematics					
System Infrastructures					
Self-Management					
Adaptability					
Willingness to Learn					

Appendix 10 industry 0.0

Islamic Golden Age

The Islamic Golden Age is the era in the history of Islam, traditionally dated from the 7th century to the 16th century (Al-Hassani, 2012), during which much of the historically Islamic world was ruled by various caliphates, and science, economic development and cultural works flourished (Saliba, 1994). This was the period when scientific progress in western Europe slowed down. It also attracted scholars from different parts of the world as they built on and improved the knowledge of ancient Egypt, ancient Mesopotamia, Persia, China, India and the Greeks and Romans.

Discovery of Knowledge and the Industrial Revolution

It is essential to know that the knowledge of science and technology was built up over thousands of years; it did not just suddenly appear in the 17th century when Industry 1.0 occurred. The people of many cultures and civilisations contributed knowledge. It is fantastic to see many modern advancements in the past and current forms of industry, but without the slow, patient accumulation of learning, humans could not have achieved them.

This study discusses an essential period of history when the foundation for modern science was laid. In this period, the knowledge of the ancient and classical civilisations of different countries, such as Greece, Rome, China, India and Persia, passed to the Middle East in a time of tolerance and cooperation among religions. Centuries later, in western European Spain, during another time of toleration among religious groups, that heritage of learning was added to and passed along again, bringing this heritage of learning from ancient into modern times, which is now.

The Idea of Zero

The discoveries in Industry 0.0 sped up mathematical calculation many times over and, eventually, made many incredible technological advances possible, including cars, computers, space travel, and robots. All these contributions come from early scholars such as Aryabhatta, Muhammad ibn Musa al-Khwarizmi and Diophantus (Kerski, 2016).

The first known use of numbers dates back to around 30,000 BC, but it is universally accepted that the system of numbering we use today (the digits 0 to 9) was invented in India. According to Arnold (2000), Aryabhata was an Indian mathematician and astrologer who contributed to the quadratic equation solution, defining the trigonometric functions, stressing the importance of Zero and determining the value of pi up to the fourth decimal place.

The system then intrigued a mathematician named Muhammad ibn Musa al-Khwarizmi (circa A.D. 780–850) in the early 9th century. This original system uses nine different symbols to represent numbers, plus a small circle around space to represent *shunya* — “nothingness”. The Hindu system included a place system to keep from having to use more and more symbols for larger numbers. The value of a number could be determined by its place in a row of numbers: there was a row for 1s, a row for 10s, 100s, 1000s, and so on. If nine numerals and a circle representing “nothing” sounds familiar, it should. Al-Khwarizmi is the one who introduced the Hindu number system (known in the West as “Arabic numerals”) to the West, and it is used in most of the world today.

In computer science, zero represents the initial point; in this case, Industry 0.0 marks the foundation of knowledge that led to industrialisation.

Inventions that Contributed to the Eras of Industrial Revolution

Irrigation Method

The irrigation method is known to be one of the main contributors to the agricultural revolution, which in turn led to the industrial revolution that required high demand for industrial products. Irrigation and water supply are said to stimulate the development of other technologies, like water-raising machines.

The ancient civilisations based upon irrigation in Mesopotamia and Egypt had been in existence for over two millennia before the start of our period, and although they had known times of decline, it is undeniable that irrigation in Islamic cultures was based upon these earlier systems. The maintenance of the irrigation systems demanded the constant exercise of engineering and administrative skills.

According to Hill (2013), the study of irrigation in Islam has been patchy and has tended to focus on Egypt, Iraq and the Iberian peninsula. Yet, the Sasanid irrigation system was developed and inherited by the Muslims in AD 762, during the significant expansion occurring after Baghdad was founded. There is a lack of information about Hellenistic and Sasanid times in the Middle East due to the scarcity of documentation. The neglect of the irrigation systems in Iraq during the later Middle Ages has rendered the assessment of earlier irrigation systems very difficult. However, the Sasanid engineers had improved the irrigation network in Iraq including extensions to the great Nahrawan Canal to the east of Baghdad. Thomas Glick has summarised the influence of the Muslims' irrigation techniques on Spanish agriculture and society (Glick, 1970). It was also stated that the Muslim irrigation in Spain had a direct bearing on developments in Europe (Hill, 2013) which received the attention of western scholar like Thomas Glick.

Crankshaft and Water Raising Machines

A crankshaft is a device which translates rotary into linear motion and is central to much of the machinery in the modern world, not least the internal combustion engine. It was known to the Chinese of the Han Dynasty which lasted from 206 BC to 220 AD. By the 1st century AD, cranks were used on Roman medical devices, but it was not until 834 AD where the evidence of the crank is found in Europe.

Al-Jazari is a well-known engineer that uses crankshaft to raise water for irrigation. Al-Jazari described the device as a crank and connecting rod system in a water pump. He incorporated a crankshaft that contributes to the agricultural revolution. Some writers have assumed that his water-raising machines had no practical purposes but Hill (2013) argued that there was a demand from al-Jazari's masters for devices that would provide amusement and aesthetic pleasure but most importantly, it is also highly probable that his responsibilities include the design and construction of public works. Moreover, his designs have the added significance of incorporating techniques and components that are of importance in the development of machine technology.

On the other hand, during this Islamic Golden Age, the people adapted and redeveloped the *norias* which are also known as large water wheels to raise water from fast-flowing waterways to higher land since 100 BC. Vitruvious, the Roman writer, architect and engineer mentioned about this device very clearly. Needham (1974) suggested that it was invented in India reached the Hellenistic world in the first century BC. And China in the second century AD. However, the eastern origin of the *noria* is still very unclear. What is sure is that the Muslims adapted it from the Romans and Persians (Al-Hassani, 2012).

Windmill

Lucas (2005) stated that the manuscript sources pertaining to the industrial uses of waterpower in early medieval Islamic countries have not been adequately assessed, partially because detailed work remains to be conducted or made known to Western scholars. However, there is clear archaeological evidence in the Middle East for the use of water mills from as early as the seventh century (Leiden, 2000; Hill, 2013; Glick, 1970). The archaeological evidence suggests that both horizontal- and vertical-wheeled water mills were in widespread use from at least the ninth century (Al-Hassani, 2012; Hill, 2013). Lucas (2005) contributed by providing the example of the remains of thirty-one mills now thought to date from between the seventh and thirteenth centuries that have been located at two sites in Iraq and Iran, while the sites of twelve horizontal-wheeled water mills in Oman have been dated to between the eighth and tenth centuries.

While there is still a substantial amount of systematic research work to be done, it seems increasingly that Islamic Spain and the Byzantine Empire provided a route for a number of Roman, Islamic, and possibly Chinese innovations in industrial milling technology to be conveyed to Western Europe from the tenth or eleventh century onward, providing a foundation for the train of developments that characterized the application of waterpower to industry in the European Middle Ages.

The invention of the windmill is important, as windmills provided power for industrial production. Industrial processes ranged from composite steel to paper making, petroleum, pottery, glass making, textiles, agriculture, ship building, fishing, mineral extraction, metal working, and chemical products. The first rotary mills were discovered in Catal Hoyuk in Turkey and existed 8,000 years ago, while the first windmills were developed much later to automate the tasks of grinding grain and pumping water.

The windmill was also described in Hero's manuscripts and then Banu Musa in Baghdad mentioned a small wind-wheel that was used to operate an alternating fountain. Hill (2013) argued that they certainly knew about Hero's works as the Arabic word used for the wheel was clearly a corruption of anemourion that was in the original Greek text. Windmills are used in Egypt in the sugar cane industry but the main purpose is for grist milling.

Steam Engine

In the 1st century AD, the ancient Greek engineer, Hero of Alexandria, worked with air pressure and steam to create sources of power. One experiment that he developed was the aeolipile, which used jets of steam to create rotary motion. Hero's aeolipile is the first known case in which steam power was used to set a machine in motion (Hill, 2013). The importance of the aeolipile is that it marks the start of the invention of engines—engines created movement and would later prove essential in the history of flight. Although it had no practical application at the time, this contribution is important as it represents the beginning of the invention of a device that was operated by using steam pressure.

In the 16th century, Taiq al-Din ibn Ma'rouf al-Rasid wrote a book on mechanical engineering called "The sublime methods of Spiritual Machines", in which he discussed the workings of a rudimentary steam engine before steam power was discovered (al-Hassani, 2012). However, the invention of practical steam engines came much later, when Edward Somerset published his new sort of steam pump which was attached to a single boiler. His key invention was the addition of cooling around the containers to force the steam to condense, which produced a partial vacuum inside the chambers that was used to draw a volume of water into the containers through a pipe, thus forming a pump. He built one of very large size into the side of Raglan Castle, apparently the first "industrial scale" steam engine (Thurston, 1878). He had plans to build them for mining but died before he could set up his company.

Much later on, Thomas Savery introduced a steam pump which he called the Miner's Friend, which was a direct copy of the previous design by Somerset. He improved it by replacing cold water flow on the outside of the cylinder with a spray directly inside it. A small number of his pumps were built, mostly experimental in nature, but like any system based on suction to lift water, they had a maximum height of 32 feet (and typically much less). In order to be practical, his design could also use the pressure of additional steam to force the water out of the top of the cylinder, allowing the pumps to be "stacked", but many mine owners were afraid of the high risk of explosion and avoided this option.

The first industrial revolution (industry 1.0) occurred when changes started to be seen in the period of mechanical refinement, when devices and machines were invented to make lives better and easier. In 1712, Thomas Newcomen, who played an important role in Industry 1.0 invented a steam engine that could assist in the process of removing water from the bottom of mines and allow miners to dig deeper. Thomas Newcomen developed an atmospheric engine which was unlike the Savery pump, as he employed a piston in a cylinder, the vacuum pulling the piston down to the bottom of the cylinder when water is injected into it. This engine enabled a great increase in pumping height and the draining of deeper mines than was possible when using vacuum to pull the water up.

Savery held a patent covering all imagined uses of steam power, so Newcomen and his partner, John Calley, persuaded Savery to join forces with them to exploit their invention until the expiration of the patent in 1733. Savery's engines were re-introduced in the 1780s to recirculate water to water wheels driving textile mills, especially in periods of drought.

Textiles

The fine textile industry spread widely up into Europe from Muslim Spain (Al-Hassani, 2012). By the mid-ninth century, the textile fabric of Muslim Spain had earned an international reputation. The cotton gin, an Indian invention, was the forerunner of all geared machines that actually paved the way for the west to bring about an industrial revolution (Singh and Kaur, 2014). Muslims traded with India and, thanks to the active role of the East India Company, in Indian Chintz was introduced to England. The fabric was cotton, painted with Muslim elements.

Automata

In Hero of Alexandria's works "Pneumatica" and "Automata", he described over a hundred machines and automata, including mechanical singing birds, puppets, a fire engine, a wind organ and a coin-operated machine. It must also be noted that Hero's works of "Mechanica" (in three books) survive only in their Arabic translations.

As for the water clock, the ancient Egyptians used a time mechanism run by flowing water. One of the oldest was found in the tomb of an Egyptian pharaoh buried in 1500 BC, and the Chinese began developing mechanized clocks from around 200 BC. The Greeks also measured time with various types of water clocks. The more impressive, mechanised water clocks were developed between 100 BC and 500 AD by Greek and Roman horologists and astronomers.

What we now know as the Antikythera mechanism was discovered in a shipwreck in 1900 off the island of Antikythera. Science historian, Derek Price concluded that it was an ancient computer used to predict the positions of the sun and moon on any given date. Michael Wright, the curator of mechanical engineering at the Science Museum in London, thinks that the original device modelled the entire known solar system. Ancient Greek sources make references to such devices, so this is highly plausible. Roman philosopher, Marcus Tullius Cicero (106–43 BC), writes of a device "recently constructed by our friend Poseidonius, which at each revolution reproduces the same motions of the sun, the moon and the five planets." Greek mathematician, physicist, engineer, inventor and astronomer, Archimedes of Syracuse (287–212 BC) is also said to have made such a device. By the 9th century AD, a mechanical timekeeper had been developed that lacked only an escapement mechanism.

The earliest known combination lock was unearthed in a Roman period tomb in Kerameikos, Athens. The ancient Chinese were also responsible for the creation of some of the earliest key-operated padlocks and beautiful letter-combination padlocks.

Number System

The number system came originally from the Babylonians and was most frequently used by the Arabic mathematicians in astronomical work. The arithmetic of the Arabic numerals and fractions with the decimal place-value system was developed from an Indian version (Al-Hassani, 2012). The numbers are still used till today. Al-Khawarizmi then wrote a book that introduced the term "Algebra" and we have been using this term till today. As mentioned before, the origins of algebra itself can be traced to the ancient Babylonians who were able to do calculations in an algorithmic fashion. The works of a mathematician, Diophantus of Alexandria, which can be traced in this period (200 and 214 AD–284 and 298 AD), included a series of books called "Arithmetica" and he is commonly referred to as "the father of algebra". Al- Khawarizmi is also known as the Father of Algebra as he is the one who preserved the knowledge, translated it and transmitted it to the west.

Discussion

Table A10.1 and Figure A10.2 show that the inventions of industry 0.0 contributed to the development of later industrial revolutions. Based on the table, irrigation methods, windmills, steam engines and the textile industry were originally invented before the 18th century. These inventions led to the growth of the agricultural sector, which became the first industrial revolution, as shown in Figure A10.1.

Inventions of machines and automata also contributed to the development of the second industrial revolution, which was the era when electricity began to be used to operate machines. The inventions in the information revolution which occurred in the 20th century did not suddenly appear, as information needs to travel on wire and copper wire came into use during that time, though both copper wire and automation had been invented before the first industrial revolution. Similarly, algorithms and humanoid robots were introduced in earlier centuries. These are all used in programming and the advanced technologies of industry 4.0, like AR, simulation, autonomous robots, IoT, etc.

Table A10.1 Inventions of Industry 0.0 and their role in Four Industrial Revolutions

Inventions of Industry 0.0	Industry 1.0	Industry 2.0	Industry 3.0	Industry 4.0
Irrigation Methods				
Windmills				
Steam Engine				
Textile Industry				
Mechanical Inventions				
Automation and Copper Wire				
Algorithms and Humanoid Robots				

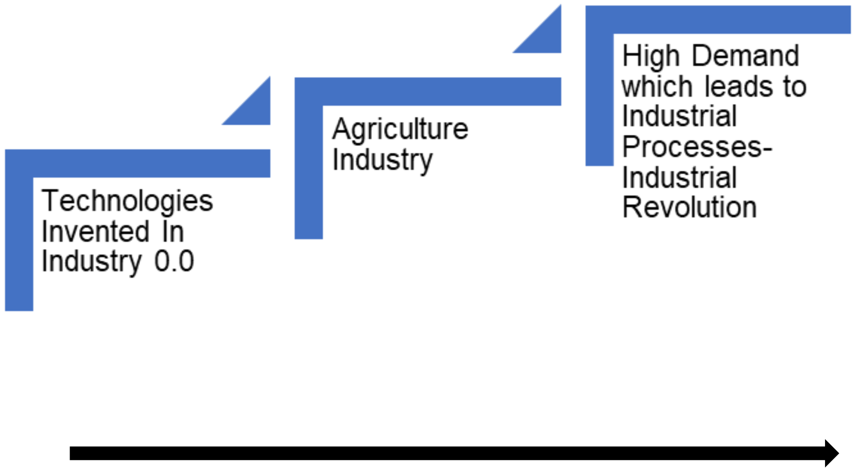

Figure A10.1 Process of Industrial Revolution from Industry 0.0

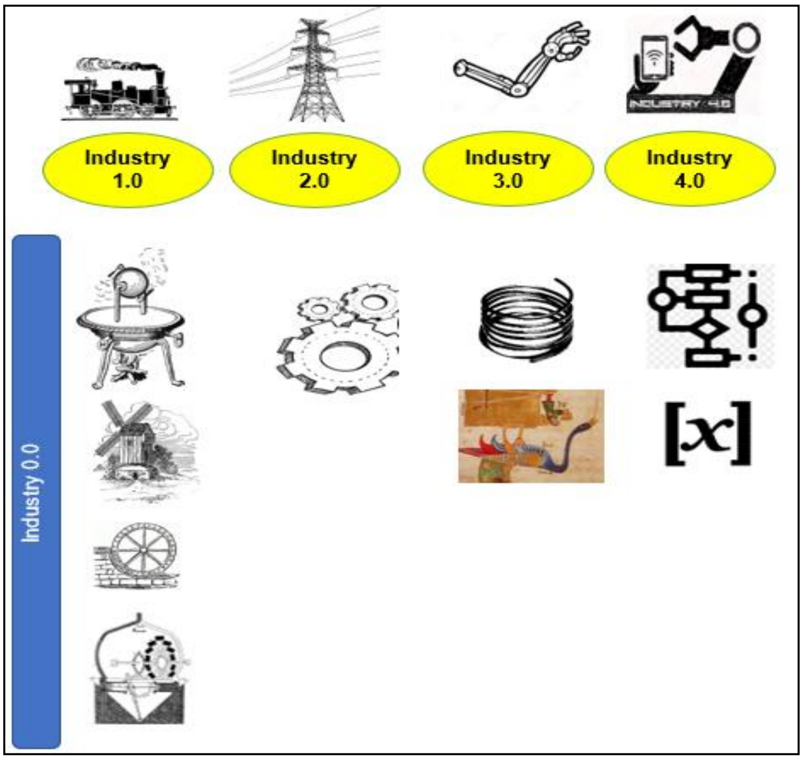

Figure A10.2 Inventions in Different Industrial Revolutions

Appendix 11 Course Analysis

In this case study, two courses from LJMU were analysed: Computer Science and Software Engineering. Both courses were undertaken in three or four years, with the latter including a sandwich year on a placement.

The proposed ASK SUMA framework was used in this experiment. Based on the ASK SUMA framework, three essential elements were assessed in relation to students' readiness to work in industry: attitude, skills and knowledge. Hence, the programme specifications for both courses were analysed to see how these three elements were evaluated at LJMU.

The analysis was divided into three areas as explained below:

1. Knowledge and Understanding

From the course specifications, it was understood that university was the place where students gained their knowledge. Students were able to monitor their progress through feedback received based on work produced. Core knowledge and understanding were acquired through lectures, tutorials, practical work, workshops and guided independent studying.

a) **Computer Science**
The combination of lectures, projects, seminars and guided independent study helped students to be critically aware of current and developing principles and practices within Computer Science. On the other hand, a mixture of lectures, tutorials, laboratory work, coursework and projects allowed students to deepen and widen their conceptual and practical knowledge by applying a range of advanced tools and techniques used in the specification of complex computer-based systems. In addition, students were able to critically analyse a range of developmental domains and be innovative in Computer Science. They also had a clear understanding of how to manage Computer Science projects effectively and creatively.

b) **Software Engineering**
Independent study was used where appropriate resource material was available and this increased as the programme progressed. Specifically, students were able to complete computer programming as applied to medium

to large systems through a combination of lectures, projects, seminars and guided independent study. A mixture of lectures, tutorials, laboratory work, coursework and projects helped students to understand the relationship of hardware to software. In addition, through the mixture of teaching and assessment methods, students were able to apply formal methods and modelling techniques, possess awareness of professional and ethical issues and have a critical awareness of developing practices in the area. Lectures, coursework, projects, seminars and guided independent study provided opportunities for students to be innovative in Software Engineering and to effectively manage software development. Students were given feedback on all work produced.

2. Skills

According to the course specifications, three types of skills were developed in the LJMU courses; namely, cognitive skills, professional practical skills and transferable skills, as shown in Table A11.1.

Table A11.1 Types of Skills Emphasised at LJMU

Courses	Cognitive Skills	Professional Practical Skills	Transferrable Skills
Computer Science	- Demonstrate systematic and comprehensive knowledge and understanding of Computer Science concepts, principles and theories. - Use such knowledge with originality in system modelling, requirements analysis and design. - Perform critical evaluation and testing for a computer-based system. - Deploy appropriate methods and tools creatively for the specification of a complex computer-based system	- Develop and evaluate Computer Science projects. - Manage Computational projects. - Use a wide range of computing tools, facilities and techniques effectively. - Work individually and/or as a team member	- Use information technology, e.g., Computer Science tools. - Apply numerical and formal methods skills to cases involving a quantitative dimension. - Communicate effectively by written or verbal means.

Software Engineering	- Complete problem-solving in the context of large computer based systems. - Provide systems modelling of computer-based systems as part of the development process. - Evaluate tools and methods for selection and use in the development process. - Evaluate and test software systems against requirements. - Undertake algorithm selection and deployment. - Demonstrate systematic and comprehensive knowledge and understanding of Software Engineering concepts, principles and theories.	- Develop and test software systems. - Effectively manage software projects. - Work as a member of a software development team. - Carry out practical systems evaluation. - Use a full range Software Development tools. - Make effective use of computer systems	

	- Use such knowledge with originality in system modelling, requirements analysis and design.	

3. Attitude

The aim was to provide students with an extended period of work experience at an approved partner that would complement their programme of study at LJMU. This would give students the opportunity to develop professional skills relevant to their programme of study as well as the attitude and behaviours necessary for employment in a diverse and changing environment.

Appendix 12

Twenty recruitment emails/ LinkedIn messages were sent to experts from the human resource departments and directors from technological companies. Some declined to participate and only eight agreed to participate. Eight of them stated that they did not have time devoting to the study. Two participants declined participation because they were worried that they were against the company's policy. Although I assured them that they would be kept anonymous, they opted to decline to participate in the study. Two never responded to the questions sent in the email despite of initially saying that they would participate.

The proposed framework was presented to the target stakeholders to empirically verify the components and processes. Volunteers were sought and recruited from the previous interviews to become part of the panel. This panel was asked to review and evaluate the framework once it was developed and to provide input for further development and refinement. The group decided that they would prefer to have all interactions with the researcher via email only because the pandemic restrictions had just started at that time. Data collection took only two rounds as all the experts have reached consensus in the second round and each round took approximately two weeks. A follow-up email was sent requesting for responses from the volunteers if there was no response received within a week.

Once a first draft of the framework was developed, the Delphi panel received an email with three file attachments:

- A short explanation of the Delphi process and a follow up email with deadlines and attachments for those agreeing to participate.
- Draft of framework with short description of all categories and sections.
- Evaluation criteria document (Appendix 3).

All experts responded with their suggestions for improvement and recommendations within two weeks in each round. In each round, volunteers added and deleted information. To make sure everything was well-organised, a template was used to track participant recruitment and dates in which key milestones were achieved as shown in Appendix 4.

Volunteers were asked to review the responses as shown in Appendix and include any additional information or rejection of any ideas through e-mail. Volunteers would respond to say there were no changes to the responses and if there were any changes to be made, volunteers would reply with comments.

After all reviews from the Delphi panel were received, the researcher modified the framework to include all the feedback and recommendations from the panel. This was referred as Round 2 of the reviews. An email was sent to the Delphi panel with two documents attached: one was the summary of changes from Round 1, and the second was the modified framework. The email also requested additional feedback from the Delphi panel if needed or to respond in support of the Framework if deemed complete by the reviewer. All other framework areas were left as previously presented, as there were no comments or suggestions for change.

After a week, I received all the replies from the e-mail with the statement: “Final framework is complete as presented”, indicating that 100% of the participants in the Delphi panel had reached a consensus and the framework was completed.

The following are representative comments received based on the evaluation criteria. Different themes emerged from the analysis.

Ability of ASK SUMA Framework in Supporting Effective Learning of Emerging Industry Trends

The framework involves industries in the students’ learning process and the employers were delighted as this would allow them to help creating the talent that they required. The technology industry is always advancing so rapidly that the current modules of the university would be outdated when the students have graduated. Experts think that using this framework would help students to stay relevant to the learning of emerging trends.

> “Yes, definitely. This framework allows students to be proactive and the fact that they could consult us, they would be able to stay updated with the latest technology used in our firm.”[E3]

> “If the students apply this framework, they would be keeping in touch with the industries and this will help them to get used to the tools and software we use at our company.” [E1]

Ability of ASK SUMA Framework in Developing TSS and Self-Management Skills

The framework allows students to do personal reflection of own skills and knowledge level. It also encourages students to get feedback from peers and industry mentors. It also allows industries to post mini projects for students to develop their technical skills and soft skills.

> “Working on mini projects could help students to learn soft skills like communication, teamwork, problem solving and creativity.”[E1]

> “Mini projects could also help students to learn the current programming language that is used by the industry.”[E5]

The stages in ASK SUMA framework also guide students through their learning process. It helps them to identify their weaknesses and strength and allow them to create a plan. It also helps the industry to understand the current situation of the students.

> “In the framework, the mini project would help students to identify what skills they needed to improve on. This would help them to be more focused on learning and hence, it would show us their attitude in learning too.” [E7]

The mini projects allow students to get a taste of what is like to work in an industry. They would also be able to apply their knowledge that they have gained at the university in the mini projects. This framework also allows collaboration as the students could ask for advice from industry mentors and also request for peer reviews.

> “Students who are proactive will be able to keep a watch for upcoming projects and upskill themselves through the projects.”[E8]

Ability of ASK SUMA Framework in Creating an Enthusiastic Learning Climate

The industry experts think that this framework helps to support students by creating an enthusiastic learning climate. It guides the students through each stage to keep the motivated. Students can share their knowledge among their friends and can review each other. This framework also encourages student to do reflection on their learning process so they would be able to know their situation. It also helps to create positive attitude in learning.

> “Through the mini projects the students would be able to learn skills from each other and would be able to get support from industry mentors too.”[E4]

All eight experts agreed that implementing the research outcomes in the framework can reduce the soft skills gap. Also, they agreed that the models were useful and applicable for technology-related education. One of the experts stressed that the integrated framework provided a useful strategy to implement either in whole or in part or to partially adapt to specific country/educational contexts.

> "The research outcomes can reduce the soft skills gaps for technology graduates over time as long as they are broadly applied in education. The research analysis is appropriate, and the results are reliable. Thus, suggestions to implement the proposed framework is logical in the educational context."[E2]

Another expert stated that the integrated framework was applicable and comprehensive in terms of the types of skills and attributes that were required or were seen as optimal in Information Technology career fields.

Five experts believed that the framework was very easy to understand and made sense. The rest disagreed and suggested adding more details to the proposed framework to clearly show how it would be transferred to education. Using their own terms, all eight experts commended the quality of the proposed theoretical framework.

> "The ASK SUMA framework is an excellent support tool for students to practise active learning skills."[E8]

> "The framework presented is well organised, easy to understand, and logical to follow. I especially like the part where I can share information on projects where we could recruit students and also, I could see students who are enthusiastic in their career. It helps me to identify bright talents and to be their mentor". [E4]

The experts stated that nothing stood out as an important question that was not considered or had been overlooked in the research. They did not mention any missing component from the learning framework or from the research in Round 2. One of the experts suggested combining role-playing/simulation-based learning into the framework.

For future research, the experts suggested the following:

* Testing the proposed framework in other courses to determine if the cultivation of the soft skills increased as a result. This can be followed by comparing the technology graduates' soft skills levels of students with the current education curriculum and using the proposed learning framework.

* Integrating the proposed framework with the existing assessment tools to measure the outcomes of implementing the proposed models in the technology related curriculum. These tools can be used to measure the freshman students' soft skills levels and then test them again following the completion of their courses and prior to graduation.

* Mapping the proposed framework to applicable course titles from current technology-related modules, considering budgetary issues such as limited funding, instructors, and resources.

* Collecting survey data from academics.

A short survey was also conducted with students to evaluate the effectiveness of the framework in creating an enthusiastic learning climate. Table A12.1 and Figure A12.1 show the result of the survey.

Table A12.1 Effectiveness of Framework in Creating an Enthusiastic Learning Climate

Type of Response	%	Count
Effective	95.3	143
Not Effective	2.0	3
Not sure	2.7	4

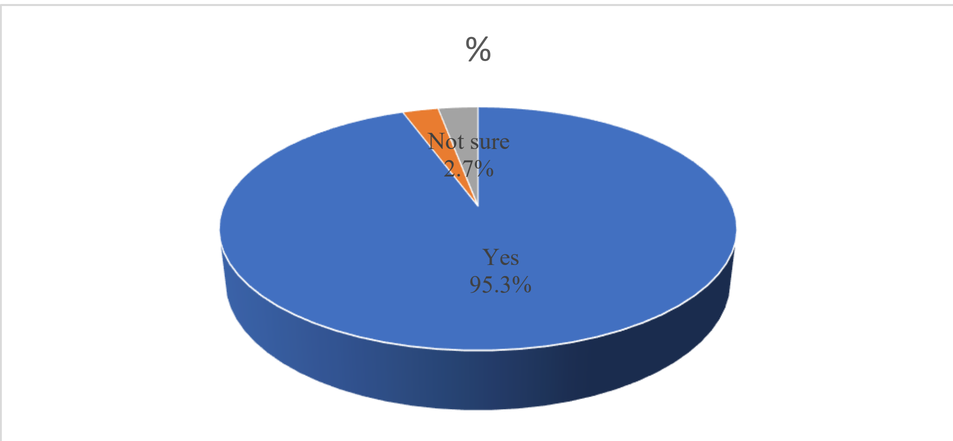

Figure A12.1 Perception of the Effectiveness of the Framework

95.3% of the students in the survey agreed that the framework is effective in supporting them in creating an enthusiastic learning climate. There is a small percentage of students who are unsure, while only 2% of the students do not think it helps them to be proactive.

Table A12.2 Effectiveness of the Framework in Developing Emerging Industry trends

Type of Response	%	Count
Effective	80.0	120
Not Effective	0.0	0
Not sure	20.0	30

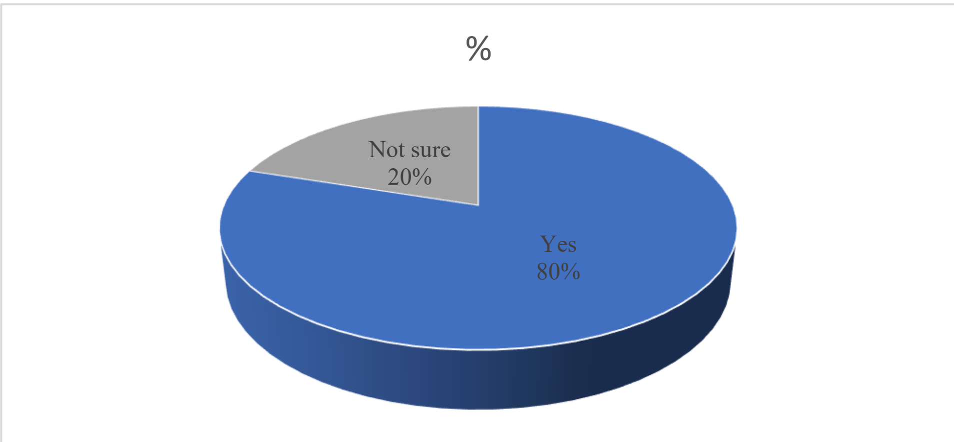

Figure A12.2 Effectiveness of Framework in Developing Emerging Trends

80% of the students in the survey agreed that the framework is effective in supporting them in developing emerging trends in industry 4.0 while only 20% of the students were not sure whether it helps them.

Table A12.3 Effectiveness in Developing Skills for Industry 4.0 and Future Industry

Aspects	Mean Score	Effectiveness
TSS Skills		
Analytical thinking and innovation	4.17	Effective
Complex problem solving	4.19	Effective
Critical thinking and analysis	4.06	Effective
Creativity, originality and initiative	4.01	Effective
Leadership and social influence	4.2	Effective
Technology use, monitoring and control	4.29	Effective
Technology design and programming	4.28	Effective
Reasoning, problem solving	4.01	Effective
Self-Management Skills		
Active learning and learning strategies	4.03	Effective
Resilience, stress tolerance and flexibility	4.13	Effective

Mean score was used to determine the perspective of students on the effectiveness of the proposed framework in supporting them to develop skills as there are ten skills to be evaluated. It clearly shows that the students think this proposed framework is supporting them to meet the needs of industry 4.0 and future industry.