

**A Knowledge Based Educational (KBEd) framework
for enhancing practical skills in engineering distance
learners through an augmented reality environment**

Venkatesh Chennam Vijay

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Abstract

The technology advancement has changed distance learning teaching and learning approaches, for example, virtual laboratories are increasingly used to deliver engineering courses. These advancements enhance the distance learners practical experience of engineering courses. While most of these efforts emphasise the importance of the technology, few have sought to understand the techniques for capturing, modelling and automating the on-campus laboratory tutors' knowledge. The lack of automation of tutors' knowledge has also affected the practical learning outcomes of engineering distance learners. Hence, there is a need to explore further on how to integrate the tutor's knowledge, which is necessary for imparting and assessing practical skills through current technological advances in distance learning. One approach to address this concern is through the use of Knowledge Based Engineering (KBE) principles. These KBE principles facilitate the utilisation of standardised methods for capturing, modelling and embedding experts' knowledge into engineering design applications for the automation of product design. Hence, utilising such principles could facilitate, automating engineering laboratory tutors' knowledge for teaching and assessing practical skills. However, there is limited research in the application of KBE principles in the educational domain. Therefore, this research explores the use of KBE principles to automate instructional design in engineering distance learning technologies. As a result, a Knowledge Based Educational (KBEd) framework that facilitates the capturing, modelling and automating on-campus tutors' knowledge and introduces it to distance learning and teaching approaches.

This study used a four-stage experimental approach, which involved rapid prototyping method to design and develop the proposed KBEd framework to a functional prototype.

The developed prototype was further refined through internal and external expert group using face validity methods such as questionnaire, observation and discussion. The refined prototype was then evaluated through welding task use-case. The use cases were assessed by first year engineering undergraduate students with no prior experience of welding from Birmingham City University. The participants were randomly separated into two groups (N = 46). One group learned and practised basic welding in the proposed KBEd system, while the other learned and practised in the conventional on-campus environment. A concurrent validity assessment was used in determining the usefulness of the proposed system in learning hands-on practical engineering skills through proposed KBEd system. The results of the evaluation indicate that students who trained with the proposed KBEd system successfully gained the practical skills equivalent to those in the real laboratory environment. Although there was little performance variation between the two groups, it was rooted in the limitations of the system's hardware. The learning outcomes achieved also demonstrated the successful application of KBE principles in capturing, modelling and transforming the knowledge from the real tutor to the AI tutor for automating the teaching and assessing of the practical skills for distance learners. Further the data analysis has shown the potential of KBEd to be extendable to other taught distance-learning courses involving practical skills.

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*“Dream is not that you see in sleep,
dream is something that does not let you sleep”*
- A.P.J Abdul Kalam

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List of Abbreviations

3D = 3 Dimensional

ABET = Accreditation Board for Engineering and Technology

AC = Abstract Conceptualization

AE = Active Experimentation

AI-Tutor = Artificial Intelligent-Tutor

AIChE = American Institute of Chemical Engineers

Amp = Amperage

AR = Augmented Reality

ASMG = Assessing State Machine Graph

BCU = Birmingham City University

CE = Concrete Experience

CR = Cognitive Rigor

DA = Drag Angle

DL = Distance Learning

DOK = Depth of Knowledge

DP = Degreasing the Plate

DSMG = Dialog State Machine Graph

ECPD = Engineers Council for Professional Development

ERS = Earth Strap

ES = Executional Skill

EWI = Edison Welding Institute

FBX = Filmbox

FPS = First Person Shooter

FS = Fundamental Skill

FSM = Finite State Machine

GA = Genetic Algorithm

GDEB = General Dynamics Electric Boat

GL = Gas Level

GUI = Graphical User Interface

HMD = Head-Mounted see-through Display

ICARE-form = Illustrations, Constraints, Activities, Rules, Entities – form

ICT = Information and Telecommunication Technology

ITSs = Intelligent Tutoring Systems

JSON = JavaScript Object Notation

KADS = Knowledge Acquisition and Documentation Structuring

KB = Knowledge-Base

KBE = Knowledge-Based Engineering

KBE_d = Knowledge-Based Education

KBS = Knowledge-Based Systems

KC = Knowledge Capture

KM = Knowledge Modeling

KNOMAD = The Global Knowledge Partnership on Migration and Development

KOMPRESSA = Knowledge-Oriented Methodology for the Planning and Rapid Engineering of Small-Scale Applications

LE = Learning Environment

MBTI = Myers-Briggs Type Indicator

MOKA = Methodology and software tools Oriented to Knowledge based engineering Applications

MOOC = Massive Open Online Course

MSMG = Measuring State Machine Graph

MTMM = Multitrait -Multimethod Matrix

NASA = National Aeronautics and Space Administration

NN = Neural Networks

NSA = Number of Second Attempts

OWL = Web Ontology Language

PC = Personal Computer

PM = Placing Magnets

PPS = Preparation Skill

PS = Procedural Skill

RDF = Resource Description Framework

RO = Reflective Observation

STELLA = Systems Thinking, Experimental Learning Laboratory with Animation

SW-On = Switching-On

SWEET = Semantic Web for Earth and Environmental Terminology

SysML = Systems Modeling Language

TO = Task Outcome

TS = Travel Speed

TSMG = Teaching State Machine Graph

UML = Unified Modeling Language

VR = Virtual Reality

VRSIM = Virtual Reality Simulator

WA = Work Angle

WFS = Wire-Fed Speed

Chapter 1 Introduction and background

*“Dream, Dream, Dream, Dreams transform into thoughts and thoughts result in action”
- A.P.J Abdul Kalam*

1.0 Introduction

The importance of practical experience in engineering courses has significantly increased since the 19th century, as the mode of teaching has shifted towards constructivist pedagogy, emphasizing the importance of knowledge through experience (Feisel and Rosa, 2005). This has been due to the increasing demand from industries for engineering graduates equipped with both theoretical knowledge and practical hands-on skills (Corter *et al.*, 2007). In university education, the relatively recent concept of distance learning (e-learning) has encouraged the participation level of learners who are physically away from the on-campus environment, by providing them with improved access (Zhu and Liu, 2009; Barbour and Reeves, 2009). Although teaching practically is different from teaching theoretically, in an educational domain learning practical skills is associated with lab instructors and workshops equipped with special equipment and involves long periods of time to practise or rehearse techniques (Ma and Nickerson, 2006); the knowledge of the laboratory instructor plays an integral part in developing and assessing the practical skills of the learner.

Therefore, in the distance learning environment ‘imparting practical experience’ and ‘assessing’ the engineering practical skills become two major challenges (Peterson and Feisel, 2002; Wu *et al.*, 2008). As hands-on ‘know-how’ practical skills are critical for engineering disciplines, delivering them by a distance learning mode becomes a major hurdle for education providers (Bennett and Lori 2004; Aguilar *et al.*, 2011; Vidal-Castro and Manuel 2012). Even though there are several new advances in current

education through technologies such as “virtual and remote learning”, one has to note that these have been extensively developed for disciplines such as management and computer science, but are relatively underdeveloped in engineering science disciplines (Murphy and Manzanares, 2008; Rajaei and Aldhalaan, 2011). Moreover, the concept of distance learning in engineering science subjects such as mechanical and automotive engineering is still in its infancy (Perry *et al.*, 2008; Anis, 2011; Laurillard 2013; Potkonjak *et al.*, 2016), as it limits practical engineering skills acquirable through the existing distance learning environment.

1.1 Problem statement

In the modern era, the acceptance and use of technologies are growing rapidly in both academic and industrial domains. Technologies such as virtual and augmented reality have taken teaching and learning down more innovative and interesting paths (Bricken, 1991). Apart from these technologies, other distance learning technologies such as Moodle and webinars have been in use for several years and are still being used by a number of universities offering distance learning courses, mainly in teaching theoretical concepts. Among these, virtual reality (VR), which is one of the components of distance learning, has been extensively used in the educational domain for teaching practically based subjects (Sherman and Craig, 2002; Youngblut, 1998). In a virtual reality environment, the virtual world replaces the real world, whereas in an augmented reality environment the system enhances the real world by superposing virtual contents onto it. The term augmented reality (AR) refers to the enrichment of the real world with a complementary virtual world, where visual information and 3D objects are tied to the physical environment (Ferdinand *et al.*, 2005; Buchmann *et al.*, 2004).

Both of these technologies are been applied in various fields of education, such as

medical, construction, engineering and aviation disciplines, among many others (Lee and Wong, 2008; Santana *et al.*, 2010; Lee, 2012; Wang *et al.*, 2013; Ong and Andrew, 2013). However, very little attention has been paid to the methods and approaches to follow in developing and automating these environments for teaching and assessing practical skills for engineering distance learners (Sottolare *et al.*, 2013; Li and Zhou, 2015). As laboratory and fieldwork activities performed by students are taught and monitored face-to-face by subject experts, capturing, modelling and codifying the on-campus tutor's knowledge and applying it to a virtual tutor in a distance-learning environment becomes a critical requirement. This research focuses on developing a method that captures and models the on-campus tutor's knowledge into a knowledge-based education (KBEd) framework for automating laboratory teaching and assessment processes in a distance learning environment and for enhancing the practical skills of engineering distance learners. Further, the study examines the effectiveness and efficiency of the proposed knowledge-based educational (KBEd) framework that integrates artificially intelligent (AI) tutors and an augmented reality (AR) environment for training students in practical engineering skills. More specifically, it aims to validate the transformation of practical skills acquired from the proposed distance-learning environment to a real on-campus one. This research was conducted at Birmingham City University (UK); the case organization runs a mechanical engineering course, in which first year students learn several fundamental practical tasks related to the subject. Among these taught practical tasks, basic welding is not part of the real academic assessment and does not influence the academic score of the student, which was chosen as the use case for testing the framework. The following are the research questions and objectives to address the above-mentioned research challenges.

1.2 Research questions

- Can the principles and practice of knowledge based engineering be applied to acquire the knowledge of a tutor to create a knowledge based educational framework?
- Can this framework be embodied into an augmented reality environment that would allow study by distance learners?
- Can engineering learners acquire practical skills in an augmented reality environment?

1.3 Research objectives

1. To establish research landscape by identifying and reviewing the ‘best practices’ and issues on delivering practical skills for engineering distance learners.
2. To capture, model and automate on-campus tutor knowledge for teaching and assessing practical skills.
3. To design and develop an augmented reality environment for learning.
4. To evaluate the performance of the augmented reality environment.

1.4 Overview of research design

This research was conducted with Birmingham City University’s first year engineering undergraduate course. The case organisation teaches a number of laboratory tasks among it which is basic welding, which is not part of the real academic assessment and is not associated with the academic score of students, was selected as the use-case for the research. The on-campus laboratory tutors’ knowledge was captured, modelled and automated by adopting knowledge-based engineering (KBE) principles to fit the educational domain. The used of KBE is found in several manufacturing industries’

applications in addressing the needs of large numbers of product variants to meet individual customer needs (Tseng and Jiao, 1996; Cooper and Fan, 1999; Wognum and Trappey, 2008). This research used KBE principles in mimicking laboratory tutors behaviour through knowledge automation by robust capturing and modelling techniques like artificial intelligence (AI) and semantics (ontology) in teaching and assessing practical skills in engineering distance learners. Furthermore, the automated knowledge was embedded into an augmented reality environment using state of the art augmented reality technology to allow student to practise hands-on engineering skill by interacting with augmented objects.

A mixed method four-stage experimental approach was used to conduct this research, which involved students with no prior experience of welding; randomly assigned participants were separated into two groups (N = 46). One group learned and practised basic welding in the proposed augmented reality environment with the guidance of an AI tutor, while the other learned and practised in the conventional on-campus environment with the guidance of a real tutor. After completion of the training, each of the participants from both groups was asked to perform the learned welding task in the on-campus environment using real equipment and resources without any guidance. A concurrent validity assessment was used in determining the usefulness of the proposed system in learning hands-on practical engineering skills. More specifically, the usefulness was determined by measuring whether the practical skills acquired by the learners from the proposed system were transferable to a real laboratory environment.

1.5 Structure of the thesis

The thesis consists of seven chapters, including this introduction (Figure 1.1). Chapter 2 provides the background of the research and the main issues surrounding engineering distance learning. Sections 2.2 and 2.3 critically review the importance of the laboratory activity and the practical ‘know-how’ skills for employers. Section 2.4 critically reviews the existing theories and practices in teaching and learning engineering laboratory activities. Section 2.5 provides the history of distance learning and its core components, while sections 2.5.1 and 2.5.2 discuss different distance learning approaches such as remote and virtual laboratories and their state of the art in universities offering engineering distance learning. Section 2.5.3 explores in detail two of the technological advances in distance learning technologies – virtual reality (VR) and augmented reality (AR). Sections 2.7 and 2.8 discuss the two key challenges facing current engineering distance learning. Taking these sections as the starting point, sections 2.8, 2.8.1, 2.8.2 and 2.8.3 introduce possible solutions by discussing the knowledge capturing, modelling and automation techniques that have been used in industries for automating expert knowledge in computer applications. Having discussed the literature and identified the research gap and possible ways of addressing it,

Chapter 3 explains the rest of the research journey in two major sections. Section 3.1 explains the research design by providing the research standpoint and understanding of research methodology. Section 3.1.2 provides different development approaches that are in practice, while section 3.1.2(b) presents the background and principles involved in the selected method rapid prototyping; section 3.1.2(c) explains how the selected development methods would be used in this research. Section 3.1.3 explores different experimental validation approaches and their limitations, and section 3.1.3(b) explains in detail the selected construct validity types and data gathering and analysis

techniques. Subsequently, section 3.1.3(c) explains how the selected validation approaches will be used in this research.

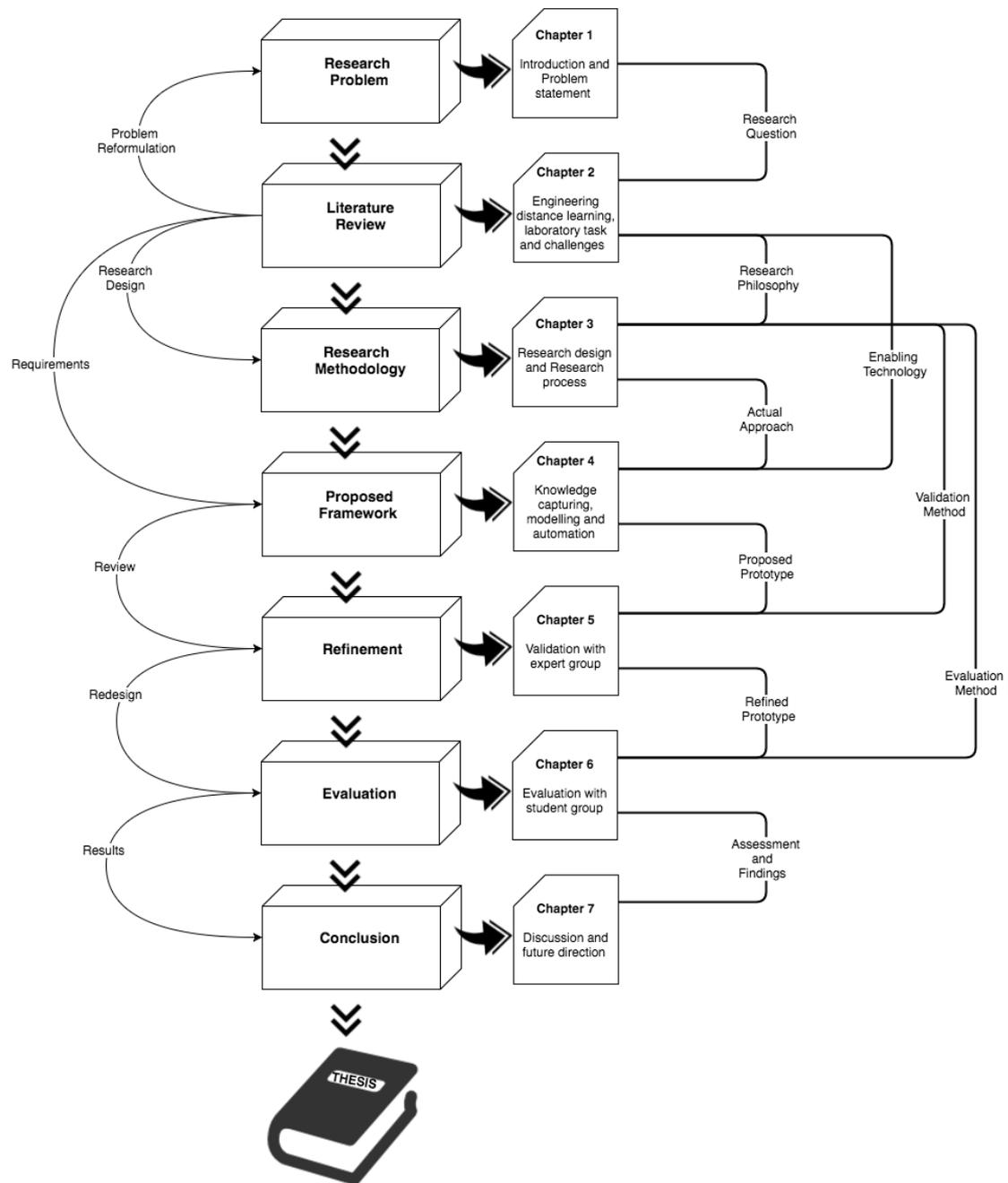


Figure 1.1: Thesis outline

Sections 3.1.3(d) and 3.1.3(f) explain how the experimental reliability and ethical issues were addressed with respect to the selected development and validation approaches.

Section 3.2 outlines the actual research process that was implemented through the

selected approaches in addressing the research objectives. Section 3.2.1 explains the KBEd blueprint and the implementation steps involved in building the prototype and sections 3.2.2 and 3.2.3 discuss how the validation and evaluation was carried out with expert groups and student groups. In addition, these sections provide a detailed explanation of the participant selection process and the data collection and analysis techniques involved in it.

Chapter 4 explains in detail each of the building blocks of the KBEd prototype that was presented in Chapter 3. Section 4.1 presents the proposed three column approach and the knowledge capturing stages involved in capturing the fundamental, task and executional knowledge of experts. With the completion of knowledge capture, section 4.2 explains how the data from the paper was modelled into a computerised environment for automation. Section 4.2.1 presents the informal modelling of knowledge, which is then formally modelled ontologically in section 4.2.2. Further, section 4.2.3 explains how the knowledge automation was performed through the ontological queries. Section 4.3 describes how the knowledge model from the ontological process was then processed into the artificial intelligence (AI) tutor through the use of state machines, while section 4.3.2 presents the structure of the teaching state machine graph (TSMG) involved in teaching the learners by feeding them with appropriate textual, audio and video knowledge. Section 4.3.3 presents the assessing state machine graph (ASMG) in automating the continuous monitoring of learners' actions and assessing them. Section 4.3.4 presents the dialog state machine graph (DSMG) in automating the dialog conversation between the AI tutor and the learner and section 4.3.5 presents the measuring state machine graph (MSMG), in which the learning outcomes of the learner are measured through a proposed Level, Depth and Rigour axis. Learning practical skills heavily relies on physical movements; in

particular, the selected use-case ‘welding’ relies heavily on hand movement. Section 4.4 elaborates on how the laboratory equipment required for performing the welding was modelled, codified and transformed into an augmented reality environment. Chapter 4 also includes a section regarding the changes made to the KBEd system in the light of information gathered from internal experts through the iterative prototyping method. Once the system had been developed and refined through internal experts’ suggestions, the next stage of the research concerned the evaluation of the proposed KBEd system.

Chapter 5 presents the face validity results from the external experts in testing the readiness and usability of the proposed KBEd system. In addition, section 5.4 discusses the outcome of the results and the changes that needed to be made before evaluating them with students. Chapter 6 presents the concurrent validity that was conducted between the two groups of students in evaluating the effectiveness and the efficiency of the proposed system in learning practical engineering skills when away from the on-campus environment. Finally, in section 6.5 the students’ evaluation results are discussed and the thesis conclusion and recommendations for future research work are presented in Chapter 7.

1.6 Chapter summary and conclusions

This chapter sought to introduce the research in hand and explored the research issues and challenges. It also establishes the research questions and presented the aim and objectives for conducting the study. In addition, it presented the overview of methodological steps of the research, which is addressed in detail in the Chapter 3. The chapter concluded with the structure of the thesis showing how the chapters

were written and connected to each other. Literature, related to key issues that are linked to the study, are discussed in the next chapter.

Chapter 2 Literature review

“All Birds find shelter during a rain. But Eagle avoids rain by flying above the Clouds”
- A.P.J Abdul Kalam

2.0 Introduction

The previous chapter introduced the research in hand and established the justification for undertaking the study. This chapter explores and reviews the existing state of the art pertaining to the key challenges related to the study. This chapter reviews the following five major topics:

1. Engineering laboratory – establishing the landscape of current research.
2. Demand for practical skills from engineering employers – exploring the importance of ‘know-how’ skills among past, current and future engineering employers and critically reviewing current engineering educators’ standpoints with respect to established practice.
3. Learning and teaching theories – an in-depth literature review of the existing cognitive theories and their applications for teaching and learning engineering laboratory activities.
4. Distance learning – state of the art distance learning approaches; tools and techniques for delivering engineering curriculums by modern technology and their limitations.
5. Knowledge automation – review of the methods and techniques that have been used in capturing, modelling and codifying knowledge into distance learning technologies.

2.1 History of the engineering laboratory

In the 1950's, engineering learning placed greater emphasis on practical work. Engineers who graduated in earlier times were more practically oriented, but lacked the underpinning theoretical concepts (Grinter, 1955; Committee of College and University Examiners, 1956). Later, the emphasis shifted more towards teaching theoretical concepts, which also led to inconsistent learning outcomes, since students lacked the practical knowledge required for industrial jobs (Roth, 1994). To overcome the above inconsistency, universities, industries and researchers constructed their own pedagogy (Loo, 1997). Among these new approaches, Kolb's (1985) experimental learning theory was widely used, as it helped to achieve the right balance between theory and practical skills. During the last decade, universities such as Cornell, Union College, Vale, MIT and many others emphasized laboratory instruction and practical experience for new generations of engineers (Bisantz and Victor, 2002; Hofstein and Vincent, 2004; Newton, 2013). The first engineering taught course that involved practical aspects and fieldwork was from the American Society of Civil Engineers (Felder and Rebecca, 2003). One of its early technical divisions was surveying, which provided a practical work environment (Kamis and Heikki, 2007). Subsequently, laboratories and fieldwork were made mandatory for engineering education (McGourty *et al.*, 2002; Wankat, 2004).

Along with new pedagogical approaches, engineering accreditation process also in parallel has increased the quality of the delivery of engineering modules; these accreditations defined a set of learning objectives that needed to be achieved (Stephan, 2002). The first engineering education accreditor was the American Institute of Chemical Engineers (AIChE) in 1925, which was followed by the Engineers Council for Professional Development (ECPD) in 1932, now known as the Accreditation Board

for Engineering and Technology (ABET) (Reynolds and Bruce, 1993; Carlson *et al.*, 1997). In the UK, Engineering Council accreditation helps to ensure that engineering education meets world-class standards and assists students in acquiring industry-relevant skills. Figure 2.1 provides the set of learning outcomes that needs to be achieved by engineering students in the UK in order to qualify as a professional engineer (Engineering Council, 2013). This research focuses mainly on the ‘know-how’ learning outcome, which focusses more on knowing how to perform hands-on activities in solving problems. Hands-on experience is one of the fundamental skills required from an industry point-of-view (Wojciechowski and Wojciech, 2013). As these ‘know-how’ practical skills in courses such as mechanical and automotive engineering are vital, imparting and assessing them requires comprehensive teaching and learning methods. The following section provides a detailed review of the importance of ‘know-how’ practical skills among engineering employers and their practice in university engineering courses involving laboratory activities.

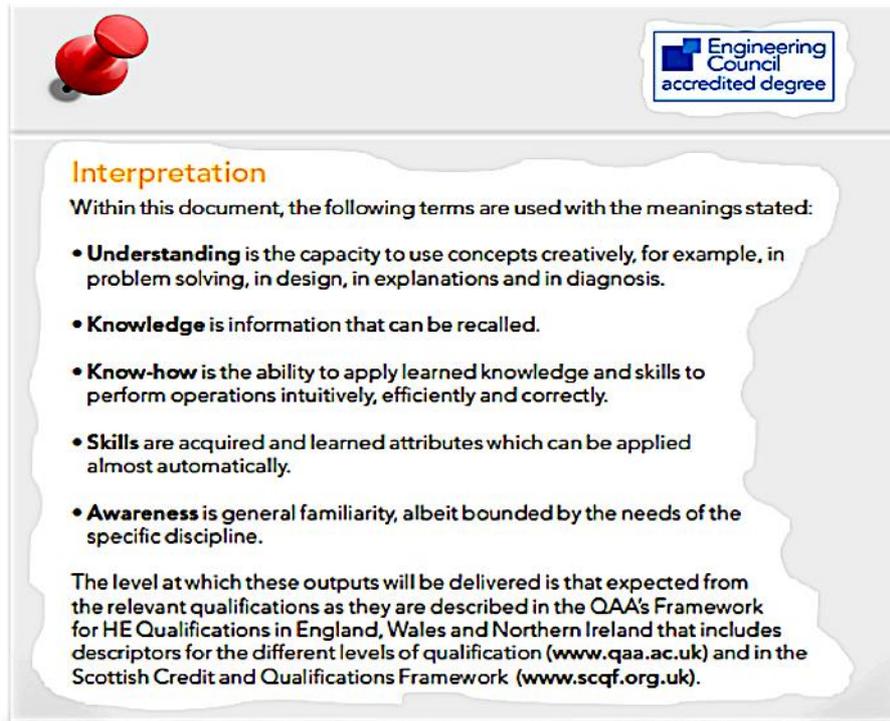


Figure 2.1: UK Standard for Professional Engineering Competence. Source: Engineering Council (2013)

2.2 Demand for practical skills from engineering employers

Practical know-how is the skills that are required by the students to become more successful learners and practitioners in their respective fields of study (Bennett *et al.*, 1999; Biggs, 2003; Allan and Clarke, 2007). The terminology regarding practical know-how skills differs from country to country, where terminologies such as ‘employability-skill’, ‘key-skill’, ‘essential-skill’, ‘necessary-skill’, ‘generic-skill’ or ‘work-ready skill’ have the same meaning (NCVER, 2003). Although academic qualifications are the most important criterion from an employer’s point-of-view, Hamzah and Abdullah (2009) and Mavrikios *et al.* (2013) suggest that possessing know-how skills such as critical thinking and problem solving through actions makes the individual different from others. This is further evident from the Committee for Economic Development’s (2015) report on the shortage of essential skills among

engineering employees (Figure 2.2); in the past decade the importance and emphasis of degree qualifications with practical know-how skills have become essential.

Further, Meier *et al.* (2000) and Adamson and Darling-Hammond (2012) state that true academic success is not defined in terms of what students can remember, but what they can do with their learned knowledge. This is evident in today's engineering profession, as technical competencies have become much needed skills for engineering graduates to secure jobs in industry (Benjamin *et al.*, 2012; Stephens, 2013). This has caused engineering institutes to face unprecedented pedagogical challenges (Lucena *et al.*, 2008; Shury *et al.*, 2010), meaning that engineering educators now face challenges in providing a balanced curriculum with both academic and practical rigours to produce 'work-ready' graduates (Gunn *et al.*, 2010). Reports in the past from The Chronicle of Higher Education (2011), BBC News Education and Family (2012) and Mail Online (2013) have stated that employers believe that college graduates lack know-how skills. According to Crawley (2002), Spinks *et al.* (2006), Crossman and Clarke (2010), Mohd-Yusof *et al.* (2011), Hassan *et al.* (2011), Phang *et al.* (2012), Hassim *et al.* (2013) and Khoo (2015), this is because the present pedagogical model in most universities is one-way, in which students are passive recipients and learning is more by rote for most of practical activities Gill *et al.* (2008) and RAEng (2010) criticise the above view, saying creating such a balance would be not easy within the limited budgets and academic timescales.

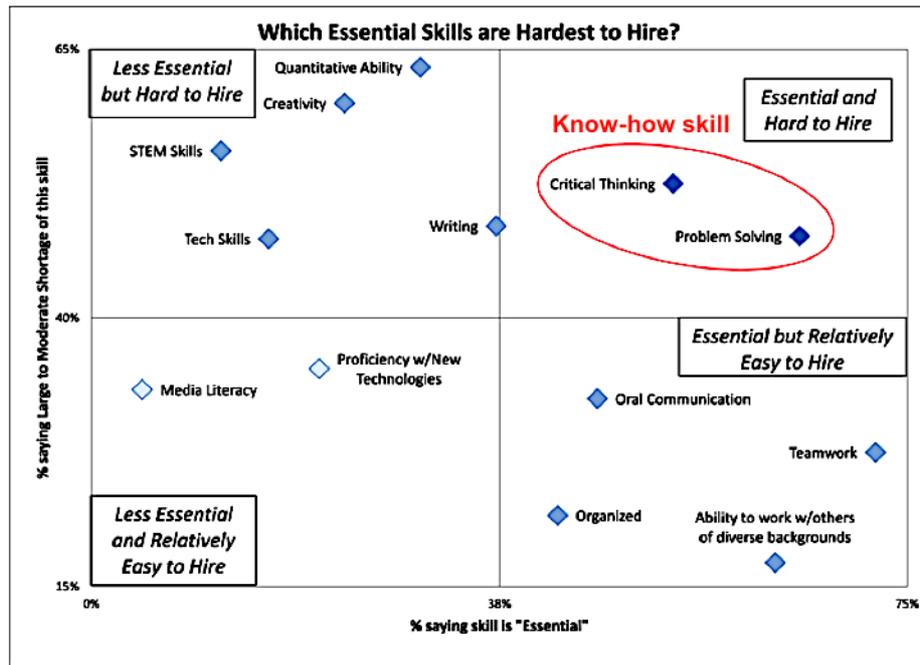


Figure 2.2: Essential and harder skills to hire. Adapted from Committee for Economic Development (2015)

In the UK, the number of dropouts from engineering science subjects in both regular and distance learning modes has increased in recent years (DIUS, 2008; RAEng, 2008). Ofsted (2010) points out the same pedagogical issue and further warns there might be an unprecedented shortage of employable graduates. In addition, Carnevale *et al.*'s (2013) report on jobs and requirements for 2020 suggests that overall employment is expected to increase from 140.6 million to 164.6 million, and thus a serious change is required in teaching and learning methods to motivate students and produce engineering graduates with employability skills (Figure 2.3). In response to this, CDIO (2013), an engineering educational research organisation, suggests that the problem could be resolved by developing academically relevant and industrially attractive curricula to improve student retention and know-how skills.

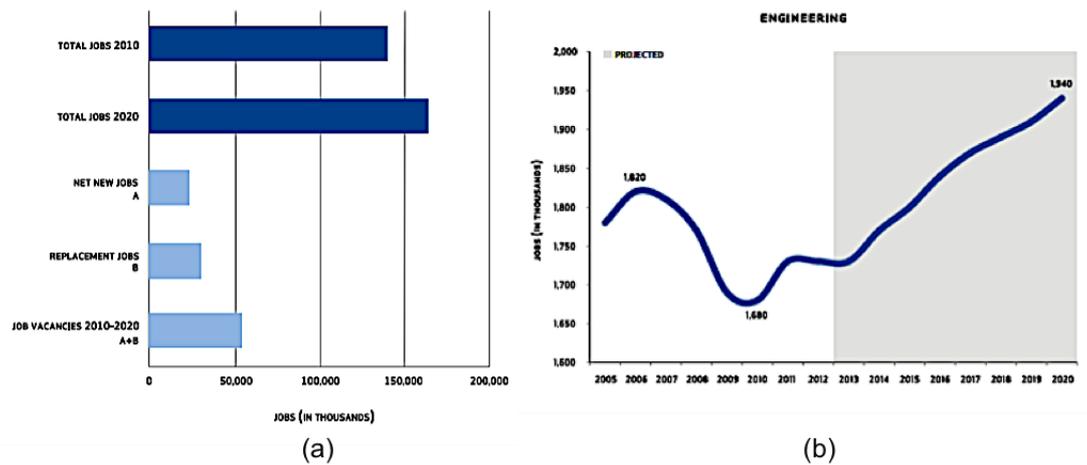


Figure 2.3: Forecast on job opportunity 2020 report: (a) overall and (b) engineering.
Source: Carnevale et al. (2013)

Apart from industries and research organizations, various engineering institutes such as the National Academy of Engineering (2005), The Royal Academy of Engineering (2007) and Duderstadt (2008) have also emphasised the importance of engineering know-how skills in helping students to progress well in their workplace. One such report was Clark and Andrews' (2013) study, in which they examined how their engineering graduates were expected to learn before delivering the course (Figure 2.4); more than 85% were interested in learning through actively building things, which was indirectly aligned with the current industrial skill requirements.

Further, several engineering institutes in different developing countries such as India, China, Brazil, Malaysia, Thailand and Nigeria have also acknowledged the skills shortages among graduates applying for industrial jobs (Skill and Work, 2015). They have also made efforts in recent years to reach their cities as well as villages through new teaching and learning technology to motivate and train students in employment skills and to equip them to compete against the rest of the world (Abdullah *et al.*, 2007; Mishra, 2010; Sunthonkanokpong, 2011; Fisher, 2013; Kalam and Rajan, 2014; Warnick *et al.*, 2014; Staubitz *et al.*, 2015; Aggarwal, 2016).

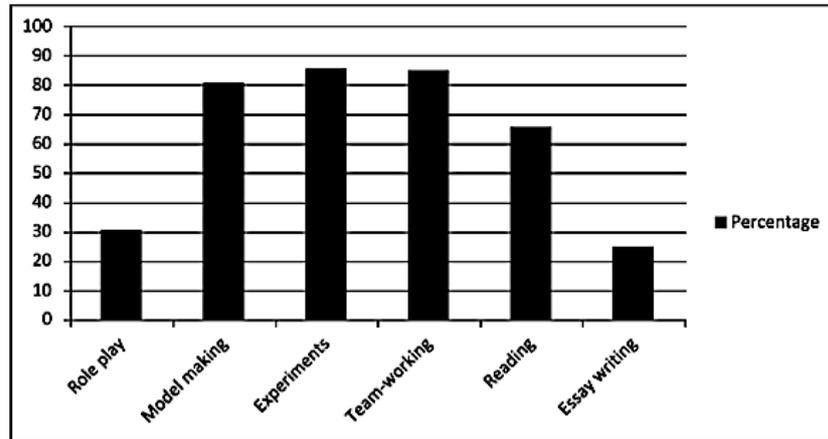


Figure 2.4: Examination of the way engineering students prefer to learn. Source: Clark *et al.* (2013)

As the literature indicates, new requirements from industries and rapid changes in technologies have emphasized not only degree qualifications, but also the need for know-how skills in engineers to understand, execute and adapt to the real-world challenges. With this in mind, engineering educators have adapted new teaching and learning theories and approaches to achieve the desired learning outcomes (UNESCO, 2012). The remainder of the chapter critically reviews and analyses how practical engineering skills are being taught, learned and assessed; further, we review the current trends and challenges facing engineering distance learners.

2.3 Learning and teaching theories involved in engineering

Learning and teaching theories are interlinked with each other as each is mutually relevant (Meyers, 1986). Various literature discusses the different theories employed for different learning and teaching purposes (Bigge, 1982; Brown *et al.*, 2000; Arends 2014). This research focuses on the engineering domain and thus has eliminated several theories developed from other fields of study. In engineering, most of the learning and teaching theories are based on Kolb's experimental learning cycle Kolb (1993), in which emphasis is placed on engineering learning through an experimental learning

cycle involving experience, observation and reflection (formulation) and then testing. Kolb suggests appropriate teaching styles for each of the phases in this cycle.

2.3.1 Kolb's experimental learning cycle

Kolb's learning cycle was based on Kurt Lewin's cycle of learning proposed for control engineering; Kolb generalized it and made it popular (Adelman, 1993). Kolb's experimental learning cycle is an iterative process consisting of four learning modes (see Figure 2.5): concrete experience (CE), reflective observation (RO), abstract conceptualization (AC), and active experimentation (AE), through which knowledge is acquired by a combination of 'grasping' and 'transforming' experience. Grasping occurs through concrete experience and abstract conceptualization (CE – AC) and transforming is achieved through reflective observation and active experimentation (RO - AE) (Abdulwahed and Nagy, 2009). In the cyclic process, concrete experience serves as the starting point; emphasis is placed on observation and then the observations made are analysed and reflected upon through reflective observation. These reflected observations are then developed into an initial implication in abstract conceptualization and actively tested in the acquisition of new experience. Vince (1988) examines the experimental cycle more closely and suggests that learners need not follow the whole cycle, but should acquire the ability to choose the right mode for their grasping and transforming process. For instance, some learners who prefer grasping new information through their own senses and concrete reality can concentrate more on concrete experience rather than abstract conceptualization. On the other hand, students who prefer processing or transforming their acquired information into knowledge by seeing and analysing actions performed by others, rather than jumping in and start doing things themselves, can concentrate more on reflective observation. Felder and Silverman (1988) state that adopting the cycle for each engineering task is virtually impossible,

but each of the cyclic processes presents us with a choice, patenting and identifying the right ones by eliminating the rest is represented as learning style.

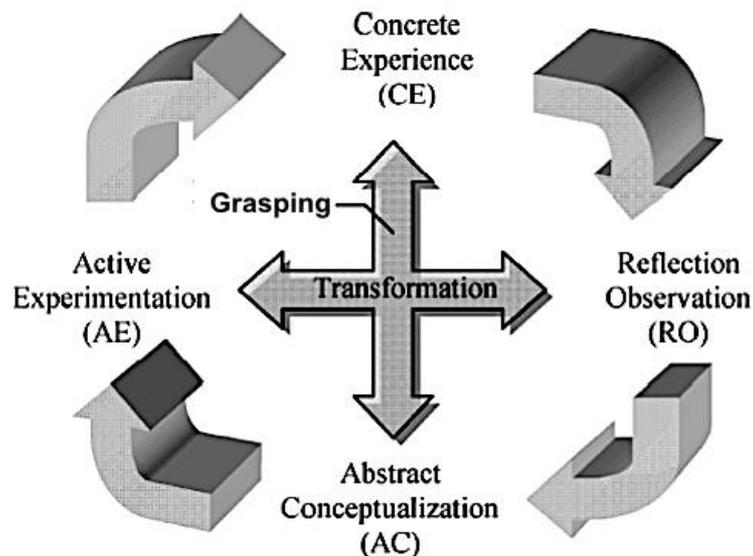


Figure 2.5: Kolb's experimental learning cycle. Adopted from Kamis and Topi (2007).

Knowing the learning style of the student is of great importance for educators, since this helps them in determining the right pedagogical approach (Fletcher *et al.*, 2008). Further, Garcia-Otero and Teddlie (1992) and Anitha and Deisy (2013) suggest that learners should be made aware of their learning style, as this helps them to have better understanding and quickly transform their acquired knowledge into practice. Moreover, Kolb has been aligned with the same thoughts, stressing that learners should know all the learning styles available for each of the learning modes and suggesting learning styles for each of the modes in the cyclic process. This involves four type of learning styles - activist, reflector, theorist and pragmatist (Kolb, 1976). However, Mumford and Honey (1986) feel that the learning styles suggested by Kolb do not satisfy all kind of learners. Later, Felder and Silverman (1988) developed a four dimensional model known as the index of learning styles, which served all the learning preferences with respect to Kolb's learning cycle and which was widely accepted in engineering academia (Woods *et al.*, 2000; Franzoni *et al.*, 2008; Hwang *et al.*, 2012).

2.3.2 The index of learning styles

Learning in a traditional engineering setting occurs through a two-stage process (Koob and Joanie, 2002) involving the reception and processing of information. At the reception stage, the teacher presents the information and students observe what they require and ignore the rest. The second stage involves the processing of the received information by memorizing or reflecting on their previous knowledge, or by interacting with the tutor by asking for further explanation. Felder and Silverman (1988) classify learners using four dimensions and asking the following questions:

- What type of information does the student tend to perceive? – Sensory or Intuitive learners
- What kind of sensory channel is more effective in transferring the information to the student? – Visual or Auditory learners
- How does the student prefer to process the received information as knowledge? – Active or Reflective / Inductive or Deductive
- Finally, how does the student progress towards understanding? – Global or Sequential learners

With these four proposed dimensions, the learning style and its corresponding teaching style can theoretically be classified into 32 or (2^5) diverse styles to satisfy each of the learner's preferences (see Figure 2.6).

<i>Preferred Learning Style</i>		<i>Corresponding Teaching Style</i>	
sensory	} perception	concrete	} content
intuitive		abstract	
visual	} input	visual	} presentation
auditory		verbal	
inductive	} organization	inductive	} organization
deductive		deductive	
active	} processing	active	} student participation
reflective		passive	
sequential	} understanding	sequential	} perspective
global		global	

Figure 2.6: Dimensions of learning and teaching styles. Source: Felder and Silverman (1988).

(a) Sensory and intuitive learners

Jung (1971) introduced the theory of sensory and intuition, as the two ways in which students tend to perceive taught concepts. Sensory students observe and gather information through their direct senses, such as listening, seeing or feeling. On the other hand, intuitive students perceive the information through the unconscious mind in indirect ways such as through the imagination, instincts and assumptions. According to Carlyn (1977), every learner can use both these ways of perception, but most of the time they tend to use only one of them. Later, this theory was further developed as an instrument known as the Myers-Briggs Type Indicator (MBTI) to measure the degree to which the learner prefers sensory or intuition in perceiving information (Briggs, 1998). The MBTI has helped the education provider, industries and other training institutes for decades to access the learning styles and various behavioural tendencies of learners. Most of the engineering subjects taught in the classroom emphasize the intuitive teaching-style and involve traditional lectures and use of words and symbols to convey the information. Godleski's (1984) studies have suggested that most

engineering learners are of the sensing type, thereby emphasising the major mismatch between the teaching and learning styles in present engineering taught subjects. However, Beetham and Sharpe's (2013) and Demirkan's (2016) studies suggest that both types are important in engineering education, as engineering tasks require a sound understanding of theoretical principles and experimental processes. Therefore, Kereluik *et al.* (2013) suggests that for engineering education to be effective the material presented should be understandable to both types of learners. The next section further classifies sensory and intuitive learner styles in receiving information.

(b) Visual and auditory learners

Students generally receive information in three different ways. Some remember things by seeing pictures, diagrams and demonstrations; these are classified as visual learners. Others remember things through listening to verbal explanations rather than visual demonstration, and are classified as auditory learners. The remaining learners are kinaesthetic; they remember things by performing activities related to the taught concept or theories. According to Koh and Chua (2012), most college students are either visual or kinesthetic. However, the information presented by teachers is largely through lectures (auditory) or through a visual representation of the lecture information consisting of words and mathematical symbols. Gohardani *et al.* (2014) and Abante *et al.* (2014) believe that irrespective of the mismatch in teaching and learning styles, delivering lectures (auditory style) with some visual content is the optimal way of teaching all students satisfactorily. This is also evident from the study conducted by Stice (1987) on the Socony vacuum oil company, which measured the efficiency and degree of information retention among all three types of learners; about 10 percent of the students retained what they learned through reading and 26 percent of them managed to retain this by listening to the information presented. The retention rate

increased when they used a combination of learning techniques; 50 percent of them managed to retain the information by learning through seeing and listening, and more than 90 percent by listening and then by performing activities. Consequently, Özyurt and Hacer (2015) suggest that engineering institutes should have a blend between lectures (auditory and visual) and hands-on tasks (kinaesthetic) in order to achieve higher information retention among different kinds of learners.

(c) Inductive and deductive learners

Students process received information in two ways; the inductive is more of a natural human learning style, in which students process the information by relating to their own experience rather than to a defined set of principles. On the other hand, the deductive is more of a natural human teaching style, in which students relate the received information to taught engineering principles (Prince and Felder, 2006). According to Chaturvedi and Haider (2015), most of the engineering curriculum falls under the deductive style, in which teachers start from basic fundamentals and then procedurally move toward design and development. Further, Felder and Silverman's (1988) study identified how teachers viewed themselves with respect to inductive or deductive styles; out of 46 professors, half identified themselves as purely deductive, meaning they required their students to follow taught principles rather than learning through their own creative thoughts. Kolb (2014) states that even though the deductive is an elegant way of teaching, students become more dependent on their teachers to solve problems rather than solving them by themselves. Spitzer (2013), Daly *et al.* (2014) and Barak (2016) support this by stating that inductive teaching is vital for engineering learners, as it increases problem solving abilities, academic achievement, creative thoughts and information retention. Ahmad *et al.* (2014) and Wankat and Oreovicz (2015) suggest a mixed method approach to satisfy both deductive and inductive learners by using a

deductive style to teach the theoretical principles and then using inductive style activities to transfer the taught principles to physical problems.

(d) Active and reflective learners

After receiving and processing the information through either of the above styles, students convert it into knowledge, which can be further classified into two categories (KoIb, 2014). Knowledge acquired through active experimentation is based on performing some physical activity in testing the processed information, whereas reflective observation is more passive, involving examination or manipulation of the processed information when converting it into knowledge. According to Entwistle and Ramsden (2015), most engineering students are active experimentation learners and Goltz-Wasiucioneck and Wierzbicka (2016) state that learners who fall under sensory type mostly acquire their knowledge through active experimentation. However, Cox and Tsai (2013) disagree on the dependence between sensory and active styles, claiming that after perceiving information sensory learners could acquire knowledge either through active experimentation or by reflective observation. According to Ozaktas (2013), active learners do not process knowledge through symbolizing, but require some kind of experimentation in order to do so. However, the outcome of the performed experiments requires reflection to acquire long-term knowledge retention and thereby suggests that both are of equal importance. In addition, although the way of processing the knowledge is classified into two categories, Kim *et al.* (2013) and Loeb (2015) believe that both the active and reflective go hand in hand by allowing engineering learners to have a better understanding of fundamental ideas through reflective knowledge and evaluation of ideas through active experimentation. The following section discusses different ways of presenting learning material for students with the different learning styles discussed above.

(e) Sequential and global learners

Learning material in most of engineering institutes is presented in a sequential way, in which once the student has learnt and mastered the presented information, they then move on to the next level (Felder and Soloman, 2000). However, this type of presentation does not suit learners who take longer to understand the presented material than other students. Silverman (1987) classifies the former/latter as global learners, who jump directly to more complex stages, rather than progressing steadily. According to Watterson *et al.* (2013), presenting the learning material in a global way to suit global learners is difficult within the academic timeline, although Hanna and Latchem (2013) state that global learners are more important for the future of engineering, as they can think about and correlate solutions from multidisciplinary domains. Stieger *et al.*'s (2014) and Pervin *et al.*'s (2015) studies have suggested that global learners have a higher risk of dropping out from engineering education, as they struggle to keep pace with their fellow classmates in meeting the expectations of the teacher. Daly *et al.* (2014) suggest that this could be addressed by providing adequate time and by encouraging students to think out-of-box through creative tasks involving multidisciplinary learning materials.

Although the learning style is of great importance for knowledge acquisition, engineering academics believe it is not only about knowledge acquisition, but also the ability to apply the knowledge in real world situations (Savery, 2015). According to Otero *et al.* (2015), imparting such a lifelong learning experience requires appropriate teaching, rigorous curricula and assessment methods in place to test the level of thinking that an individual has achieved through the performed learning task. The following section presents a review of the theories and attributes involved in levels of

thinking, depth of knowledge and rigor required for engineering learning and teaching processes.

2.3.3 Levels of thinking and assessment theories involved in engineering learning

(a) Bloom's taxonomy

Taxonomy means a set of classification principles or categories. Bloom originally identified three taxonomical models for educational activists, but most educationists paid attention to the one that was associated with thinking skills (Churches, 2008). Over 50 years Bloom's taxonomy has helped academia to formulate learning and teaching methods to impart and assess learners' thinking skills over a wide range of cognitive complexities (Bloom *et al.*, 1956). However, this was revised by Anderson *et al.* (2001), educational researchers who kept the overall principle of the taxonomy but changed some of its terminology and structure to make it relevant to 21st century work; this is referred to as the revised Bloom's taxonomy (Figure 2.7). The taxonomy is viewed from bottom to top, the lowest level representing the 'remembering' or recalling of the information presented. The second from bottom represents 'understanding', testing whether students can explain the ideas or concepts, while the third level represents the 'applying' of acquired information to a new idea. The fourth level represents the 'analysing' of ideas by segmenting them into different parts and the fifth and sixth levels represent 'evaluating' and 'creating', whereby students justify their stand point and start developing new products or points of view from their existing knowledge. In this model, each level requires appropriate teaching and assessment methods to respond to the learners (Goel and Nalin, 2004).

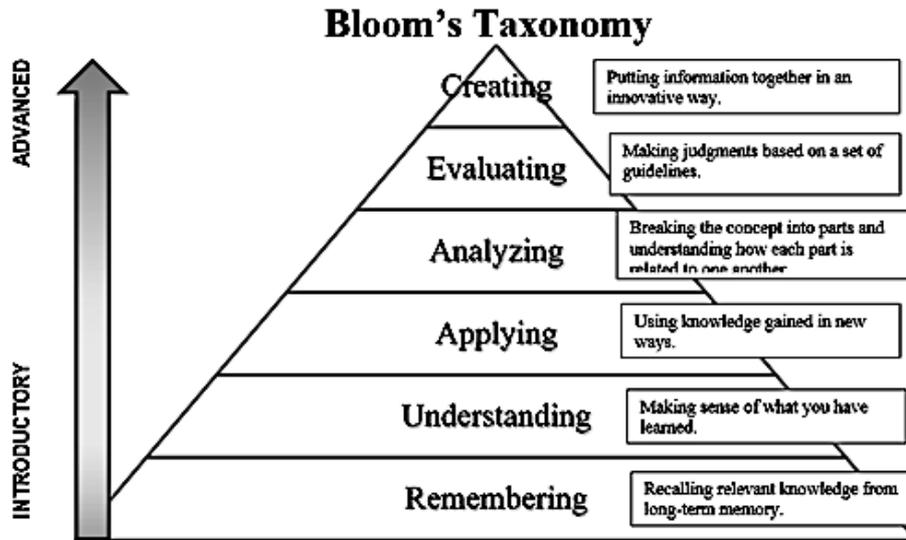


Figure 2.7: Revised Bloom's taxonomy. Source: Baruch College (2014).

According to Cannon and Feinstein (2014), even though teachers were able to formulate questions to address each of the distinct thinking processes, Bloom's taxonomy still offered insufficient guidance for formulating activities and assessing them. In addition, Holmes (2012) points out the gap between the taxonomy levels and the depth of understanding required to achieve the learning outcomes set for each level, resulting in the problem of designing clear assessment strategies. To address this, Norman Webb suggested a new measure of rigour in bridging this gap through Depth of Knowledge (DOK) theory, which is explained in detail in the section below.

(b) Webb's Depth of Knowledge

Webb developed a theory known as Depth of Knowledge (DOK) to assess the rigour of the student; in other words, how deeply the student has understood the related content (Webb, 1997, 1999). He proposed four DOK levels (Figure 2.8) and suggested that educators should define both content assessment as well as the required task assessment at each DOK level to address assessment problems (Webb, 2002). In other words, each of the DOK levels consists of standard understanding in relation to the content and also the actual required understanding in relation to the designed task. Goodson (2014)

(c) Hess' Cognitive Rigor Matrix

Hess combined Bloom's taxonomy and Webb's DOK to form a comprehensive structure known as the Cognitive Rigor (CR) Matrix which allows educators to examine both students' thinking capacity and rigour in performing the learning task (Hess, 2012). By making them sit in one matrix, Hess eliminated the complexities by allowing them to share many common features (Figure 2.9). In mathematical terms, Bloom's taxonomical levels reside on the y-axis, while Webb's DOK levels are arranged on the x-axis with respect to each of Bloom's cognitive levels. Although the Hess CR matrix is relatively new, its usefulness has been acknowledged in many instructional studies (Walkup (2014); Goldman and Zielezinski, 2016; Weldon *et al.*, 2016). Simpson *et al.* (2015) state that the CR matrix, apart from providing a single view, also helps educators to identify appropriate teaching processes and assessment strategies. Furthermore, the CR matrix allows educators to plot the cognitive rigour achieved at each intersection of the matrix and to analyse it in relation to other cells that have under- or over-performed.

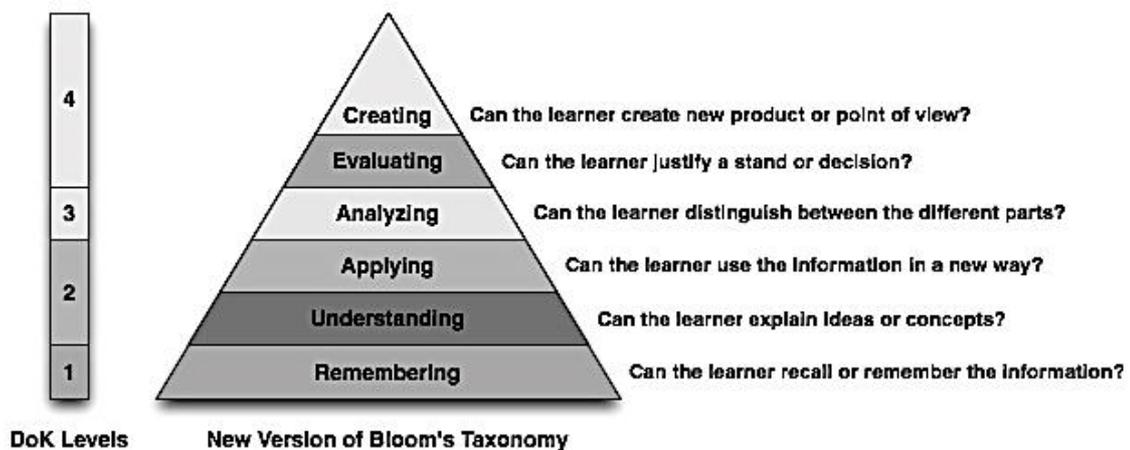


Figure 2.9: Hess' Cognitive Rigor matrix, integrating the DOK levels of Bloom's taxonomy levels. Adapted from Edtech (2015).

From the above literature we can conclude that both Bloom's taxonomy and Webb's DOK have played an important role in assisting engineering educators to design a more creative skills development curriculum with appropriate assessment incorporated. Further, with Hess' Cognitive Rigor matrix, the complexity of content of the two cognitive measures was reduced by having a matrix intersection which enhanced usability for educators to design and develop teaching and assessment processes for all kinds of students across different subjects and grades. Having said that, imparting and assessing these creative skills and knowledge in an on-campus environment through traditional teaching and assessment strategies by adopting the cognitive and rigour measures discussed above is already in place (Cormier and Hagman, 2014; Rolston and Cox, 2015). But it becomes a huge challenge for engineering educators to impart and assess the skills and knowledge of their distance learners (Deborah *et al.*, 2014; Brinson (2015), which leads us to our next review topic: distance learning and its methods of evaluation with respect to engineering.

2.4 Distance learning background

Distance learning in general is defined as the paradigm that provides formal education, in which the learners are geographically separated, and information and telecommunications technology (ICT) are used to connect learners, teachers and resources (Simonson *et al.*, 2014). According to Schlosser and Simonson (2006), distance learning comprises four components (see Figure 2.10). The first component refers to the education provider, who offers the distance learning and the second component represents the targeted participants. The third and fourth components are the methods and communication channels through which the learning experience takes place. According to Moore (2007), with respect to these four components the purpose of distance learning for any subject can be clearly defined. The root of distance learning

is at least 100 years old; mid-19th century Europe and the United States initially provided correspondence education to those with physical disabilities and women, who were not allowed to enrol in educational institutions, which were open only to men (Holmberg, 1986; Moore and Kearsley, 2011). With the advancement in technology, institutes started offering full degree programs and student enrolment on these courses continues to rise (Brown and Duguid, 1996; Allen and Seaman, 2007a, 2007b). This educational advancement was known as e-learning (Moore *et al.*, 2011).

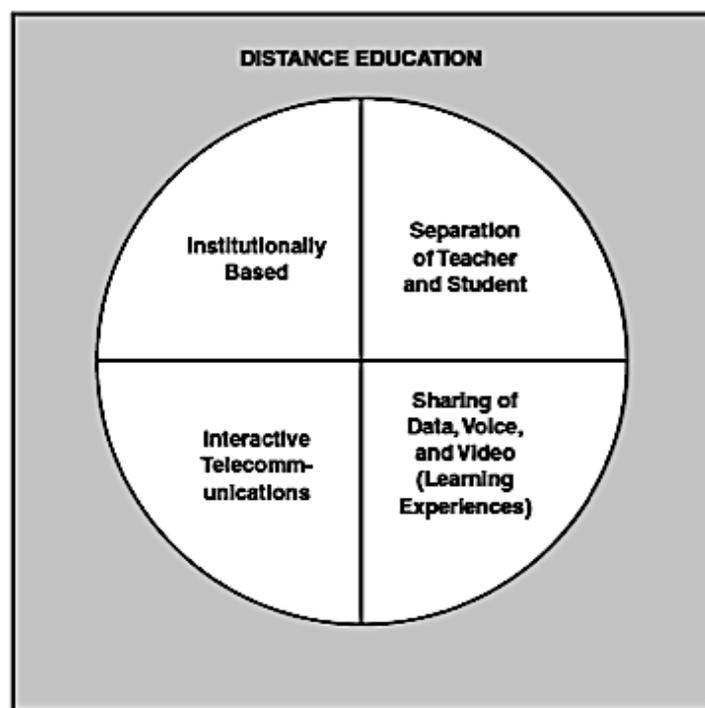


Figure 2.10: Four components of distance education. Adapted from Schlosser and Simonson (2006).

This development changed the distance learning approach across the globe, with traditional text books and course curricula made available online round the clock (Barbour and Reeves, 2009; Means *et al.*, 2014). The e-learning platform can be traced back to the early 1970s, when a small web-based system was used in teaching mathematics (Zhang and Nunamaker, 2003; Stevens, 2004). From then, the e-learning platform and the learning outcomes achieved from it have grown rapidly, which is

evident from the recent report by Allen and Seaman (2015), which states that learning outcomes have grown from 57.2% in 2003 to 77.0% in 2012, but then decreased in 2013 to 74.1%. However, Brinson (2015) explains that these learning outcomes were not for science courses involving a physical laboratory presence. Moreover, Murphy and Manzanares' (2008a) studies also show that e-learning is of more benefit for learning theoretical concepts, rather than courses that depend heavily upon physical practical tasks with tutor intervention, which are difficult to implement (Rajaei and Aldhalaan, 2011).

Gurkan *et al.* (2008) believe that teaching practical-based courses through an e-learning environment by the use of electronic text, images and videos is no different from traditional classroom teaching. However, Moor and Piergiovanni (2003) and Abdulwahed and Nagy (2009) argue that traditional methods are the best way to teach practical subjects, as the e-learning platform fails to provide the hands on experience gained in a traditional method with real tutor involvement and appropriate rigour. Nonetheless, efforts made by the UK Open University and a few other engineering distance-learning educators have shown clear progression towards achieving these practical criteria in a distance learning mode (Liyanagunawardena *et al.*, 2013; Cooper and Sahami, 2013; Bates, 2014). Moreover, to overcome this issue, many institutes and research organizations have tried to expand the e-learning platform by using various technologies to enhance the practical learning experience, resulting in the development of several remote and virtual laboratories with various new deliverable technologies (Murphy and Manzanares' (2008b)). The following section critically reviews the different distance learning technologies that have been used in engineering education.

2.4.1 Engineering distance learning approaches

Several distance education thinkers, such as Andrew (2000), Zubía and Alves, 2012; Laurillard (2013) and Beetham and Sharpe (2013) have proposed various ideas and practices for teaching and assessing practical skills for engineering distance learners. Among these ideas, allowing students to take laboratory classes from local colleges, permitting them to access on-campus laboratory equipment through the internet, and allowing them to practise through computer simulation are the three methods mostly implemented by distance learning educators. These three delivery methods are commonly known as study centres, remote laboratories and virtual laboratories respectively. To date, engineering in distance learning modes uses these three approaches to teach laboratory skills (Tait, 2000). The first approach involves study centres, where the practical skills are imparted and assessed. These test centres are usually engineering colleges or polytechnics which are located within accessible distance for the distance learners. Moreover, these centres are mostly not under full control of the distance educator, hence the support or assessment carried out may not be up to the standard of the distance educator's on-campus standard (Bates, 2005).

The second approach involves a physical laboratory that provides remote access by using remote sensors, known as remote laboratories. These are similar to traditional laboratories, requiring space and physical equipment, and thus the cost of implementing and maintaining them is more or less the same. The characteristics that separate a remote laboratory from a traditional one are the distance between the learner and the equipment required to perform experiments (Gravier *et al.*, 2008). The third approach involves replacing the physical laboratory with a digital software-based laboratory, known as a virtual laboratory. This differs from the other two approaches in terms of two different characteristics: first, neither the equipment nor the environment exists in

reality, meaning the students and the equipment are in no danger of being hurt or damaged (Balamuralithara and Woods, 2009). In addition, in the virtual laboratory, apart from observing and performing practical task with the equipment, students also have the comfort of multiple opportunities to access resources and a greater amount of time to complete the practical tasks (Tzafestas *et al.*, 2006; Charuk, 2010).

However, the studies of Muster and Mistree (1989), Williams and Gani (1992); Dewhurst *et al.* (2000), Dibiase (2000) and Sicker *et al.* (2005) have presented virtual and remote laboratories as educational hindrances, while others such as Barnard (1985), Ertugrul (1998), Hartson *et al.* (1996), Livshitz and Sandler (1998), Magin and Kanapathipillai (2000), Raineri (2001), Finn *et al.* (2002) and Striegel (2001) in the past two decade have preferred remote and virtual laboratories as the delivery method for teaching their distance learners and have continued to advance their usability through various creative technologies (Table 2.1). Furthermore, Ma and Nickerson (2006) reminds that even though the above literatures have shown a positive impact on the distance learners by the use of remote and virtual laboratories, some have compromised over the usability issues influenced by cost and handling complexities, which have hindered the intended learning outcomes. Jakob Nielsen's (1994) heuristics are the most used usability heuristics in validating the non-traditional laboratories (Hollingsed and Novick, 2007 and de Guimar and Martins, 2014), where the usability can be measured through four different evaluation methods, which are *automatic*, *empirical*, *formal* and *informal*. The automatic one involves testing of the systems usability by running the user specifications through computer simulation.

Table 2.1: List of engineering virtual and remote laboratories developed for academic propose in the last decade. Adapted from Potkonjak et al. (2016)

Laboratory name/type	Field	Reference
COSIMIR / Virtual laboratory	Robotics	Freund and Pensky (2002) University of Dortmund, Germany
iLabs / Remote laboratory	Microelectronics	Harward <i>et al.</i> (2008) The Massachusetts Institute of Technology, USA
USARSim / Virtual laboratory	Robotics simulation	Carpin <i>et al.</i> (2007) University of Pittsburgh, USA
NetLab / Remote laboratory	Electronics	Nedic and Machotka (2007) University of South Australia
LiLa / Virtual laboratory	General engineering	Richter <i>et al.</i> (2011) University of Stuttgart, Germany
LabShare / Remote laboratory	Industrial electronics	Lowe <i>et al.</i> (2009) University of Technology Sydney, Australia
VccSSe / Virtual laboratory	Physics	Tlaczala <i>et al.</i> (2009) Valahia University of Targoviste, Romania
Situation Engine / Virtual laboratory	Construction	Newton <i>et al.</i> (2013) The University of New South Wales, Australia
VISIR / Remote laboratory	Electronics circuits	Tawfik <i>et al.</i> (2013) Spanish University for Distance Education (UNED), Madrid, Spain
TriLab / Virtual laboratory	General engineering	Abdulwahed and Nagy (2013) Loughborough University, UK

According to Karat (1994) this evaluation method does not formally work for all types of systems. The *empirical method* involves real users, in most cases, who are the domain experts assessing the usability of the system. The third and fourth methods are *formal* and *informal*, which use calculated usability measures and experts thumb rule, respectively. Among the four of them, empirical one is the most commonly used method to test remote and virtual laboratories (Tzafestas *et al.*, 2006 and Pescarin *et al.*, 2012). Although Desurvire (1994), Hix and Gabbard (2002) and Joshi *et al.* (2009) suggest that combining one or more methods would be ideal to achieve best results.

According to Brinson (2015), remote and virtual laboratories can be categorised under one group known as the ‘non-traditional’ laboratory, and he also suggests the use of technologies in these non-traditional laboratory methods has varied depending on the cost and complexity of the practical task that is being taught. The following sections review and explore the technological advancements and limitations of the two non-traditional laboratories.

2.4.2 Non-traditional laboratories (remote and virtual)

A virtual laboratory is a simulated model of a real laboratory, where the learner gains practical experimentation experience without physical contact (Mikropoulos and Natsis, 2011). On the other hand, a remote laboratory is a mediated reality, which is similar to a traditional on-campus laboratory, in that they both require space and real equipment (Forinash and Wisman, 2005; Fabregas *et al.*, 2011). Both these non-traditional laboratories eliminate limitations such as safety protocols and access time. Moreover, Cook *et al.* (2010) indicate that there is a high percentage of satisfaction when using non-traditional laboratories, although they do not replace the hands-on experience gained through traditional ones. Both these non-traditional laboratories have the same goal in terms of providing laboratory experience regardless of geographical boundaries by incorporating their own tools and techniques (Chaos *et al.*, 2013). However, Guimarães *et al.* (2003), Khalifa and Lam (2002), Scheckler (2003) and Shin and Chan (2004) state that examining their characteristics individually in their contribution to practical engineering learning is of great importance.

Gallardo *et al.* (2007) and Koutsabasis *et al.* (2012) point out aspects such as real time interaction with 3D models in the virtual laboratory and interaction with real equipment in remote laboratories as added value from them. Moreover, Nedic *et al.*'s (2003) study

clearly provides their overall advantages and disadvantages by comparing them with real laboratory functions and actions (Table 2.2). Burkle (2009) and Abdelaziz *et al.* (2014) state that the cost involved in running these laboratories is one of their major drawbacks, which is also evident from Sala's (2016) experience in implementing a virtual learning environment. In this regard, Steidley and Bachnak (2005) and Demeter *et al.* (2011) highlight the implementation strategies for availability and accessibility to technology as a critical bottleneck for virtual and remote learners. This is why policies and strategies are important to ensure readiness and retention in virtual learners. Barbour *et al.* (2011) supports these awareness measures by suggesting that a successful non-traditional laboratory is not only dependent on technology but also on the processes and strategies implemented to support the learning experience.

Table 2.2: Comparison between virtual and remote laboratories. Adapted from Nedic *et al.* (2003).

Laboratory Type	Advantages	Disadvantages
Virtual	<ul style="list-style-type: none"> - Effective interactive medium - No restriction over time and place - Low maintenance cost compared to remote laboratory - Compatible with multiple users 	<ul style="list-style-type: none"> - Lack of real-time collaboration - No interaction with real-equipment - Requires more time for development and implementation
Remote	<ul style="list-style-type: none"> - Interactive with real equipment - Provides realistic data - Real time collaboration with other users 	<ul style="list-style-type: none"> - Higher maintenance cost compared to virtual laboratory - Does not support multiple user access at the same time – requires scheduling - Limited to simple practical tasks

However, Barbour and Hill (2011) warn that the non-traditional laboratory framework should vary depending upon the nature of the course, and Fernandez *et al.* (2012) suggest that incorporating subject matter and technical expertise will ensure higher readiness and usefulness of the system. Studies by Nickerson *et al.* (2007), Balamuralithara and Woods (2009), Corter *et al.* (2011) and Pereira *et al.* (2012) have made comparisons between real, remote and virtual laboratories in terms of overall student practical experience, usability and other educational benefits, but their conclusions vary. According to Pereira (2012), use of simulation is not sufficient for a practical learning experience, and Corter *et al.* (2011) claim that use of remote or virtual laboratories may highly reduce motivation levels. However, Nickerson *et al.* (2007) find that the use of remote laboratories is no different from real ones. Moreover, Ma and Nickerson's (2006) study reviews the results from other literature and provides a summarised conclusion of non-traditional laboratories' contribution to the acquisition of practical skills under four characteristics: conceptual understanding, professional skills, design skills and social skills (see Figure 2.11). While the virtual laboratory is considered to be more beneficial in acquiring design and professional skills, Ma and Nickerson (2006) conclude their study by suggesting that the effectiveness of virtual and remote laboratories in learning outcomes seems to vary from study to study.

Further, the selection of either one of them as the delivery method would depend upon the nature of the practical task and the targeted participants. According to Hargis (2014) and Mettler and Pinto (2015), the education built around games-based environments has attracted a large online education community. Among these, virtual reality (VR) and augmented reality (AR) technology have been the latest trends in providing a fully immersive learning experience for distance learners. The following section explores

these two new technologies, which are considered to be revolutionary breakthroughs in providing an enhanced learning experience through virtual and augmented reality.

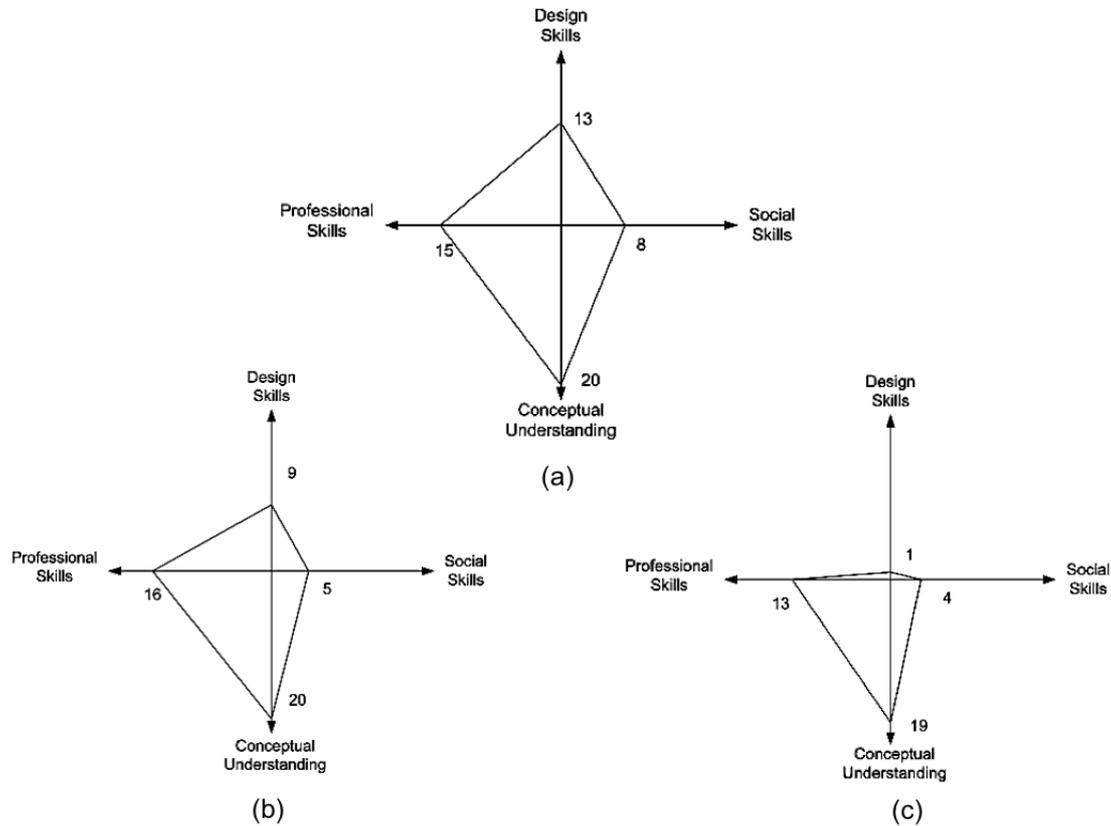


Figure 2.11: Comparison between real, virtual and remote laboratory practical learning outcomes. Adapted from Ma and Nickerson (2006).

2.4.3 Virtual and augmented reality

Recent advancements in computer technology, along with increased power and miniaturization in computer hardware, have allowed distance-learning educators to provide their learners with a fully immersive learning experience. Among these advancements, virtual and augmented reality technologies are currently being used in many educational applications (Lee, 2012; Wang *et al.*, 2013; Ong and Nee, 2013). The term “virtual reality (VR)” is a computer interface that provides the user with completely immersiveness within an experimental simulation (Pimentek and Teixeira, 1993).

According to Burdea and Coiffet (2003), VR is enhanced visualization experience providing more intuitive links between the computer and the user. Virtual reality allows users to step into the computer screen and walk through the 3-dimensional world, interacting with it (Seymour, 2008). The difference between augmented reality and virtual reality is their interface; in other words, in virtual reality the real environment is completely replaced by a virtual one, whereas augmented reality uses a real environment and superimposes virtual objects on it (Milgram and Kishino, 1994). Further, for Milgram *et al.* (1995) the reality-to-virtual continuum differentiates augmented and virtual reality in a much simpler way (see Figure 2.12), by having the real and virtual environments as the two ends, with augmented reality the intermediary between them.

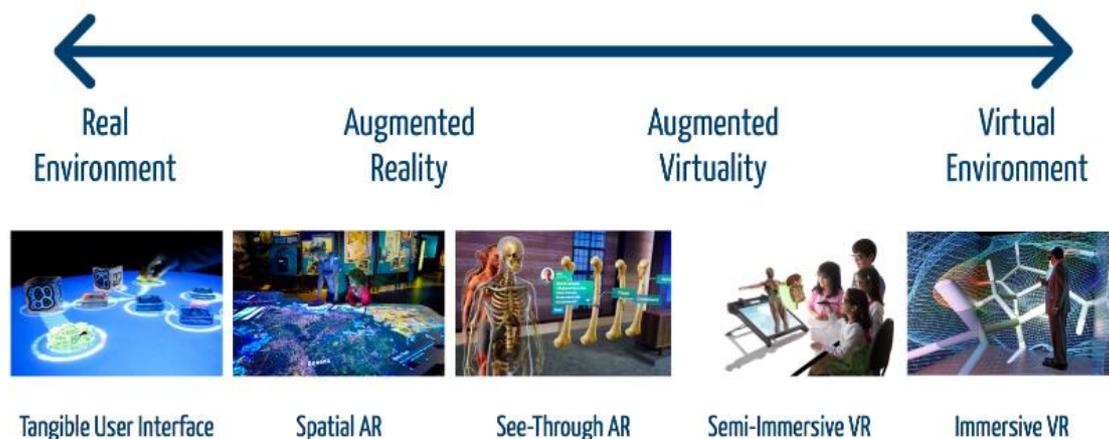


Figure 2.12: Reality-to-virtual continuum. Source: Milgram and Kishino (1994).

The concept of virtual and augmented reality can be traced back to the 1960s, when Sutherland (1968) developed a head-mounted see-through display (HMD) to provide virtual enrichment by overlaying graphics and sound on a person's natural sight and hearing (Figure 2.13). Later, this technique was further enhanced by researchers such as Robinett (1992), Quinn (1993), Bajura and Neumann (1995) and Webster *et al.* (1996), who designed and suggested new software and hardware to track user movement and provide visual information over the physical objects. However, Benford

et al. (1998), Azuma (1997) and Azuma *et al.* (2001) have argued that the VR and AR experience is simply one through a head-mounted display (HMD), but goes beyond that, by involving the use of daily devices such as computers and mobile phones.

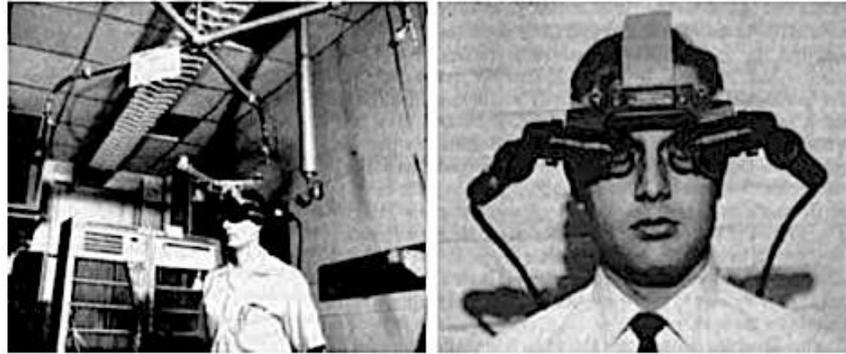


Figure 2.13: World's first AR head-mounted display. Source: Tamura (2002).

According to Shirley *et al.* (2008), one common principle that governs the display technique of both VR and AR is stereoscopic or binocular vision, where a single image is projected onto both eyes in creating a 3-dimensional illusion (Figure 2.14). Even though the origin of VR and AR can be traced back a long way, its commercial use in education and industry for training purposes was only recognized from 2007; according to Ong and Nee (2013), this was mainly because of the advancement in personal computer (PC) and mobile phone human-computer interfaces. In this past decade, the use of VR and AR in training skills has increasing been seen in military, industrial and educational sectors such as medicine, construction and engineering (Borrero and Márquez, 2012; Lele, 2013; Webel *et al.*, 2013). In particular, medical education institutes have used virtual reality integrated with haptic devices in the training of practical skills for their students (Nagendran *et al.*, 2013; Peterson and Robertson, 2013). Haptic devices are physical hand-held equipment that provide tactile feedback such as roughness, rigidity and temperature (Benali-Khoudja *et al.*, 2004). However, these devices are little used in augmented reality as they impede the use of real hand

activity (Buchmann *et al.*, 2004).

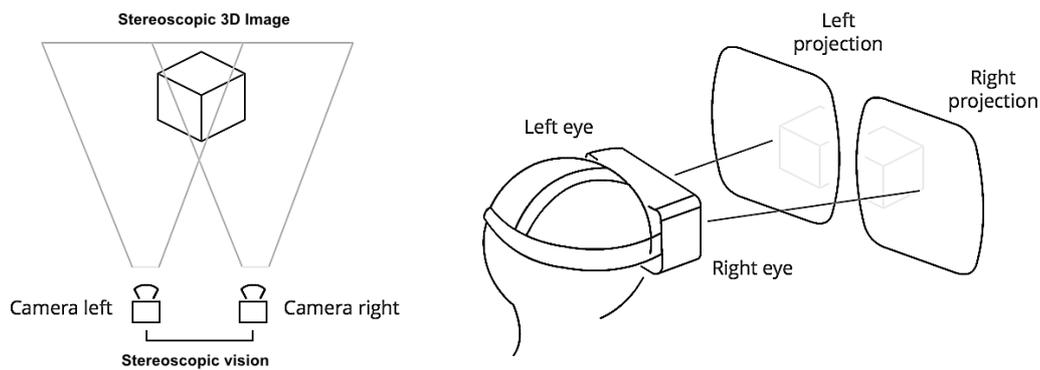


Figure 2.14: AR and VR stereoscopic vision principal. Source: Mozilla Developer Network (2016).

The use of AR is found more in engineering applications, where the movement of the real hand is tracked to draw a conclusion as to whether the user has performed the task in a correct manner or not (Foxlin and Harrington, 2000; Liarokapis *et al.*, 2004; Ahmad and Musilek, 2006; Tomi and Rambli, 2011). Fiorentino *et al.* (2002) developed an AR application that allowed the user to change car door design by visualising the virtual car door over the real one (see Figure 2.15). Apart from that, automotive industries such as Volkswagen and many others have used AR in augmenting design spec, interiors and actual crash tests (Vaissie and Rolland, 2000; Friedrich *et al.*, 2002; Tonnis *et al.*, 2005). Moreover, in training practical skills BMW, Volkswagen, Boeing and Airbus have used AR to improve their employees' welding, assembly and wiring skills (Curtis *et al.*, 1999; Piekarski and Thomas, 2001; Schowengerdt *et al.*, 2003; Willers, 2006). Zhou and Billingham (2008) believe with current development in VR and AR technology, training could be possible anywhere, as already envisioned by Licklider in the 1960s.

Similar to other technologies, even VR and AR have their limitations, in terms of field of view, focus depth, cost, weight, power and ergonomics, among others (Drascic and

Milgram, 1996; Azuma *et al.*, 2001; Vlahakis *et al.*, 2001; Wagner and Dieter, 2003; Bengler and Passaro, 2006; Saito *et al.*, 2008). With new emerging VR and AR technology such as Oculus, META and HoloLens these challenges are being addressed significantly and there are further increases in the use of these technologies in industry and education for training skills (META, 2016; Oculus, 2016; Microsoft HoloLens, 2016; Castar, 2016; HTCvive, 2016).

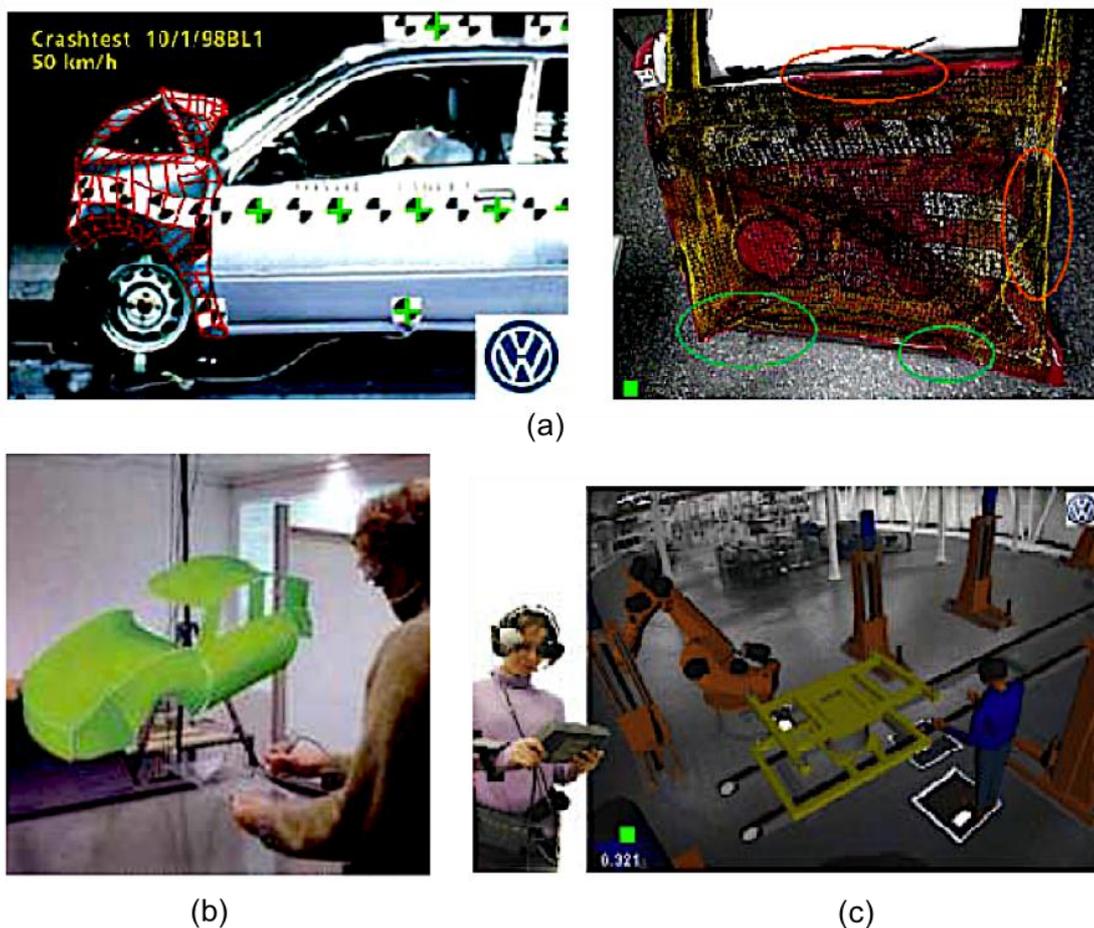


Figure 2.15: AR technology used in industrial applications: (a) Volkswagen's AR after car crash analysis, (b) a car body resized through AR and (c) AR-assisted factory and plant planning. Adapted from Fiorentino *et al.* (2002) and Friedrich *et al.* (2002).

Although different literature has incorporated the use of virtual or remote laboratories with VR and AR technology (Chen *et al.*, 2010; Wang and Xu 2010; Chen *et al.*, 2011; Potkonjak *et al.*, 2016) to enhance the practical experience from a technical point-of-

view, these fail to incorporate an experimental learning cycle with tutors' knowledge included. In engineering education, development of subject knowledge along with practical skills is set to be vital, as these skills prepare the student to solve real world problems (Splitt, 2003). Engineering practical skills mean the physical hands-on skills required in performing activities using engineering equipment, tools and techniques. In an on-campus environment, learning practical skills is associated with a physical laboratory, equipment and lab instructor. The laboratory instructor is the source of knowledge for the students, explains and demonstrates the experiment, and assesses their performance by providing feedback (Prince and Felder, 2006; Wankat and Oreovicz 2015). Different practical skills taught have different complexity levels and require varying levels of knowledge and skills in executing them (see Figure 2.16). According to Ferris and Aziz (2005), this knowledge and the skills of physical dexterity along with understanding of the procedure, processes and sequences required to execute the practical task are imparted frequently through the tutor's visual clues, text and audio prompts.

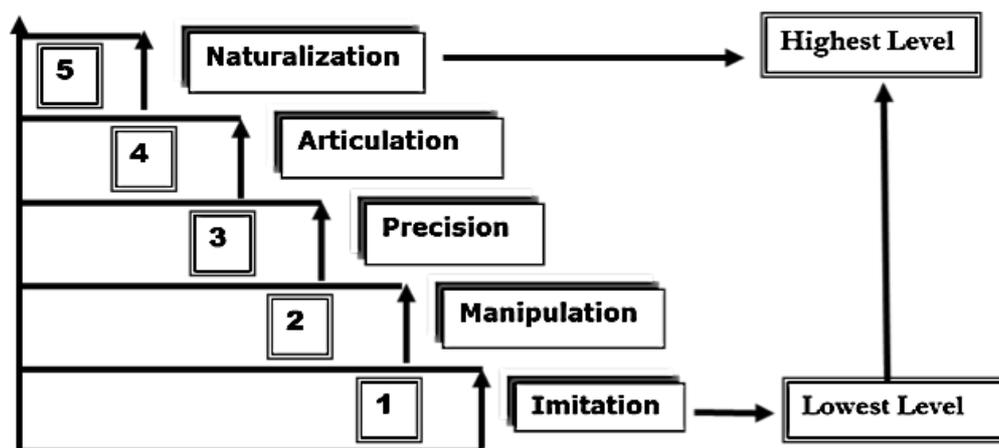


Figure 2.16: Taxonomy of psychomotor domain. Source: Ferris and Aziz (2005).

Apart from that, learning these practical tasks also depends upon the learning style of each individual. For instance, some students may be tentative in grasping and acquiring

the practical skills with less iteration, whereas others may observe, analyse and repeat several times before achieving them. In a traditional environment, the lab instructor alters the procedure and the teaching style depending upon students' cognitive rigour and the complexity of the task and provides feedback for each individual to improve their practical skills (Litzinger *et al.*, 2011). When delivering these to distance learners it becomes more complex, as the learner and teacher are physical separated from each other. However, with the use of new technology through virtual/remote laboratories teaching and assessing can be automated by capturing the knowledge from the instructor. But this captured knowledge has to be mapped to the right rules to provide appropriate feedback. Furthermore, hands-on experience is more achievable in an on-campus environment than a distance-learning one (Fabregas *et al.*, 2011; Al-Samarraie *et al.*, 2013). According to Bennett and Lockyer (2004), Aguilar *et al.* (2011) and Vidal-Castro *et al.* (2012) the 'know-how' practical skills in courses such as mechanical and automotive engineering are set to become vital, but delivering them to students away from the on-campus environment has caused the following two key challenges.

2.5 Challenge one: imparting practical skills to engineering distance learners

Distance learners have more diversity in their learning styles as they come from different geographical locations, with varying subject knowledge and work experience (Andrade, 2013). According to Anitha and Deisy (2013), recognizing their preferences and providing flexibility are important factors in developing their practical skills. Further, by making students sit in front of a computer for long hours listening to a lecture or doing some keyboard and mouse-based tasks becomes frustrating (Gallace *et al.*, 2012). As pointed out in the literature above, apart from the physical equipment and environment, the laboratory tutor plays an important role in developing engineering

skills (Prince and Felder, 2006; Wankat and Oreovicz 2015). However, there has been very little literature on how to capture and model laboratory tutors' knowledge for imparting practical skill development in distance modes (Sottolare *et al.*, 2013; Li and Zhou, 2015). Moreover, embedding and automating this knowledge into distance learning technology to assess and provide feedback has been the second major challenge (Butler, 2013; Mohammad *et al.*, 2013; Wenger, 2014).

2.6 Challenge two: assessing practical skills in engineering distance learners

As part of skills development, assessment also plays a very important role (Treffinger and Patricia, 2012). Moreover, practical assessment cannot be determined by pen and paper, as it involves several parameters such as fundamental, procedural, executional ones, which require experienced individuals to assess them (Hurst *et al.*, 2013; Wickens *et al.*, 2015). The assessment process that has been carried out by the laboratory tutor in the traditional on-campus environment is tedious, and automating such a complex process has been little explored with respect to the engineering educational domain (Porayska-Pomsta *et al.*, 2013; Ammor *et al.*, 2014). However, Holden *at al.* (2012), Lajoie and Derry (2013) and Aggelopoulou *et al.* (2014) suggest that the process of knowledge capturing and automation have been explored more in other domains and could be adapted to local settings. This has lead us to explore and review the capturing, modelling and automation principles and techniques that have been used in other domains and to further explore how this can help to bridge the gap between the on-campus tutor and off-campus learners.

2.7 Knowledge capturing, modelling and automation approaches and practices

During the past 200 years there have been a number of revolutions in the field of automation, mainly in three main sectors: the agricultural, industrial and service (Wu and Shaw, 2011). The goal of automation is to decrease costs and increase efficiency, reusability and reliability. According to Freiberg *et al.* (2012), for knowledge automation, irrespective of the field, there are three primary requirements that need to be satisfied: the capturing of available knowledge, the modelling of acquired knowledge in a meaningful way, and finally the codifying of the knowledge into desired applications. At present, the education sector is undergoing a revolution in automating instructional delivery, using Intelligent Tutoring Systems (ITSs) at a minimal cost to provide improved accessibility and achieve better learning outcomes by providing individualized learning experiences (Zvonov *et al.*, 2008; Rus *et al.*, 2013; Kulik and Fletcher, 2015). However, the key challenge, as pointed out above, remains underexplored in the literature and there is a lack of standard approaches and practices that could be used in capturing, modelling and automating tutors' knowledge. Although Brown and Duguid (2000) claim that education today is no different from business, as the need for knowledge acquisition from subject experts is of equal importance. Therefore, they suggest re-engineering the industrial knowledge capturing, modelling and automation approach that is been practised and refined for a number of years in terms of educational automation. This is reiterated by Jones and Sallis (2013), who believe that it is now time to spread the benefits of this revolution in education, especially the new approach of distance learning (DL) based on technology.

According to Alavi and Leidner (2001), knowledge differs from raw data and information, as it is personalized and exists only in an individual's mind. Thus,

capturing this personalized knowledge and transforming it in an interpretable way is a difficult task (Nottingham and Park, 1999; Feghali and El-Den 2008). In the industrial context, many organizations have resolved these issues by adapting various knowledge acquisition and automation methods and techniques (Davenport and Prusak, 2000; Chapman and Pinfold, 2001; Akhavan *et al.*, 2014), as most consider 'knowledge' to be the resource that gives them a sustainable competitive advantage through improved productivity and innovation (Drucker, 1993; Kamara *et al.*, 2002). The practices of expert knowledge acquisition for automating industrial applications can be traced back to the 1970s; there is varied literature on the refinement of standards for knowledge automation through appropriate capturing and modelling techniques (Buchanan and Shortliffe, 1984; Tschritzis *et al.*, 1987; Neale, 1988; Grant and Baden-Fuller, 1995). In 1994, Nonaka categorised knowledge into two dimensions: that which is extracted from pre-existing resources such as books or documents is known as explicit knowledge; whereas the knowledge that is embodied in experts' minds is known as tacit knowledge.

Nonaka and Takeuchi (1995) call this the knowledge spiral, where knowledge creation occurs by these two knowledge dimensions interacting continuously with each other through four phases: socialization, externalization, combination, and internalization (see Figure 2.17). Socialization and externalization create knowledge sharing, then convert the acquired tacit knowledge into a human-interpretable knowledge model; with combination and internalization, however, it is the opposite, involving transformation of simple human- interpretable explicit knowledge into complex tacit knowledge (Nonaka and Konno, 1998). When it comes to acquiring tacit knowledge, Scharmer (2000, 2001) claims that capturing should target expert embodied knowledge as well as not-yet-embodied knowledge, by asking 'what-if' questions or creating

situations to trigger new ideas, solutions or designs that experts may previously not have considered. Alavi and Leidner (1999) and Feghali and El-Den (2008) believe that capturing both these types of knowledge allow the receiving individual, group or organization to analyze better and reflect on the procedure, process and standards for actions that pre-existed alongside the individual's actual actions.

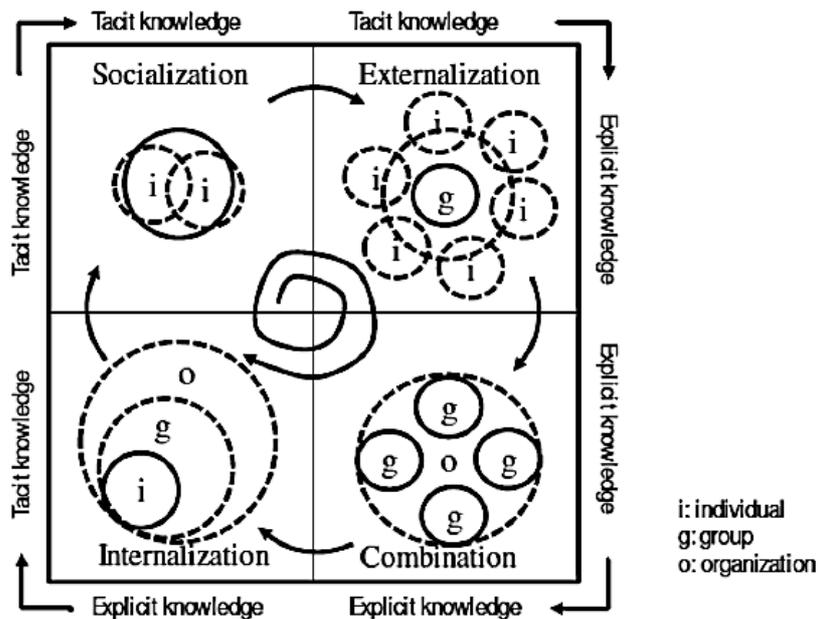


Figure 2.17: Nonaka's knowledge model. Adapted from Nonaka and Konno (1998).

Apart from capturing experts' tacit knowledge, for automation we require the formulizing as well as the codifying of knowledge into applications; each of these processes requires a combination of tools and techniques (Minsky 1975; Uschold, 1996; Balconi, 2002). In recent years, some researchers and industrial experts have combined these three processes into a single methodology to decrease knowledge automation complexity (Chandrasegaran *et al.*, 2013; Xu *et al.*, 2014). These knowledge-based systems (or Expert systems) have been extensively used for various industrial knowledge automation (Figure 2.18). The root of knowledge-based systems (KBS) is artificial intelligence (AI), which can be traced back to the early 1970s (Negnevitsky, 2005). Similar to human experts, KBS is capable of solving posed

problems through their inference mechanism involving dependency and reasoning techniques (Lassila, 1991; Rumbaugh *et al.*, 1991). Although the solutions are limited to the body of knowledge that has been captured and modelled in the system, Shortliffe (1976) and Englemore and Feigenbaum (1993) call this the knowledge-base (KB); moreover, this knowledge-base (KB) is retrievable in two different ways, known as rules and frames. According to Milton (2008), rules are a set of what-if constructs, whereas frames are a set of slots that consist of attributes linked to a set of what-if constructs.

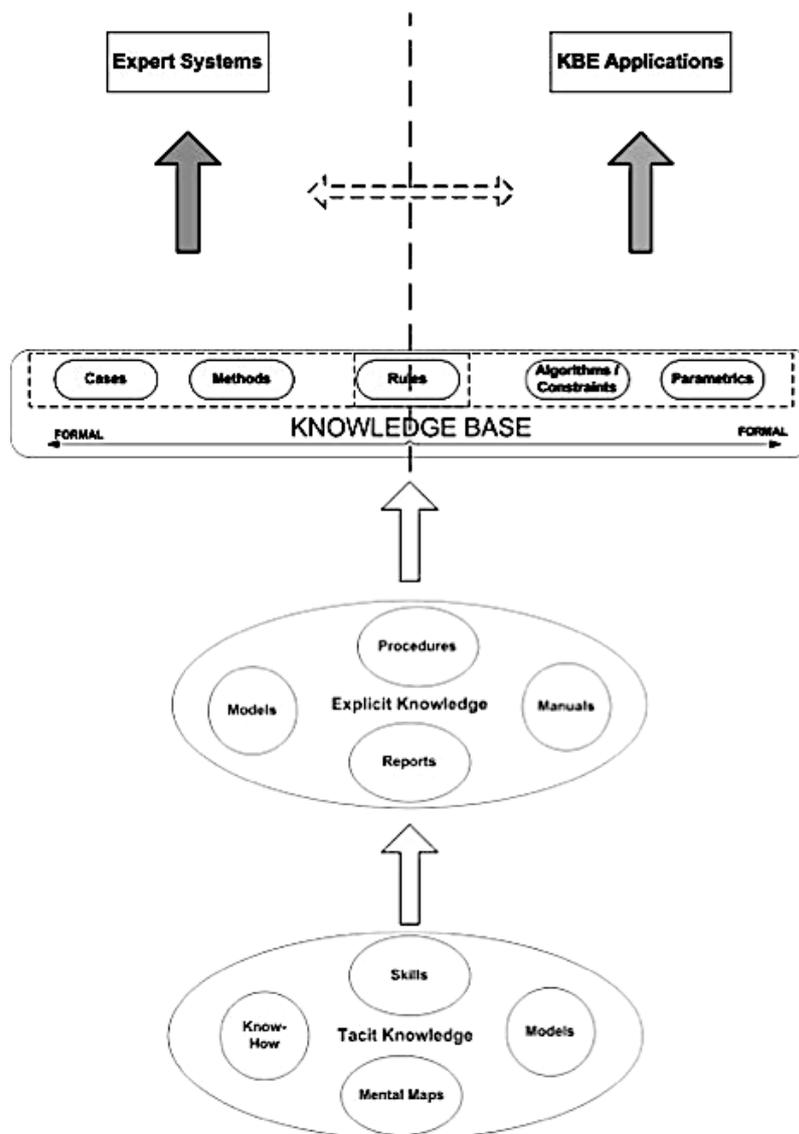


Figure 2.18: Knowledge automation framework. Source: Curran *et al.* (2010).

Even though the ways of retrieving the knowledge differ (rule-based or frame-based), the barrier for both was the methodology adapted to capture and formalize the knowledge (Shreiber 2000; Milton, 2007). However, the use of KBS was not tailored to engineering automation; later the KBS methodology was re-engineered to solve engineering problems known as knowledge-based engineering (KBE) (Lovett *et al.*, 2000; La Rocca and Van Tooren, 2007). This eventually mimicked human experts through knowledge automation by robust capturing and modelling techniques (Chapman and Pinfold, 1999). The following section explores in detail knowledge-based engineering (KBE) methods and techniques that have been used to capture, model and codify expert knowledge for knowledge automation.

2.7.1. Knowledge-based engineering (KBE) approach

Knowledge-based engineering is a research field that explores and develops methodologies and technologies for capturing, modelling and re-using expert knowledge. Its definitions by Sainter *et al.* (2000), Chapman and Pinfold (1999), Fan *et al.* (2002), Cooper and La Rocca (2007) and Van-der-Laan (2008) have varied. Ammar-Khodja *et al.* (2008) explain that however different the definitions may be, the core concept in each of them remains the same. According to Chapman and Pinfold (2001), KBE is more than a methodology, as it represents a revolutionary step in automating the captured and modelled knowledge through artificial intelligence (AI). The origin of KBE can be traced back to the early 1980s, when industries needed a large number of product variants to meet individual customer needs (Tseng and Jiao, 1996; Cooper and Fan, 1999; Wognum and Trappey, 2008). This required the capturing, modelling and automation of design experts' knowledge into an application to produce rapid and modular product design in a cost effective way (Elgh, 2008; Danjou *et al.*, 2008). According to Cooper and La Rocca (2007) and Van-der-Laan

(2008), the core of KBE relies on the precision of rules that has been captured from the experts, although Fan *et al.* (2002) and Baxter *et al.* (2007) point out that acquisition of this knowledge is complex, as it is neither easily accessible nor understandable.

There are a number of KBE methodologies that help in strategizing how to develop a KBE application by capturing, modelling and automating knowledge (Sleeman, 2002; Lovett *et al.*, 2000; Skarka, 2007; Van-der-Laan, 2008; Curran *et al.*, 2010). Among these, MOKA methodology is the most well known one, and is carried out through six phases (Figure 2.19).

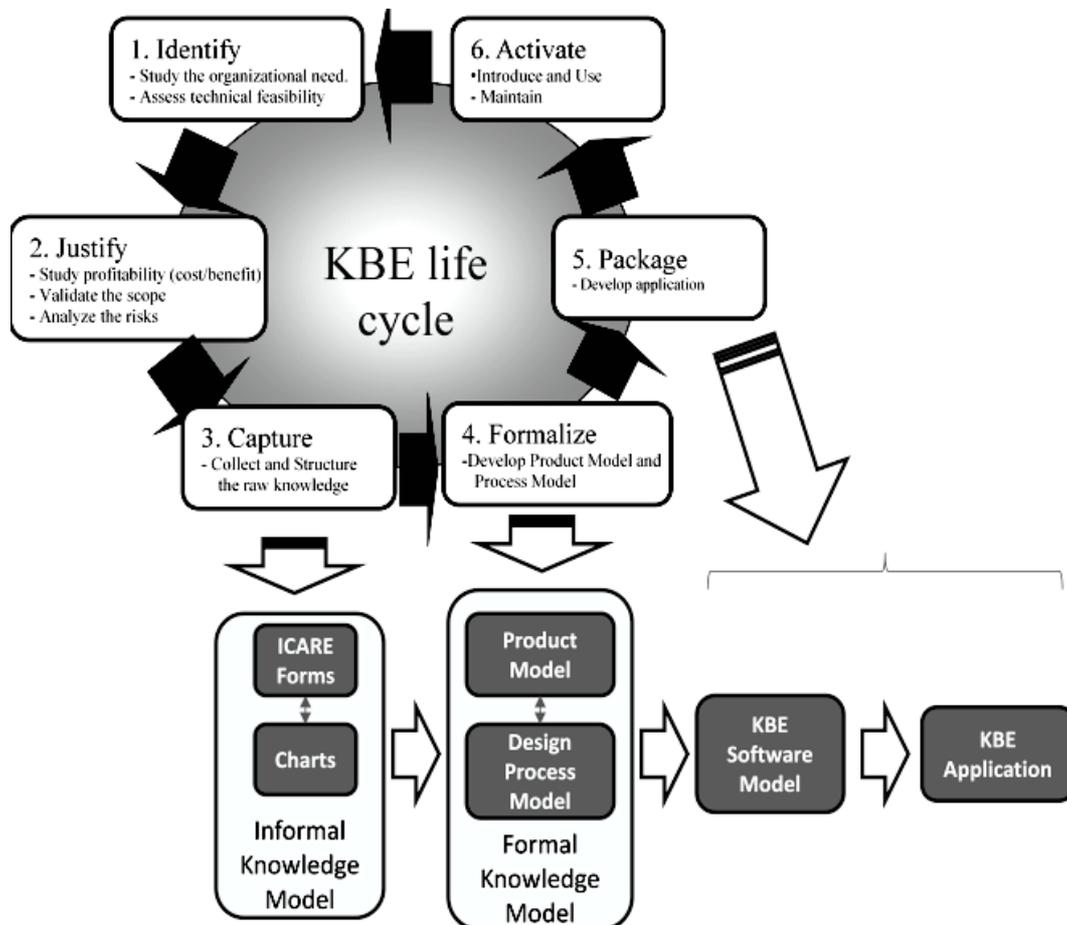


Figure 2.19: KBE methodology. Source: Lohith and Devaraja (2013).

Stokes (2001) categorises the first three phases as “capturing”, generally using ICARE forms, in which all the data with respect to the task are gathered under five parameters: Illustrations, Constraints, Activities, Rules and Entities. These data are then linked with the elements to create a structured web of knowledge. According to Sanya and Shehab (2014), the template for capturing knowledge can be tailored by having different parameters with respect to the domain needs. The expert knowledge for each of the assigned parameters can be captured through different data acquisition techniques (see Table 2.3). Among these, storyboard is the most used data acquisition technique, as it helps to gather the complex task data and the rules implied from it from the experts in a structured and easily interpretable way (Akhavan *et al.*, 2011).

The second half of the MOKA phases involves “formalising” this captured and structured knowledge by converting it into an acceptable format that can be read by the application side. Apart from MOKA methodology, KBE applications also use methodologies such as KOMPRESSA, KNOMAD and CommonKADS (Schreiber, 2000; Lovett, 2000; La Rocca, 2007), all of which share many principles with MOKA and some overcome some of the shortcomings of MOKA. According to Kuhn (2010), the choice of KBE methodology depends upon the domain and complexity of the task that needs to be automated. Although Stokes (2001), Cooper and Fan, (1999), Bermell-Garcia and Ip-Shing (2008) and Darai *et al.* (2010) argue that the KBE approach may not be suitable for all domains, previous KBE implementation works across various domains such as automotive, aerospace, military, construction and medical, and has already proven its adaptability and successful efforts (Curran *et al.*, 2010; Verhagen and Curran, 2011; James and Dasarathy, 2014; Zhao *et al.*, 2015). However, Emberey *et al.*’s (2007) and Corallo *et al.*’s (2009) case studies have illustrated that almost 67%

of previous KBE implementation case studies have not mentioned the resulting time and cost involved and warn about the hidden consequences that might result.

Table 2.3: Various knowledge acquisition techniques. Adapted from Akhavan and Shahabipour (2014).

Category	Techniques	Use-cases
Interview	Concept mapping Task action mapping	Shadbolt and Smart (2015) Gentner and Stevens (2014)
Case Study	Forward scenario simulation Retrospective case description	Cooke (1999) Littell (2016)
Protocols	Protocol analysis	Kidd (2012)
Critiquing	Critiquing	Gruber (2013)
Role Playing	Role plays	Marcus (2013)
Simulation	Wizard of Oz Problem analysis	Mok and Ju (2014)
Prototyping	Storyboarding Rapid prototyping	Schneider <i>et al.</i> (2013)
Teach back	Teach back	Shadbolt and Smart (2015)
Observation	On-site observation Active participation	Nakano <i>et al.</i> (2013)
Goal Related	Reclassification Distinguishing goals	Bareiss (2014)
List Related	Decision analysis	Gruber (2013)
Laddering	Laddered grid	Akhavan and Dehghani (2015)
Sorting	Card sorting	Da Rosário <i>et al.</i> (2015)
Construct Elicitation	Repertory grid Proximity scaling	Shadbolt and Smart (2015)
20 Questions	20 questions	Marcus (2013)
Document Analysis	Collect artefacts of task performance Goal directed analysis	Fan <i>et al.</i> (2012)

Although KBE principles and methodology contribute many advantages towards knowledge automation, they have some disadvantages. Verhagen *et al.*'s (2012) and Reddy *et al.*'s (2015) studies present some commonly criticized elements of KBE. Among these, Choi (2005), Kulon *et al.* (2006) and Ko *et al.* (2007) mention KBE as a 'black-box', meaning the mechanism of deriving the actual meaning from different linked data leads to unclear understanding. In addition, Bermell-Garcia *et al.* (2007) state that although one of the hallmarks of KBE is its single integrated knowledge

representation, there is lack of high-level reasoning capability, which makes it difficult to transfer or share knowledge across different domains. However, Ahmed *et al.* (2007), who tailored a semantic methodology to model KBE-captured knowledge, and Sanya and Shehab (2014), who developed a platform-independent knowledge model using KBE and ontology for the aerospace industry, suggest that this could be addressed by having a semantic way of linking data to provide better understanding and reasoning. Therefore, the following section explores and reviews work on semantic-based knowledge modelling, along with its uses and shortcomings.

2.7.2 Semantic-based modelling

Knowledge modelling has become sophisticated in the past decade, yet very rarely are self-content to be understood by humans or machines without the intervention of the modeller's mediation (Kohler *et al.*, 2000; Ludaescher *et al.*, 2001). In past years, Ang (1997), Kim *et al.* (2001), Bourdakis (2003), Ceccaroni *et al.* (2004), Stevens (2006), NASA (2006), McGuinness *et al.* (2007) and Yu and Wu (2015) have contributed various modelling approaches which re-use, communicate and integrate with other data models. Among these, the one that was inspired by popular computer science programming in the 1980s known as 'declarative-modelling' was suggested as the solution to the 'black-box' issue (Robertson *et al.*, 1991; Wenzel, 1992; Muetzelfeldt, 1996; Keller and Dungan, 1999). While 'declarative-modelling' used graphical language to produce readable and self-explanatory data model, this modelling approach later became more popular and several graphical modelling languages such as UML, Simile, SysML and STELLA emerged (Richmond, 2005; Tiller, 2012; Muetzelfeldt and Massheder, 2003; Salles *et al.*, 2006; Batarseh *et al.*, 2013; Grönninger *et al.*, 2014). Even though 'declarative modelling' has helped in designing, communicating between and integrating models, according to Villa *et al.* (2007) it has not addressed the whole

issue. One main reason is that the modelling emphasises more enhancement of the readability of the knowledge component through graphics rather than the underlying-semantics, meaning that there is insufficient precision over semantic understanding of the modelled data.

In this regard, a large community known as Semantic Web started investigating the problem of making the meaning more explicit and the knowledge automatically associable (Kiryakov *et al.*, 2003; Athanasiadis, 2006, 2007; Parr *et al.*, 2006; Khatri *et al.*, 2006; Rizzoli *et al.*, 2008; Villa, 2007; Chen *et al.*, 2007; Lee *et al.*, 2007; Madin *et al.*, 2007). The tool that was used in the unification of knowledge is known as structured knowledge or ontology (Milicic *et al.*, 2014). The term ‘ontology’ originated from the field of philosophy, referring to the study of being (Gruber, 1993 and 1995), although ontology in the real context refers to the conceptualisation of domains, usually through a set of statements or propositions to define the concept and the relations between concepts (Wand *et al.*, 1999). In recent years, languages (RDF, OWL) and tools to create, programme, store and communicate ontology have been developed widely (Guinness and van Harmelen, 2004; Beckett, 2004). In ontology, the meaning of each individual object (instance) is stored in its property and this property acts as the statement in associating different concepts (Paterson *et al.*, 2004). For example, let us consider a person as an example, whose properties can be name, gender and other personal data that help in deriving explicit meaning; moreover, these properties interlink with other instances with similar properties to create more explicit and reusable models. According to Goguen (2005), a collection of instances from the same ontology that have been related to each other form a knowledge base (KB), although this is not well accepted by everyone in the ontology domain (Gangemi, 2013). The use of

knowledge-based ontologies has been applied in different domains, varying from simple loose structures to complex and more explicit ones (see Figure 2.20). One example was the SWEET ontologies by NASA, which formularised a common understanding in applications used by space scientists (Raskin and Pan, 2005; NASA, 2006). Further, Ceccaroni *et al.* (2004) used ontology for decision support systems in an augmented environment, and some education applications by Chrysafiadi and Virvou (2013), Kim (2014) and Flotyński and Walczak (2015) have also used ontology to build their knowledge base (KB).

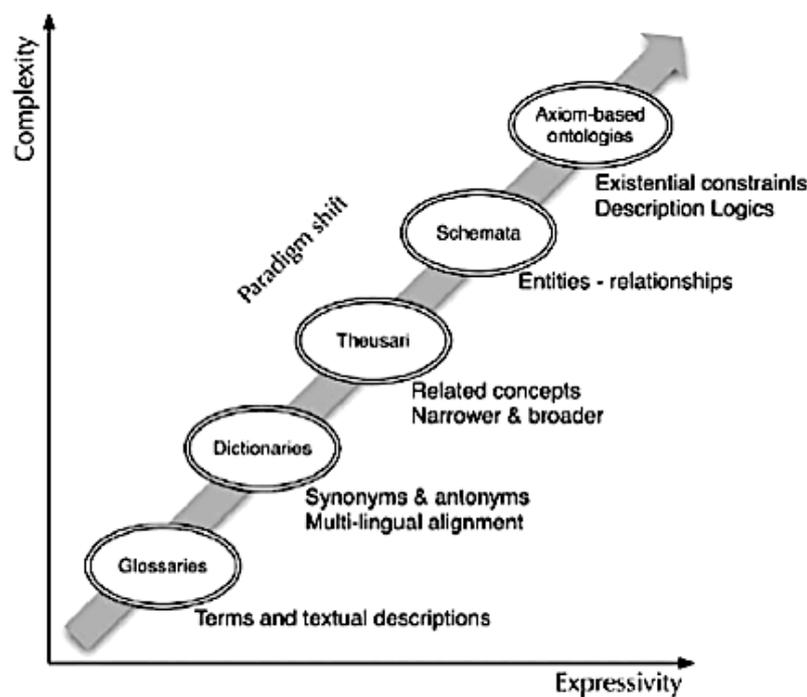


Figure 2.20: Various knowledge acquisition techniques. Adapted from Akhavan and Shahabipour (2014).

Apart from that, other initiatives from Kepler (2004), Goguen (2005), GEON (2005), SEAMLESS (2005), Pennington *et al.* (2007) and Villa *et al.* (2008) have laid the groundwork to make ontology more adaptable to different domain knowledge (Table 2.4). However, Agyapong-Kodua *et al.* (2013) claim that we are yet to acquire the full

benefit of ontology-based modelling, as more knowledge needs to be captured and modelled, which requires more time and resources. In addition, Musen *et al.* (2014) study points out some of the other challenges; among which is that the ability of ontology to answer ‘what-if scenarios’ is limited, as this may need one form of ontology in communication or the querying of other ontologies. Indeed, this requires more system power to generate high quality reasoning; although there are several open-source high performance reasoners available today, these have not been tested to their highest limits (Villa *et al.*, 2007).

Table 2.4: Use of ontology in various sectors for modelling domain knowledge. Adapted from Sanya and Shehab (2014).

Nature of domain	Application	Source
Aerospace	Knowledge sharing among aerospace sectors	Dadzie <i>et al.</i> (2009)
Government	Content management for extensive web information	Horrocks (2008)
Telecommunications	Semantically-driven knowledge management practises	Davies <i>et al.</i> (2009)
Medical and pharmaceutical	Building common understanding for domain terminology	Hawker (2010)
Automotive	Ontology-based methods for troubleshooting configurations	Liang (2012)
Product service	Knowledge re-use and configuration of product extension	Doultsinou <i>et al.</i> (2009) Shen <i>et al.</i> (2012)
Railways	Decision support system for cost and design optimisation	Saa <i>et al.</i> (2012)

Although these consequences have hampered the use of ontologies in engineering and education domains which involve a number of ‘what-if scenarios’, Krcaronemen and Kouba (2012) suggest that this gap could be bridged by the use of techniques such as artificial intelligence (AI). This has already been evident in studies by Davies *et al.* (2003) and Sanya and Shehab (2014), who have stated that despite the clear potential

offered by ontology in various knowledge domains and suggestions in addressing its limitations, only a few case studies are available. The following section explores the nature of artificial intelligence and critically reviews its application in ‘what-if-scenarios’ in knowledge automation.

2.7.3 Artificial intelligence

In the early 1950s an American scientist called Norbert Wiener was the first to link human intelligence with machines, theorizing human behaviour into a heating system to control itself by reading the actual room temperature (Rosenblueth and Wiener, 1950). Later, the term artificial intelligence (AI) was coined from a 1956 conference at Dartmouth College in Hanover, which integrated theorists and practitioners in several disciplines such as cybernetics, psychology, linguistics and neurophysiology in building an intelligent computer application (John, 1992; Kao *et al.*, 2012). The aim of AI was to discover how to mimic the intelligence (or laws) of the human brain into a computer application to enhance its thinking capabilities (Farmer *et al.*, 1986). According to Billinghamurst *et al.* (2015), this field has been one of the frontier research subjects in the past 20 years, and as a result different disciplines such as expert systems, knowledge-based systems, intelligent databases, robotics and gaming are currently using AI as the core in automating systems embodied with human intelligence (Figure 2.21). In the early days, engineering applications were capable of solving problems that required mathematics, physics and mechanical calculation; however, they failed to solve complex ‘what-if-scenarios’, which required the experience of practitioners (Hayes-Roth *et al.*, 1983). Artificial intelligence addressed this problem through its various techniques that imitated experts’ way of thinking (De Kleer, 1986).

The earliest AI technique that were used widely in engineering applications to solve ‘what-if-scenarios’ was known as fuzzy-logic, which helped engineers to move on from traditional Boolean logic to a more intermediate approach (Bauer *et al.*, 1996; Bassuoni and Nehdi, 2008). Unlike the traditional Boolean method, which just presented two values (0 or 1) to the ‘what-if-scenario’, fuzzy logic provided a number of possibilities that might occur between 0 and 1 through its fuzzy values (LaMothe, 2002; Köse, 2012). But these were time consuming for simple and liner problems, which had predefined mathematical solutions (Logic Programming Associates, 2002). In addition, Zarozinski (2002) states that although fuzzy logic suceeded Boolean logic by answering a number of ‘what-if’ possibilities they were limited by their ‘if-then-else’ statements to solving complex scenarios. This was addressed by the use of neural networks (NN), which extended AI’s capacity to handle more complex ‘what-if-scenarios’. The principle of NN was based on the theory that it is involved in the human brain, where knowledge is not constrained through predefined sets of values, but the values are self-learned by themselves (LaMothe, 2000). The use of NN is widely found among industrial applications involving complex analysis and prediction for various situations (Keller, 2002).

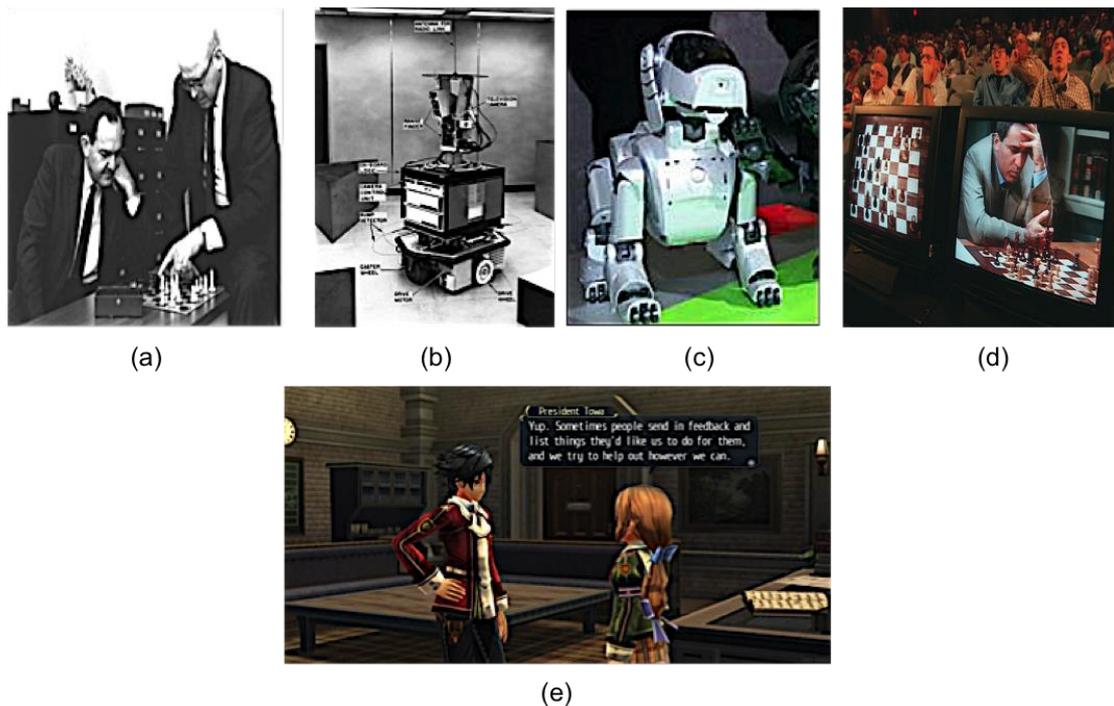


Figure 2.21: Use of AI. (a) First AI program, (b) First self-maneuvering robot, (c) First robot (AIBO) to mimic actual dogs' behaviour, (d) First AI to match human thinking in playing chess and (e) AI in serious gaming from early 2000 for dialogue. Sources: Newell et al. (1957); Nilsson (1984); Hornby et al. (2000); Schaeffer and Plaat (1997) and Factor-Tech (2015).

Further, Aminian *et al.* (2011) explain NN as an efficient AI-technique that can make decisions or interpret answers based on previously learned experience. However, Champandard (2002) warns that providing the right boundary conditions for NN is not easy, and that failure to do so will make the system learn wrong experience. This limitation was reduced in Genetic Algorithm (GA), another AI technique that uses neural selection in answering 'what-if-scenarios' (Leung *et al.*, 2003). The idea that separates GA from NN is the way the solution evolves; GA, unlike NN, starts with a very small boundary condition and then gradually extends the boundaries until it addresses the desired problem, which makes it more reliable (Yang and Honavar, 1988). According to Dulay (1996), specifying the right boundary condition over a large set of data is difficult; however, by providing meaningful fitness functions in acquiring the right set of data (or samples) makes GA more successful.

At present, the gaming sector is the other discipline that is extensively making use of AI principles in automating human thinking and behaviour into gaming avatars (Table 2.5). Among these, one of the most extensively used AI-technique is the finite state machine (FSM), since it is simple and easy to program human behaviour into computer models (Dybsand, 2000; Diller *et al.*, 2004). The backbone of FSM is formed by fuzzy-logic and neural networks (Unal and Khan, 1994), two of the above mentioned AI-techniques. The concept of FSM is based on logical states, where different behaviours are represented through different states in exhibiting the desired characteristics (Yannakakis, 2012). The change in FSM-states depends upon the input received from the user. Fernando (2013) explains this in a more elaborate way through a gaming scenario, in which if the gamer moves across the monster inside the gaming environment the state of the monster changes (or transitions) from silent to attack on receiving the input (Figure 2.22); similarly, FSM could trigger different states for different user actions. However, Rabin (2014) claims that mimicking human intelligence thorough FSM may not be an optimal solution, as the use of algorithms to handle complex what-if-scenarios is minimal. Walkinshaw (2015) discusses this limitation and believes the capability of FSM should not be judged by the lack of more advanced algorithms but by its potential to address the problem. Ivanov (2015) points out the attributes that make FSM more popular are its low computational costs and shorter implementation and development time. Treanor *et al.*'s (2015) and Aktaş and Emre's (2016) studies have criticized the difficulty in maintaining the structure of FSM as it becomes challenging for developers to review or debug for it in order to mimic complex behaviour. Yannakakis (2012) suggests that one of the possible ways to overcome this issue is by planning well in advance over the development cycle and by having intermediate behavioural testing throughout the development process.

Table 2.5: List of merits and demerits of AI-techniques and their application in current serious games in mimicking real-world characters' behaviour. Adapted from Sweetser and Wiles (2002).

AI techniques	Merits	Demerits	Games that have used these AI-techniques
Fuzzy Logic	Useful for solving non-linear 'what-if-scenarios' Automates expert knowledge More flexible and variable to use	Time consuming when there is a simple solution Complicated to build from scratch	SWAT 2; Call to Power; Close Combat; Petz and The Sims
Neural Networks	Useful for solving complex 'what-if-scenarios' More flexible than fuzzy logic	Requires more computational power Difficult to assign boundary conditions Requires more expert knowledge	Black & White; BC3K; Creatures and Heavy Gear
Genetic Algorithms (GA)	Effective in solving larger and complex 'what-if-scenarios'	Resource intensive Slower and more complicated to build than the others	Cloak Dagger & DNA; Creatures and Return Fire II
Finite State Machine (FSM)	Simple and less complex to use Combines with other techniques Computationally inexpensive	Poorly structured Becomes unmanageable for complex behavioural modelling Needs proper planning	Age of Empires; Half-Life; Doom and Quake

Further, Alimov and Moffat (2015) suggest that this could also be addressed by the use of intelligent agents, which could be used to link sets of FSM in a more structured way. This means that an agent acts like a manager in handling each of the FSMs, by distributing inputs across the FSM rather than directly interconnecting it, which leads to an unmanageable situation.

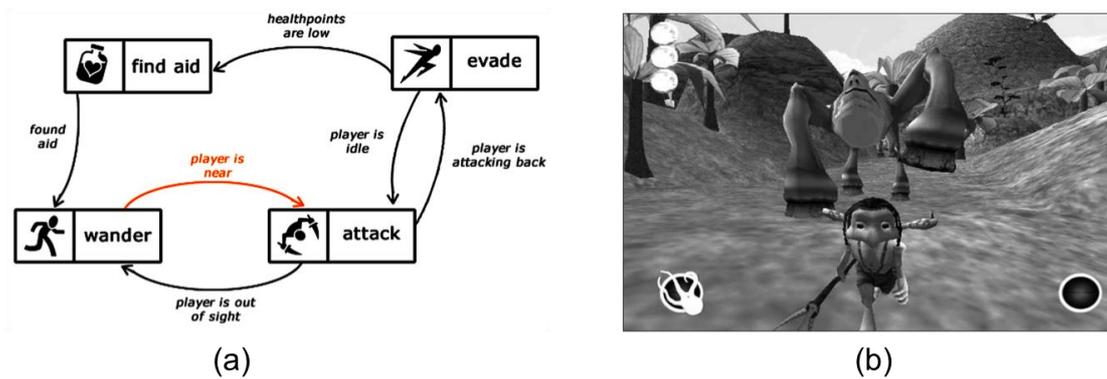


Figure 2.22: A simple finite state machine: (a) FSM representing the brain of a monster; (b) monster avatar attacking player on seeing him. Adapted from: Fernando (2013).

It is therefore evident that engineering industries and gaming sectors have used the power and flexibility of different AI technologies in solving a range of what-if-scenarios. However, the complexity of engineering tasks continues to raise new challenges in their automation. As we have seen from the gaming sector, the use of new techniques such as FSM integrating two of the core AI techniques has made knowledge automation effective and less time consuming. Thus for knowledge automation new techniques along with the underlined core principles from traditional methods will be vital for the next generation of knowledge automation, with much more complex what-if-scenarios.

2.8 Chapter summary and conclusions

This chapter explored literature concerning the following five major topics:

1. Engineering laboratory

It was evident that there has been greater emphasis on practical skill in engineering subjects in the past. However, professional accreditation bodies have ensured engineering education meets world-class standards by creating a balance between theory and practice. These bodies include:

- American Institute of Chemical Engineers (AIChE)

- Accreditation Board for Engineering and Technology (ABET)
- Engineering Council

This research has chosen Engineering Council accreditation standards as the benchmark, since they have been used in most of the UK universities offering engineering courses. There are five key learning outcomes that need to be achieved by engineering students in the UK under Engineering Council standards. They are:

- Understanding
- Knowledge
- Know-how
- Skill
- Awareness

This study focuses on the ‘know-how’ learning outcome. Teaching and assessment in support of this learning outcome remains a challenge for universities offering engineering distance learning courses.

2. Demand for practical skill

This study will use ‘know-how’ as the terminology to refer to practical skill as it is commonly used in UK universities and industries. Further the literature review explored the different types of skills that are required from engineering employers:

- Creativity
- Critical thinking
- Problem solving
- Proficiency with new technologies
- Oral communication

- Team work

Among them critical thinking and problem solving are in high demand from engineering employers. This study will use these two critical elements in selecting the practical task, which will be developed under the proposed prototype.

3. Learning and teaching theories

This chapter also explored various appropriate teaching and assessment methods involved in delivering engineering subjects:

- Kolb's experimental learning
- Bloom's taxonomy
- Webb's depth of knowledge
- Hess' cognitive rigor matrix

Among them the theory of Hess' cognitive rigor matrix was chosen as the key pedagogical element in the prototype development, where this theory would be put into practice in automating the assessment process of engineering distance learners. This theory best fitted the research need as it integrated Bloom's taxonomy and Webb's depth of knowledge in providing a holistic learning experience by identifying learners' preference and knowledge limitations. Further the review conducted also explored various dimensions of engineering learning styles:

- Sensory and intuitive learners
- Visual and auditory learners
- Inductive and deductive learners
- Active and reflective learners
- Sequential and global learners

This study has chosen tell-me (audio), show-me (visual) and have-a-go (kinaesthetic) as the three dimensions of learning styles, as they provided greater adaptability for the different kind of learners. These three chosen learning styles will be used for developing a learning object repository for the chosen practical task where the learners would be able to learn through their preferred learning style.

4. Distance learning

The chapter then reviewed large body of literature in the field of distance learning approaches such as:

- Study centres
- Remote laboratories
- Virtual laboratories

Where these approaches were analysed in terms of the practical learning outcome achieved by the distance learners with respect to:

- Design skill
- Professional skill
- Social skill
- Conceptual understanding

This study has chosen virtual laboratories as the distance learning approach, as it provided better design and professional skill outcome compared to that of the other approaches. In addition, the chapter reviewed two major virtual laboratory technologies:

- Virtual reality (VR)
- Augmented reality (AR)

Between these two current virtual laboratory technologies, augmented reality (AR) was chosen as the technology enabler for the prototype development because it provided better hand and eye coordination for distance learners in learning practical skills without the need of physical equipment.

5. Knowledge automation

Tutor's knowledge was identified as the most important element in engineering practical learning, which requires constant monitoring and provision of feedback. The chapter reviewed different knowledge automation methodologies:

- Knowledge-based system (KBS)
- Experts system
- Knowledge-based engineering (KBE)

This study has chosen KBE as the methodology on how to capture, model and automate tutor's knowledge into the intended AR environment. The choice of KBE as the methodology was made for the following reasons:

- KBE is a widely used methodology in automating expert's knowledge into computer applications.
- It not only provides understanding and guidance on the capture, modelling and automation of an expert's explicit knowledge but also their tacit knowledge, which is set to be vital for laboratory learning outcomes.
- Further, KBE has already been adapted in several domains like aerospace, construction and medical, which has encouraged in adapting them to an educational domain.

The chapter then reviewed different knowledge capturing, modelling and codification techniques used under:

- Knowledge acquisition
- Semantics
- Artificial intelligence

This study has chosen storyboard as the knowledge acquisition technique, as this technique helps to gather the complex task data from the experts in a structured and easily interpretable way. This technique will be used in capturing the teaching, monitoring and assessment process involved in the engineering practical task that would be selected in the later chapters. In terms of the knowledge modelling technique, ontology was selected as it provides knowledge modelling through semantically linking educational data, which enables better understanding of the tutors' knowledge. In the later part of the thesis ontologies would be used in modelling the complex knowledge of the tutor into a computerised knowledge model. The chapter further explored different artificial intelligence techniques such as:

- Fuzzy logic
- Neural network
- Genetic algorithm
- Finite state machine

Among those FSM was chosen as the AI technique, as it provides a simple and effective technique for mimicking an expert's intelligence to address complex 'what-if-scenarios' in distance learning environment. This study will use FSM in mimicking laboratory tutors' teaching, monitoring and assessment process by making use of the computerised knowledge model.

Having established the “what” components from the literature, the following chapter will address the “how” component, by discussing in detail the research methodology describing how these critical components were used in designing, developing, testing and evaluating the proposed Knowledge-based Educational (KBEd) framework.

Chapter 3 Methodology

“Creativity is the key to success in the future, and primary education is where teachers can bring creativity in children at that level”

- A.P.J Abdul Kalam

This chapter explains the research journey in two sub-sections; the first, ‘research design’, provides the research standpoint, understanding of the research methodology and selection of appropriate methods used in the research (section 3.1). The second sub-section, ‘research process’, then explains how the chosen methods were implemented in the study to address the research objectives (section 3.2).

3.1 Research Design

3.1.1 Introduction

It is important to reiterate the research question, objectives and null hypotheses that the study intends to address before explaining the undertaken research design, since this provides the reader with a better understanding of how the presented methodology plans will address the research questions. The ultimate research questions are as follows:

- Can the principles and practice of knowledge based engineering be applied to acquire the knowledge of a tutor to create a knowledge based educational framework?
- Can this framework be embodied into an augmented reality environment that would allow study by distance learners?
- Can engineering learners acquire practical skills in an augmented reality environment?

The following are the research objectives:

1. To establish research landscape by identifying and reviewing the ‘best practices’ and issues on delivering practical skills for engineering distance learners.
2. To capture, model and automate on-campus tutor knowledge for teaching and assessing practical skills.
3. To design and develop an augmented reality environment for learning.
4. To validate the performance of the augmented reality environment.

As examined in the literature review chapter, how to acquire hands-on practical skills in an off-campus environment has been the landscape for this research exploration. Many frameworks and systems have tried to address the needs of distance learners, but they are mostly focused on non-engineering domains. Some approaches have attempted to address engineering needs with respect to practical skills, but there is no acceptable method of how to capture and automate on-campus tutors’ knowledge for practical teaching and assessment purposes. This has led to this research in designing a framework and building a prototype to evaluate the efficiency of learning practical skills through experimental results. Several methodologies are suggested for building the prototype and experimentally testing it, but it is necessary to understand and explore the use of methodology before choosing the appropriate one.

Saunders *et al.* (2009) classified research methodology into six layers (Figure 3.1) to provide a structured understanding for constructing the right research design. The first layer helps in identifying the philosophical position of the research and the choice of this influences the way the research is conducted and the data is analysed. In accordance with this research, the philosophical standpoint is positivist, as the research question is addressed by testing the hypothesis (section 3.2.3) through actual performance results

against standard results. Generally, this kind of research uses the mixed method, which involves both qualitative and quantitative results (Andrew and Halcomb, 2009).

The second layer helps the researcher to identify the right approach by narrowing the choice of data collection and analysis techniques for the research; normally, the chosen approach is heavily influenced by the decision made at the previous level (Marczyk *et al.*, 2005; May, 2011). This research adopts a deductive approach as it tries to answer the questions posed at the beginning of the research. The third layer helps in identifying the research style, the way the research will be conducted. This research adopts an experimental style, as the set hypotheses require testing of the effect of the proposed prototype on student group training and comparison with the control group training through traditional methods (Section 3.3). Layer four helps in further narrowing down the choice of data that needs to be collected to prove or disprove the research hypothesis.

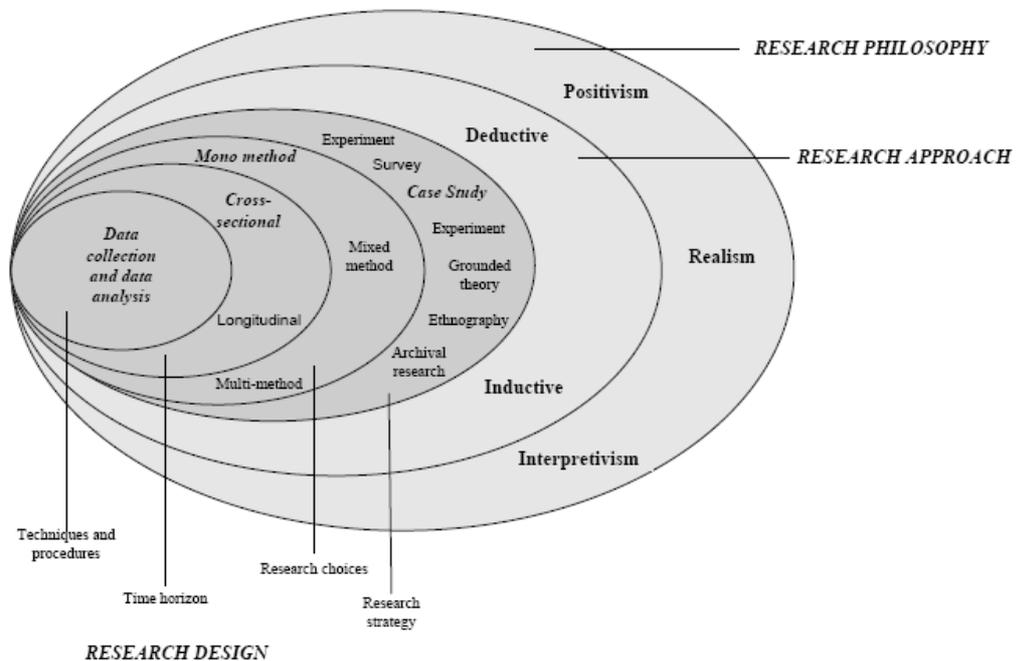


Figure 3.1: Research onion diagram. Adapted from Saunders *et al.* (2009).

This research uses mixed methods (section 3.2.2) in collecting experts' opinions and suggestions to improve the usability of the proposed KBEd system and a further quantitative measure of student performance in testing the hypotheses (section 3.3.2). The fifth and sixth layers help to review the decisions made at the previous level and further guide the chosen data collection and analysis methods in mapping to the exact research needs (Brace, 2008). Sections 3.1.2 and 3.1.3 further elaborate the above constructed research design in detail and explain how it was actually used in the research process.

3.1.2 Approach to the prototype

(a) Introduction

The choice of methodology in developing a prototype depends upon the domain and also upon the environmental characteristics (Luqi, 1989; Lantz, no date). The domain characteristics represent the field of research; in this case it is the educational domain, whereas the environmental characteristics are the physical (hardware) and logical (software) definitions of the prototype. Therefore, there is a need to explore instructional design and software design methodology to identify the method that best fits these characteristics. According to Ingram (1988) and Maher and Ingram (1989), software design and the instructional design field have similar methodologies and purposes. Designers from both these fields use systematic phases to solve large and complex problems, the only difference being the degree of depth that is explored in each of the phases (Reigeluth, 1989; Streibel, 1989; Garg *et al.*, 2014).

Among the different software design methods, rapid prototyping has been recently used in building many educational applications (Dufour *et al.*, 2010; Pahl and Beitz, 2013; Danahy *et al.*, 2014; Violante and Vezzetti, 2014; Page, 2015; Calvert and Mazumder

2016; Braghirolli, 2016) as it provides a common ground to validate and test the proposed construct through physical application rather than understanding and revising it by paper images (Boyle, 1997; Preece *et al.*, 2002). Therefore, this research employed the rapid prototyping method to design and develop the required prototype.

(b) Rapid prototyping background

In a rapid prototyping method, a prototype is built through iterative cycles involving stakeholder or expert intervention through the development phase (Carroll and Rosson, 1985). The stakeholders make very clear and specific suggestions on what they like or dislike about the presented prototype (Webb, 2000; Alaraj, 2015). These changes and suggestions then become the input for the next development cycle. This iteration process is repeated until the prototype readiness is acceptable (Jenkins, 1985). Traditional prototype development methodologies, such as system life cycle methodology, involve four linearly sequenced phases to develop a prototype (David and Fitzgerald, 2003). The first phase involves analysis, when all the system requirements are gathered and analysed. The second phase involves design, when the concept or blueprint of the entire system is laid down. The third phase involves development, when no design idea is changed until the final implementation phase. This methodology can lead to prototypes with unsatisfactory outcomes (Boar, 1984; Feather, 1982; Naumann, and Jenkins, 1982).

This limitation was overcome by rapid prototyping methodology combining all the four traditional phases into one single phase, revisited in parallel with stakeholder or expert group for several iterations (Figure 3.2). Although the gradual refinement through the iteration method helps to improve the performance of the prototype, this can increase the cost and the time spent on the development cycle (Längle *et al.*, 1984; Bibb *et al.*, 2014; Lantada and Morgado, 2014). Therefore, to have a balanced development cycle

Naumann and Jenkins (1982) emphasise the importance of a shorter iteration cycle of no more than 1 to 2 days to avoid problems such as lack of motivation and enthusiasm in the participants. Naumann and Jenkins (1982), Alavi (1984) and Boehm *et al.* (1984) have also shown that rapid prototyping methodology in general reduces the development time by exactly mapping the current available technology to the requirement.

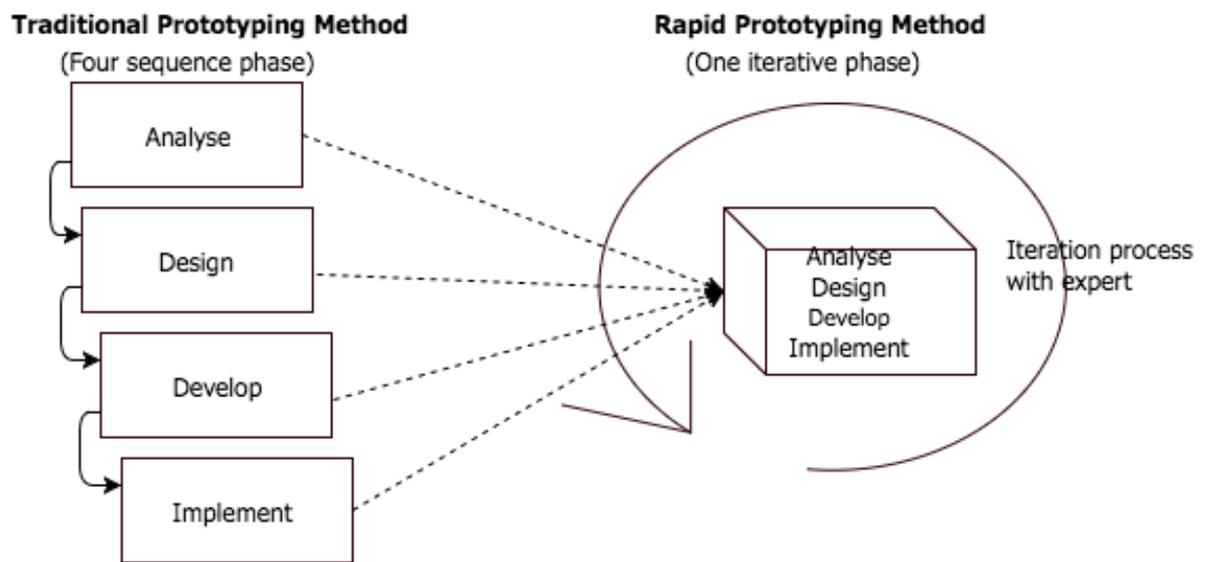


Figure 3.2: Traditional prototype method vs rapid prototype method

(c) Application of rapid prototyping in this research

In this work, the intended prototype was designed and developed through the rapid prototyping methodology based on ideas drawn from the literature, in particular Naumann and Jenkins (1982), Boar (1984), Bibb *et al.* (2014) and Alaraj (2015). The development cycle processes employed are as follows:

- Design of intended system blueprint to address the research requirement (see section 3.2.1).
- Development and pre-testing of the prototype with expert groups using quantitative and qualitative methods (see section 3.2.2).

- Use of the gathered data to refine the prototype (see section 3.2.2).

As we can see from the list above, successful application of the methodology depends upon the approaches used to gather and analyse the evidence from the experts. Moreover, the type of evaluation methodology employed also depends on the two characteristics mentioned above: domain and environment (Miller *et al.*, 1998). The following section discusses the different evaluation approaches that could be used with respect to the chosen prototyping approach and the research domain.

3.1.3 Approach to validation

(a) Introduction

There are different types of validity (Miller *et al.*, 1998); the type of validation undertaken depends upon the nature of the research and the type of results that it needs in order to address its objective. Validation in general refers to the degree to which evidence and theory support the interpretation of the conducted test results (American Psychological Association, 1999). In an educational context, validity refers to the measure of performance over an intended learning outcome (Dunn *et al.*, 2003).

This research needs a validation approach to refine the proposed prototype by interpreting expert opinion and also an approach to test the set hypotheses through experimental assessment with students. Therefore, the validation approaches that were considered to be of greatest relevance to this research are as follows:

- Face validity
- Predictive validity
- Concurrent validity and
- Construct validity

Although all these validation approaches seem to be individual, with their own measuring technique to determine the outcome, according to Messick (1995), Porath *et al.* (2012) and Diamantopoulos *et al.* (2012), the idea of validity is unified and construct validity is the overarching quality of measurement consisting of all the other validity labels within it. Thus this study explores and analyses all these approaches under one general category - construct validity - and identifies appropriate measuring techniques that best fit the research validation.

(b) Construct validity background

The concept of construct validity emerged from work conducted in the Second World War, when psychologists developed a series of tests for fighter pilots to measure battlefield effects such as reaction time in making critical manoeuvres and confidence in making decisions (Cronbach and Meehl, 1955). This led to various validity approaches when the work was modified to suit the civilian context. Among the developed validity approaches, the nomological network and multitrait multimethod matrix (MTMM) were the two most used for many civilian purposes. The basic principle of these two validity approaches, pattern matching, was later adopted to develop construct validity (Charles and McCallum, 1988; Marquart, 1990). When researchers claim construct validity it means that they observe a pattern of data and compare and analyse it with a theoretical pattern or standard in validating the outcome (Jalink, 2014; Henry, 2016). The measurement that is taken to identify the pattern varies according to the research needs. To have a summarised analysis of the list of different validity measuring techniques, this research has grouped them into two categories: transitional validity and criterion-related validity (Figure 3.3).

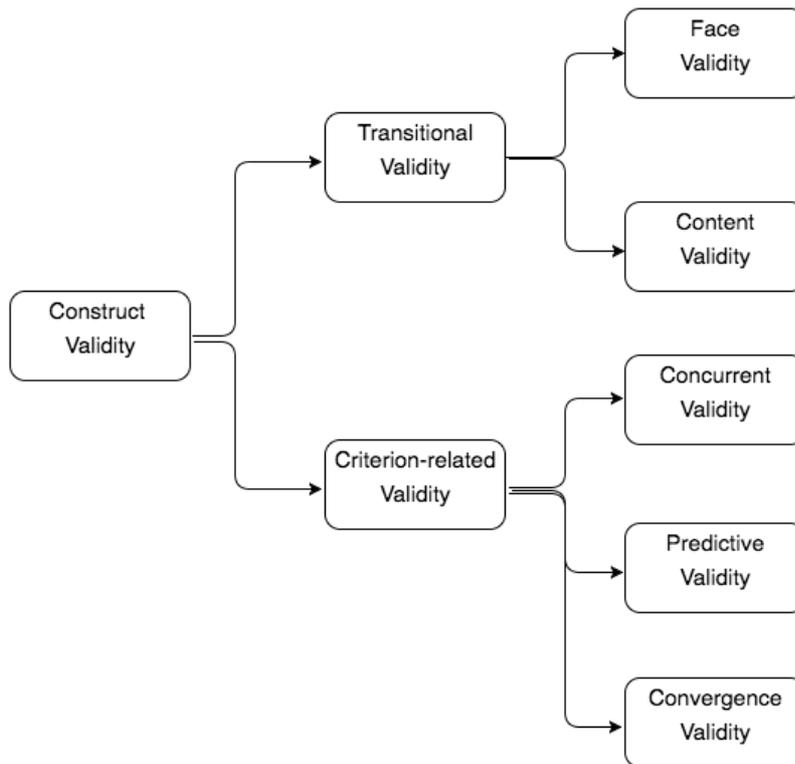


Figure 3.3: Categorisation of validity approaches. Adapted from Diamantopoulos *et al.* (2012)

Transitional validity comprises methods such as face and content validity, which measure whether the presented construct is good enough by reflection on the opinions made (Newton and Shaw, 2014; White *et al.*, 2014). Face validity, as the name suggests, is the validity of the overall construct as judged by expert opinion. This type of validation is criticised for its reliability, as the result relies heavily upon experts' judgement (Rutherford, 2015). However, Lindner *et al.* (2014), Brewin *et al.* (2015) and Braman *et al.* (2015) have addressed this issue by carefully selecting the sample of experts as participants in acquiring the judgement. Content validity has a very similar approach to face validity in terms of assessment through participant reflection, but the validation is more focused on the content that is made available inside the construct (Xiao *et al.*, 2014; Barsness *et al.*, 2015). Generally, content validity is executed by

having a checklist and verifying whether the information represented in the construct has met the domain standard or not.

On the other hand, criterion-related validity comprises methods such as concurrent, predictive and convergence validity, which examine whether the proposed construct when implemented behaves in the way that it should by comparing it to a standard construct. The measuring techniques for the approaches in these categories involve both qualitative and quantitative data for result analysis (Jalink *et al.*, 2014). Concurrent validity is generally used in establishing criterion relations between two groups with two different treatments and verifying their significance through performance measurement (Gil *et al.*, 2016). On the other hand, in predictive validity a construct developed for one specific domain is evaluated as to how well it would be useful for other similar or different domains (Ramos *et al.*, 2014). Convergent validity examines the degree of similarity existing between a proposed construct and other pre-existing constructs (Goldring *et al.*, 2015). This study, as mentioned earlier, needs measuring techniques from both the transitional and criterion-related categories. Firstly, this is to refine the proposed prototype (implemented construct) by gathering and interpreting expert opinions, and secondly to measure the performance of students and comparing it to a performance standard. The following section explains which of the techniques in each of the construct categories were used as validation approaches in addressing the validity needs with respect to the research.

(c) Application of construct validity approaches in this research

The validation of this research involves a mixed method approach using construct validity approaches to make the required evaluation. A construct validity approach was selected since the research involves validating the transformation of conceptual ideas into a real system and measuring their usefulness (Newton and Shaw, 2014). In this

work, construct is the proposed framework and its implementation refers to the prototype, which acts as the instrument to transfer the skills acquired from the AR environment to a real environment. The construct validity approaches used are as follows:

- Face validity with a selected expert group to test the validity and reliability of the proposed KBEd prototype (Section 3.2.2).
- Use of concurrent validity to measure the performance between two student groups practising in different environments (Section 3.2.3).

The evaluation process, data collection and analysis technique involved in the above mentioned construct were developed based on the educational system evaluation methods of Boyle (1997), Laurillard (2002), Barker and Barker (2002), Bull and McKenna (2004), Jalink *et al.* (2014) and Braman *et al.* (2015) and are explained in the research process (section 3.2).

(d) Experimental validity and reliability issues

Reliability is the degree to which the experimental measurement used for a group of test-takers is kept consistent throughout the experimental study (American Psychological Association, 1999). Ward (1981) adds that this consistency should be assured for each individual test-taker. However, Miller *et al.* (1998) argue that experimental reliability is only the extent to which the assessment is consistent and warn that achieving 100 % reliability is unrealistic. Ward (1981) suggests that conducting the experimental test under supervised conditions with a checklist could increase its reliability by ensuring that the results obtained are solely based on the test-takers' own task.

This research adopted the ideas of Ward (1981) and Miller *et al.* (1998) in assuring the reliability of the experiment results by maintaining consistency in the experimental task and measurement. In addition, while performing concurrent validity with student groups care was taken in avoiding a number of possible validity issues:

- Ensuring students in both groups did not have any prior experience of the experimental task; this avoided differences in experiences among test-takers.
- Student were not allowed to change groups, but were allowed to train in both environments after the experimental study, as this avoided perception inequality in the learning resources.
- All participants were encouraged to complete the study, hence avoiding the issue of students quitting in the middle of the study.

Furthermore, the research design also considered some external factors that may influence the research outcome, which are addressed in the section below.

(e) Ethical considerations

It is important to identify and address potential ethical issues throughout the research process to protect the participants and the data collected. The research adopted Birmingham City University's (2010) Research Ethical Framework to address the confidentiality and security of the information gathered and used. The research further ensured that informed consent from participants was obtained through the case organisation (Birmingham City University Faculty of CEBE) through the standard BCU informed consent form. The consent form summarised the purpose of the study to the participants, clarified their role in the data collection process and addressed the confidentiality and security of the information that was collected.

Further, the participants were able to withdraw consent at any time to participate in the study and their data would no longer be utilised. Since the research involved measuring student satisfaction and outcome in using the developed prototype, the selected practical task was not part of the real academic assessment and did not influence the academic score of the student. According to Neuman (2000), ethical issues do not stop with data collection and analysis, but are also present in the writing up of the research results. Thus this research ensured the report was presented in unbiased language at an appropriate level and eliminated potential falsification of data to meet research needs.

3.2 Research Process

The study involved four major phases to develop and evaluate the KBEd prototype (Figure 3.4). Phase one involved exploring and reviewing extant literature relating to the key issues pertaining to the study. Phase two involved designing and developing the prototype by capturing and automating on-campus tutors' knowledge into the AR environment for teaching and assessing AR learners. Phase three involved evaluating the usability and reliability of the prototype with an expert group. This phase used face validity assessment in gathering and validating experts' reflections on the proposed prototype and was iterated in improving prototype usability before testing it with students (Redmond-Pyle and Moore, 1995). Phase four involved performance evaluation of a common experimental task by AR trained learners and on-campus trained ones; this phase used concurrent validity assessment to evaluate the differences between the two groups in their demonstrated skills and task outcome.

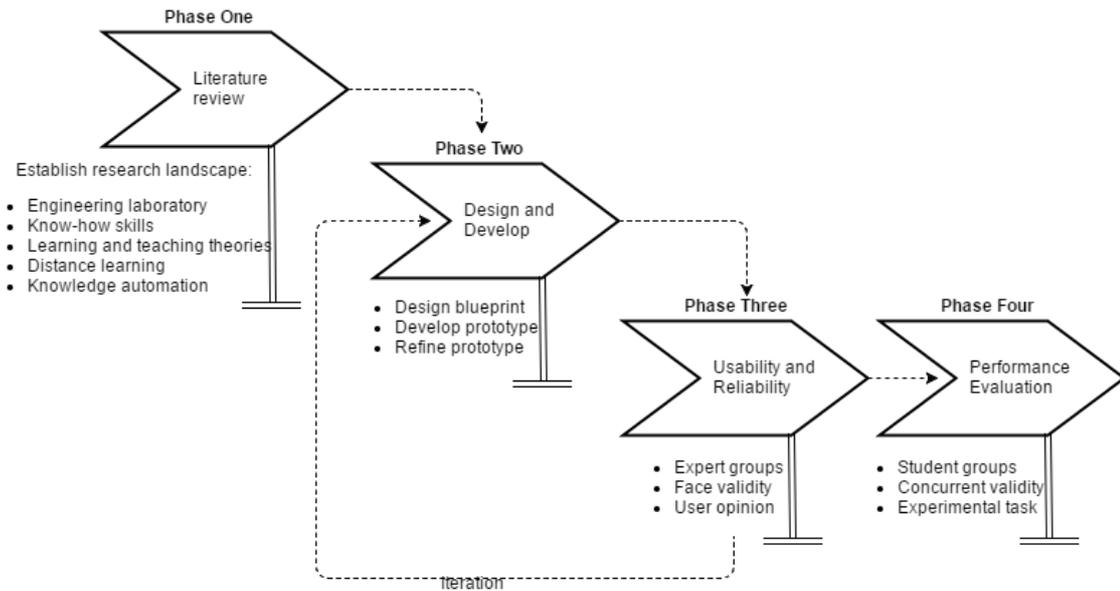


Figure 3.4: Procedural phases involved in the study

3.2.1 Phase 1: Literature review

The literature for this research ranges across several disciplines in order to address the research objectives and is therefore challenging to survey (see Chapter 2). In order to reduce the complexity and increase the accuracy of the search results from each of the disciplines, the literature search involved a three-stage process, adopting Ma and Nickerson’s (2006) search method (see Figure 3.5). The first stage involved the identification of key words and then an independent open federated search was performed across different databases including conferences, journal articles, industrial white papers, tactical reports and dissertations. Boolean parameters such as “engineering distance and online learning”, “engineering distance or online learning”, “know-how skill and industrial skill”, “know-how skills or industrial skills”, “engineering learning and teaching theories” and “engineering or practical teaching theories” (see Table 3.1) were then used as key strings to yield high quality articles across multiple disciplines. This resulted in the identification of more than 1000 articles from the search results for further analysis in the second stage.

The second stage involved manual filtering of the search results by two criteria; firstly by title, and then by reading the abstract and conclusion. The articles with more relevance to the research were chosen. Secondly, the citations of the filtered articles and documents were again manually scanned as before, so acquiring new articles and keywords. Some of the keywords such as “virtual reality”, “augmented reality”, “expert system”, “knowledge-based-engineering”, “ontology” and “artificial intelligence” were acquired from the initial search result citations. The above stages were then repeated for the new key strings. Stage three involved extensive reading of the selected papers, prioritising them by year of publication and the research requirements.

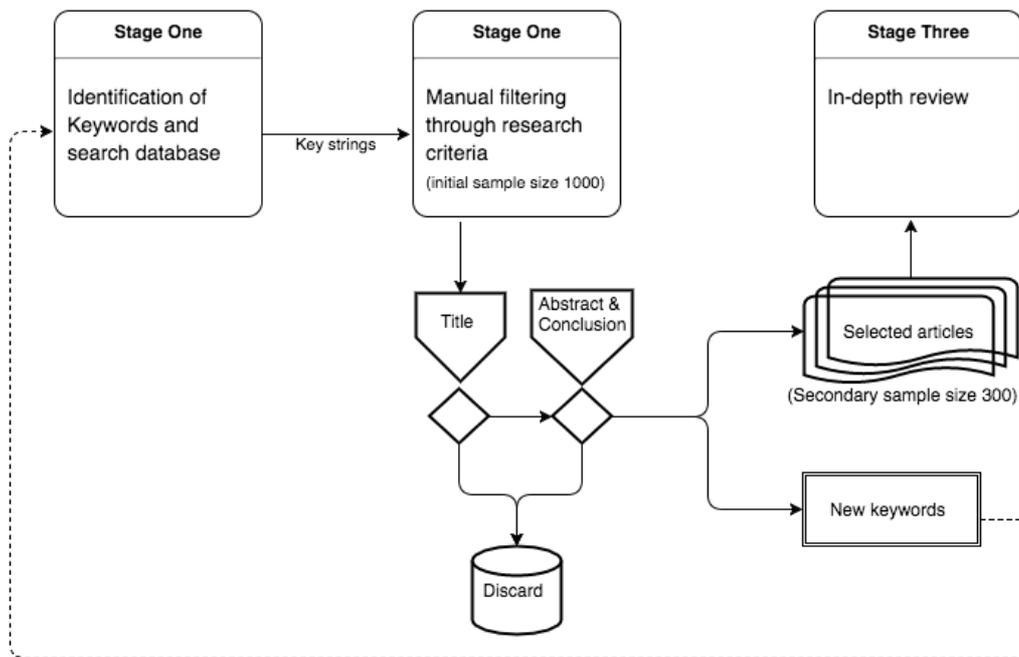


Figure 3.5: Three-stage literature search process

The literature search did not explore the overall effectiveness achieved by applications of KBE, ontology or artificial intelligence in their respective domains, but rather explored the effectiveness of their techniques individually with respect to knowledge capture, knowledge modelling and knowledge automation (section 2.7). For example, Chapman and Pinfold’s (2001) study explains time and cost effectiveness by using KBE

applications; this was not considered, but instead the knowledge automation techniques suggested and implemented in the same study were explored in detail (section 2.7.1).

Table 3.1: Keywords, key strings and search engines used in the literature search

Keywords	Key strings	Search database
<ul style="list-style-type: none"> - Engineering laboratory - Practical skills? - Engineering learning styles - Engineering teaching theories - Distance learning - Virtual laboratories - Remote laboratories - Virtual reality - Augmented reality - Knowledge capturing - Knowledge modelling - Knowledge automation - Expert system - Knowledge-based engineering - Semantic technology - Ontological modelling - Artificial intelligence 	<p>“distance and online learning”, “engineering distance or online learning”, “know-how skill and industrial skill”, “know-how skills or industrial skills”, “engineering learning and teaching theories”, “engineering or practical teaching theories”, “engineering distance learning challenges and issues”, “engineering distance learning challenges or issues”, “traditional and non-traditional laboratories”, “traditional or non-traditional laboratories”, “knowledge capture and acquisition”, “knowledge capture or acquisition”, “knowledge modelling and formalizing”, “knowledge modelling or formalizing”, “knowledge automation and codification”, “knowledge automation or codification”, “virtual and remote laboratories”, “virtual or remote laboratories”, “expert system and KBE”, “expert system or KBE”, “semantic and ontology modelling”, “semantic or ontology modelling”, “AI and computer intelligence” and “AI or computer intelligence”</p>	<p>Primary: ACM digital library, Science Direct (Elsevier), IEEE Xplore, GOLC, Emerald, EBSCO Suite, JSTOR, EdITLib and ERIC.</p> <p>Secondary: Google scholar, Google and On-campus library</p>

Further, in this review the terms ‘virtual’ and ‘remote laboratories’ were classed and explored together as non-traditional laboratories rather than individually; for example, Brinson’s (2015) article classifies all engineering laboratories apart from traditional ones as ‘non-traditional laboratories’ so avoiding any complexities (section 2.4.2). However, the characteristics, merits and demerits possessed by each of the non-traditional laboratories pointed out by studies such as Nedic *et al.* (2003), Gallardo *et*

al. (2007) and Settapat *et al.* (2009) were still explored in detail together. Having established an in-depth understanding related to the research issues, the next phase of the research involved design and development of a knowledge based educational framework to teach and assess practical skill for distance learners.

3.2.2 Phase 2: Design and development of the KBEd prototype

The objective of this phase was to design and develop a system by capturing and automating an on-campus tutor's knowledge to allow engineering distance learners to learn and train practical skills while away from the physical laboratory. The phase was executed through two sub-phases; the first involved the design of the proposed systems framework. Generally, a framework presents the blueprint of the proposed system before implementation. The proposed framework was constructed by identifying key elements that are needed in building the required system. The proposed KBEd framework (Figure 3.6) consists of four major elements:

- Knowledge capture (KC)
- Knowledge modelling (KM)
- Artificial intelligent (AI) tutor
- Augmented reality (AR) environment

The knowledge capture block involved the capture of all the required data for teaching and assessing the chosen practical task. These captured data then became the input for the knowledge modelling block, where the data were classified and relations were provided in an ontological structure through relational rules. The knowledge model acted as an AI tutor brain in querying, converting and publishing the knowledge models depending on the needs.

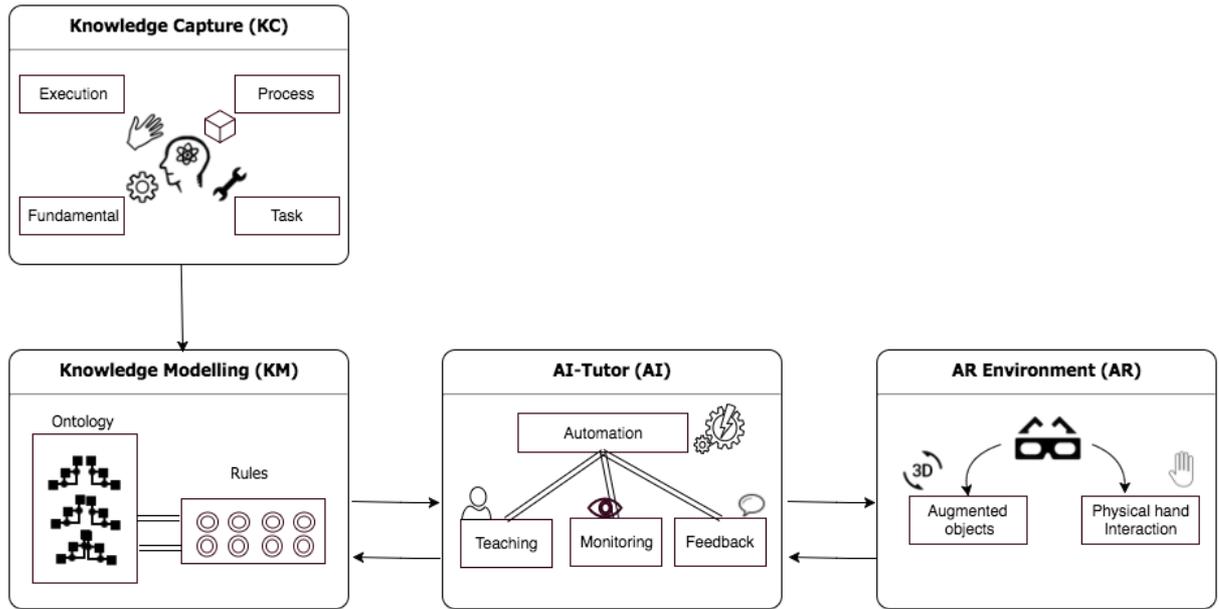


Figure 3.6: Knowledge based educational framework (KBEd)

The AI tutor block teaches, monitors and provides feedback on the practical skills of the learners performing through the AR environment. The AR environment block provides enrichment of the real world with complementary virtual 3D objects made interactable through real hand gestures in order to execute the desired practical task. The study applied knowledge-based engineering (KBE) principles that are used in the design and manufacturing industrial domain (Vijay *et al.*, 2015) to an educational domain in order to capture an on-campus tutor's knowledge (section 4.1). Further, it used ontological methods to model the captured knowledge through appropriate relations and state machines to automate this knowledge (section 4.2). With the completion of the proposed system blueprint, the next sub-phase involved implementation of the conceptual blueprint (Figure 3.7).

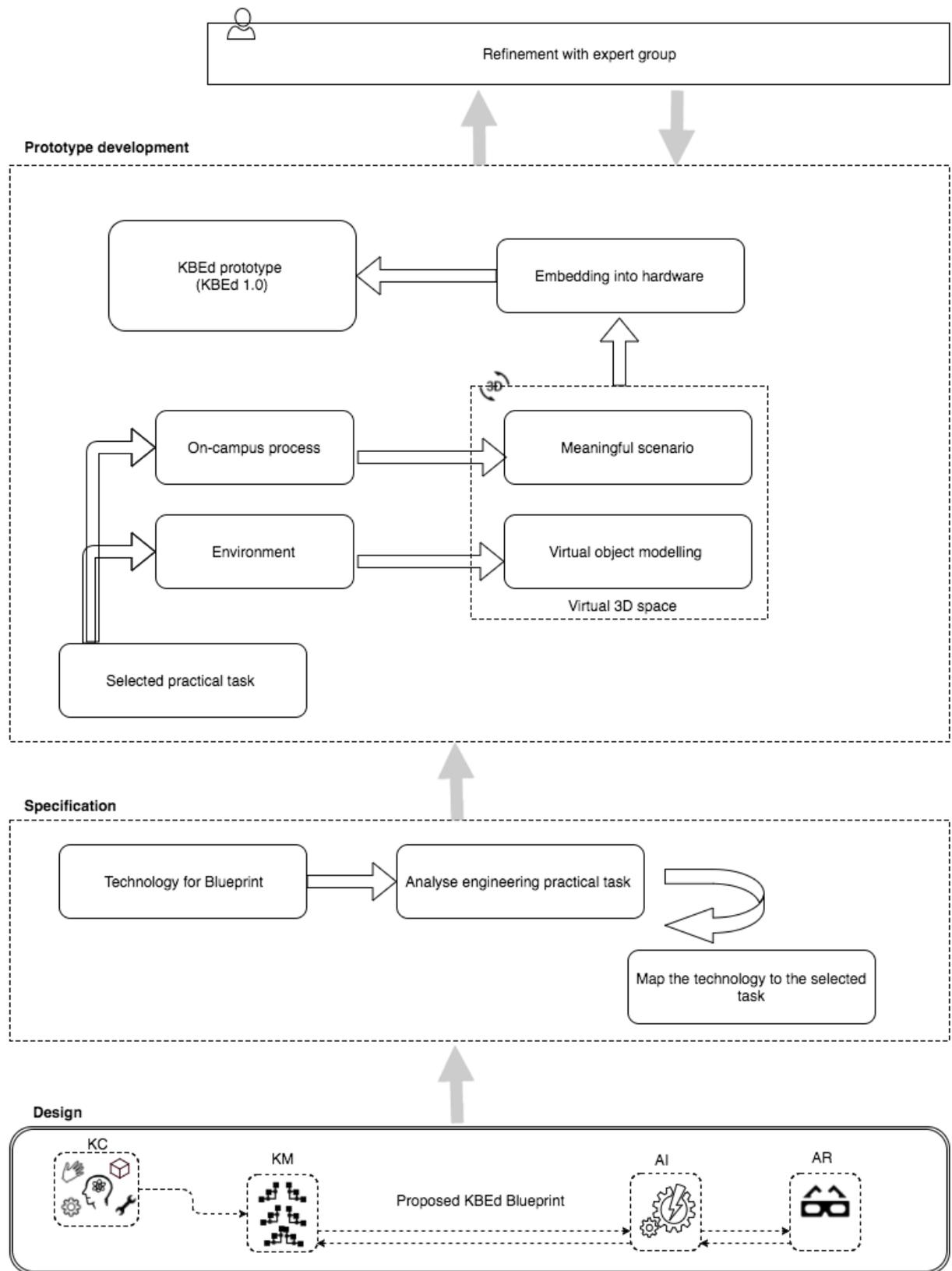


Figure 3.7: Implementation method for the proposed KBEd framework

The implementation phase started by identifying the technologies needed, based on McFarlan's (1981) and Davis and Olson's (1985) studies on building a prototype by analysis and mapped with respect to the chosen practical task requirement. The captured teaching and monitoring processes were then grouped into meaningful scenarios and automated through the artificial intelligence (AI) tutor (section 4.3). The learning environment and equipment involved in the chosen practical task (welding) were also modelled virtually (section 4.4) and embedded into the AR environment (section 4.4.4). The above discussed implementation stage for knowledge capture (KC), knowledge modelling (KM), AI tutor and AR environment is elaborated in detail in chapter 4.

3.2.3 Phase 3: Validation with expert group

The main aim of the evaluation phase was to assess the extent to which the proposed KBEd prototype was adequate for the intended research evaluation and to refine it based on the findings from the expert evaluation. This involved evaluating the prototype (KBEd1.0) with internal and external experts before testing it with students. The internal experts were two academic staff from the case organisation (Birmingham City University) who teach engineering subject practical tasks. This ensured that the initial readiness and the training capacity of the proposed system were equivalent to that of the traditional one (Lilley and Barker, 2002). The validation of the training system with internal experts was through heuristic evaluation (Molich and Nielsen, 1990; Redmond-Pyle and Moore, 1995; Preece *et al.*, 2002), which involved evaluating welding output, welding characteristics, augmented graphics, sound and virtual models with respect to the practical task (Figure 3.8).

In addition, any suggested changes were addressed to reduce errors and increase the training capacity of the system to that of the traditional one. The process involved pre-testing with internal experts and the changes made according to their suggestions are elaborated in chapter 4 (section 4.4.5). After refining the prototype with internal experts (KBEd2.0), it was then validated with a group of external experts from other universities and industries through both heuristic evaluation and experts' advice (McAteer and Shaw, 1994). This ensured the quality of augmented realism, usability, content and the capacity of the system to train welding tasks. This process used face validity assessment to capture user experiences and suggested changes. The results and the resulting changes that were made are elaborated in Chapter 5. By performing evaluation on reliability through pre-testing with internal and external experts, the usability and realism of the system was increased and operational errors were decreased in the proposed KBEd prototype (KBEd3.0).

(a) Participants

It is often said that identifying the right set of participants is very important to acquire the right set of data to address the research needs (Churchill and Lacobucci, 2006). The expert evaluation phase involved two categories of experts, targeting internal and external ones with expertise in the research domain (Barker and Barker, 2002). The initial evaluation with internal experts involved two of the case organisation's academic staff who were involved in teaching the same practical task that was captured and modelled in the proposed system (section 4.4.5). These two internal experts played a crucial role in reviewing and validating the developed AR system's teaching and assessment process equating to that of the existing on-campus systems (McAteer and Shaw, 1994).

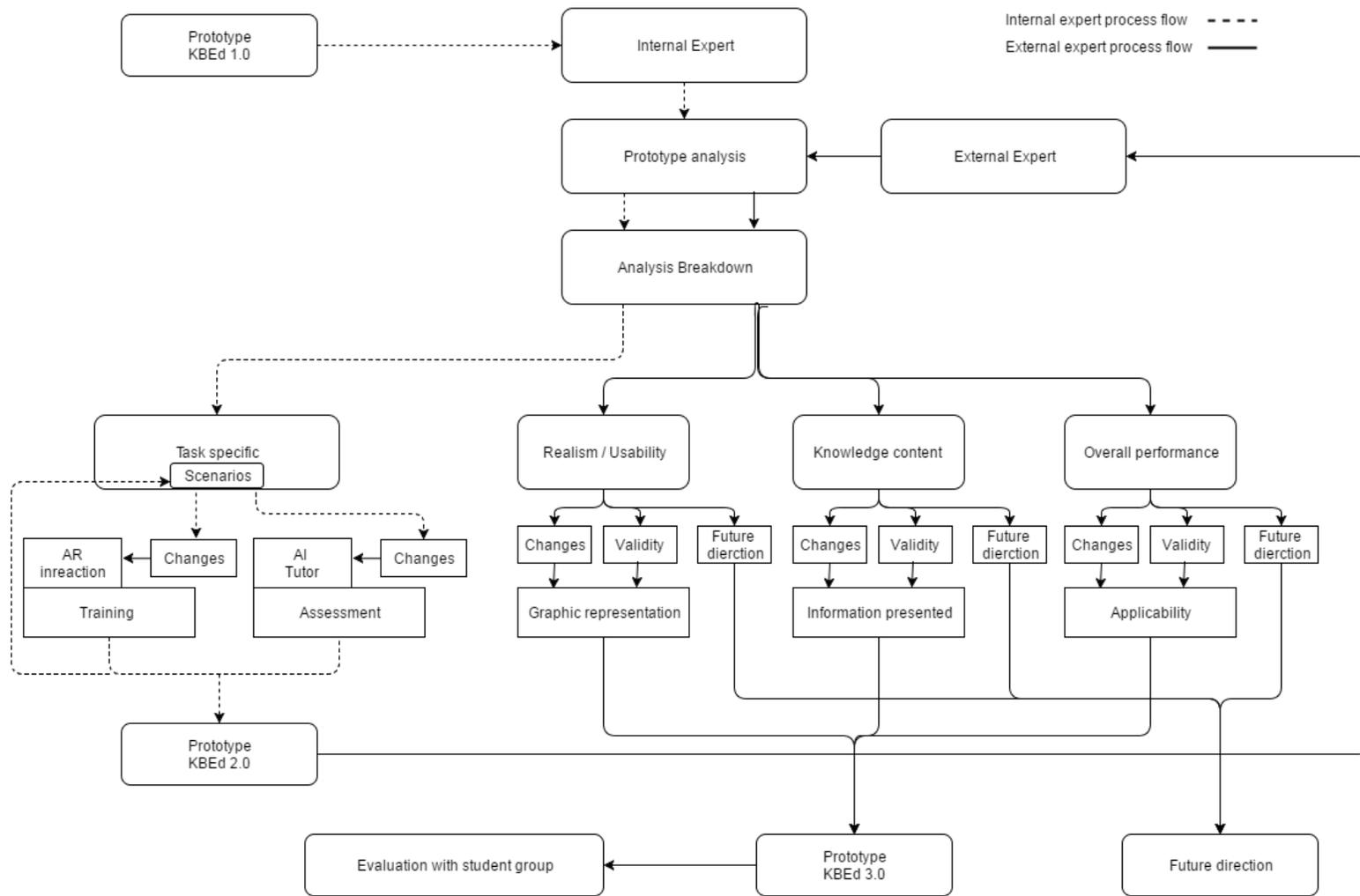


Figure 3.8: Process involved in validity and reliability testing with experts

Subsequently, face validity with an expert group involved twelve experts from various domains with expertise in teaching practical skills, knowledge modelling, semantics and gaming (section 5.1). These experts made validations and gave their opinions on the proposed system's interface realism, the controls of the training tool, the correctness of the modelled knowledge augmented in the AR environment and the overall usefulness of the system.

(b) Data collection

The data collection process with both expert groups started with a brief explanation of the research being undertaken and the process involved in the data collection. The experts were given a demonstration of how to use the KBEd system and then asked to perform the modelled welding task in the AR environment. The evaluation with internal experts was an iterative process, in which each of the seven modelled scenarios for the welding task was presented and observed individually. The data collection technique involved in this iteration cycle was through observation and by a discussion at the end of each cycle (Redmond-Pyle and Moore, 1995; Boyle, 1997; Dunn *et al.*, 2003; Bull and McKenna, 2004). This was in order to identify errors and any potential usability problems. These observations were then recorded in the observation table. The suggestions and corrections gathered at the end of each cycle (output) became the changes that needed to be addressed (input) for the next cycle. The captured suggestions and the respective changes made for each of the scenarios are presented in section 4.4.5. Each of the improved versions of the scenarios were saved for review; these iteration changes are available in Appendix CD (Folder 1).

The external expert evaluation process involved determining face validity through questionnaires and observations. This is considered to be a useful data collection technique in the educational domain (McAteer and Shaw, 1994; Boyle, 1997; Bull and

McKenna, 2004). Face validity was captured through eighteen questions covering the proposed system's realism, usability, quality of the captured knowledge content and its overall applicability (Table 3.2). These questions were developed based on Jettmar and Nass' (2002) human-computing interaction studies questionnaires. Seven questions were related to issues of the realism and usability, such as interface, AR interaction, visuals, user experience, satisfaction and confidence after using the system. Along with the realism and usability of the proposed system, the information it presents is more important to its overall success (Mason and Carey, 1983). With that in mind, six other questions were related to the knowledge content and teaching and training capabilities (learning object adaptability; assessment axis; training capacity, such as task completion; domain usefulness; and usefulness of the proposed capturing and modelling method).

The remaining five questions were related to the overall performance and applicability of the system, such as usability in their domain, overall capacity, usefulness and applicability to other practical tasks. At the end of their evaluation session, each of the external experts was asked to fill in the answers to all eighteen questions using a 5-point Likert scale to gather quantitative data on their subjective reaction to the system (Boyle, 1997). The Likert scale was chosen as it contains a defined choice, which posed less constraint on the experts as scales with more than five points may cause more difficulty (Preece *et al.*, 2002). In addition, the questionnaires incorporated of text boxes for each question to allow the experts to add comments if they wished to do so. All the sessions were video recorded for analysis purposes and these recordings are available in Appendix CD (Folder 2).

Table 3.2: Questionnaire framework

Item	Sub item	Elements	Number of questions
Realism and usability	<ul style="list-style-type: none"> • Design principle • Graphical representation 	<ul style="list-style-type: none"> • Previous experience • Interface • AR Interaction • Visuals • User experience • Satisfaction • Confidence 	7
Knowledge content	<ul style="list-style-type: none"> • Information representation • Learning and training capability 	<ul style="list-style-type: none"> • Learning adaptability • Assessment axis • Training capacity • Task completion • Domain usefulness • Capturing and modelling method 	6
Overall applicability	<ul style="list-style-type: none"> • Generalization 	<ul style="list-style-type: none"> • Usability in their domain • Overall training capacity • Usefulness to other practical tasks 	5

(c) Data analysis

The objective of the data analysis was to determine the consensus of the experts' opinions and obtain suggestions about the readiness of the proposed KBEd system. At first, the experts were categorised by filtering them through their previous experience in welding and use of AR/VR hardware. This initial categorisation helped to compare the data with the same set of individuals with similar experience and also to identify the common ground amongst the individuals with different expertise. Furthermore, all

the questions were grouped into three major categories (realism and usability, knowledge content and general validity) for analysis purposes. Convergence in opinion is generally determined through the plurality in the answers for each question related to the five possible answers (Elo *et al.*, 2014). This study used 'mode' as the analysis technique, which is suitable for non-parametric data in determining the level of agreement (Brown, 1988). The mode calculation was performed using the Statistical Package for the Social Sciences (SPSS 21.0), in which mode values equal to 1 or 2 are considered as very low and low, mode value equal to 3 is considered as unsure, and mode values with 4 or 5 are considered as high and very high.

The plurality in the comments provided was determined by classifying the comments provided under each of the questions into three statement categories: validity statement, changes statement and future direction statement. Moreover, the summarised raw data were tabulated and a comparison bar chart was prepared to show the differences in agreement of the experts. The calculated mode value, classified comments, the summarised raw data and comparison bar chart were tabulated together for every question and are shown in chapter 5. High priority was given to repeated suggestions by addressing them before evaluation with the student group. In addition, the video recordings were used to identify user difficulties in using the system and also to perform cross-analysis of video evidence with paper evidence.

3.2.4 Phase 4: Evaluation with student groups

The aim of this phase was to determine the usefulness of the proposed KBEd prototype in learning hands-on practical engineering skills. The usefulness was determined by the transfer of practical skills acquired by the learners from an AR environment to a real laboratory environment. The skills to be acquired were:

- Fundamental health and safety protocol involved in basic welding
- Preparation skills in setting up the required equipment
- Procedural skills in knowing what to do
- Executorial skills in knowing how to do it

The performance was measured by how accurate the learners were in setting up and then executing a quality basic weld joining two flat plates (section 6.3). Skill transfer was assessed by comparing the performance between the AR trained learners and the on-campus trained learners. The evaluation process started with the selection of 46 engineering students with no prior experience of welding and by randomising them into two groups of 23. One group learned and practised basic welding in the KBEd prototype with the guidance of an AI tutor, while the other group learned and practised in the conventional on-campus environment with the guidance of a real tutor (section 6.1 and 6.2). After training, each of the students from both the groups was asked to perform the welding task in the on-campus environment using real equipment and resources with no guidance. Their performance and the task outcome were measured through error detection and accuracy level (see chapter 6 Table 6.1). The data was then analysed to determine the quality of skill transfer and to test the acceptance or rejection of the null hypotheses. The section below explains in detail the criteria and process involved in participant selection in order to execute the concurrent validity assessment.

(a) Participants

To maintain concurrency between both groups in terms of learners' prior experience and exposure to the chosen practical task, novice engineering students were targeted as participants. First year engineering students in mechanical and automotive courses at Birmingham City University (UK) participated in the study. 46 students with no

previous experience in welding were randomly selected and were then further randomized into two groups of 23 using sealed envelopes. The students in both training environments had the same learning content and learning mission; therefore, the amount of knowledge made available for both groups did not differ significantly. However, the AR and conventional on-campus environments had their own limitations and benefits in their learning processes, which are further elaborated in chapter 6 (section 6.2). The practice time between both the environments varied; as this was the independent variable it did not affect the result of the study. The other external issues that might have influenced the participants' equality and data quality were identified and addressed (see section 3.1.3 (d) and (e)). The section below explains the critical variables and parameters involved in the data collection process to measure students' practical performance.

(b) Data collection

Measuring practical skills not only involves performance measurement of executional skills, but also the skills acquisition involving understanding, relating and patterning of activities. To measure learners' performance in these aspects for the given practical task, the concurrent validity assessment used one independent variable and six dependent variables. The independent variable denoted the type of learning environment (LE) in which the learners worked and the environmental factors were considered to be non-influential on the results achieved. The six dependent variables were fundamental skill (FS), preparation skill (PPS), procedural skill (PS), executional skill (ES), task outcome (TO) and number of second attempts (NSA).

(c) Independent variable

There are two possible modes that derive the value for the independent variable; if the learners trained in the proposed AR environment with the AI tutor then LE for them is represented as mode 1 (Figure 3.9). If they trained in the on-campus environment with a real tutor, then the LE for them is represented as mode 2.

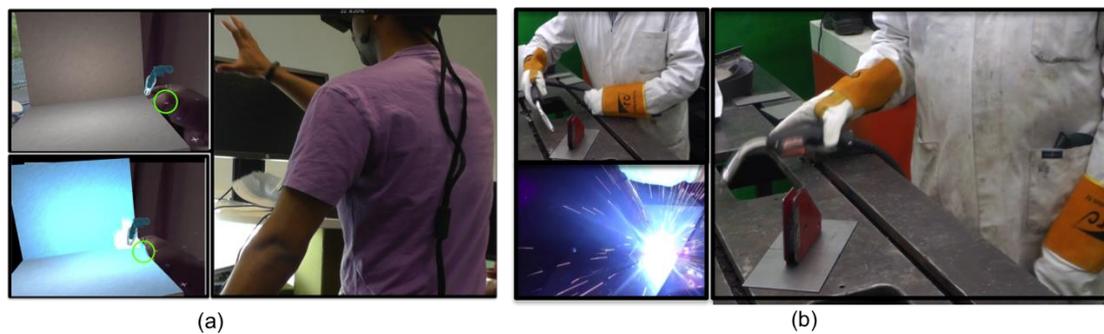


Figure 3.9: Learning environment (LE) variable's two possible modes: (a) mode 1, AR environment and (b) mode 2, on-campus environment

(d) Dependent variable

This study used a parametric assessment method to measure each of the dependent variables. This method used all the critical elements involved in each dependent variable as parameters to measure the respective skill level. Each of the parameters was then measured through error detection or a scoring system technique, depending upon the nature of the skill (Boud *et al.*, 1999; Wang 2005; *Sturm et al.*, 2008; Ramos *et al.*, 2014). The parameters for measuring fundamental skills involve all the safety protocols that need to be satisfied, which include wearing of a safety mask, gloves, coat and closing of the curtain. These fundamental parameters were measured by the error detection technique by checking whether all the parameters were satisfied or not. Very minor or major mistakes in satisfying any of the safety parameters were all considered

as errors. Further elaboration on the other parameter and the measuring techniques is provided in chapter 6 (section 6.3).

(i) Fundamental skill (FS):

The parameters used for measuring fundamental skills involved all the welding safety protocols that need to be satisfied. This included the wearing of a safety mask, gloves and coat and the closing of curtains. These fundamental parameters were measured using an error detection technique (Ramos *et al.*, 2014; Wang 2005; Seymour *et al.*, 2012) by checking whether the task related to the parameters was satisfied or not. However, both very small or major mistakes in satisfying any one of the fundamental parameters were all considered as errors. A single error made in any one of the safety parameters affected the entire FS variable and the score given was 0. All the safety parameters had to be satisfied without any errors to score 1; these values were recorded in the measuring table (Table 3.3).

(ii) Preparation skill (PPS):

The parameters used for measuring preparation skill were the setting up of the earth strap (ERS), amperage (Amp), wire-fed speed (WFS), gas level (GL) and switching on (SW) the welding console. These were also measured through the error detection technique. Similarly, even slight deviations from the accurate settings value were considered as errors and scored 0, but this affected only the particular preparation parameter and not the entire PPS variable.

(iii) Procedural skill (PS):

The parameters used for measuring procedural skill were degreasing the plate (DP) and placing magnets (PM) on specific location on the plate. These were also measured through error detection technique, where only exact procedural execution were not considered as error and scored as 1, any alterations in procedural were all considered as error. During the concurrent validation experiment it was made clear to all participants that speed was not a measuring parameter and instead emphasis was made on increment in safety and quality and decrement in error.

(iv) Executorial skill (ES):

The parameters used for measuring executorial skill were torch holding, hand speed, penetration, technique, tack weld, 20mm weld and the main weld. These executorial parameters were measured using a scoring system ranging from poor to excellent. The scores given were based on the objective performance measure, by having benchmarks for each of the executorial skills. Learners who demonstrated a higher level than the benchmark were given “good” or “excellent” depending on their consistency, learners who demonstrated a level close to the benchmark were give “satisfactory” and other learners were given “below average” or “poor” depending on how inconsistent they were. The scores were recorded in each of the executorial columns, which gave an insight of each individual’s performance while analysis into how good or bad a particular executorial skill was compared to the other group.

Table 3.3: Concurrent validity measuring table for the experimental task

Measuring parameters	Value (0 or 1)					
Fundamental skill (FS) Welding safety protocol						
Preparation skill (PPS) Checking the setting: - Earth strap (ERS) - Amps (Amp) - WFS - Gas level (GL) - Switching the machine ON (SW)						
Procedural skill (PS) - Degreasing the plate (DP) - Placing the magnet (DM)						
Execution skill (ES)	Scoring system	Poor	Below Avg	Satisfactory	Good	Excellent
	- Torch holding					
	- Hand speed					
	- Penetration					
	- Technique					
	- Tack weld					
	- 20mm weld					
	- Main weld					
Task outcome (TO)						
Number of second attempts (NSA)						
Comments on overall performance from tutor:						

(v) Task outcome (TO):

This measured the overall outcome of the practical task performed; the learners themselves self-measured their final outcome by placing the welded plate on an engineering vice and by hitting it with a hammer. The weld that stayed unbroken even when the plate bent was considered as a pass and the score given for TO was 1. On the other hand, if the weld broke it was considered as a fail and the student was given 0 for the TO.

(vi) Number of second attempts (NSA):

This variable measured the number of attempts that a learner took to complete a successful weld after having failed at the first attempt. This involved measuring only the final outcome; if they managed to produce a quality weld at their second attempt, then the NSA was given a 1, which referred to the number of attempts a learner made to produce a quality weld, after excluding the first attempt. Similarly, if the learners completed the task at their third or fourth attempt, then the NSA was 2 or 3, depending upon the number of second attempts. In addition to the measuring parameters, a comment box was also provided for the tutor to gather their overall opinion on each of the learner's performances.

(e) Data analysis

After all the data were collected, they were grouped under their respective independent variables; that is, either under mode 1 (learners who trained in the AR environment), or mode 2 (learners who trained in the on-campus environment). The scores given under each of the parameters were added up for each of the groups. All the fundamental, preparation and procedural skill data were analysed using a distribution graph to

compare the error percentage between the two groups. This provided a visual comparison of the errors made between the two groups for each of the parameters for the fundamental, preparation and procedural skills. In addition, the summarized raw data sets for each of the preparation and procedural parameters were tabulated and a comparison bar chart was produced to cross validate the performance differences.

As the study involved two individual groups of students practising in two different environments, the use of non-parametric Mann Whitney U-test can be considered (Corder and Foreman, 2014). However, there are insufficient data sets to fully justify this analysis. Recognising the lack of data set it was still considered worth undertaking such an analysis and the following null hypotheses were made:

- There is no significant difference between the basic welding skills acquired by learners who practised in an AR environment with an AI tutor and those who practised in an on-campus environment with a real tutor.
- There is no significant difference between the final welding task outcomes achieved by learners who practised in an AR environment with an AI tutor and those who practised in an on-campus environment with a real tutor.

By comparing the two population median values with a desired threshold value (α), we were then able to determine whether the executional performances of the two groups were similar or not (de Winter, 2015). The assigned threshold value (α) for the conducted U-test was 0.05, which emphasises that the performance difference between the two groups should be nearly zero. The calculations were conducted using the Statistical Package for the Social Sciences (SPSS 21.0), in which if the calculated z-score is lesser than -1.96 or greater than +1.96 we either reject the null hypothesis or we accept it and conclude that the two populations' medians are different at the desired threshold level (α) or the same (Pandis, 2015). In addition, the collected raw data were

tabulated and a bar graph with the scores of each executional parameter for both the groups was produced to show the performance comparison between each parameter of the executional skill. Finally, the overall task outcome (TO) and number of second attempts (NSA) differences between both the groups were calculated to determine the number of learners who failed or passed the given experimental task after training in one of the environments, and also a comparison bar chart was plotted to show the differences graphically.

3.3 Chapter summary and conclusions

This chapter explained in detail the methodological steps on how the research was conducted. The first half of the chapter presented the research design which outlined the research philosophies and different possible approaches in undertaking the research. Then the second half presented the research process which elucidated the reasoning behind the methodological selection i.e., rapid prototyping and construct validity. This chapter also explained the each phases involved under the selected research approaches in developing and evaluating the KBEd prototype to address the research questions. Having reviewed key literature related to the research in Chapter 2, and established the research methodology and proposed KBEd framework in this chapter, the next chapter presents in detail the implementation process involved in the developing the entire KBEd prototype.

Chapter 4 Implementation

“While children are struggling to be unique, the world around them is trying all means to make them look like everybody else”
- A.P.J Abdul Kalam

This chapter explains in detail each building block of the proposed knowledge-based educational (KBEd) framework (see Chapter 3 Figure 3.6) and its implementation procedures by adapting knowledge-based engineering (KBE) principles that are used in the design and manufacturing industrial domains (Cooper and La Rocca, 2007) to an educational domain in order to address the following two objectives:

- To capture, model and automate on-campus tutor knowledge in order to teach and assess practical skill within an augmented reality (AR) environment.
- To design and develop an AR environment in which to learn practical skills.

The chapter consists of four main sections and explains how the on-campus tutors knowledge was captured through the proposed three-column approach, modelled into an ontological structure, and then automated through artificial intelligence (AI) embedded in augmented reality (AR) in order to train practical engineering skills.

4.1 Knowledge capture

For any automation, irrespective of the domain, there are three main processes that need to be carried out: capturing, modeling and reuse of knowledge. First comes the subject data that needs to be captured; the data capturing technique depends upon the nature and purpose of the task or process that needs to be automated. This research requires the capture of data from the tutors on how the practical laboratory task is taught and assessed in an on-campus environment. It adopts knowledge-based engineering (KBE) techniques that have been applied in design and manufacturing industries to capture

complex knowledge from experts in automating design and manufacturing systems. The value of knowledge-based engineering is the way the data is captured and mapped to a greater granularity through dependency. Generally, the KBE capturing technique starts by capturing data about the product and its associated processes from a wider perspective and then drills deep into the critical elements to collect the meaningful data required for automation.

This data collection involves multiple techniques such as semi-structured interviews, discussion, storyboarding, acquiring document, video, audio and other pictorial evidence. The research in the course of automating the teaching and assessment processes involved in engineering laboratory tasks takes a four-stage approach (Figure 4.1) in capturing the process, fundamental, task and executional knowledge required for automation. In addition, the research proposes a three-column approach consisting of procedure, product and diagnostics to capture the task knowledge from the experts. These four stages involved data gathering techniques such as discussions to gather the procedural knowledge, audio and video recording of the task performed, and its visual product outcome. In addition, documents and pictures were gathered to capture the geometry and materials of the tools and equipment used in the practical task. The knowledge capturing stage involved Birmingham City University's engineering laboratory tutors, who have been teaching and assisting with several practical tasks for engineering students for more than a decade.

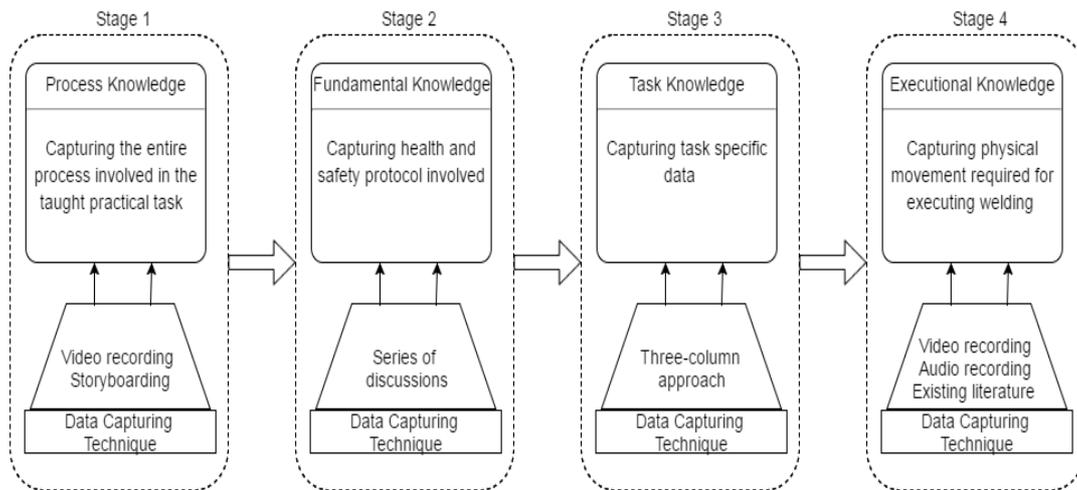


Figure 4.1: Knowledge capturing technique stages

4.1.1 Capturing process knowledge

The process of knowledge capturing started by gathering the general information on the list of first year engineering laboratory tasks that are taught, and their respective learning outcomes. Initially, laboratory manuals were gathered to establish the various practical tasks that are taught to on-campus students (Table 4.1).

Table 4.1: List of practical tasks for first year on-campus engineering students

Topic	Practical Tasks Taught
Applied Mechanics	<ul style="list-style-type: none"> - Strain gauge application on beam - E by bending of aluminium beam - Bending stress of beam - Damped vibration of beam - Photo-stress experiment - Boundary stress of beam
Materials and Manufacture	<ul style="list-style-type: none"> - Metal joining exercise -manufacturing and programming on CNC machine - Metal joining exercise – tensile testing on testometric machine - Tensile testing of carbon steel materials and microstructures - Corrosion of metals - Creep test - Basic welding
Thermodynamics	<ul style="list-style-type: none"> - Heat exchangers - Temperature calibration - Engine test cell demo

Among these taught practical tasks, basic welding, which is not part of the real academic assessment and is not associated with the academic score of students, was selected as the use-case for the research. Although the welding task is not part of the main assessment, acquiring welding skills is vital for third year practical work, when the students team up to build a student formula car. The taught welding task consists of four major learning outcomes: health and safety, flat plate welding, t-joint welding and saucer welding (Table 4.2).

Table 4.2: Learning outcomes of basic welding

Outcome	Knowledge acquired
Fundamental understanding	Understanding general principles and safety procedures involved in basic welding.
Preparation knowledge	Knowledge to identify required welding tools and setting them up with appropriate values.
Executorial skill	The skill to execute a smooth weld on a flat, vertical and circular surface.

The processes involved in teaching and assessing these welding tasks were then established and documented from a live laboratory session, in which the case organization’s laboratory instructor demonstrated and gave guidance on how to perform basic welding, while the students observed and practised in order to acquire the skills. At first, the laboratory instructor guided them through the health and safety procedures, followed by a brief introduction about the tools and equipment required for the task. In addition, the instructor paused and clarified doubts for the students during his explanation. He then demonstrated how to weld two flat plates and while performing the welding provided information about the key checks that need to be carried out. After observing how to use welding to join two flat surfaces, the students attempted to do the same. The instructor monitored them by creating a checklist in his mind and observing their corresponding actions while providing relevant feedback.

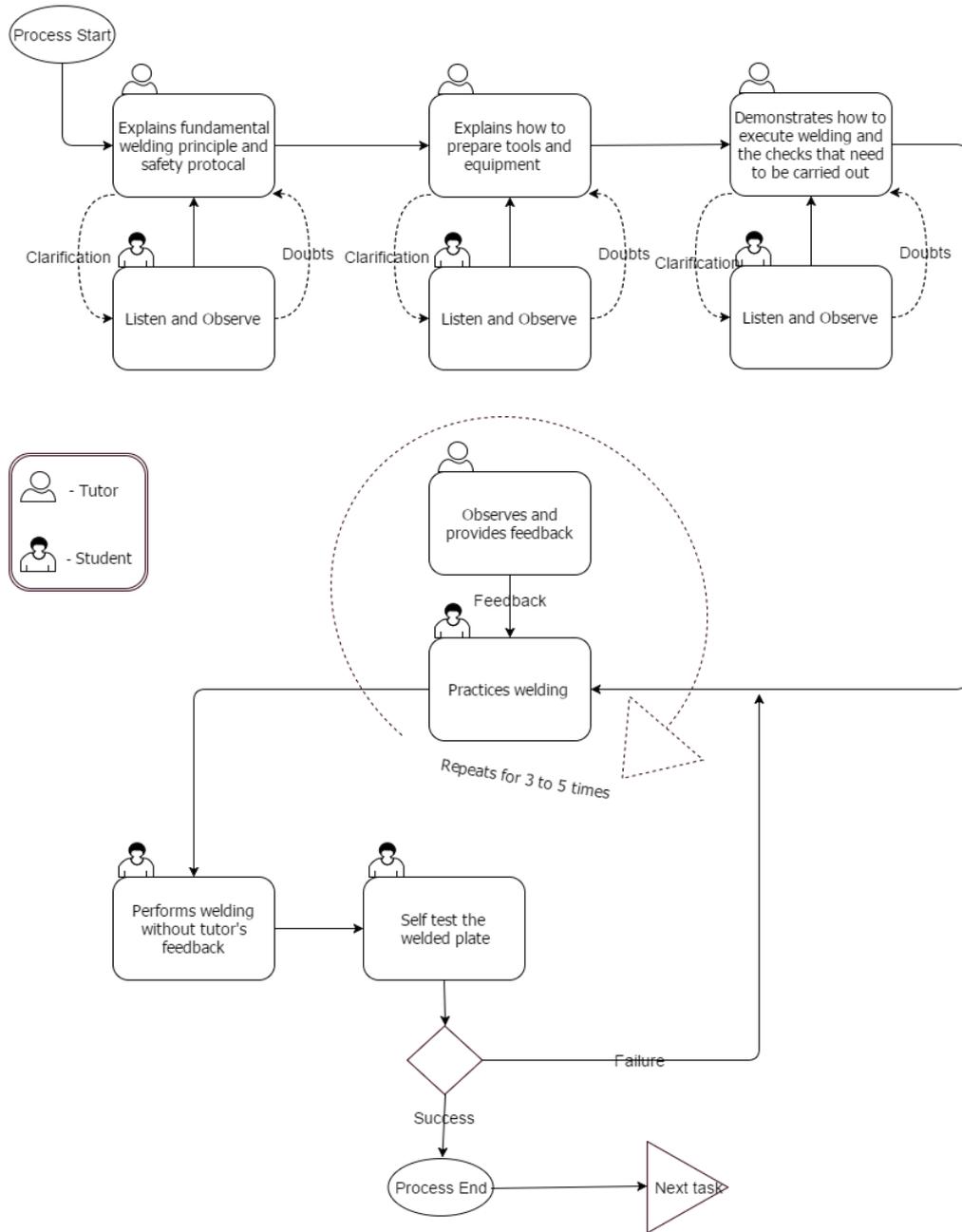


Figure 4.2: Process storyboard for teaching and assessing the welding task

The students then repeated the exercise in order to avoid the mistakes that they had made in the previous attempt. Each student practised at least three to five times before executing the final weld that was to be tested. The final weld was a self-test by the students in measuring the outcome; to overcome their mistakes the tutor guided the students who failed in producing a proper weld. After each student successfully

completed the flat plate welding, the tutor demonstrated how to execute a t-joint weld, which was followed by a demonstration of saucer welding. All these processes were video recorded and were then converted into graphical blocks with directional connectors to understand the logical flow between the processes involved in teaching and assessing the welding skills (Figure 4.2). The next phase involved establishing the fundamental knowledge that is required to perform basic welding.

4.1.2 Capturing fundamental knowledge

Fundamental knowledge here refers to the health and safety protocols that need to be satisfied with respect to the practical task. The safety protocol for welding requires the knowledge and understanding of protection of oneself and others from getting injured by knowing the use and application of appropriate safety measure. Various critical elements involved in the safety protocol such as safety equipment, and its applicability and use in different circumstances, were obtained from the laboratory tutor through a series of discussions. These were then represented in a hierarchical chart in order to gain a clear understanding (Figure 4.3). The hierarchical structure of health and safety has six levels, with each level providing in-depth knowledge of the previous level.

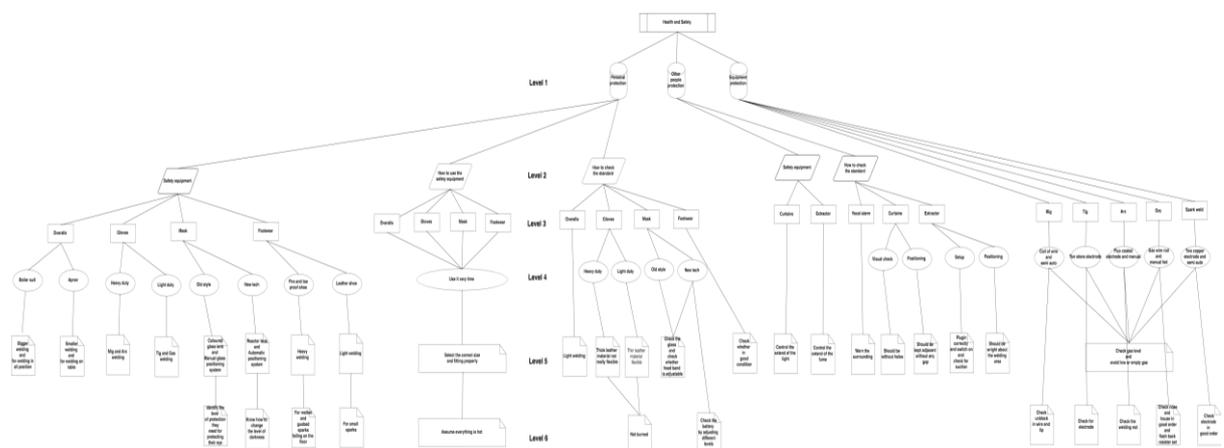


Figure 4.3: Health and safety hierarchical structure (for magnified image refer to Appendix 2)

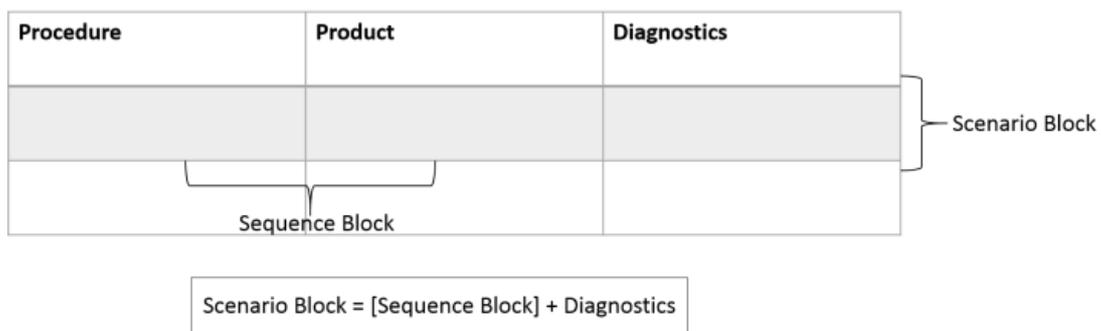
Level one captured the different protection involved in health and safety, namely personal protection, protection of other people and equipment protection. Specific knowledge of each of these forms of protection were then expanded in level two, which captured knowledge of three of their critical aspects: the equipment required, how to use it, and how to check its standard before using it. Levels three and four established the respective safety equipment involved and its types. Levels five and six captured the detailed information related to each of the types with respect to the welding task. The hierarchical structuring of the captured health and safety data helped to have a better understanding of the relations between different safety protocols and the necessity to follow them when performing welding. The next stage involved capturing task-specific knowledge through the proposed three-column approach.

4.1.3 Capturing task knowledge

This knowledge capture involved gathering the procedures to perform the welding task, followed by the intermediate checks that need to be carried out during its execution, and also the tutor's diagnostic knowledge of these checks in order to establish why students have failed to complete the task satisfactorily. This knowledge is critical in any automation involving knowledge-based engineering, as it acts as the building blocks in developing intelligence. Moreover, the learning process involves curiosity, which potentially leads to a 'why' question? Pointing out and answering why students have gone wrong or how they could avoid ending up with a bad weld is also a vital part in learning. The research proposes a three-column approach to establish this knowledge, which consists of procedure, product and diagnostics in identifying and structuring the procedural sequence, intermediate checks and the diagnostics ('why') knowledge required for automation.

The procedural column shows the sequence of procedures that are required to perform the task. An individual or sequence of procedures had one or more intermediate visual checks that needed to be carried out before moving on to the next sequence of procedures. These visual checks are shown in the product column; the captured procedure and its corresponding visual checks form a sequence block (Table 4.3). Each of the sequence blocks consists of a diagnostics column which shows the ‘why knowledge’ of what could possibly go wrong if the procedure were not performed or/and the product check were not satisfied. In addition, the diagnostics column also includes the practical ‘know-how’ that is needed by an individual to complete the particular sequence block. The sequence block consisting of the procedural and product columns, along with the appropriate ‘why knowledge’ in the diagnostics column, together form a scenario block. The number of scenario blocks depends upon the number of sequences and intermediate checks that need to be performed for the task.

Table 4.3: Proposed three-column approach



The chosen use-case welding has three separate tasks: flat plate welding, t-joint welding and saucer welding. In flat plate welding students learn to weld on a flat surface, whereas in t-joint welding students learn to weld on a horizontal surface. Saucer welding involves the skills gained through the previous two techniques in welding on a circular surface (Figure 4.4). All three welding tasks have seven scenario blocks with

their own procedural, product and diagnostics columns (see Appendix 3). The data for these columns were obtained through a series of discussions with the laboratory tutors. The discussions also involved identification of the other executional knowledge that needed to be identified, such as critical hand movement, eye coordination, and visual and audio feedback while performing the welding task (Table 4.4). On completion of the data capturing required for the three-columns, the data for the other identified critical knowledge were obtained at the executional knowledge stage.

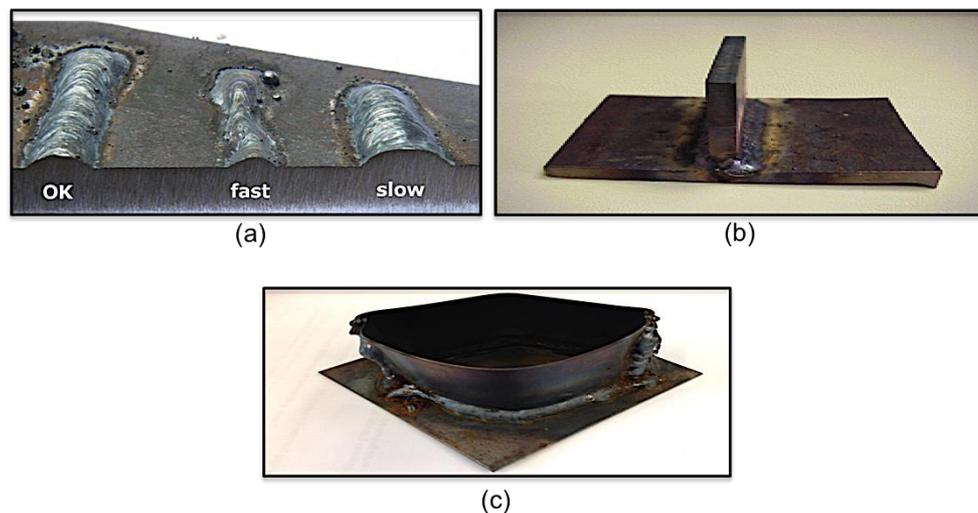
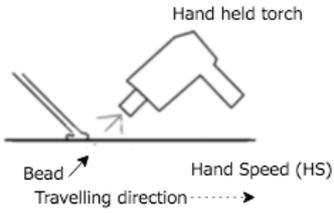
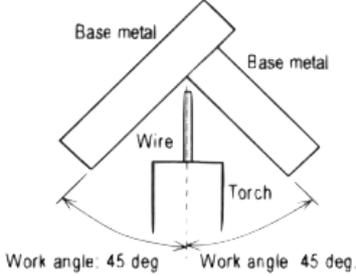
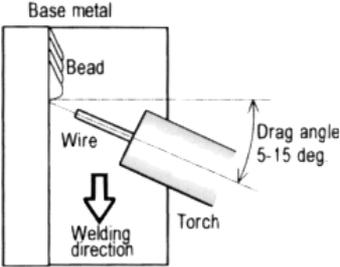


Figure 4.4: Three welding tasks performed by students. (a) flat plate welding; (b) t-joint welding and (c) saucer welding.

4.1.4 Capturing executional knowledge

This stage involved capturing all the executional knowledge that is required to perform the practical task. One of the most important skills that needs to be acquired when performing welding is hand movement, which requires the correct torch angle and steady hand speed. These critical parameters were obtained from the existing literature, including ‘VR welding trainer’ developed by the Edison Welding Institute (EWI), General Dynamics Electric Boat (GDEB) and VRSim, which have been the benchmarks in virtual welding (Table 4.4).

Table 4.4: Executional parameters. Adapted from Porter *et al.* (2006)

Parameters	Graphical representation
Travel Speed (TS)	
Work angle (WA)	
Drag angle (DA)	

Porter *et al.*'s (2006) two year experimentation samples consisting of both “good” and “bad” welds in acquiring the optimal range for executional parameters from the real environment to the virtual environment have been vital knowledge in developing the virtual welding environment (Table 4.5). The range value of the executional parameters influences the welding outcome, and the optimal range captured from the ‘VR welding trainer’ was used as the boundary in developing the proposed AR welding environment. In addition, the AR environment was further tested with the lab tutors to validate the accuracy of the AR welding outcome with respect to hand speed and orientation (section 4.4.5)

Table 4.5: Critical range for executional parameters. Adapted from Porter *et al.* (2006)

(Measurement: Speed - > *Inches per minute (ipm)*, Angle - > *degree*)

Execution	Parameters	Description	Condition	Range
Hand Speed	Travel Speed (TS)	Speed of torch movement while progressing from side to side.	Correct	10 – 15 (<i>Ipm</i>)
			Too fast	Above 16 (<i>Ipm</i>)
			Too slow	Below 9 (<i>Ipm</i>)
Hand Orientation	Work angle (WA)	Angle of the torch nozzle in relation to the face of the metal plate	Correct	Approximately 45° angle
	Drag angle (DA)	Angle of the torch tip in relation to the direction	Correct	5° - 15° angle

Audio recordings were made for welding sounds related to different hand movements in the laboratory environment. Lab tutors were asked to perform welding with various hand speeds to demonstrate different welding sounds, which were as follows:

1. Welding sound heard with correct hand movements (within speed range) ♪
2. Welding sound heard with incorrect hand movements (exceeding the range)
 - (a) Welding sound for too slow hand movement ♪
 - (b) Welding sound for too fast hand movement ♪

These varying welding sounds in accordance with the hand movement are also critical. By hearing these variations, learners can be cautious on whether they are using the correct hand speed or one which is too fast or too slow. All the equipment and the tools that were used while performing the welding were captured through detailed camera images, as this provided a clear geometry of the objects and a rendering of the material that needed to be modelled in the augmented environment (Section 4.4.1 Table 4.9). The knowledge capturing stages have made the process richer and more focused on the data that need to be captured for the required automation. Moreover, the proposed three-

column approach has allowed the capture of in-depth task knowledge in a structured way, which was then easily interpretable by the lab tutors in verifying and validating the correctness of the knowledge obtained. All the captured images, video and audio recordings are available on a DVD attached to this document (Appendix CD (Folder 3)). The following section involves the modelling of this knowledge with relations and rules in an ontological environment in order to feed the AI tutor and automate the teaching and assessment of the practical skills of the learners performing in the AR environment.

4.2 Knowledge modelling

With the completion of knowledge capture, the data was modelled into a computerised environment for automation. To do this, data need to be individualised and arranged in a meaningful way. The first step in the knowledge modelling is to eliminate duplication of data and then provide a relation between them. As the core knowledge was captured through a structured three-column approach involving procedure, product and diagnostics, the arrangement of the data and establishment of the relation for knowledge modelling was made easier. The knowledge modelling consisted of three phases: informal modelling, formal modelling and knowledge automation. The informal modelling phase used a spreadsheet as the modelling environment to construct and test the initial logic, and then these logics were enhanced further through the formal modelling phase using ontology (Figure 4.5). The final phase involved the triggering and representation of the knowledge model from an external environment. This three-phase approach provided a clear road map for the construction and testing of the logic with complex rules in a modular way in order to model the captured knowledge.

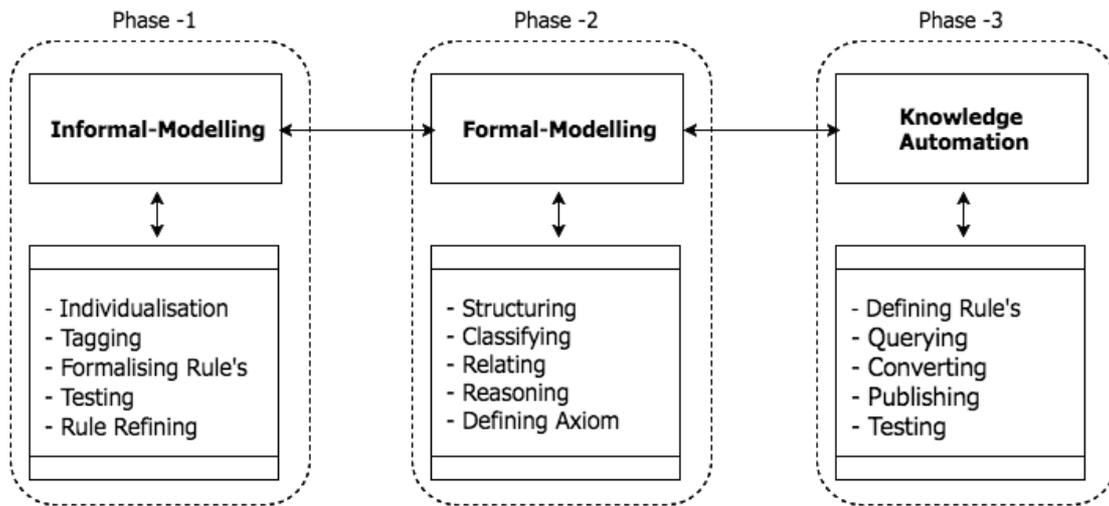


Figure 4.5: Knowledge modelling phases

4.2.1 Informal modelling

The aim of the informal modelling phase was to construct and test the required logic in a smaller environment before modelling it in a larger environment. In this case, the smaller and larger environments refer to the amount of time and coding required to construct and test the logic. Although there are limitations in generating a complete knowledge modelling in a smaller environment (Excel) compared to that of the larger environment (ontology), defining, testing and refining the conceptual logic in a smaller environment was more efficient and less time consuming. The informal modelling started by eliminating duplication and individualising the data under each of the procedure, product and diagnostic columns. Each of these was then arranged in a separate cell and given a tag (Figure 4.6). Here, tag or tagging refer to a unique identifier given to each of the classified individuals.

With the completion of individualisation and tagging, a group of individuals or a single individual from a procedure cell were related to their respective product and diagnostics cell through cross-tags. A cross-tag creates a relation between two tags, meaning it provides a relationship between different cells. Cross tagging the procedural tags to

their appropriate products and diagnostic tags generates the welding scenario blocks for all the three welding tasks. With the completion of the assignment of tags to each of the individuals and the definition of the cross-tags for each scenario block, the rules that automated the knowledge modelling were written.

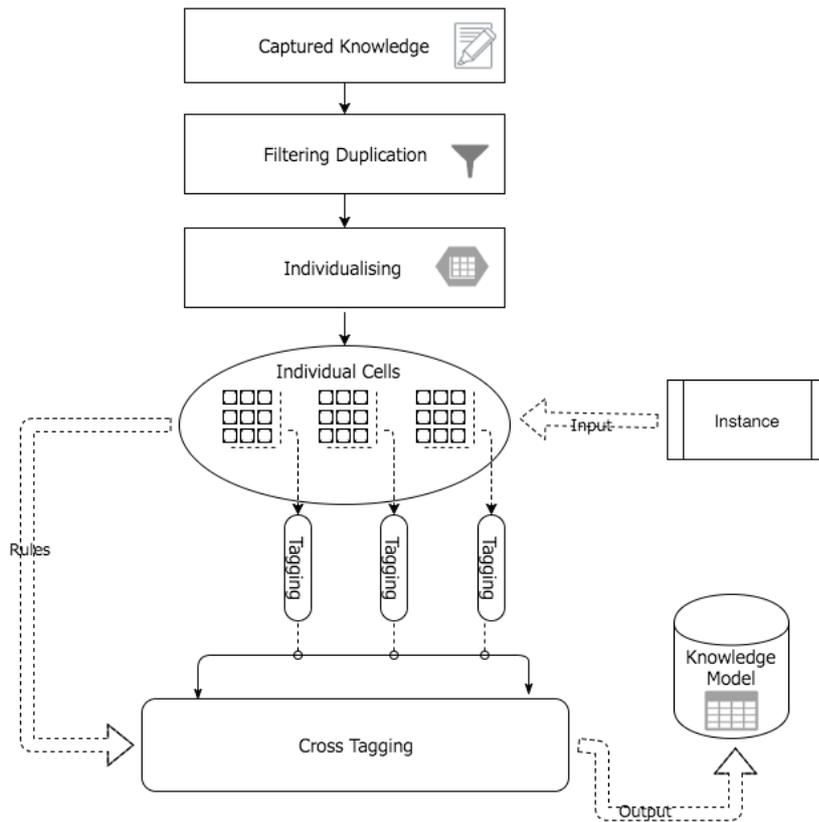


Figure 4.6: Informal modelling logical blocks

A rule in the spreadsheet environment refers to the formula that is written to generate the knowledge model for any given instance. In this case, an instance could be ‘flat plate welding’, ‘t-joint welding’ or ‘saucer welding’. Depending upon the instance, the rule generates the knowledge model by calling the appropriate tags and by relating them through their cross-tags. The rule written consists of a number of if-statements, first checking the type of instance that has been instantiated and then executing the conditions that need to be satisfied for that particular instance. The rule governs all the

knowledge modelling by querying what procedure, product and diagnostics need to be generated (Figure 4.7).

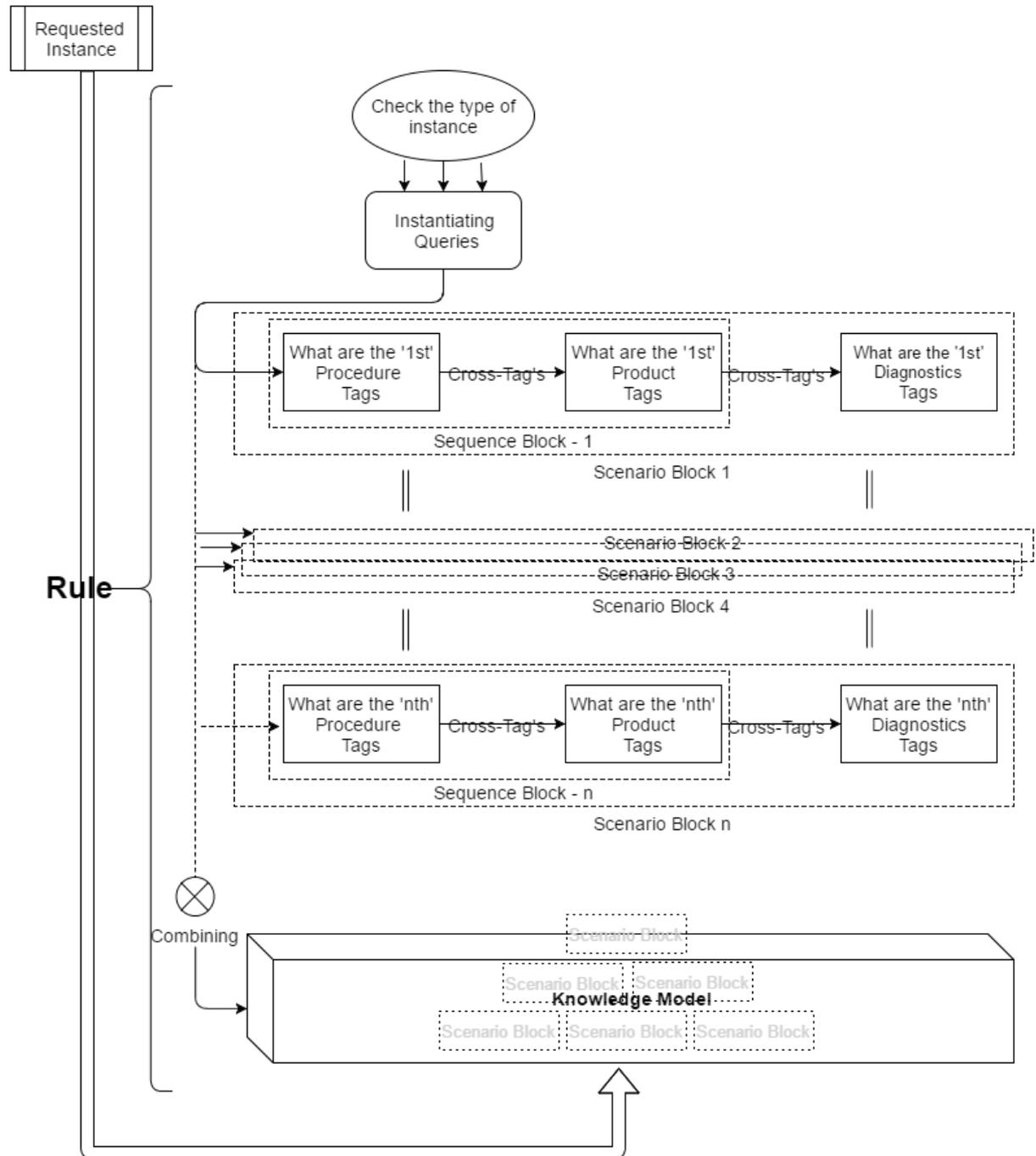


Figure 4.7: Algorithm from the constructed rule

For instance, if the flat plate welding has been instantiated the rule checks the type of instance, queries the list of procedures tagged to it and queries the respective cross-tags in relating the kind of product check that needs to be executed to generate the sequence block. The rule also queries the cross-tag by relating the appropriate diagnostics with respect to the sequence block in modelling a scenario block. The same is repeated in modelling all the scenario blocks for the instance. The rules written for each of the knowledge queries are then tested with different instances and redefined to achieve accurate modelling results. Initially constructing the informal knowledge models and testing them in the spreadsheet environment helped to refine the core logic and provided an optimal path for enhancing the formal modelling technique in an ontological environment.

4.2.2 Formal modelling

The formal modelling phase involved not only the data detailed in the three columns but also the modelling of all the knowledge needed to automate the teaching and assessment process involved for the chosen practical task. This research proposes a structure in modelling the knowledge by having the learning object as the core and its sub-learning objects around it; these sub-learning objects are then encapsulated by the learning structure and each of the learning structures is further encapsulated by learning modes (Figure 4.8). With respect to the use-case, the core of the learning object is welding and the sub-learning objects around it are flat plate welding, t-joint welding and saucer welding. The learning structure refers to the different learning levels under each of the sub-learning objects; the research proposes three levels in the learning structure, namely Introduction, Preparation and Execution. Learners could start from any of the preferred levels depending upon their previous knowledge and experience with respect to the learning task. The learning mode refers to the preferred way of

learning these different levels through different modes by providing the learners with audio content (tell me) to listen to, video visuals (show me) to see, or an AR environment (have a go) in which to practise their laboratory skills.

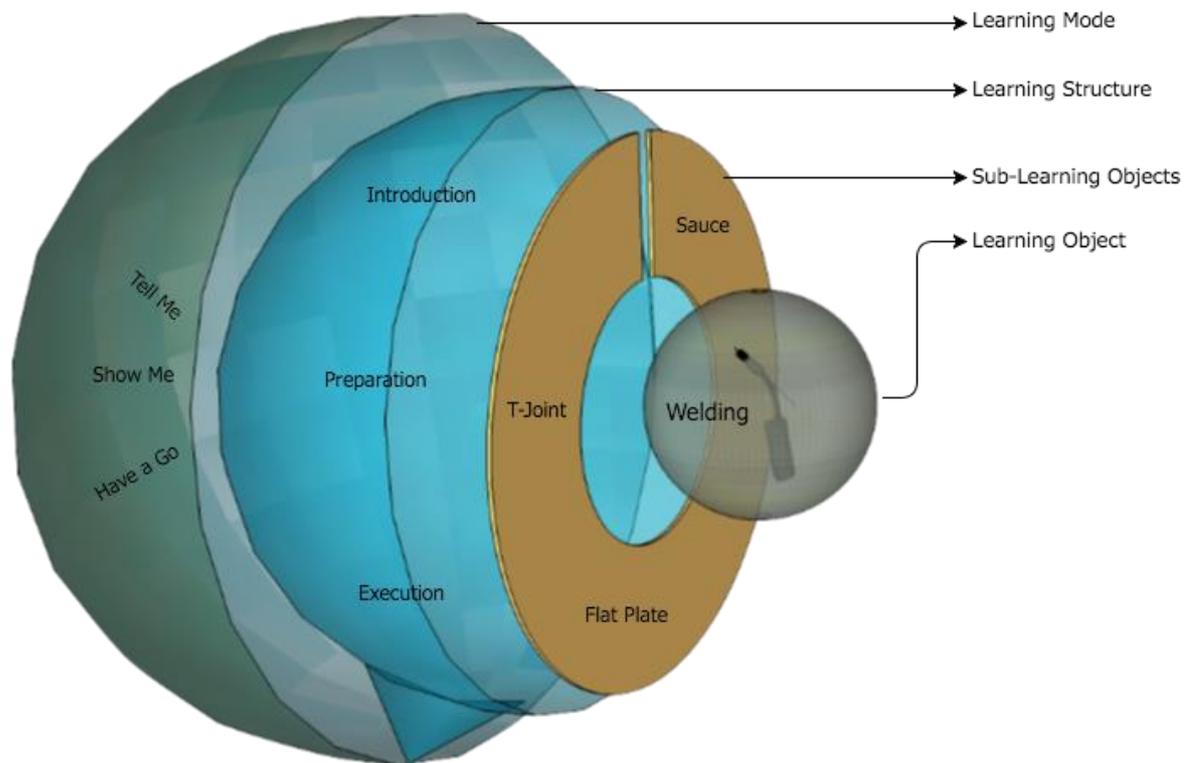


Figure 4.8: Learning object structure

The research used Protégé, an open source ontology editor, to model the proposed knowledge structure consisting of learning object, sub-learning objects, learning structure, learning mode and their knowledge content in an ontological environment through classes, sub-classes and individuals. In this use-case, the core learning object, welding, was modelled as a class and its sub-learning objects were modelled as sub-classes of welding. Defining the sub-learning objects under the main learning object in an ontological structure (using the IS_A sub-sumption relation) makes the relation between them explicit by default without any additional relational definition. The learning structure and the learning mode were modelled as separate classes with their

different levels and modes as their sub-classes (Figure 4.9). The term ‘knowledge content’ is considered to be individuals, which could be any source of information such as text, audio or video.

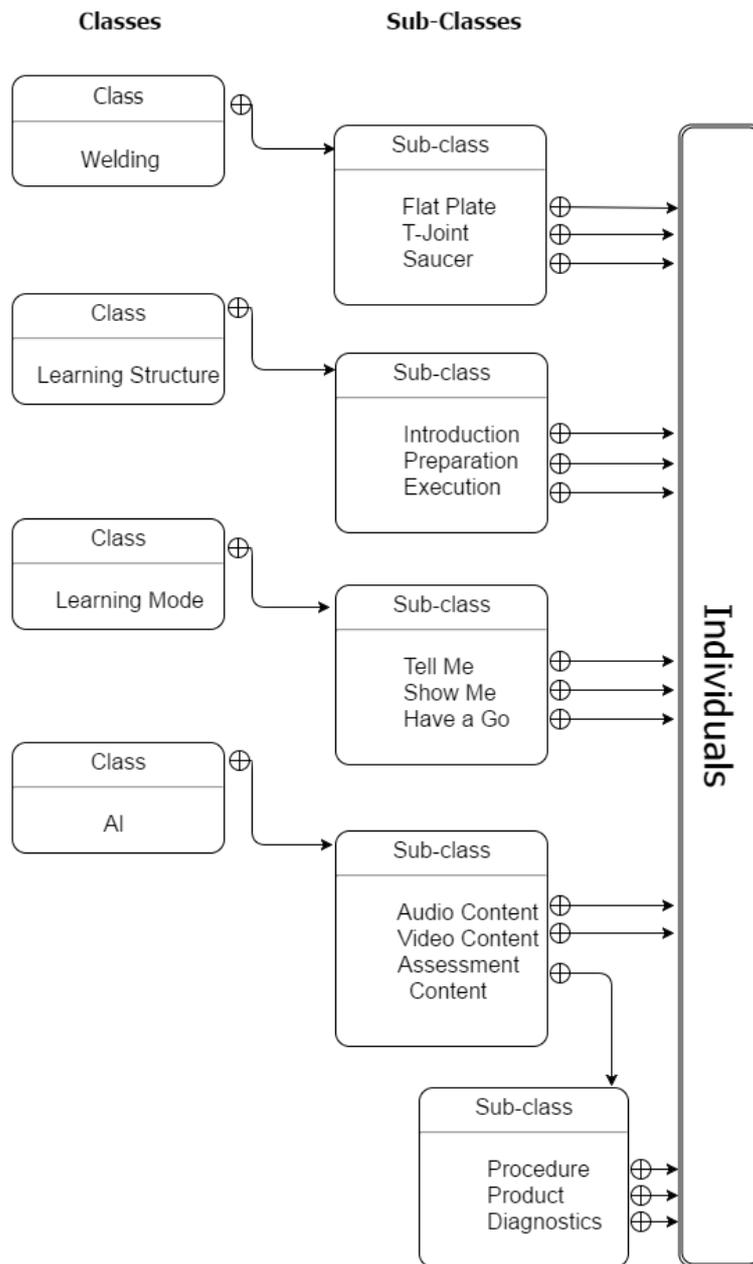


Figure 4.9: Ontology class diagram

The knowledge content for all the above classes were stored under the AI class, which has three sub-classes to further classify the knowledge content by audio content, video content and assessment content. All the captured text and auditory knowledge were

stored individually under the audio content. In an ontological environment an individual is a singular element or object, which can be reused to relate it to the n-number of classes or its sub-classes. Similarly, all the captured video knowledge was stored under the video content. The data displayed in the three columns were modelled under the assessment class, with procedure, product and diagnostics as its sub-classes. Each of the procedural sequences, product checks and diagnostics knowledge which were individualised in the Excel environment as cells were modelled as individuals under each of these sub-classes. All these modelled individuals were then tagged to different levels of the learning structure class. The individuals with information related to overview and primary health and safety about the practical task were tagged to the introduction class. Similarly, individuals with information about how to set up the tools and required equipment were mapped to the preparation class and individuals with information about how to perform a task and test its output were mapped to the execution class.

With the completion of the modelling of all the classes, sub-classes and individuals separately, these separate objects were then related in a meaningful way to generate the knowledge model. For that to take place, the core logic and the formulated rule that were written and tested in the spreadsheet environment were transformed into propositions. In an ontological environment, propositions are used to provide reasoning about the classes, sub-classes and the individuals by relating them in a meaningful way. The number of propositions defined could vary depending upon the complexity of the relations. For the welding use-case, we have defined eight different propositions in creating the relation between the modelled classes, sub-classes and individuals (Table 4.6). The name given to each of the propositions reflects the relation that it provides; the 'hasLearningObject' proposition was defined to find all the sub-learning objects

under a given learning object. For instance, if the ‘hasLearningObject’ proposition was called upon for welding, it would provide the list of sub-learning objects that were modelled under the welding learning object.

Table 4.6: List of propositions and their relational functions

Proposition	Relational Function
‘hasLearningObject’	Provides all the sub-learning objects related to the referred learning object.
‘hasLearningStructure’	Provides all the learning structure levels related to the chosen sub-learning object.
‘hasLearningMode’	Provides all the learning modes applicable to the chosen learning structure.
‘hasAI’	Provides complex relations between the procedural, product and diagnostics individuals for the “have-a-go” learning mode.
‘hasAfter’ / ‘hasBefore’	Arranges each procedural, product and diagnostics individual in the right sequence by relating their tagging occurrence order.
‘hasScenarioBlock’	Combines the entire scenario related to the sub-learning object to one block.

Similarly, the propositions with the relations ‘hasLearningStructure’ and ‘hasLearningMode’ were defined to provide the list of learning structures and learning modes for a given sub-learning object. The ‘hasAI’ proposition was defined to provide the knowledge content for a given sub-learning object with respect to the preferred level of learning structure and type of learning mode. To call a ‘hasAI’ proposition and generate the knowledge content requires three inputs; the first is the preferred task from the sub-learning object class. For instance, the task could be flat plate, t-joint or saucer welding. The second is the preferred level from the learning structure class; for instance, it could be introduction, preparation or execution. The third is the preferred mode from the learning mode class, namely tell me, show me or have a go. With respect to the given three inputs, the proposition with the ‘hasAI’ relation then links them and provides the respective knowledge content. For example, if we consider flat plate

welding, introduction and tell- me as the three inputs for ‘hasAI’, the query for the ‘hasAI’ relation first retrieves all the objects modelled in relation to flat plate welding. It then acquires all the relevant knowledge content with respect to the introduction level, such as overview of the practical task and the basic safety that needs to be satisfied (Figure 4.10). Finally, ‘hasAI’ filters the acquired knowledge content with respect to the third input; in this case it is tell-me, so all the auditory content is modelled as the output.

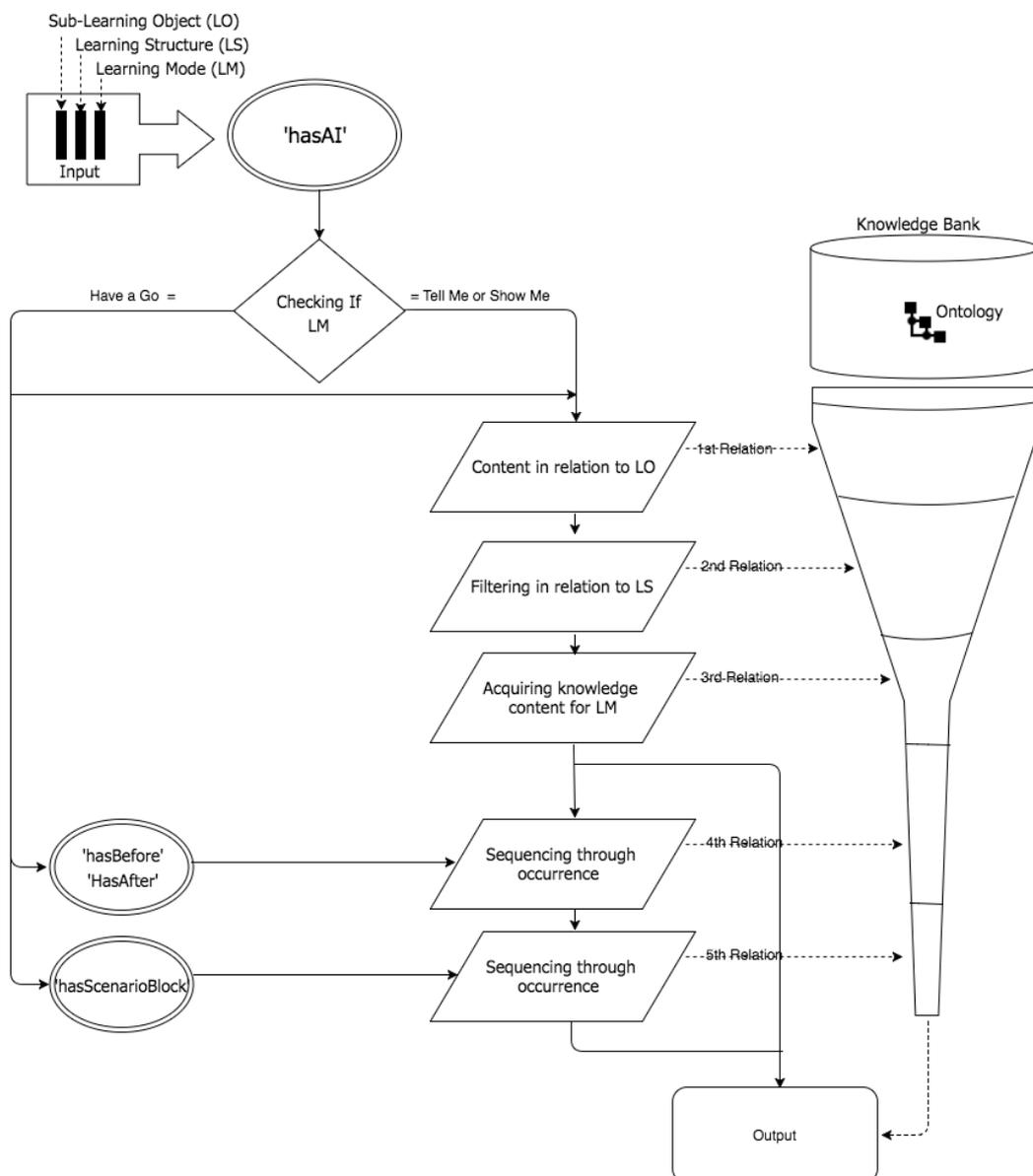


Figure 4.10: Relational logic involved for the ‘hasAI’ proposition

Similarly, if the third input is show-me, then all the video content would be modelled. However, if the third input is have-a-go, the 'hasAI' proposition calls the three other propositions before generating the knowledge model, as this involves more complex relations from assessment content consisting of procedure, product and diagnostics information on how to execute the task and evaluate the outcome. The 'hasAfter' and 'hasBefore' propositions arrange the acquired procedure in the right sequence by checking the tags on each of the individuals in verifying which comes before or after each of them.

These sequenced procedures are then mapped to their intermediate product check and diagnostics knowledge by the 'hasScenarioBlock' proposition by arranging them into different scenario blocks. Finally, all these different scenario blocks are grouped as one knowledge model output. The next step involved knowledge automation, which consisted of rules and instances that trigger the entire knowledge model from the modelled ontological environment to an external environment.

4.2.3 Knowledge automation

Even though the efficiency of any automated system depends heavily upon the quality of data, the execution method that is used in mapping the appropriate data in real time is more critical. The knowledge automation in this research refers to the generation of knowledge that is required by the system to teach, monitor and assess the practical skills of the learners in an external environment. Here, the external environment refers to the augmented reality environment where the students will be learning and performing their practical task. To do so, the system needs to instantiate the knowledge automation by querying the appropriate knowledge that is required from the modelled ontology. Triggering the knowledge modelling with respect to the actions performed by the user

from the external environment requires two important elements. The first is the instance, which acts as the trigger, and the second is the event, which needs to be executed in relation to the instance. An instance can be a single or set of inputs that are driven by the user's action when deciding what and how they want to learn. In addition, an instance could be any of the four key entities individually or grouped together; these entities being learning object, its preferred sub-learning object, learning structure and learning mode. The event is executed through three event blocks, query block, convert block and publish block, with all the blocks driven by the rules associated with them (Figure 4.11).

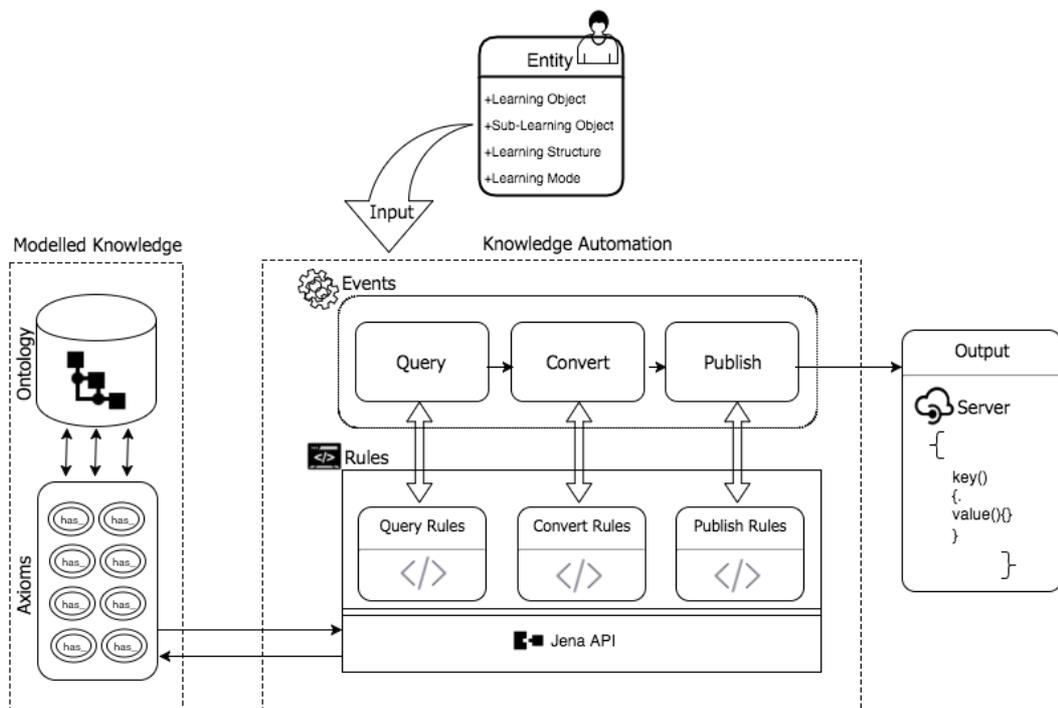


Figure 4.11: Knowledge automation process flow

The rule provides logical connections between event blocks and carries out the event by linking it to the right propositions with respect to the entities (Table 4.7). The query event block consists of rules that query the ontological structure by calling appropriate propositions and providing them with the required input.

Table 4.7: Rule syntax and description

	Rules	Syntaxes	Description
Querying rules	Input query	<i>ontology.sparqlQuery("entities to query")</i>	This initiates the query when provided with a single entity or multiple ones.
	Individual queries	<i>hasSubLearningObject ?lo. hasLearningStructure ?ls. hasLearningMode ?lm.</i>	Initiates queries for a single entity; this could be just to query the kinds of learning mode under a particular learning structure.
	Multiple queries	<i>hasScenarioBlock ?sb. isBefore ?x isAfter ?x hasAI ?ai.</i>	Used for multiple entities, mostly to know the entire knowledge model required to assess and provide feedback.
	Output query	<i>map.get("gathered output");</i>	Gathers the generated output by mapping it to the instantiated knowledge query.
Converting rules	Individual conversion	<i>toJson("gathered output".map)</i>	Converts the gathered output to the JSON format for an individual query.
	Multiple conversion	<i>toJson("scenario output".map) put("key", Knowledge_Variable) put("value", Knowledge_Content)</i>	Converts the gathered output to the JSON format for multiple queries.
Publishing rules	Publish Knowledge Model	<i>@PublishToServer("Output").json)</i>	This publishes the converted output to the server as a complete knowledge model.

The kind of rules used in the query event block are determined by the entities provided by the instance; for example, if the instance is to query the list of sub-learning objects under the learning object called welding, then the rule associated with querying the sub-learning objects comes into play (Figure 4.12). Alternatively, if the instance is to query the whole knowledge model for a particular sub-learning object, learning structure and learning mode, then the rule associated with querying the whole knowledge model is used.

The rule feeds the required input for the propositions called upon to generate the output, and this is then passed on to the convert event block. This block converts the acquired output into a JSON format; the type of conversion format is determined by the capability of the chosen external environment. The chosen AR environment was developed in Unity3D, which determined the conversion format as JSON and in addition was one of the effective communication formats in interpreting the generated knowledge models from one machine language to another. Finally, the converted output was published in an accessible location; in this case, this refers to the server, which acted as the communication channel between the ontological environment and the Unity3D environment (Figure 4.12).

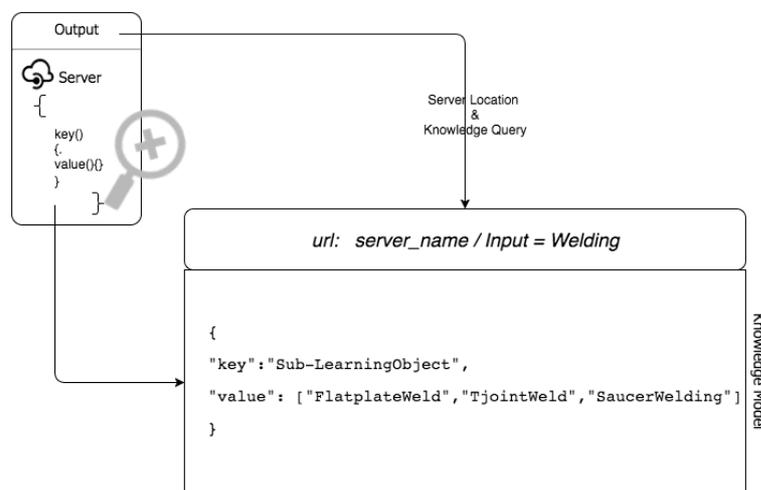


Figure 4.12: Published JSON output for an individual query

All the above-mentioned rules for communicating with the ontology from the external environment were coded in the Java programming language by making use of Jena API. The codes are made available in the Appendices 8. The following chapter explains the use of the AI tutor in interpreting the published knowledge model from the server and teaching and assessing the learner when performing their practical task in the AR environment.

4.3 Artificial intelligence (AI) tutor

The knowledge model from the server was processed into the artificial intelligence (AI) tutor in the AR environment by interpreting it through the client API. The received knowledge model is categorised through its 'key' and 'values', and this categorised information is then sent to the AI tutor. This research used the state machine to develop the AI tutor to be able to monitor and assess the learners' performance in the AR environment (Figure 4.13). The state machine is made up of logical blocks connected to each other. There are three possible states that a block can exhibit at a time: success state, failure state or running state. The success state denotes that the block is successful in satisfying the condition or action connected to it, while the failure state denotes the opposite. On the other hand, the running state denotes that the block is active and could exhibit a success or failure state depending upon the actions. The change from running state to success or failure state is known as transition. A transition denotes exit from the current block and entry to a new one. In addition, if the state is about to enter a new block, the transition also allows prioritisation of the block that it needs to enter if there are a number of similar successor blocks to choose from.

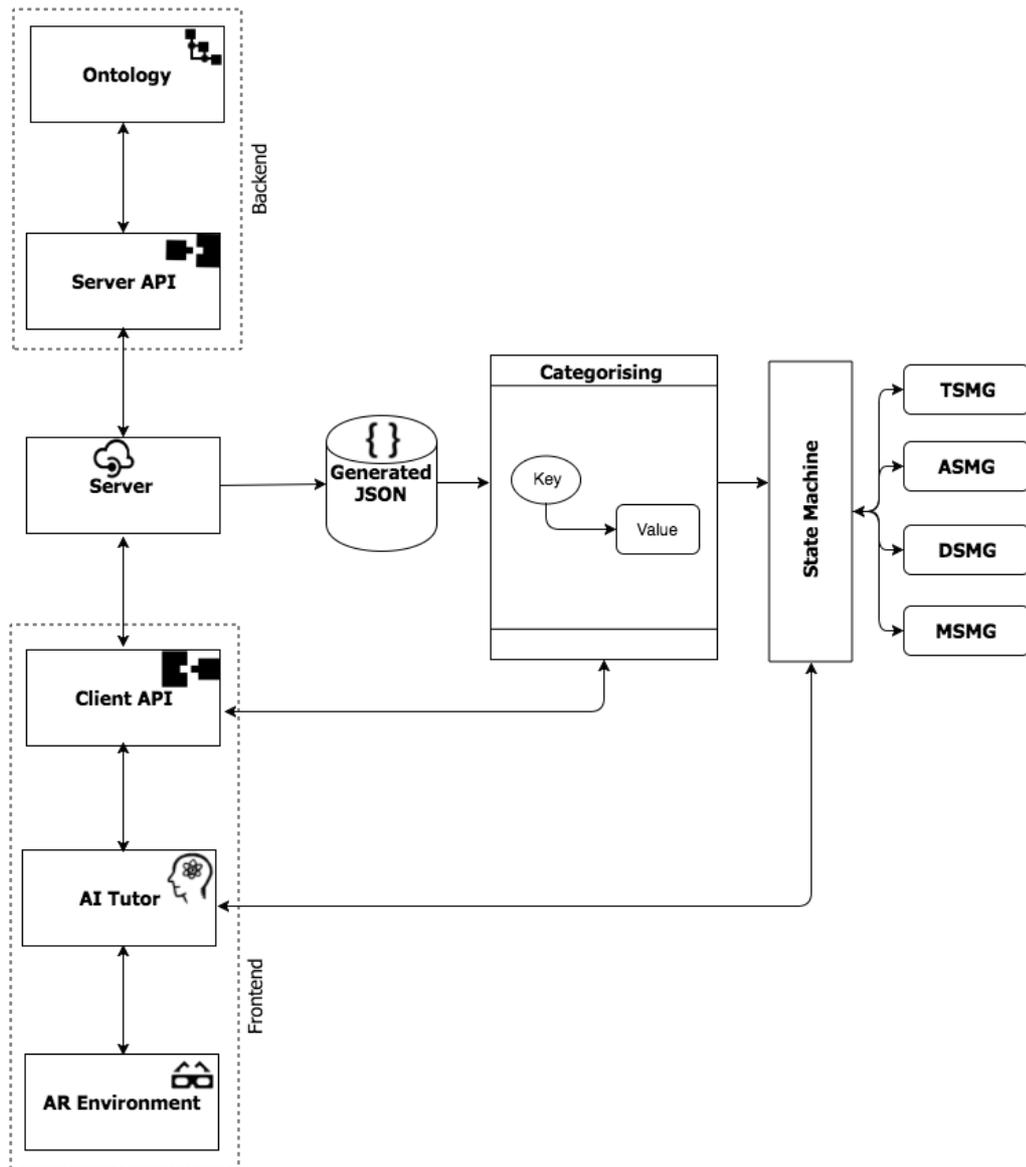
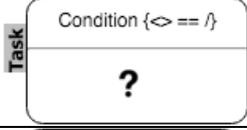
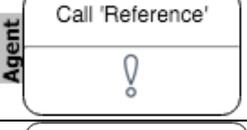
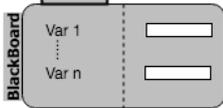


Figure 4.13: Processing the knowledge model into the AI tutor.

A logical block could be a node, task, agent, dialog or a blackboard depending upon the function of the logic (Table 4.8). A node block on its own cannot execute any action but it warps up the actions under it; in other words, a node can point to another block in executing an action or condition. A task block consist of actions or conditions that need to be executed or evaluated through an agent; an agent block could be an open block to which groups of tasks, actions or conditions could be assembled or could be referred to a pre-existing logical blocks. The dialog block helps with communication

with the learner in real time by opening a dialog conversation between the AI tutor and the learner.

Table 4.8: Logical blocks used in various state machine graphs.

Block	Representation
Node	
Task	
Agent	
Dialog	
Blackboard	
Various States: Success / Running / Failure	

The final block type is the blackboard block, which allows the AI to store, retrieve and transfer data between the different logical blocks. The blackboard block can also be used to retrieve and store data from the external source. The knowledge fed into the AI tutor's state machine from the ontology depends on the knowledge query instantiated by a learner's actions from the AR environment; for instance, when the learner goes wrong or struggles to execute the task. The AI tutor's intelligence is capable of querying appropriate knowledge from the ontology and storing it into the blackboard block to assess it through the other logical blocks and provide feedback through the dialog blocks. The proposed AI tutor uses four different state machine graphs, the word

‘graph’ meaning the graphical representation of all the logical blocks and their functions.

4.3.1 State machine graphs (SMG)

The use of different state machine graphs by the AI tutor depends upon the chosen learning mode, which could be ‘Tell me’, ‘Show me’ or ‘Have a go’. The four state machine graphs are the teaching state machine graph (TSMG), assessing state machine graph (ASMG), dialog state machine graph (DSMG) and measuring state machine graph (MSMG). The ‘Tell me’ and ‘Show me’ modes are automated by the AI tutor through the teaching state machine graph. This involves teaching the learners by feeding them with appropriate textual, audio and video knowledge. The ‘Have a go’ mode is automated by the assessing state machine and dialog state machine graphs, which involves monitoring the learning outcome and providing feedback on the performed actions. Each of these graphs has its own set of logical blocks when performing the assigned function. The overall learning outcome of the learner is monitored and measured by the AI tutor by the use of the measuring state machine graph.

4.3.2 Teaching state machine graph (TSMG)

The TSMG graph consists of four levels (Figure 4.14). The first level has the starting node block, which starts the transition by changing the states of the two task blocks in the second level to the running state. The output state of these two task blocks depends upon the user action. The user action data are stored in the blackboard; generally, these actions are captured and from the AR environment and stored in the blackboard block by communicating with the state machine. The task blocks then check the condition assigned to them with respect to the action; if the condition is satisfactory they change

their state to success, and if not, then to failure. The block that transits from the running to the success state progresses to the next level of the graph by exiting its current block and entering its level three block.

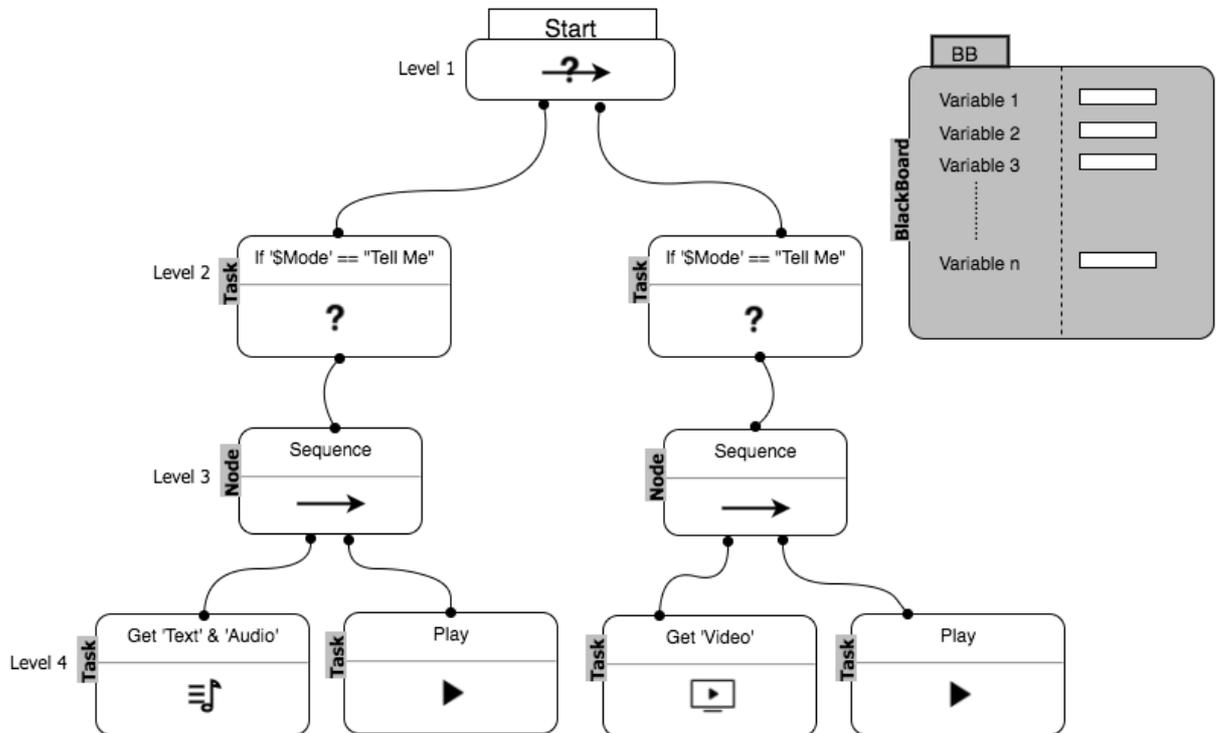


Figure 4.14: Teaching state machine graph (TSMG)

Level three consists of a node block, which immediately executes the task blocks under it in a prioritised sequence. The small horizontal arrow over the node block drawn from left to right emphasises that the execution is prioritised sequentially from left to right. Level four consists of two task blocks. The left one is designed to obtain the required knowledge from the blackboard, and the right one to execute the play action by telling or showing the acquired knowledge in the AR environment. Apart from user action data, the blackboard also stores the text, audio and the video content that is required for the learning scenario.

Scenario example for TSMG:

Presuming that the learner has chosen 'Tell me' as the learning mode for a learning scenario, this data is then automatically sent and stored in TSMG's blackboard block. With respect to the type of scenario that the learner has selected, the text and audio knowledge contents for that scenario are also queried and stored in the blackboard block. The start node block then executes both the task block under it simultaneously, and the condition is checked with the user data stored in the blackboard. In this case, the state of the 'Tell me' task block becomes successful and the node block under it is executed. The node block executes the left hand task block under it first, which pulls the text and audio content that has been stored in the blackboard and passes it to the right hand task block. This then types and plays the text and audio file in the AR environment. Similarly, if the condition is 'Show me', then the respective video content would be pulled and played in the AR environment.

4.3.3 Assessing state machine graph (ASMG)

The ASMG graph consists of five levels of logical blocks (Figure 4.15) to automate the continuous monitoring of learners' actions and assess them. Similar to the TSMG, the first level consists of the start node block, which executes the blocks under it simultaneously. The second level consists of three node blocks: procedure, measure and diagnostic nodes. The procedural node block consists of two task blocks under it; the load level task block takes the learner to the next scenario when its state becomes 'success', and the other task block with two inverted T-symbols facing each other denotes the interrupt function. This means that if all the blocks connected to this satisfy the given conditions, then this will exit all its blocks by changing its state to success.

The fourth level under the interrupt block consists of a product node block with a dynamic sequence function, which checks all the product checks continuously in no particular sequence. This means that the blocks under them can be executed in any sequence and it also transits itself to a success state only if all the blocks under it exhibit the success state.

The fifth level consists of a number of conditional task blocks, each of which carries the condition that needs to be checked while the learner is performing the task. These conditions vary according to the task that is being performed by the learner in the AR environment; if all the conditions are satisfied, then the product node block state changes to success and triggers the interrupt function in level three. The other two node blocks parallel to the procedural node block in level two are the diagnostics and measure node blocks. The diagnostics node block is connected to a timer task block and a dialog agent block; the timer task block counts to a certain given time and then triggers the dialog agent block. This establishes the dialog conversation between the AI tutor and the learner by initiating DSMG. The measure node block consists of a measure agent block, which initiates MSMG in measuring the learning outcome. The blackboard block stores all the procedural sequences that need to be carried out and the product checks that need to be performed, as well as the diagnostic knowledge associated with them.

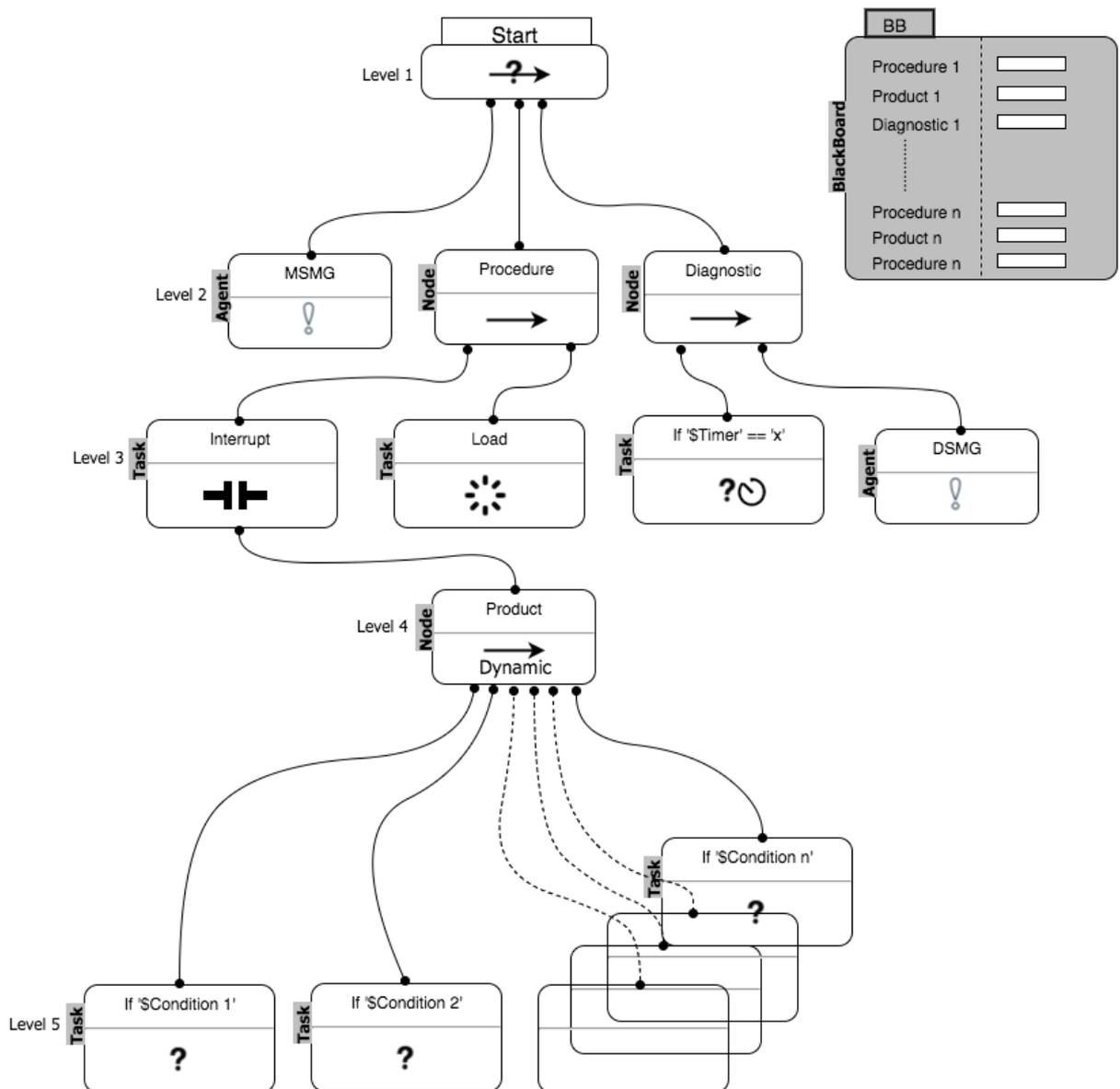


Figure 4.15: Assessing state machine graph (ASMG)

Scenario example for ASMG:

If the learner has chosen ‘Have a go’ as the learning mode for the health and safety scenario, the blackboard block acquires all the procedural sequences, product checks and the diagnostics knowledge with respect to health and safety and stores them. The start node block then executes the procedural node block, diagnostics node block and MSMG agent simultaneously, and all the stored procedural knowledge is assigned to the procedural node block. This allows the

AI tutor to monitor the learner's procedures when executing the task; the product check knowledge is assigned to each of the conditional task blocks under the product node block. This helps the AI tutor to check whether all the procedure have been carried out properly in achieving the desired output.

In this scenario, the learner needs to know all the safety gear that is required and to virtually wear it in the AR environment to achieve the outcome. When these are successfully identified and worn, the AI tutor changes the relevant conditional task blocks to the success state. When all the condition task blocks change to success, this means that the learner has completed all the required safety protocol. Eventually, by exhibiting complete success, the interrupt task block in level three automatically becomes active and interrupts all the blocks under it and changes the load level task block to the success state in taking the learner to the next scenario. If the learner fails to satisfy the required safety protocol, then the dialog agent block can be triggered by the learner from the AR environment by opening the dialog conversation with the AI tutor. In this case, the AI tutor uses the stored diagnostic knowledge from the blackboard block to point out what they have done wrong and helps them to correct the mistakes by suggesting appropriate learning contents.

4.3.4 Dialog state machine graph (DSMG)

The DSMG graph is instantiated through the dialog agent block from the ASMG. It consists of six levels of different dialog blocks (Figure 4.16) to automate the dialog conversation between the AI tutor and the learner. The first level consists of the start dialog block, which opens the dialog conversation by typing out the text that has been assigned to it. The start dialog block text is stored in the blackboard block; this could

be any conversation opener such as “hi” or “hello”. Level two consists of the title dialog block, which types out the name of the scenario that the learner is performing. The third level comprises the problem pointing dialog block. As the name suggests, this dialog block types out the mistakes that have been made, which generally are captured by the assessing state machine graph (ASMG) and are stored in the blackboard block.

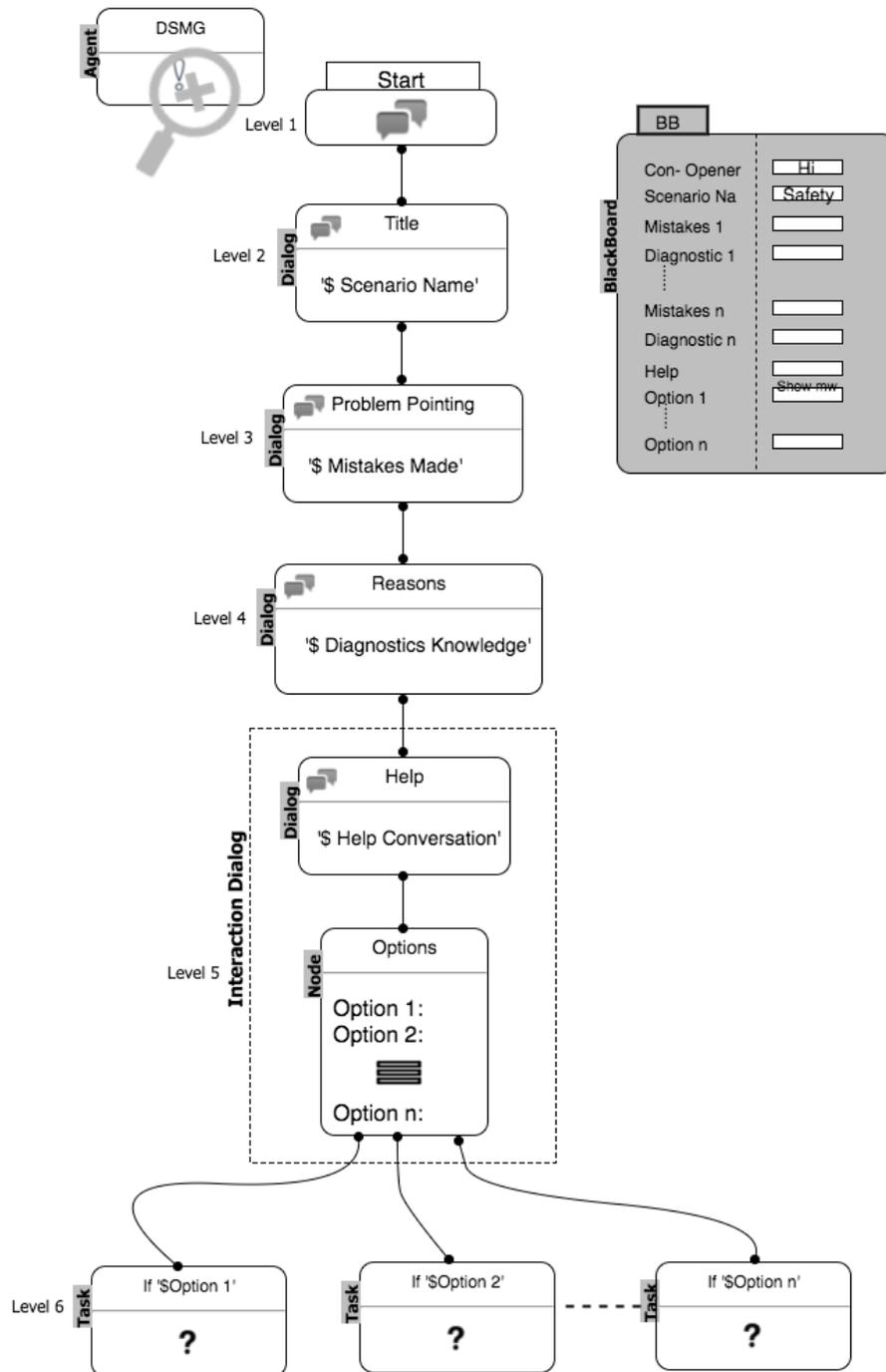


Figure 4.16: Dialog state machine graph (DSMG)

The fourth level consists of the reasoning dialog block, which types out more insightful reasons for the mistake committed, using the diagnostic knowledge that has been stored in the blackboard block. In other words, the reasoning dialog block provides the potential reasons why the mistake may have occurred by making use of the diagnostic knowledge. Level five comprises the interaction dialog blocks, which allow the learner to interact with the AI tutor. The interaction dialog blocks start with interaction text, which is generally dialog such as “How can help you?”, and then provides the options of different learning modes that the learner can choose from in learning the suggested learning content in correcting their mistakes. Level six consists of action dialog blocks connected to each of the given learning mode options, which execute the action relevant to the options. For instance, if the learner selects ‘Tell me’ as the learning mode option to learn about their mistakes, then the action dialog block plays the audio content and text. Similarly, for the ‘Show me’ learning mode option, the action dialog block plays the video content relevant to the mistake committed in teaching how to resolve it.

Scenario example for DSMG:

Let us consider the same scenario example that was used in ASG and imagine the learner struggling to satisfy the safety protocol. When the learner triggers the dialog conversation from the AR environment, the DSMG starts by executing the start dialog block, which initiates the dialog between the learner and the AI tutor by saying “hi” and indicating the name of the scenario that they are performing. In this case, the name typed out would be “health and safety”, which would be followed by the dialog mentioning the mistakes that have been made. This could be phrases such as, “You have not worn your mask or gloves or Not closed the safety curtains”, which are then followed by more insight about the mistake. This could be advice such as “Lack of fundamental

knowledge” in identifying appropriate safety gear, or “Lack of execution knowledge” in wearing it. This is then followed by the execution of the interaction dialog blocks to provide learning mode options such as “Tell me” or “Show me” to learn about how to correct the mistake. If the learner chooses “Tell me”, then the text and audio content on how to fulfil the health and safety protocol will be played, or if “Show me” is chosen, then the video content demonstrating the safety protocol will be shown.

4.3.5 Measuring state machine graph (MSMG)

The MSMG graph is instantiated through the measuring agent block from the ASMG, where the learning outcomes of the learner are measured through the Level, Depth and Rigour axis (Figure 4.17). Level represents the complexity of the task that the learner is performing, depth represented the depth of knowledge that the learner needs to execute the task, and rigour represents the measure of successful completion. This concept of measuring the learning outcome is an extension of the “Hess cognitive rigor matrix” principle, which suggests two axis, level and depth, to measure a learner’s performance. In the course of automating the assessment process for practical skills this study has integrated rigour as a third axis to measure learners’ confidence in executing the task. MSMG has four levels of logical blocks to automate the above three scale axis and measure the learner’s performance. The first level consists of the start node block, which simultaneously triggers the achieved task block and measures the task block with the interrupt function. Similar to the interrupt node block used in ASMG, this block only interrupts if all the blocks under it satisfy their given condition.

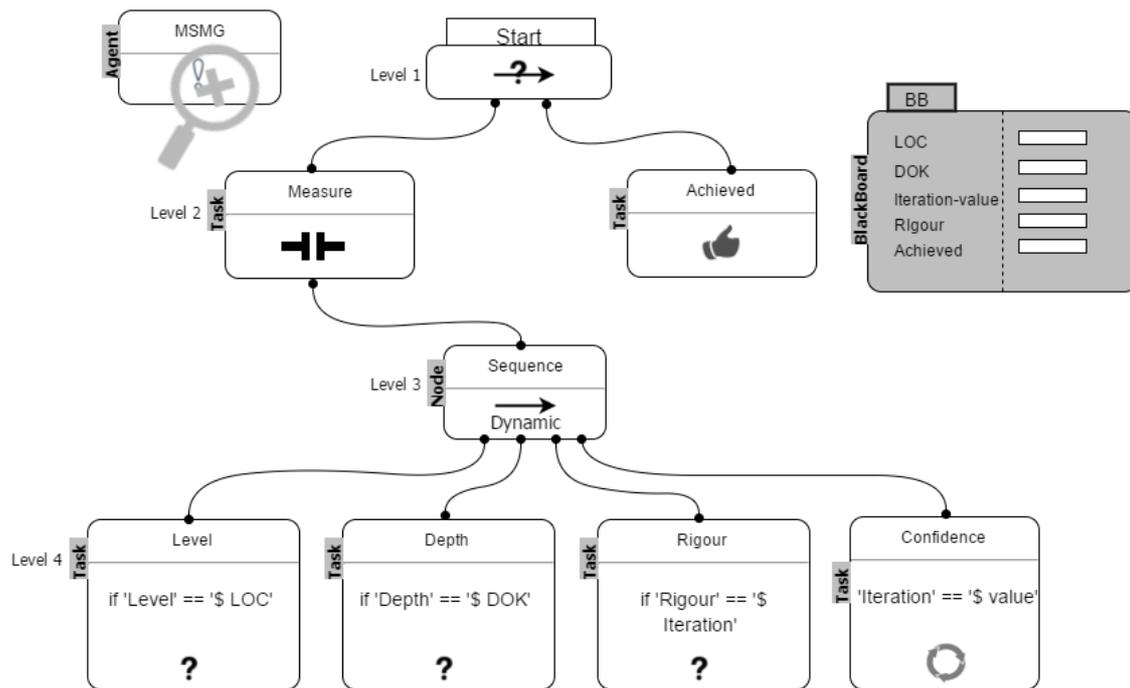


Figure 4.17: Measuring state machine graph (MSMG)

The third level consists of a dynamic sequence node block connecting the three task blocks; the level task block is assigned to the value that represents the complexity of the task, which is captured from the tutor in the knowledge capturing phase. The depth task block stores the actions that have been successfully completed by the learner; these actions are monitored by the ASMG through the conditions of its product node block. In other words, the satisfied product node block conditions from ASMG are stored under the depth task block. The rigour task block stores the number of successful completions; for example, if the task of making cupcakes in the cookery domain is given five from a scale of one to ten in the level of complexity compared to other relevant cookery tasks, this value would be assigned to the level task block.

To execute the assigned task level, an individual should for example possess knowledge such as ingredients, understand the procedure and know how to use the equipment needed. Whenever these actions are completed, they are stored in the depth task block, which collects the knowledge that the individual possess. Finally, each time an

individual is able to produce a tasty cupcake by possessing the required depth of knowledge, this successful completion is stored in the rigour task block. When the number of successful completions has been stored equals with the required iteration number assigned to the confidence task block, it triggers the interrupt function in level two. This exits all the blocks under it and changes the achieved task block to success, meaning that the individual has achieved the rigour to make tasty cupcakes.

Scenario example for MSMG:

Let us consider a scenario where the learner has chosen to ‘have a go’ at flat plate welding. The level of complexity for flat plate welding is set to be low compared to the other two sub-learning objects under welding. In other words, the level of complexity involved when performing welding on a flat surface is lower compared to performing it on a horizontal or circular one. Moreover, the level of complexity is higher when performed on a circular surface (saucer), thus meaning the horizontal surface (t-joint) has a medium complexity. So in this scenario, the level task block is assigned to low; similarly, if the chosen task was t-joint or saucer, then the assigned level would be medium or high. As the learner starts to perform, all the successfully completed actions are stored in the depth task block, referring to the knowledge that the learner possesses. These actions are monitored by the ASMG through the assigned conditions under the product node block. By satisfying all these conditions, such as ‘selecting plates’, ‘degreasing the plate’, ‘setting up the welding console’, ‘tacking the corner’, ‘hand speed’ or ‘angle of the torch’ through their actions in the AR environment, the learner is able to achieve correct welding on a flat surface.

The measure of rigour is the number of successful completions of the same task, reflecting on whether students could exhibit the know-how that they possess for n-number of iterations. For this use-case, the iteration value is set to five; this value was captured in the knowledge-capturing phase from the experts teaching welding tasks to on-campus students. When the learner successfully executes welding on a flat plate for five iterations, the rigour count become equal to the required iteration value, which triggers the measuring node block to interrupt all the blocks under it. This means that it exits the monitoring and measuring processes and changes the achieved task block to success. This confirms that the learner has achieved the set learning outcome for flat plate welding. By achieving the same results for t-joint and saucer welding (Figure 4.18), the learner would be able to achieve the overall learning outcome for welding.

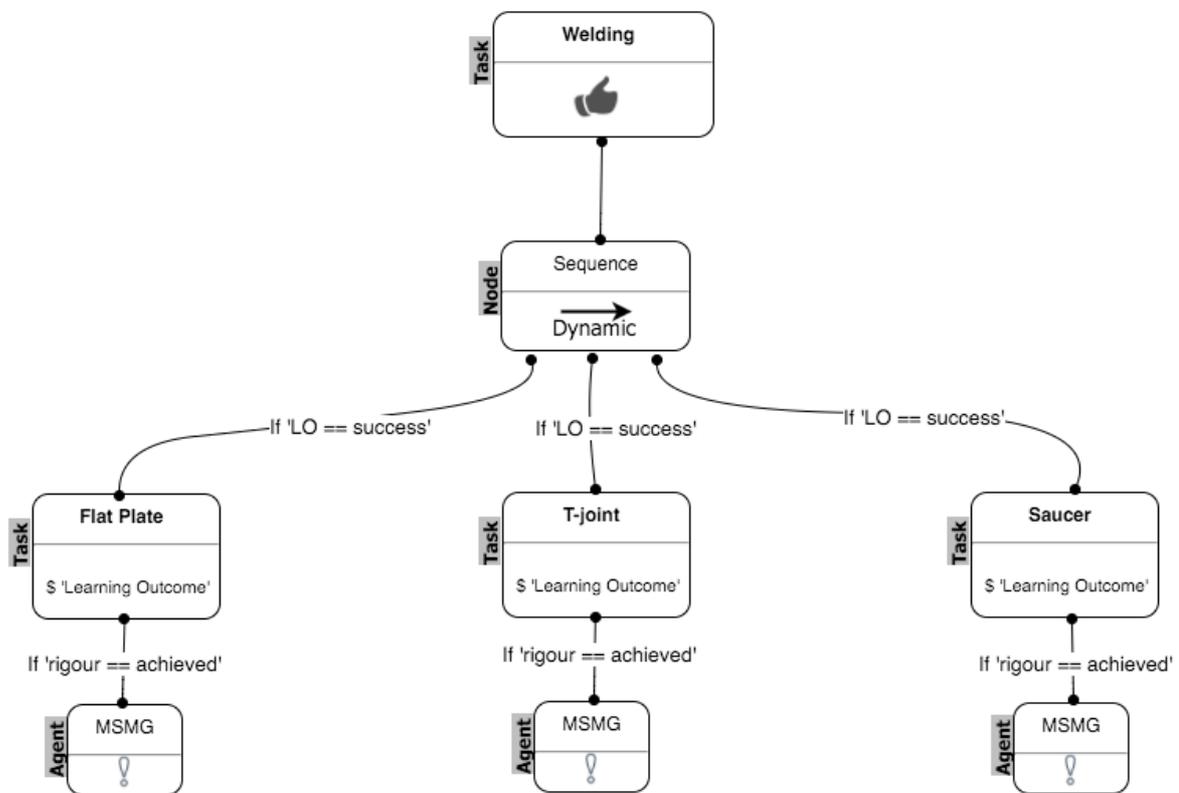


Figure 4.18: MSMG for measuring overall learning outcome

4.4 Augmented reality environment

Learning practical skills through an Augmented Reality (AR) environment relies heavily on physical movements. The success of the selected use-case, 'welding', relies heavily on hand movement and spatial procedural memory in its execution. In order to accomplish this in an Augmented Reality environment, the research involved four phases in its development: object modelling, object codifying, pre-testing and object transforming (Figure 4.19). The object modelling phase involved the modelling of all the 3D objects required for the welding task using the SketchUp tool and rendering them closely to the real object to increase the immersiveness while handling them in the AR environment.

In the object codifying phase, each of the modelled objects was codified with intelligence in the virtual environment using the Unity3D platform, in which their interactions and movements were mapped to the AI tutor. The codified virtual object functions were then refined in the pre-testing phase. The final phase involved transforming the codified 3D objects into an AR environment, which incorporated state of the art wearable technology (META AR-glass) to provide an immersive hands-on learning experience. By wearing the AR glasses, the learners were able to visualise the existing real environment with augmented objects over them and were able to interact, grab and move the augmented 3D objects with encoded intelligence in order to learn the practical task.

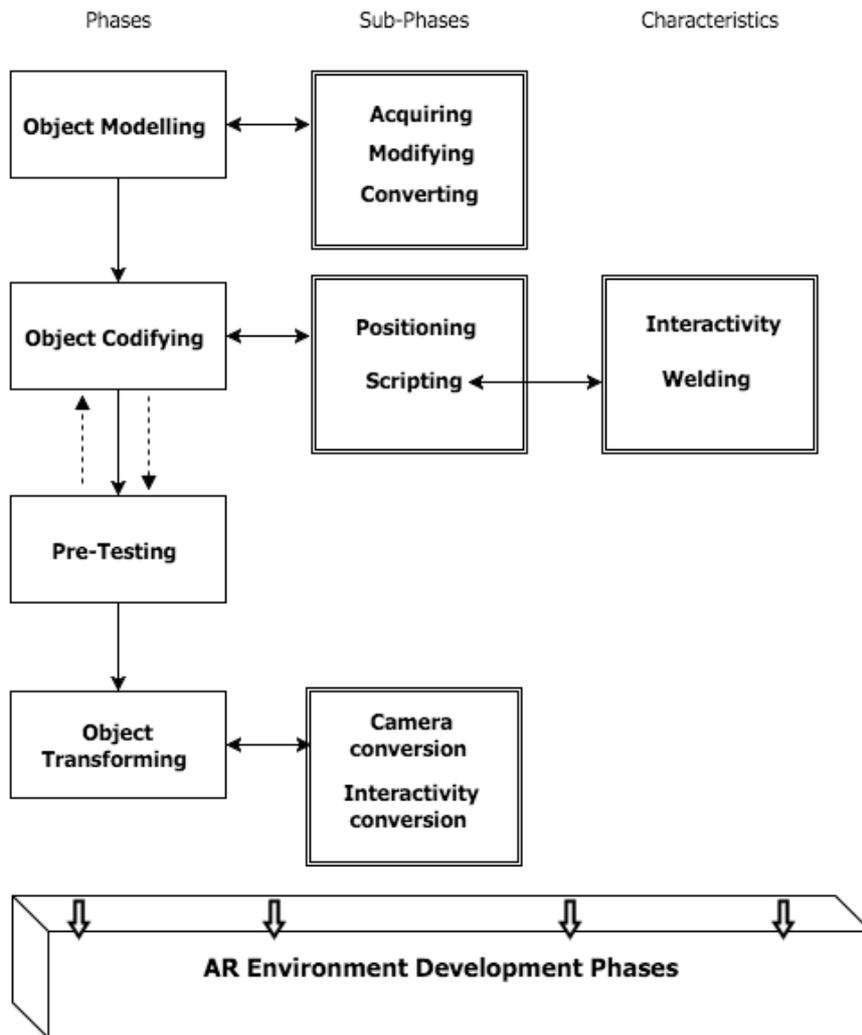


Figure 4.19: AR development phases

4.4.1 Object modelling phase

The list of 3D models required for the welding task were identified in the knowledge-capturing phase; developing these models involved three sub-phases: acquiring, modifying and converting. These sub-phases involved the acquisition of the pre-existing 3D models similar to the required models, modifying them according to the needs, and finally converting them to an appropriate 3D format.

(a) Acquiring:

This research used 3D Warehouse, a repository of free 3D models, to acquire pre-existing models; the models were searched through key terms consisting of the real object name and its context. For instance, the mask, apron or glove 3D objects were searched not only by referring to their name, but also by adding their context, such as “mask for welding” or “apron for welding”. The acquired results were then filtered by matching the similarity with the real model; the models with higher similarity and less storage size were selected.

(b) Modifying:

This sub-phase involved importing the selected models into the SketchUp software and modifying them close enough to the real object. The modification process involved changing shapes and dimension to one or more components of the 3D object and rendering their colour and texture with respect to the real one (Table 4.9).

(c) Converting:

This sub-phase involved exporting the modified model into a format that was importable into the Unity3D environment. Although Unity3D is compatible with the import of various 3D object formats, the models were exported to Filmbox (FBX), as this was more interoperable when imported into a gaming environment such as Unity3D from a native modelling environment like SketchUp. The interoperability included features such as storing data such as animation within the 3D object file and retrieving it when importing it to a non-native environment.

Table 4.9: Modelled 3D objects

Welding equipment's	Real Objects	Modelled objects
Mask		
Gloves		
Overall		
Shoes		
Curtains		
Torch		
Console		
Vice		
Hammer		

4.4.2 Object codifying phase

In this phase the converted objects were imported into the Unity3D environment; the chosen virtual environment platform is a popular game engine to develop high graphic 3D games. It also allows the developer to embed intelligence into the 3D objects by making use of the various internal and external libraries for physics, audio, animations, programming scripts and so on. This research on the process of developing an AR environment for teaching and learning welding skills used some of the internal and external libraries (Table 4.10). This phase was executed through three sub-phases: positioning, scripting and testing.

Table 4.10: List of internal and external libraries used for object codification. Adapted from Unity3D (2016).

Library name	Contextual use
Internal	
Physics engine	Makes objects behave like real world objects with respect to gravity, mass and other forces.
Graphics	Renders the material of 3D objects close to real material through texture, lights and camera.
Audio	Audio communication link between AI tutor and learners.
User interaction	Textual communication link between learners and AI tutor.
Animation	Recreates object movement and behaviour patterns.
Particle system	Generates welding arc and molten weld-bead.
Rigid body & mesh collider	Makes objects like a metal plate solid and detecting collisions.
Scripting	Essential ingredient in transforming the learner's actions or inputs into machine interpretable language.
External	
Waypoint object tracking plugin	Tracks the position and movement of the welding torch.
State machine plugin	Establishes communication link between the AR environment and the AI tutor.

(a) Positioning:

Once all the models were imported into the Unity3D environment through the import function, each was tagged with a unique name. The tag is an internal property used in Unity3D, and one is provided to each of the objects; in this way, they can be easily called or referred from any programming script. The models were then scaled and oriented in the virtual environment so that they were similar to the real laboratory environment. A first person shooter (FPS) view was used to provide the field of vision for the learners to visualise the positioned objects; an FPS view is similar to that which an actual person would see, and they are generally used in action video games to provide the actual view of the character inside the game in order to gain more immersiveness.

The FPS view was created by adding an FPS camera from Unity's graphics library to the environment, then appropriate light sources were added to the virtual environment to create a realistic laboratory feel (Figure 4.20). Unity provides different light sources; for this use-case only directional and spotlights were used. Directional lights were used to light up the entire virtual laboratory environment, whereas spotlights were used to brighten and create shadows for individual 3D objects. With the completion of scaling, orienting, lighting and creating the field of vision, the objects were made intractable and intelligent in order to exhibit the same characteristics as the real ones through scripting.

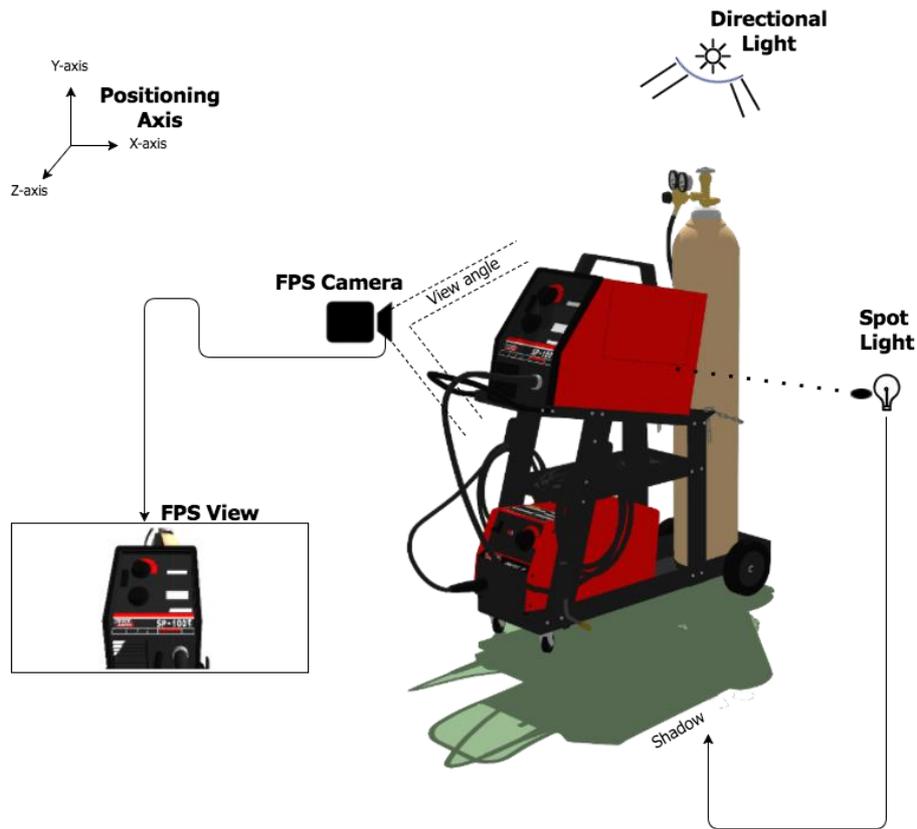


Figure 4.20: Positioning of objects in 3D space

(b) Scripting:

The research used c# as the programming language to write the scripts; a programming script could be blocks of logic or conditions that are written in a machine interpretable language. The programming scripts were embedded into the 3D objects to define their characteristics and properties with respect to the learning scenario. In addition, the scripts also acted as a bridge to transfer information between the 3D objects and the AI tutor. The characteristics and the properties defined in these modelled 3D objects are bound to this particular learning scenario (welding). In other words, although these objects may exhibit several other characteristics and properties in the real world, only the ones that are relevant to the welding task were scripted in the virtual world. This stage involved scripting for interactivity and welding characteristics.

(i) Interactivity characteristics:

Irrespective of the various individual characteristics, all the modelled objects had interactivity as the default characteristic. As in the real world, for objects to be touched, moved or dropped, they need to be solid by having mass relevant to gravity. The modelled objects were made solid by using Unity's physics engine, which allows the assignment of properties such as mass and gravity by adding an internal component called rigid-body to each of the objects. These solid objects were then encoded with interaction programming scripts (Appendix 4), which allow the learner to pick up, move, rotate and drop objects in the virtual environment.

(ii) Welding characteristics

The purpose of welding is to join two separate metal plates together by making the wire feed out from the torch's nozzle in contact with the edges of the two metal plates. During this process they exhibit several characteristics such as welding sound, welding arc and formation of molten weld-bead. Scripting all these welding characteristics started by identifying the critical objects and their components that should possess the scripts in exhibiting these characteristics. With respect to the chosen learning scenario, the welding torch and the metal plates were the two critical objects, whereas the wire fed out from the torch nozzle and edges of the metal plate were the respective critical components under them. The edges of the plates were encapsulated by a collider object; generally, collider objects in the virtual environment are used to detect collisions between objects.

In addition, these colliders were encoded with a collision detection script, which finds the tag name of the object that comes into contact with the edges (Appendix 5). For instance, if the torch nozzle comes into contact with the collider, it finds the

name of the objects by querying the name that has been tagged to it. By having the collision object and collision script over the edges, the other virtual objects that come into contact with these edges can be identified. Moreover, if those collided objects possess any characteristics scripted in relevance to the metal edges, then these characteristics can be exhibited. The welding sound and arc were produced using Unity's audio source and particle system feature, which consists of the different welding sounds and arcs that were captured in the knowledge-capturing phase. These two features were driven by sound and arc scripts (Appendix 6) attached to the wire component coming out of the torch object (Figure 4.21).

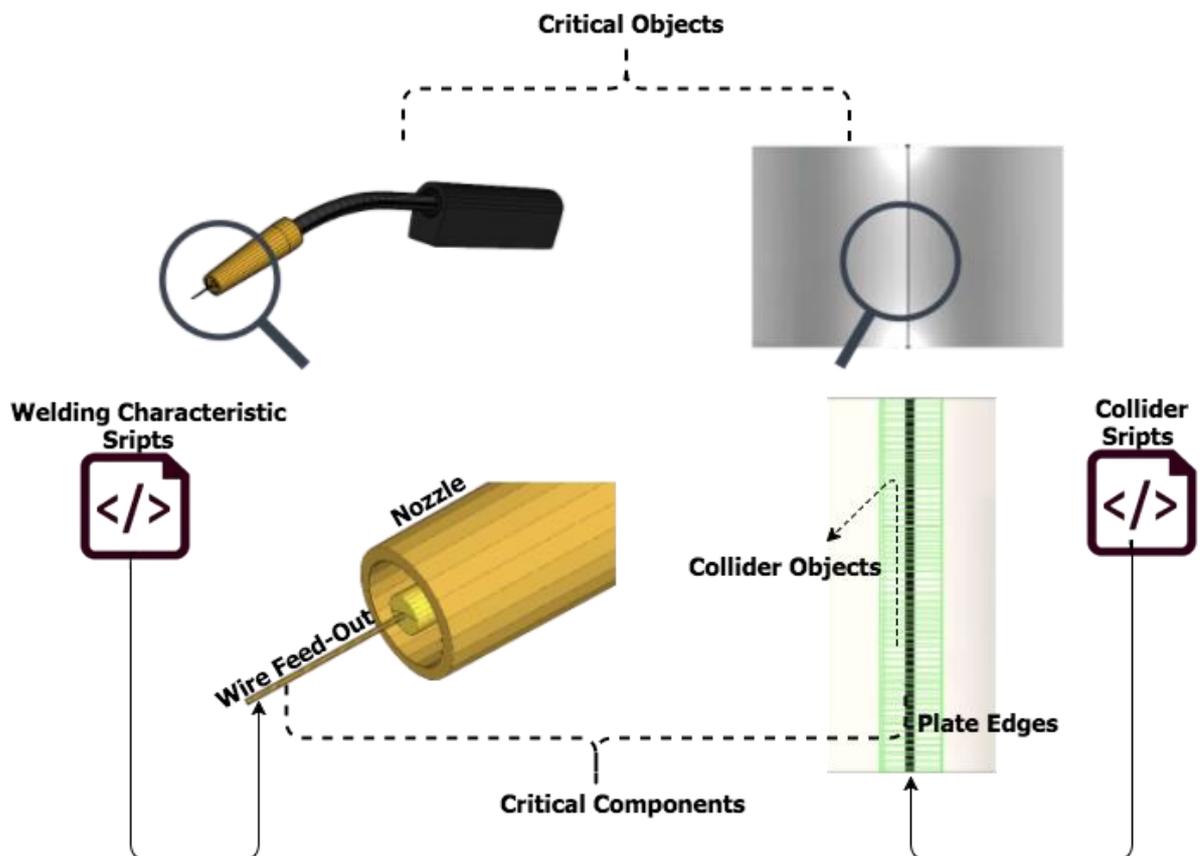


Figure 4.21: Critical objects and components embedded with scripts

These scripts varied the sounds and arcs exhibited with respect to the angle and speed of the torch held and moved by the learner. The speed and angle of the torch

held by the learner in the virtual environment were determined by the hand movement script, which used waypoints as a reference technique to measure the position, time and distance of an object moving in the virtual environment (Appendix 7).

A waypoint in a virtual environment is a series of points created to track object movements; each of these points generated has position and time stamp attributes. Generally, the position attribute consists of x, y and z coordinate data, which represent the object position in the 3D space. The time stamp attribute keeps track of the time at which each of the waypoints was created (Figure 4.22). By attaching this script to the identified critical component, in this case the wire component that comes through the torch nozzle, its movements were tracked through the waypoints. The movement and speed were computed from the waypoint data through the welding characteristic algorithm by varying the welding sound, arc and weld-bead (Figure 4.23).

This algorithm processes the generated waypoint data in real time and classifies the position and time stamp attributes under its respective waypoint. The position coordinate data are then used to filter the waypoint further by eliminating the ones that are away from the plate edges; in other words, only the waypoints that were generated when wire tip of the nozzle was in contact with the edges of the plate were considered. The time stamp of each filtered waypoint was then used to compute the speed; the time stamp of the current waypoint was subtracted from the time stamp of the immediately previous waypoint. Subsequently, the computed speed was compared with the threshold speed range, which was derived from the knowledge-capturing phase. If the subtracted value was less than 1.40 seconds, then the movement of the objects was considered to be fast, and this would trigger the welding sound and welding arc associated with fast hand speed. For fast hand speed, the molten weld-bead that appears

did not penetrate to the back of the plate, meaning the weld-bead was not strong enough to hold the edges intact.

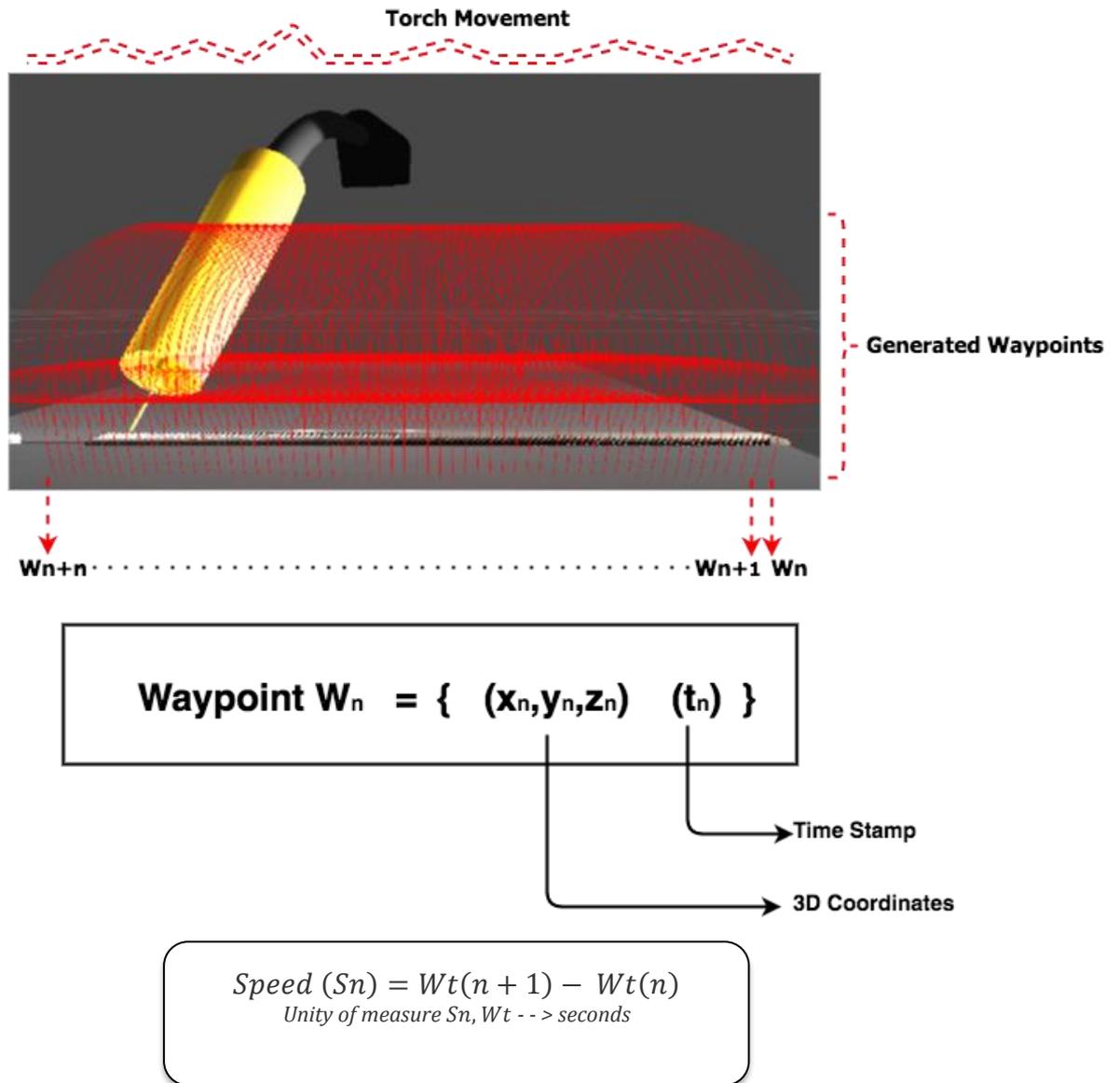


Figure 4.22: Generated waypoint with coordinates and time stamp

Similarly, if the subtracted value is more than the threshold range, the weld-bead appears to be too thick to hold the edges together. Only if the subtracted value is within the threshold range are the welding characteristics for a proper weld triggered. By having a steady angle and correct hand speed in moving the torch, learners will be able to make a proper weld-bead over the plate edges, and moreover, by having this

consistency throughout the execution, they will be able to achieve the learning outcome. On completion of the scripting of the interactivity and welding characteristics, the codified virtual environment was tested to refine the scripted characteristics.

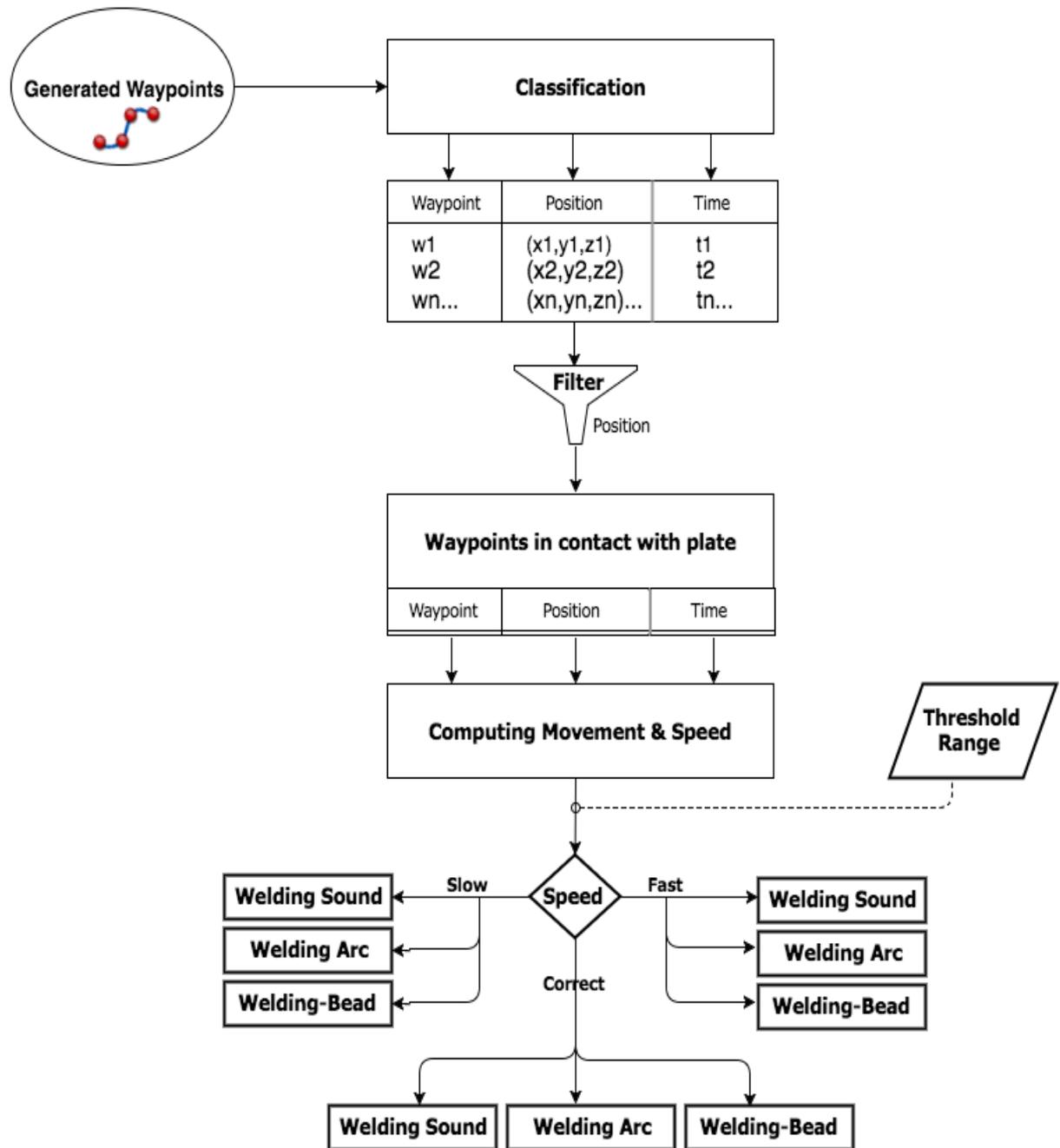


Figure 4.23: Welding characteristics algorithm logic

4.4.3 Pre-testing phase

Testing the codified characteristics in the virtual environment was critical before transforming them into the augmented environment, as identifying and refining the problems in the virtual environment was easier and less time consuming than in the augmented environment. The pre-testing phase involved identifying and fixing various bugs in the interactivity and welding characteristics scripts. First, the interactivity characteristics were tested by using the mouse to select the different objects positioned in the virtual environment.

Failing to interact with any of the objects involved verifying the physics component and scripts attached to them. Finally, the scripted welding characteristics were tested by moving the torch using the mouse to the edges of the plates with different speeds and angles in order to trigger different welding characteristics. The positions of collider objects over the plates edges were fine tuned to produce smoother colliding with the torch at various hand speeds and angles. With the completion of testing and refining the interactive and welding characteristics scripts, the modelled and codified virtual environment was transformed into an augmented reality environment.

4.4.4 Object transforming phase

The research used META AR glasses to develop an augmented reality environment for learning and practising the welding task. The hardware consisted of head mounted glasses with a camera and two sensors to augment objects and interact with them. The transformation of the modelled and codified objects into augmented reality glasses (META) involved two sub-phases: camera conversion and interactivity conversion.

(a) Camera conversion:

To augment the modelled objects over the real environment requires real-time camera feeds. The selected AR glasses provide this through their front-mounted camera; to replace the existing virtual camera with the AR camera needs integration tools. The integration between Unity's virtual camera and META's augmented camera was achieved through the existing APIs, as the chosen AR platform provides built-in APIs to be integrated with the Unity platform. In other words, with the help of these APIs the META glasses camera was communicable from the Unity environment. By replacing the virtual camera with the AR camera, the modelled objects were augmented over the real environment (Figure 4.24). Therefore, by wearing the AR glasses the learners were able to see the modelled object mounted onto the real environment. The next stage involved converting the mouse interactivity to hand gesture interactivity.

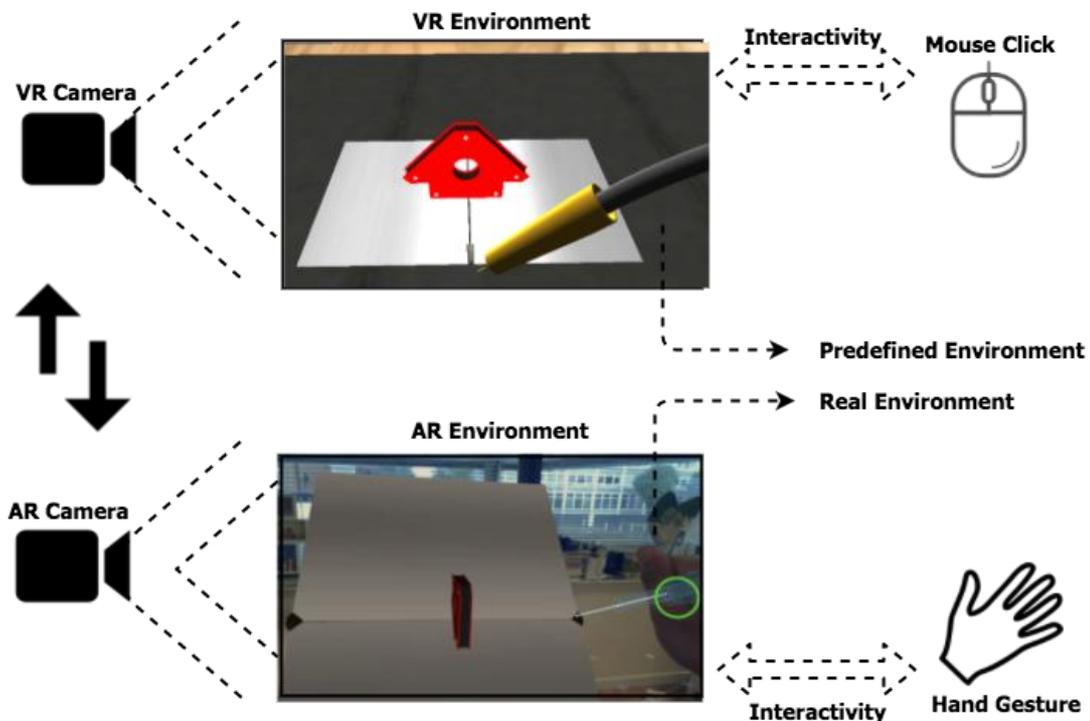


Figure 4.24: Converting the VR camera to an AR camera

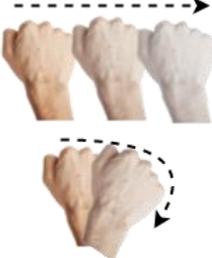
(b) Interactivity conversion stage:

The interaction with the augmented objects through hand gestures instead of the mouse was achieved by making use of the two sensors mounted beside the camera of the AR glasses. The research used the built-in algorithm provided by the AR glasses to detect hand gestures through the colour and depth sensor (META, 2016). The same APIs that were used to communicate with the camera were used for these sensors. Replacing the interactive events such as clicking and dragging with the mouse with events such as grabbing, holding and rotating with a real hand was achieved by replacing the existing mouse methods with the AR sensor method. In other words, the scripted mouse interactions in section (4.4.2 (b) (i)) were all replaced by AR sensor interaction, allowing the learners to interact with the objects through hand gestures. The built-in algorithm provides several hand gestures, but for this use-case we only use four of them (Table 4.11).

The reference hand gesture is used to locate the objects, by having the palm and fingers wide open over the augmented object in order for the reference mark to appear. With the appearance of the reference mark, learners were able to grab the referenced object through a grab gesture by closing their fingers tight into their palm. By performing the two hand gestures in the right sequence, the objects are grabbed. The third hand gesture helps in moving and rotating the objects; this was performed by having the object grabbed, meaning having the hand with closed fingers and moving the hand or rotating the wrist to rotate and move the objects. Leaving the object that has been grabbed back onto the augmented environment was performed through the un-grab gesture by opening all closed fingers. With the use of these four gestures learners were able to interact and perform the welding task by grabbing the torch and moving it along the

edges of the plates with their hand and acquiring more hands-on experience. The next phase involved post-testing the developed prototype with internal experts.

Table 4.11: List of hands gestures to interact with augmented objects

Operation	Hand Gestures
To reference object	
To grab object	
To move and rotate object	
To un-grab object	

4.4.5 Post testing with internal experts

The post testing phase was an iterative process involving the case organization’s main engineering laboratory instructor and his technical assistant. Each of the scenarios developed in the AR environment was given to the experts and observations were made while they were performing the practical task. Each session was recorded and then discussions were held at the end of each session to collect their feedback (Table 4.12).

Table 4.12: Changes suggested by the experts in each of the iteration

Iteration	Related Scenarios	Suggested changes and feedback
Iteration 1	Scenario 1	“The selection of safety equipment through the use of GUI could be replaced by gazing and touching the 3D object placed over the table (which represents the real lab environment), as the GUI that appears on the AR environment is not really clear and it is difficult to select it?”.
Iteration 2	Scenario 2	“The degreasing and removal of burrs could be combined as one procedural task and the visualization for it could be done through graphical changes in the plate texture.” “For instance, before degreasing and removing the burrs the plate could be shown with texture and a glossy and dirty surface. After the degreasing procedure has been carried out it could be represented with the texture of a rough and clean surface”
Iteration 3	Scenario 3	“Have two plates with different thicknesses to provide a better understanding of the voltage and wire feed speed that needs to be altered according to the difference in plate thickness.” The two different plate thicknesses that were suggested by the experts were 1.6mm and 3mm.
Iteration 4	Scenario 4 Scenario 5 Scenario 6	“The welding arc that appears was bright and made the user’s visibility poor; the experts suggested making the welding arc less intensive so that the visibility of the user increased and they were able to see the plate when contact was made” “The orientations of the welding torch and the metal plate were too far apart when accessing them, so the torch positioning was suggested to be closer to the body of the user than before and the plate positioning needed to be lower to give the user a clearer view while executing the task.”
Iteration 5	Scenario 7	“The orientation of the plate placed in the vice needs to be changed, so that the weld bead appears on top of the vice.”

The suggestions provided by the experts from the previous iteration became the input for the next iteration. This helped to refine the AI logic and AR environment for better usability. Post testing was conducted scenario-by-scenario and involved six iterations before validation of them with the external experts. The modelled AR welding task involved the following seven scenarios to complete the task.

(a) Scenario One:

The first scenario involved health and safety, in which the individual needed to pick the appropriate safety equipment. The developed AR environment consisted of 3D objects for welding masks, overalls, gloves, footwear and safety curtains (Figure 4.25). In choosing the appropriate safety equipment, the objects were mounted onto an Avatar to provide the user with a visual representation of what they had selected and how it should be worn.

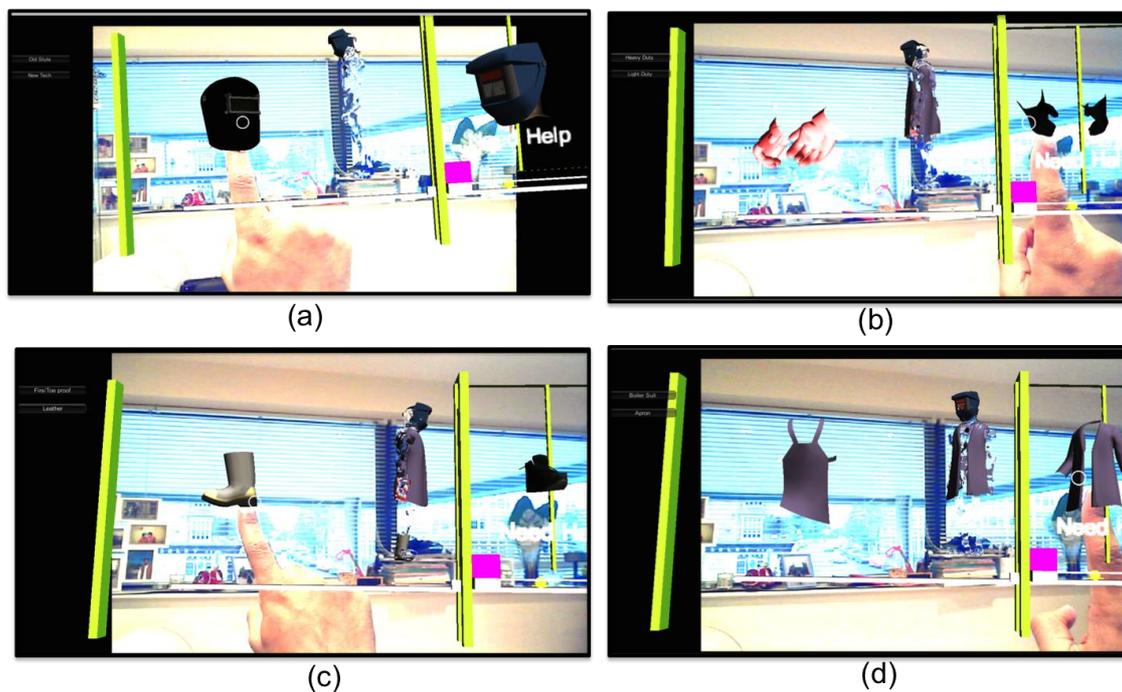


Figure 4.25: Scenario one: user selection of safety equipment (a) mask; (b) glove; (c) footwear and (d) apron.

(b) Scenario Two:

The second scenario involved plate selection, degreasing and removal of burrs. The user needed to select the plate and pick the appropriate tooling for degreasing and removing the burrs (Figure 4.26).

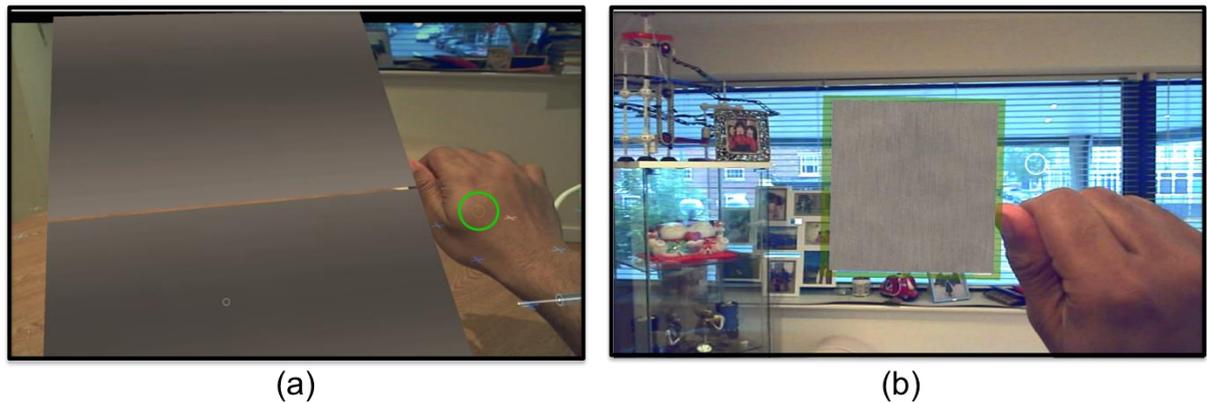


Figure 4.26: Scenario two: (a) user placing the selected plate and (b) degreasing and removing the burrs on the plate.

(c) Scenario Three:

Scenario three involved the setting up of the voltage and wire fed speed required for the selected metal plate. The user is able to see the welding console, where the highlighter blinks over the two dials which need to be adjusted to alter the voltage and wire fed speed (Figure 4.27).

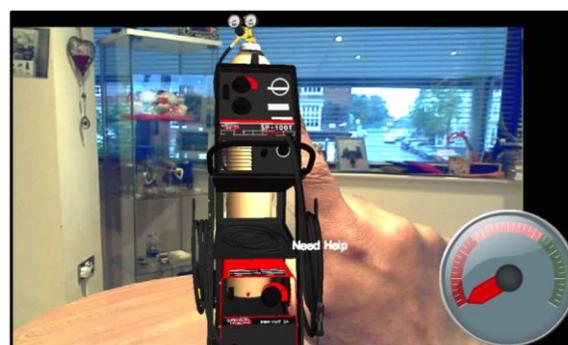


Figure 4.27: Scenario three: user set-up of voltage and wire fed speed for the chosen plate thickness.

(d) Scenario Four:

With the successful completion of the previous scenarios, the user is able to move to the welding execution. This includes the placing of magnets on the middle of two separate metal plates to make sure they stay in contact while welding them. The user then executes a tack weld by welding the two corners of the plate (Figure 4.28). The welding arc and welding sound launch when the nozzle comes into contact with the metal plate, and the weld bead appears once the execution has been carried out correctly.

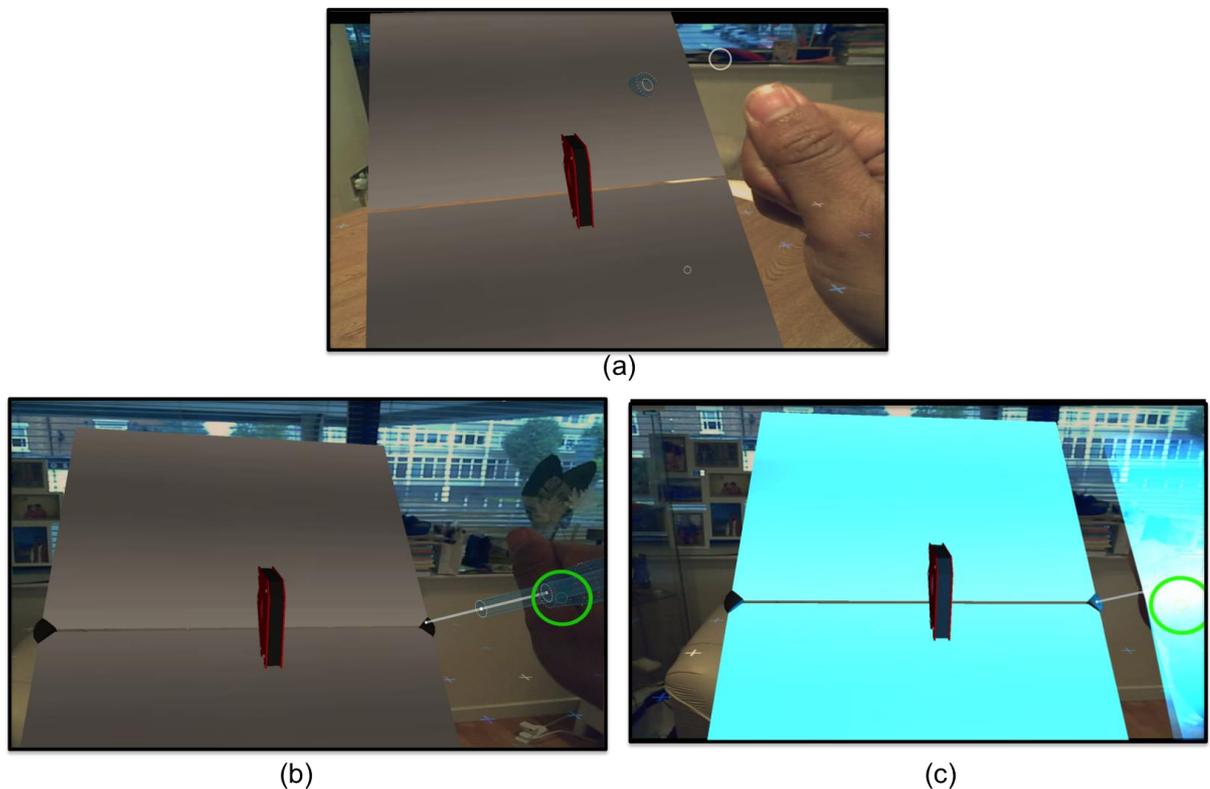


Figure 4.28: Scenario four: (a) user placing the magnet; (b) tack welding the corners and (c) appearance of welding when contact is made at the plate edges.

(e) Scenarios Five and Six:

These scenarios involve welding 20mm inside from either side of the tacked corners, followed by the main welding in the middle of the plate. The AI tutor measures the

hand speed and provides feedback on altering it if needed; the weld bead appears with appropriate execution (Figure 4.29).

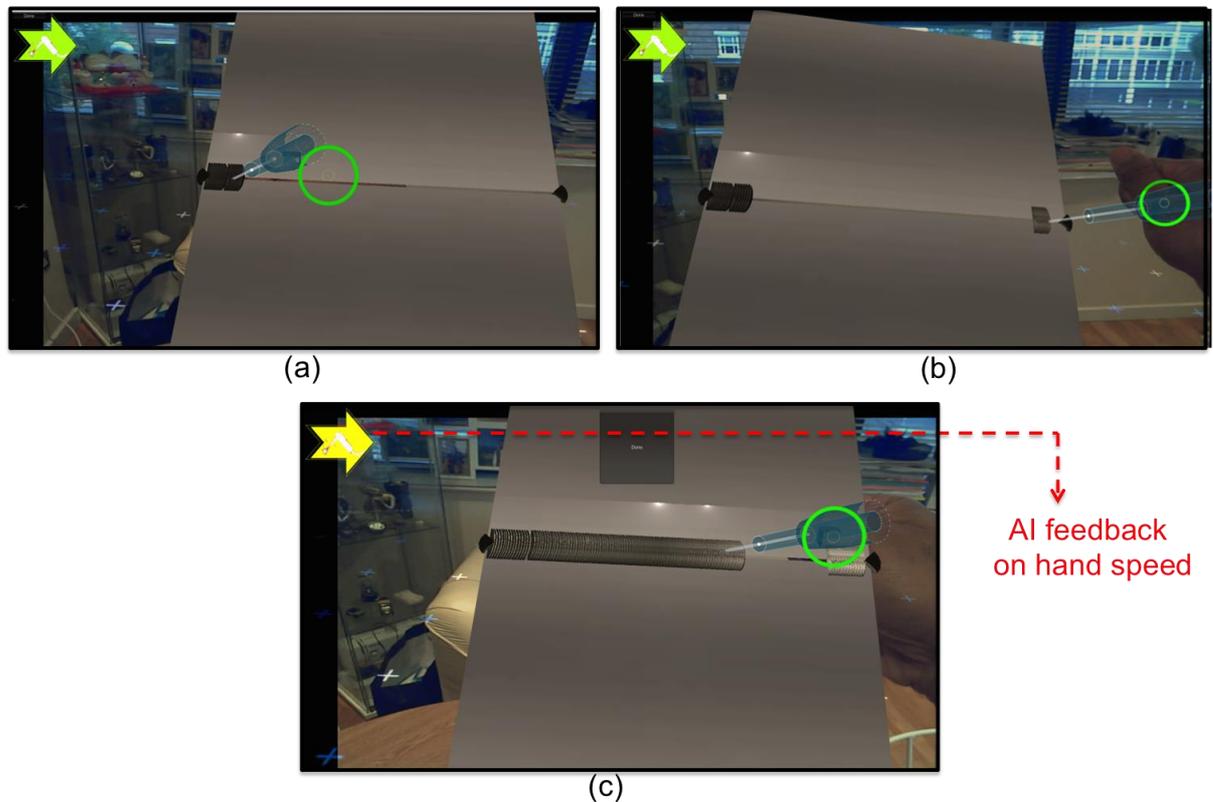


Figure 4.29: Scenarios five and six: (a) user performance of 20mm welding from left corner; (b) 20mm welding from right corner and (c) user performing main welding in the middle, with AI continuously notifying the hand speed of the user.

(f) Scenario Seven:

On completion of the main welding, the user is allowed to assess their welding quality by placing the welded plate in a vice and hitting it with a hammer. The user is able to grab the hammer and hit the plate (Figure 4.30); if the plate has been welded properly it bends when it is hit. It breaks if the welding is not up to standard.

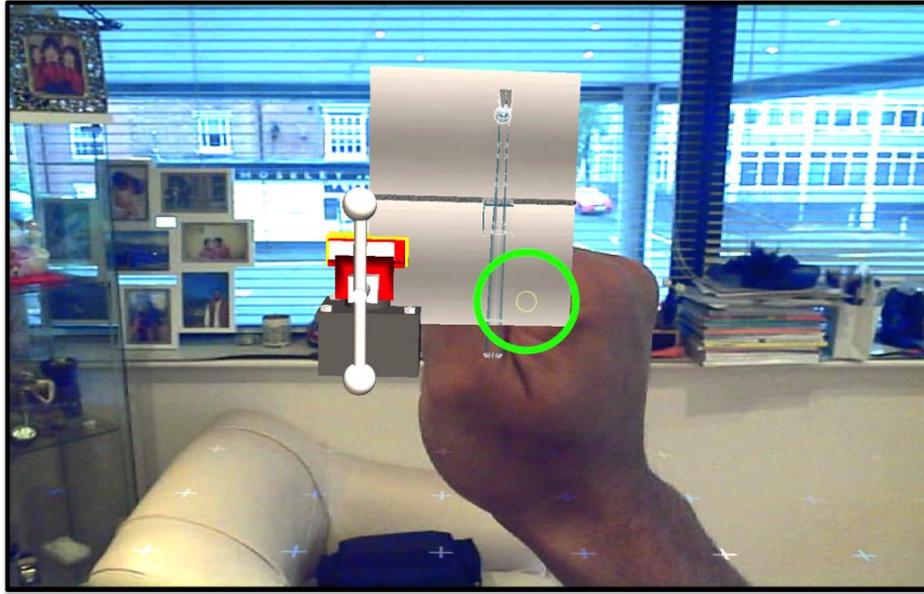


Figure 4.30: Scenario seven: user hitting the welded plate with the hammer to test the welding outcome.

In all the scenario blocks the AI tutor monitors the actions of the user by recording what they are doing, the same as how the on-campus tutor monitors the students while performing tasks in the real laboratory environment. By satisfying all the appropriate conditions by physical actions, users are allowed to proceed to the next scenario. If they fail to do so, they are guided with help me text. By clicking this, the AI tutor points out the mistake that they have made and gives them options by showing or explaining it, in order for the learners to learn and correct their mistakes in completing the task (Figure 4.31). The following chapter presents the validation results conducted with the external experts.

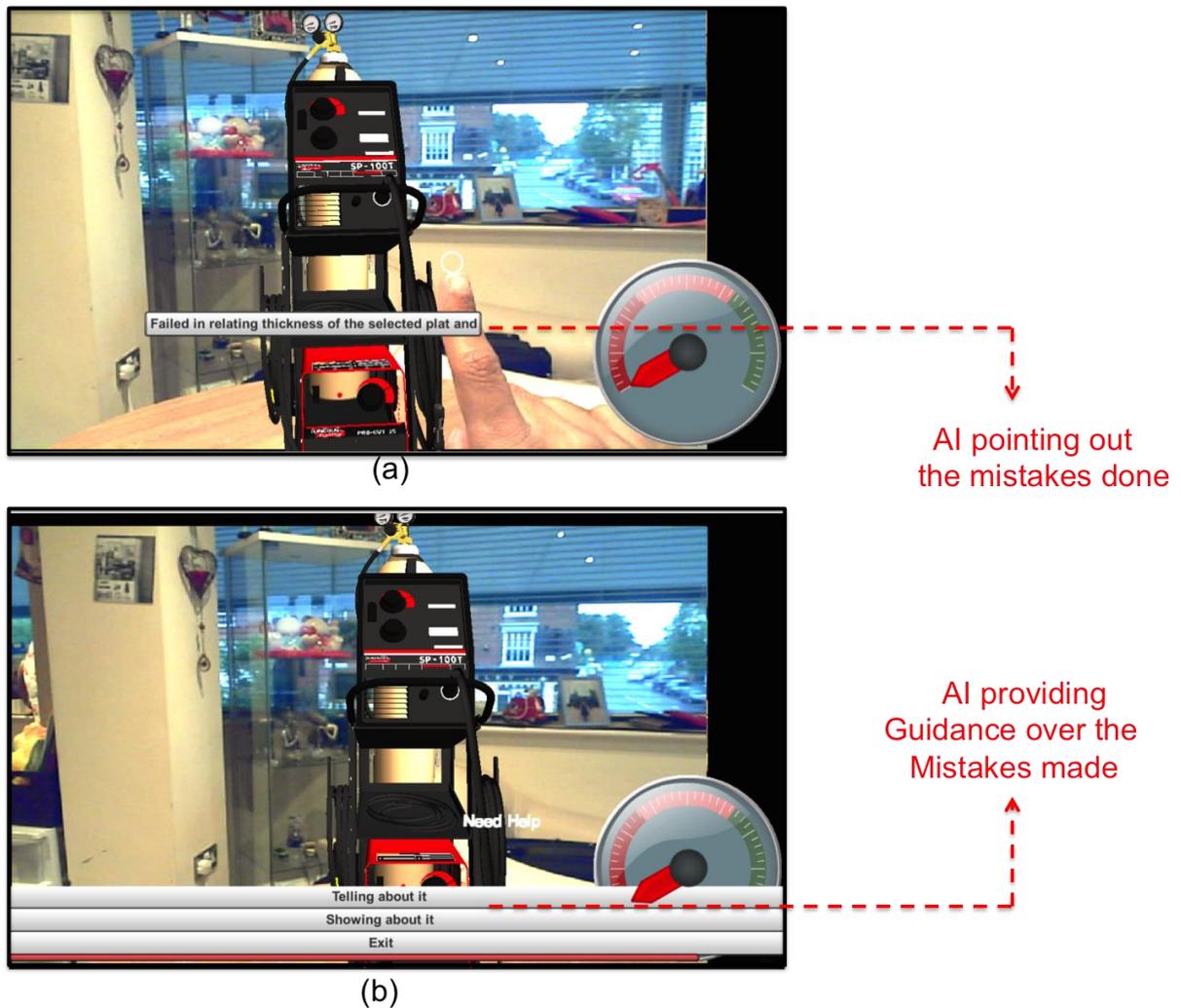


Figure 4.31: AI tutor's actions: (a) pointing out the mistakes made by the learners and (b) guiding learners on how to rectify them.

4.5 Chapter summary and conclusions

This chapter presented how the KBEd framework in teaching and assessing practical skill through an augmented reality environment was developed as a prototype through appropriate tools, techniques and technologies. Further, the chapter presented how the knowledge was captured from the on-campus laboratory tutors through the three-column approach, consisting of procedure, product and diagnostics. Then the captured knowledge were transformed into learning objects through ontological structure, by having main learning object as the core its sub-learning objects, learning structure and learning mode around them. Finally, the chapter concluded by presenting how the

modelled knowledge was codified into the Artificial Intelligent (AI) tutor for teaching and assessing practical skills. Having developed the prototype, the next stage of the research involved refining them with the expert group. Accordingly, the next chapter presents the validation process and the finding from the domain experts.

Chapter 5 Validation with the expert group

“To become 'unique,' the challenge is to fight the hardest battle which anyone can imagine until you reach your destination”

- A.P.J Abdul Kalam

5.1 Introduction

The objective of this chapter is to test the usability of the proposed augmented reality (AR) environment for learning practical skills, before investigating it with the student group. The study involved experts' validation to test the readiness and usability of the proposed KBEd system for learning practical skills through the augmented reality environment. The validation was carried out through face validity assessment, which included validation for interface realism, controls of the training tools, correctness of the modelled knowledge augmented through the AR environment, and the overall usefulness of the system (Figure 5.1). Individuals with more than ten years' of experience in teaching practical skills for students and also individuals with expertise in knowledge capturing and automation from industries and universities were targeted. The validation process started with a brief description of the research objectives and the purpose of the validation. First, the modelled knowledge that was captured from the case organization's laboratory tutor was shown and it was explained in detail how the knowledge was modelled in an ontological structure. The explanation included how the knowledge was structured into classes, subclasses and individuals, and how this structured knowledge was grouped as learning object, sub-learning object, learning structures and learning modes.

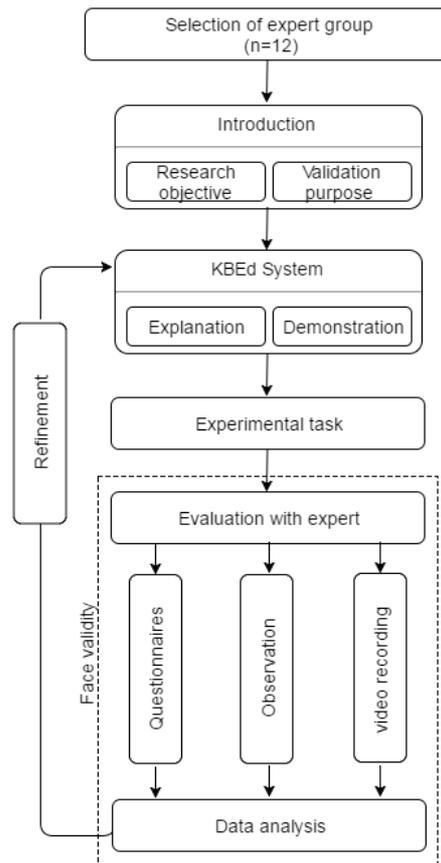


Figure 5.1: Process involved in the expert validation.

This was followed by an explanation and demonstration of how the modelled knowledge was mapped through relational propositions. For a random instance of the learning object, learning structure and learning mode, the knowledge was modelled and shown. Then an in-depth explanation of how this modelled knowledge was interpreted by the AI tutor in the AR environment was given. The experts were then asked to perform the experimental welding task in the AR environment. Subsequently, they were asked to answer 18 structured questions about the usability and readiness of the proposed system in training practical skills. Rating was scored on a scale from 1 (very low/bad/strongly disagree) to 5 (very high/good/strongly agree), direct observation was made while they were performing, and in addition video was also recorded to have a better analysis of the user experience with the prototype. The following subsection

explains in brief the face validity assessment, data generated and the method used in obtaining them.

5.2 Face validity

Face validity is an assessment tool based on the plurality of subject's opinion (Cronbach, 1984). In the last decade, face validity has been gaining more attention in several research domains, especially in the education domain for testing the validity of newly developed learning systems with expert groups (Alderson *et al.*, 1995). Face validity helps the researcher to gain subject experts' valuable insights into the usability and applicability of the system by reflecting upon their experience (Krippendorff, 2004). Table 5.1 provides a summary of other similar research that has used face validity to acquire experts' insight to measure the readiness and usability of their proposed system.

Face validity relies heavily on gathering experts' opinion mainly through observation and questionnaires that have been carefully formulated to address objectives. This study uses both observation and questionnaires for the face validity assessment, and direct observation was made along with the video recording to gauge the user experience while using the system. Eighteen questions in total were handed out to each of the experts to obtain the required evidence (Table 5.2). All these questions were given multiple-choice answers to choose from and in addition each of the questions had a comment box in order to gather more insight into the given answer, although providing comments for each of the questions was not made mandatory.

Table 5.1: Face validity assessment used in similar studies

Study	Purpose	Method	Sample size	Measure
Sulbaran and Baker (2000)	To provide the teaching community with a valuable alternative educational medium to convey engineering knowledge.	Questionnaires (7-point Likert scale).	41	User acceptance and suggestion.
Wang (2005)	To evaluate prototype systems from the aspect of benefits validation and usability in engineering.	Questionnaires (5-point Likert scale) and observation.	16	User benefit and usability.
Semeraro <i>et al.</i> (2009)	To evaluate the acceptance of a virtual reality enhanced mannequin (VREM).	Questionnaires (5-point Likert scale).	39	User acceptance.
van der Mast and van der Berg(1997)	To compare the process and the opinions of expert store designers and managers using different media.	Construct validity.	8	Experts' opinions and usefulness.
Exner and Stark (2015)	To evaluate a prototype involving both virtual and physical aspects in the Product Service System(PSS).	Concurrent validity.	12	Feedback system and user experience. Comparison matrix.
Ramos <i>et al.</i> (2014)	To evaluate robotic dry laboratory exercises.	Questionnaires (3-point Likert scale) and observation.	36	User experience.
Seymour <i>et al.</i> (2012)	To demonstrate that virtual reality (VR) training transfers technical skills to the operating room (OR) environment.	Concurrent validity.	16	Timing of length of procedure. Error detection. Eight events associated.
Verdaasdonk <i>et al.</i> (2005)	To teach hand and eye coordination as particle skills in VR and to evaluate them.	Questionnaires (5-point Likert scale) and observation.	24	User experience, task validation.
Windsor <i>et al.</i> (2008)	To determine whether skills acquired by simulation-based training transfer to the operative setting.	Questionnaires (5-point Likert scale).		Training capacity and realism.

Table 5.2: Questions used to gather experts' feedback

Question Number	Questions
Q1	Have you used AR hardware before?
Q2	What do you think of the realism of Interaction with objects in AR environment?
Q3	The multiple learning structure and learning mode presented in the system will help in adopting to different kinds of learners
Q4	Does this system simulated curiosity to learning hands on skills
Q5	How likely would you be to make use of the system
Q6	I learned and visualised some things that were surprising or unexpected
Q7	Your level of confidence in perform the same task in the real environment
Q8	Do you think the rigour of the exercise is achieved?
Q9	What is your opinion according to the Training capacity of the system?
Q10	The proposed three scale assessment axis can become useful to measure the performance of engineering distance learners
Q11	The proposed system can become useful to train engineering students at home in acquiring hands-on laboratory skills
Q12 (a) (b) (c) (d)	What is your opinion in using the system on the following training capacities (a) Torch grabbing and moving (b) Hand-eye coordination (c) Depth perception in reaching out when welding (d) Visual and sound effects while welding
Q13 (a) (b) (c)	The KBEd system will be useful for training practical skill in (a) Undergraduate distance learners (b) Postgraduate distance learners (c) industrial training
Q14	Your opinion on the proposed knowledge capturing and modelling technique for automate on-campus tutor knowledge
Q15	Would you like to have the KBEd system in your school/university/industry – virtual learners?
Q16	Completing the exercise in this course gave me a satisfying feeling of accomplishment
Q17	I enjoyed this system so much that I would like to know more about this
Q18	KBEd system in general

The 'validity' of face validity assessment is derived from the convergence of expert opinions, statement comments and experience that have been gathered through each of

the questions and observations made. The convergence is generally determined through the plurality in the answers provided. This study used ‘mode’ as the analysis technique to find the most “agreed” or “disagreed” answers from the questionnaires; furthermore, the comments provided were classified into three statement categories, validity statement, changes statement and future direction statement, for cross-validating the acquired ‘mode’ value.

5.3 Expert group and results gathered

The external experts’ selection process for face validity assessment involved three stages. The first stage involved identifying the experts with appropriate expertise. This is either a minimum of ten years’ of experience in the area of teaching engineering laboratory task or expertise in knowledge automation and virtual/augmented reality. These terms were used as the key words in identifying an initial pool of experts from web-based professional networks such as LinkedIn, BranchOut and ResearchGate. This resulted in the identification of more than 100 experts from the initial search. The second stage involved manual filtering of the initial pool of experts by two more criteria; firstly by making sure that the experts were independent of the development work but were familiar with heuristic evaluation. Secondly, experts with expertise in teaching welding task and experts with implementation experience with virtual/augmented reality (VR/AR) and individual with combination of expertise in welding and VR/AR were filter. In total 45 experts were identified under the secondary filter. The third stage involved reaching out to the experts through email explaining about the undertaken research and the evaluation process that was intended; out of 45 identified experts, 12 of them agreed to participate in the evaluation. Each of the 12 individuals was categorized by filtering them through the following two aspects: their previous experience in welding, and use of AR/VR technologies (Figure 5.2). The

number of experts with previous experience in welding and who had also used some of the VR/AR technologies was two; the number of experts with no experience in welding and use of AR/VR technologies was also two.

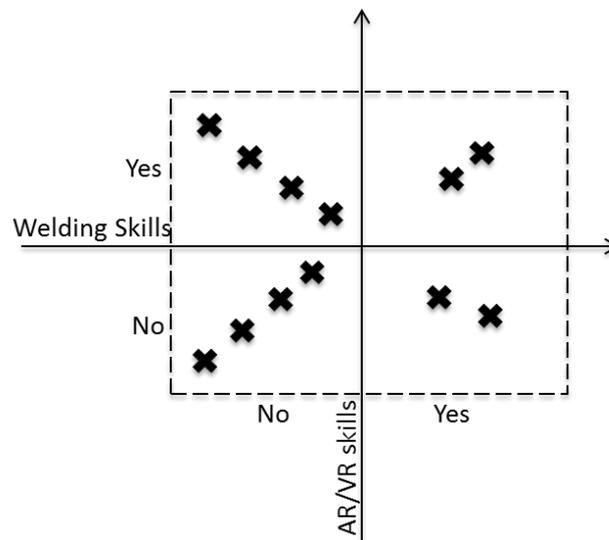


Figure 5.2: Expert group categorization with respect to welding and AR skills

The number of experts with experience in welding but none of the AR/VR technologies was four, and the number of experts with no welding experience but who had used the AR/VR technologies was also four. The categorization of experts helped in the comparison of the data with the same set of individuals with similar experience and also to identify the common ground of the individuals with different expertise. Furthermore, all the questions were grouped into three major categories for analysis purposes: (i) realism and usability questions relating to the visual and controls of the training system; (ii) knowledge content validity questions relating to the quality of the AI tutor’s performance; and (iii) general validity questions relating to the overall performance of the system (Figure 5.3).

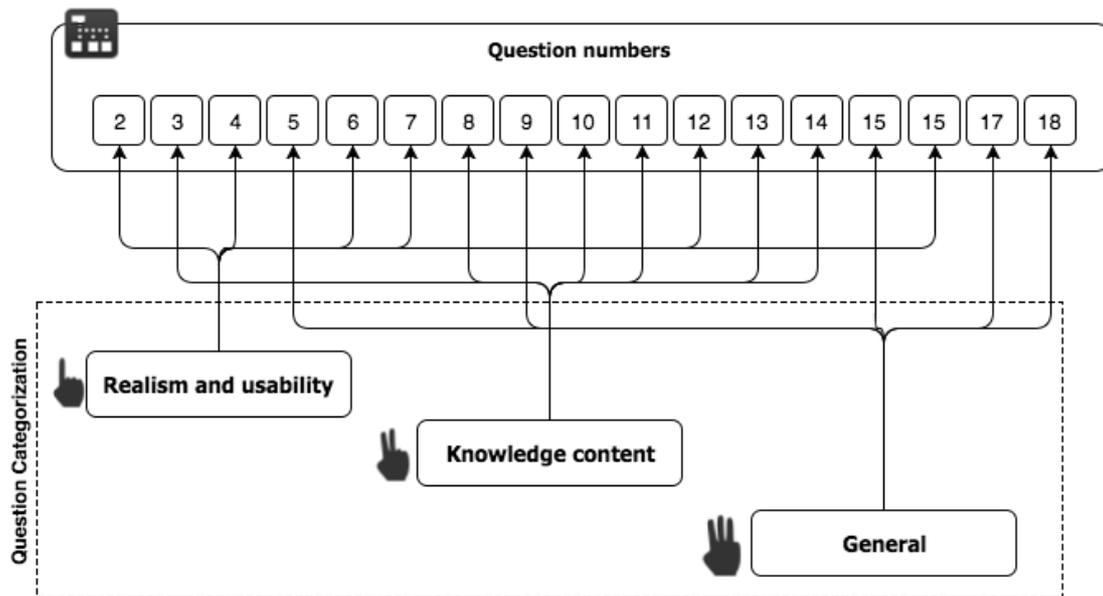


Figure 5.3: Categorization of questions

(i) Realism and usability validity questions results

When asked about their opinion on the realism of interaction with objects in the AR environment, nine said this was “high” regarding the realism of the augmented 3D objects and the graphics in the AR environment. One expert was “unsure” and commented that technology would improve over time and consequently the realism. One individual said “low” and another “very low” with regard to the proposed AR environment being realistic and commented that the torch handling was nothing like a real one and moreover that no glove was seen on the hand while welding (Table 5.3).

Table 5.3: Results and interpreted comments for question two

(Option 1 = very low (VL) to Option 5 = very high (VH)), n= 12

Question No 2	Options & Results (n = 12)					Mode	Commented Statement													
							Validity	Changes	Future direction											
Raw data	VL	L	U	H	VH	4 (High)	“the level of realism was just right” “Object representation mostly realistic though I found it difficult at the beginning but got used to the tool”	“Torch handling was nothing like the real thing and moreover no glove was seen on the hand while welding” “takes a bit of practice in reengaging the torch” “depth is hard to get used to, also the angle of the tool”	“I believe the technology will be improved over time to increase the realism”											
	1	1	1	9	0															
Graphical representation	<table border="1"> <caption>Data for Graphical Representation</caption> <thead> <tr> <th>Option</th> <th>Frequency</th> </tr> </thead> <tbody> <tr> <td>VL</td> <td>1</td> </tr> <tr> <td>L</td> <td>1</td> </tr> <tr> <td>U</td> <td>1</td> </tr> <tr> <td>H</td> <td>9</td> </tr> <tr> <td>VH</td> <td>0</td> </tr> </tbody> </table>					Option	Frequency	VL	1	L	1	U	1	H	9	VH	0			
Option	Frequency																			
VL	1																			
L	1																			
U	1																			
H	9																			
VH	0																			

However, another individual commented that the level of realism was just right. The mode value determined for the above question is four, which determines the plurality in experts’ opinion as “high”. Although the plurality among the categorized comment statements was equal between validity and changes statements, when analysed, the lack of realism in handling the torch was one of the most resonating statements. This was considered as one of the changes that needed to be addressed before testing the system with students.

When asked whether the system stimulated curiosity to learn hands-on skills, four of them “strongly-agreed” and seven just “agreed” that the system triggered their curiosity to learn and practise the practical skills (Table 5.4).

Table 5.4: Results and interpreted comments for question four

(Option 1 = strongly disagree (SD) to Option 5 = strongly agree (SA)), n= 12

Question No 6	Options & Results (n = 12)					Mode	Commented Statement													
							Validity	Changes	Future direction											
Raw data	SD	D	U	A	SA	4 (High)	“the AR interaction makes very curious to grab the object “you can make mistakes and not damage the real life equipment” “makes you want to complete the task, and learn more about it” “the cost effectiveness and time-saving properties made me really curious to use the AR systems to learn engineering and technical skills”	“as I am practical and enjoy the physical reactions of materials and processes, I am not pre-disposed to the virtual environment”	“learner-dependent ; further evaluation would be needed” “I am very interested to see how this field develops. It could be a very powerful paradigm shift in teaching practice”											
	0	0	1	7	4															
Graphical representation	<table border="1"> <caption>Data for Graphical Representation</caption> <thead> <tr> <th>Option</th> <th>Frequency</th> </tr> </thead> <tbody> <tr> <td>SD</td> <td>0</td> </tr> <tr> <td>D</td> <td>0</td> </tr> <tr> <td>U</td> <td>1</td> </tr> <tr> <td>A</td> <td>7</td> </tr> <tr> <td>SA</td> <td>4</td> </tr> </tbody> </table>					Option	Frequency	SD	0	D	0	U	1	A	7	SA	4			
Option	Frequency																			
SD	0																			
D	0																			
U	1																			
A	7																			
SA	4																			

One individual commented that it motivated you to complete the task and learn more about it, although one was “unsure” and commented that he was more involved in and motivated by the real physical objects rather than the virtual ones. The calculated mode value was four, which determined the plurality in the experts’ opinions as “agreed” on the fact that the system stimulated curiosity to learn the practical task. The majority of the categorized comments were validity statements in terms of leveraging their

curiosity in learning and practising the hands-on practical skills. There were two future direction statements, indicating their interest in seeing the enhancement that it could bring to the students through its validation with them, which mapped exactly towards the second phase of the chosen validation process.

When asked whether they had learned and visualized any things that were surprising or unexpected there was a mixed reaction; two experts answered “unsure” and one said “very low”, commenting that he had been familiar with a similar visualization before. But the majority of six said they were “highly” surprised to learn hands-on practical skills in an AR environment. In addition, three said they were “very highly” surprised to see the knowledge had also been augmented (Table 5.5). One further commented that she was surprised to see the knowledge capture and choice of different learning modes in the learning and believed that it was a very strong concept. The plurality over the validity statement was high; moreover, these validity statements not only reflected the presented AR environment, but also the core principle that was applied in developing it.

Table 5.5: Results and interpreted comments for question six

(Option 1 = very low (VL) to Option 5 = very high (VH)), n= 12

Question No 2	Options & Results (n = 12)					Mode	Commented Statement													
							Validity	Changes	Future direction											
Raw data	VL	L	U	H	VH	4 (High)	“probably as I am a novice welder!” “I was surprised to learn the knowledge capture and mode of learning – I think it’s very strong as a concept” “I started with no knowledge of welding. I felt that I learned very quickly. I was surprised how much, and was stunned when moving the welding torch at the correct speed”	“already familiar with a similar assert”												
	1	0	2	6	3															
Graphical representation	<table border="1"> <caption>Data for Graphical Representation</caption> <thead> <tr> <th>Option</th> <th>Count</th> </tr> </thead> <tbody> <tr> <td>VL</td> <td>1</td> </tr> <tr> <td>L</td> <td>0</td> </tr> <tr> <td>U</td> <td>2</td> </tr> <tr> <td>H</td> <td>6</td> </tr> <tr> <td>VH</td> <td>3</td> </tr> </tbody> </table>					Option	Count	VL	1	L	0	U	2	H	6	VH	3			
Option	Count																			
VL	1																			
L	0																			
U	2																			
H	6																			
VH	3																			

When asked about the level of confidence they would have if asked to perform the same task in the real environment, eight said they were “highly” confident and one was “very highly” confident of doing this. Two were “unsure” about whether they would be able to or not, with one commenting that he needed a bit more practice with the AI tutor’s feedback before executing the task in the real environment (Table 5.6).

Table 5.6: Results and interpreted comments for question seven

(Option 1 = very low (VL) to Option 5 = very high (VH)), n= 12

Question No 2	Options & Results (n = 12)					Mode	Commented Statement										
	VL	L	U	H	VH		Validity	Changes	Future direction								
Raw data	1	0	2	8	1	4 (High)	<p>“I am confident within our workshop to weld effectively”</p> <p>“my confidence grew the more I used it”</p> <p>“more confident than before using the system than just reading about it or watching someone else do it”</p> <p>“seeing an augmented reality set up of the key tools and equipment made things a lot easier than solely reading about the process in a book or attending a lecture. I believe I would also have a better tacit knowledge welding torch of handling and correct speed of welding ”</p>	<p>“I would need a few more practice runs and feedback first”</p> <p>“I need a little more practice before I use the real tools”</p>	<p>“it’s good preparation for the students, before the real thing”</p>								
Graphical representation	<table border="1"> <caption>Data for Graphical Representation</caption> <thead> <tr> <th>Option</th> <th>Count</th> </tr> </thead> <tbody> <tr> <td>VL</td> <td>1</td> </tr> <tr> <td>L</td> <td>0</td> </tr> <tr> <td>U</td> <td>2</td> </tr> <tr> <td>H</td> <td>8</td> </tr> <tr> <td>VH</td> <td>1</td> </tr> </tbody> </table>									Option	Count	VL	1	L	0	U	2
Option	Count																
VL	1																
L	0																
U	2																
H	8																
VH	1																

One expert said he had “very low” confidence in achieving this and made the same comment as the previous participant, saying that he needed a little more practice in acquiring the confidence before using the real tools. Most of the people who said “highly” or “very highly” regarding confidence added that the system built more confidence than watching videos or reading books. Although with a mode of four, representing “highly” as the majority of answers provided, one has to take into consideration the experts’ previous expertise.

By previously segregating the experts into novices and non-novices in welding and AR/VR (Figure 5.2), the number of people who had previous experience in welding was six. By eliminating them and analyzing the answers provided by the remaining six experts with no experience in welding, three said they were “highly” confident, two were “unsure” and one had “very low” confidence. This still proved that the majority of experts with no experience in welding still felt “highly” confident about executing the real task.

When asked about their opinion on using the system for the following training capacities

- (a) Torch grabbing and moving
- (b) Hand-eye coordination
- (c) Depth perception in reaching out when welding
- (d) Visual and sound effects while welding

Taken into consideration that 50% of the experts had no previous experience in using any of the VR or AR systems before (Figure 5.2) have made the validity over the capacity of proposed systems to be healthier by having a different point of view. Regarding the touch grabbing and moving in an AR environment, eight of the experts

accepted that it was “easy” and “very easy”. Two were “unsure” as it was their first experience and another other felt it was “very hard” to grab (Table 5.7).

Table 5.7: Results and interpreted comments for question twelve

(Option 1 = very hard/bad (VL) to Option 5 = very easy/good (VH)), n= 12

Question No 12	Options & Results (n = 12)					Mode	Commented Statement		
							Validity	Changes	Future direction
	VH	H	U	E	VE				
(a)	1	1	2	6	2	4 (High)	“I think the graphics were just about right, they did not distract from the task to be performed” “I would add that the one scored lows that this was done to the experimental AR glasses”	“practice needed first”	“maybe if the student progresses to an advanced level the weld seam could show variation in thickness/shape. Also it would be great to have a closer view of the weld seam”
(b)	1	2	2	5	2	4 (High)			
(c)	0	8	2	1	1	2 (Low)			
(d)	VB	B	U	G	VG	4 (High)			
	0	0	1	7	4				

But all the participants were able to grab and move the torch when performing the task. The only difference between the participants who felt it hard or easy was the amount of time it took them to become familiar with the system, which was revealed when analysing the recorded video. The more time they trained in the system, the easier it was for them to interact with the objects. One of them also commented that practice was first needed before performing the task. With respect to the hand and eye coordination that is required when performing the practical task in the AR environment, there was a mixed reaction in the answers provided. Two of them said it was “very easy”, five that it was just “easy”, four said it was “hard” or “very hard” and the remaining two were “unsure”. Even though there were mixed answers, the determined mode value suggests that the maximum number of experts said “easy” with regard to the required hand and eye coordination. With the depth perception when handling the tool, eight out of the twelve found it was “hard”.

Taking that into consideration along with the comments provided, the video recording was used to further analyse the problem by establishing the key element that caused difficulty for them to assess the depth while handling the torch. One of the reasons was due to visual error, as the majority of the experts assumed the augmented object to be two-dimensional, but in reality it was three-dimensional involving the z-axis and therefore more time was needed by the experts to get used to it. The second reason was that the current hardware used is a development kit, in which all the augmented objects and their interaction and behaviours are modelled and coded for the research need, which is more advanced.

In future, more enhancements in hardware and software will eventually make the depth perception easier. This was understood by some of the experts, with one of them commenting that “I would add that the one scored lows that this was done to the experimental AR glasses”. For the visual and sound effects, overall 90% of them said they were very good or good, although one expert was “unsure”, although commenting positive that the graphics were just right as they did not disturb the user while performing the practical task.

(ii) Knowledge content questions results

When asked whether the multiple learning structures and learning modes presented in the system helped the system to adapt to their different learning style, four of the experts “strongly agreed” while the remainder just “agreed” that the proposed learning structure and mode adapted to people with different learning styles by allowing them to construct their own starting point to learn (Table 5.8).

Table 5.8: Results and interpreted comments for question three

(Option 1 = strongly disagree (SD) to Option 5 = strongly agree (SA)), n= 12

Question No 3	Options & Results (n = 12)					Mode	Commented Statement													
							Validity	Changes	Future direction											
Raw data	SD	D	U	A	SA	4 (High)	“sound in principle whilst allowing for a variety of learning objects” “fascinating insight into the learning structure” “there is no right or wrong way of learning. It will give students the confidence to make mistakes and try” “gives appropriate starting points for use, and adapts to different strengths and weaknesses” “its helps learners to start from any point they think they need to complete the task” “the learning structure design was impressive. It managed to capture the tacit elements of what it actually means to learn very well”													
	0	0	0	8	4															
Graphical representation	<table border="1"> <caption>Data for Graphical Representation</caption> <thead> <tr> <th>Option</th> <th>Count</th> </tr> </thead> <tbody> <tr> <td>SD</td> <td>0</td> </tr> <tr> <td>D</td> <td>0</td> </tr> <tr> <td>U</td> <td>0</td> </tr> <tr> <td>A</td> <td>8</td> </tr> <tr> <td>SA</td> <td>4</td> </tr> </tbody> </table>					Option	Count	SD	0	D	0	U	0	A	8	SA	4			
Option	Count																			
SD	0																			
D	0																			
U	0																			
A	8																			
SA	4																			

All the comments provided were validity statements, with one common theme among the statements being the flexibility in the starting point and the choice of preferred mode in learning the task. Apart from that, the principle and the execution of creating learning objects with different combinations of learning structures and learning modes were acknowledged by more than one individual

When asked if they had achieved the rigour to complete the task in the AR environment, two experts answered “very high”, six answered “high” and the rest were “unsure” about this (Table 5.9). This question validated the confidence that the experts had gained in completing the given task successfully in the AR environment. The determined mode value was four, which denotes that the majority of the participants felt “high” confidence to complete the given AR task successfully.

Table 5.9: Results and interpreted comments for question eight

(Option 1 = very low (VL) to Option 5 = very high (VH)), n= 12

Question No 8	Options & Results (n = 12)					Mode	Commented Statement										
	VL	L	U	H	VH		Validity	Changes	Future direction								
Raw data	0	0	4	6	2	4 (High)	“it gives you the demonstration to achieve the goal” “with this system you can practise until you have achieved a high level of skill”	“with more practice I think I could achieve consistency”	“it would be interesting to have more dynamic difficult levels and conditions if a trainee wants to repeat”								
Graphical representation	<table border="1"> <caption>Data for Graphical Representation</caption> <thead> <tr> <th>Option</th> <th>Count</th> </tr> </thead> <tbody> <tr> <td>VL</td> <td>0</td> </tr> <tr> <td>L</td> <td>0</td> </tr> <tr> <td>U</td> <td>4</td> </tr> <tr> <td>H</td> <td>6</td> </tr> <tr> <td>VH</td> <td>2</td> </tr> </tbody> </table>									Option	Count	VL	0	L	0	U	4
Option	Count																
VL	0																
L	0																
U	4																
H	6																
VH	2																

There was no significant plurality in the comment statements as the opinions given were mixed, two stating that the system drove them to achieve the goal and allowed them to keep practising until they had achieved a high skill level. In addition, two who answered “unsure” suggested that more practice could make them more consistent, while another

expert suggested having different dynamic levels to provide motivation to train repeatedly.

When asked whether the proposed three scale assessment axis was useful for measuring the performance of learners in the AR environment, three answered that they “strongly agreed” and seven that they “agreed” that the proposed assessment axis consisting of level, depth and rigour was effective in measuring the performance of the AR learners. However, one was “unsure” but commented that it was a promising foundation (Table 5.10). The comments provided were more validity statements acknowledging the importance of measuring learners’ performance through the proposed assessment method, leading to better diagnostics in order to make further improvements.

Table 5.10: Results and interpreted comments for question ten

(Option 1 = strongly disagree (SD) to Option 5 = strongly agree (SA)), n= 12

Question No 10	Options & Results (n = 12)					Mode	Commented Statement												
							Validity	Changes	Future direction										
Raw data	SD	D	U	A	SA	4 (Agree)	“promising foundation” “it’s important to measure learning knowledge and application, to further the student understanding of the process” “I really liked this design as a method for better diagnosis of practice and to support learners”	“rigour is clear but at the beginning the other two parameters (level & depth) were fairly hard to correlate with the assessment”											
	0	0	1	7	4														
Graphical representation	<table border="1"> <caption>Data for Graphical Representation</caption> <thead> <tr> <th>Option</th> <th>Count</th> </tr> </thead> <tbody> <tr> <td>SD</td> <td>0</td> </tr> <tr> <td>D</td> <td>0</td> </tr> <tr> <td>U</td> <td>1</td> </tr> <tr> <td>A</td> <td>7</td> </tr> <tr> <td>SA</td> <td>4</td> </tr> </tbody> </table>					Option	Count	SD	0	D	0	U	1	A	7	SA	4		
Option	Count																		
SD	0																		
D	0																		
U	1																		
A	7																		
SA	4																		

When specifically asked about the usefulness of the system with respect to training engineering students away from the laboratory environment by making use of the system in their homes to acquire hands-on laboratory skills, out of the twelve experts eleven answered either “very high” or “high” (Table 5.11). One was “unsure” and commented that this would be useful to students with additional practical experience, meaning that students with previous real world experience would benefit more as they could enhance their existing performance.

Table 5.11: Results and interpreted comments for question eleven

(Option 1 = very low (VL) to Option 5 = very high (VH)), n= 12

Question No 11	Options & Results (n = 12)					Mode	Commented Statement										
	VL	L	U	H	VH		Validity	Changes	Future direction								
Raw data	0	0	1	6	5	4 (High)	“the system allows student, to work any time, day or night and have multiple goes at tasks” “good for tasks involving hands-on training” “not only useful but potentially revolutionary as it could lower student and teaching costs as well as making skills and applied education available to all”	“with additional practical experience”	“3 axis milling point visualization in a process point which can be modelled” “I can see many applications”								
Graphical representation	<table border="1"> <caption>Data for Graphical Representation</caption> <thead> <tr> <th>Option</th> <th>Count</th> </tr> </thead> <tbody> <tr> <td>SD</td> <td>0</td> </tr> <tr> <td>D</td> <td>0</td> </tr> <tr> <td>U</td> <td>1</td> </tr> <tr> <td>A</td> <td>6</td> </tr> <tr> <td>SA</td> <td>5</td> </tr> </tbody> </table>									Option	Count	SD	0	D	0	U	1
Option	Count																
SD	0																
D	0																
U	1																
A	6																
SA	5																

The mode value of four clearly suggested that the plurality among the answers provided by the experts was “high” with respect to the usefulness of the system in acquiring hands-on laboratory skills. The comments provided were further validity statements acknowledging the usability of the system for practising multiple times in any place and the revolution that it could provide by reducing teaching and learning costs by making the skills and education applicable to all. Finally, two experts said that they wanted to see a similar method for learning and practising 3-axis milling tasks.

When asked if the system would more benefit undergraduates, postgraduates or industry in training practical skills, almost 80% of the experts either “strongly agreed” or “agreed” that the proposed system would benefit all the three levels. The remainder were “unsure” whether it would be helpful, apart from one who “disagreed” that it would benefit postgraduates and went on to comment that the system would be useful when students started to practise and learn at the early stages of their education (Table 5.12).

Table 5.12: Results and interpreted comments for question thirteen

(Option 1 = strongly disagree (SD) to Option 5 = strongly agree (SA)), n= 12

Question No 13	Options & Results (n = 12)					Mode	Commented Statement		
	SD	D	U	A	SA		Validity	Changes	Future direction
(a)	0	0	2	5	5	4 (Agree)	“promising start” “useful at early stages to acclimatize students to this type of learning” “it will give the students a feel of what to expect in the real world”	“could be useful with postgraduates rather than undergraduates; could work in industry” “assume that for postgraduates it is less likely to be useful as students have done the manual tasks”	
(b)	0	1	2	4	5	5 (Strongly agree)			
(c)	0	0	2	4	6	5 (Strongly agree)			

Another expert was unsure whether it would be helpful for undergraduates, commenting that it could be more useful to postgraduates and industry. The majority accepted that it would benefit all different levels in training their learners, while some of the experts gave their opinion on the specific level that it might benefit more. The plurality of the comments was equal among the validity and changes statements, with the validity statements acknowledging the presented method as a promising start and that it would be of more benefit if integrated into the early stages of students' learning. As discussed above, the two changes statements were contradictory with regard to the usefulness at undergraduate and postgraduate levels.

When asked about their opinion on the proposed three column approach using procedure, product and diagnostics to capture and model on-campus tutors' knowledge, seven of the experts "strongly agreed", three just "agreed" that the proposed way of capturing and modelling knowledge was efficient, while the other were "unsure" (Table 5.13). The comments provided were all validity statements, with one participant saying that the idea and execution of the capture and modelling of the knowledge was useable and reasonable as it had been proved with substantial data. Another expert followed this up by saying that the chosen semantic technology for knowledge representation would be easy to extend to complex practical tasks with more data than the current one. The determined mode value of five suggested that the majority of experts "strongly agreed" that the proposed three-column approach method was useful in capturing and modelling on-campus tutors' knowledge.

Table 5.13: Results and interpreted comments for question fourteen

(Option 1 = strongly disagree (SD) to Option 5 = strongly agree (SA)), n= 12

Question No 14	Options & Results (n = 12)					Mode	Commented Statement													
							Validity	Changes	Future direction											
Raw data	SD	D	U	A	SA	5 (Strongly agree)	“the idea and model for capturing knowledge is usable and reasonable. The model is already proven by instating it with a substantial amount of practical data” “As the semantic technology has been chosen for representing models, if some tasks involve more kinds of data, it can be easily extended to accommodate them too”													
	0	0	2	3	7															
Graphical representation	<table border="1"> <caption>Data for Graphical Representation</caption> <thead> <tr> <th>Option</th> <th>Frequency</th> </tr> </thead> <tbody> <tr> <td>SD</td> <td>0</td> </tr> <tr> <td>D</td> <td>0</td> </tr> <tr> <td>U</td> <td>2</td> </tr> <tr> <td>A</td> <td>3</td> </tr> <tr> <td>SA</td> <td>7</td> </tr> </tbody> </table>					Option	Frequency	SD	0	D	0	U	2	A	3	SA	7			
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(iii) General validity questions

When asked how likely they would be to make use of the system to learn practical tasks from home, two of the panel “strongly agreed”, and eight “agreed” on the use of the proposed system to learn practical skills while away from the laboratory environment. The other two were “unsure” and commented that although this was not a criticism of the research contribution, it was not applicable to their current role (Table 5.14).

The plurality of the comments provided for this question was more validity statements, in which most of them reasoned on the usefulness of the AI and the clear visualization of the internal process which they could see while carrying out the task. In addition, one expert commented that he could see the applicability of the system in other knowledge domains. The determined mode value of four suggested that the majority of the experts “agreed” that they would use the system to train and practise hands-on laboratory skills from home.

When asked about their opinion of the overall training capacity of the system, ten of the twelve experts said that its overall performance was either “high” or “very high” in learning and practising hands-on skills. However, two of them answered “unsure” were one commented that it was fair and might appeal to some learners but not all (Table 5.15). The comments provided had more future direction statements, saying that this seemed to be a paradigm shift by opening up possibilities for many practical applications in distance- and MOOC- (massive open online course) type educational courses competing with traditional full time applied and lab-based courses.

Table 5.14: Results and interpreted comments for question five

(Option 1 = strongly disagree (SD) to Option 5 = strongly agree (SA)), n= 12

Question No 5	Options & Results (n = 12)					Mode	Commented Statement										
	SD	D	U	A	SA		Validity	Changes	Future direction								
Raw data	0	0	2	8	2	4 (Agree)	<p>“If I was learning to weld, I would be interested in trying this AR system”</p> <p>“it’s fantastic to be able to see the welding happen – usually using darkened lenses it’s difficult to track and demonstrate the process clearly”</p> <p>“very likely to use and or demonstrate it”</p> <p>“if it’s available I and other people would use it”</p> <p>“useful for research into how AI can assist in tasks when the accuracy of a system is a limitation”</p>	<p>“not a criticism of the research contribution, more that it is less applicable to my current role”</p>	<p>“I can see how this system can be used for other knowledge domains”</p>								
Graphical representation	<table border="1"> <caption>Data for Graphical Representation</caption> <thead> <tr> <th>Option</th> <th>Count</th> </tr> </thead> <tbody> <tr> <td>SD</td> <td>0</td> </tr> <tr> <td>D</td> <td>0</td> </tr> <tr> <td>U</td> <td>2</td> </tr> <tr> <td>A</td> <td>8</td> </tr> <tr> <td>SA</td> <td>2</td> </tr> </tbody> </table>									Option	Count	SD	0	D	0	U	2
Option	Count																
SD	0																
D	0																
U	2																
A	8																
SA	2																

Table 5.15: Results and interpreted comments for question nine

(Option 1 = very low (VL) to Option 5 = very high (VH)), n= 12

Question No 11	Options & Results (n = 12)					Mode	Commented Statement										
	VL	L	U	H	VH		Validity	Changes	Future direction								
Raw data	0	0	1	6	5	4 (High)	“good; will stimulate the person who wants to learn” “as a framework for capturing performance and giving feedback”	“Fair- I think it will appeal to some learners”	“it opens up possibilities for many practical applications, especially in our area of 3-D” “the system can be very in-depth if more resources were allocated to the product” “it could be a paradigm shift in teaching. Distance and MOOC type educational course in particular could be with traditional full time applied and lab based courses”								
Graphical representation	<table border="1"> <caption>Data for Graphical Representation</caption> <thead> <tr> <th>Option</th> <th>Count</th> </tr> </thead> <tbody> <tr> <td>SD</td> <td>0</td> </tr> <tr> <td>D</td> <td>0</td> </tr> <tr> <td>U</td> <td>1</td> </tr> <tr> <td>A</td> <td>6</td> </tr> <tr> <td>SA</td> <td>5</td> </tr> </tbody> </table>									Option	Count	SD	0	D	0	U	1
Option	Count																
SD	0																
D	0																
U	1																
A	6																
SA	5																

When asked if they would use the proposed KBEed system in their respective domains for teaching and training practical skills in their employees or students, three of the experts considered they would “very highly”, seven answered “highly,” and the rest were “unsure” (Table 5.16). All comments provided were validity statements. One of them said it would be great to have this system as a compulsory module to pass before students entered the welding bay to make sure that they had a better understanding of and knowledge about health and safety.

Table 5.16: Results and interpreted comments for question fifteen

(Option 1 = very low (VL) to Option 5 = very high (VH)), n= 12

Question No 15	Options & Results (n = 12)					Mode	Commented Statement													
							Validity	Changes	Future direction											
Raw data	VL	L	U	H	VH	4 (High)	“it would be great as a compulsory module for students to pass before entering the welding bay to make sure they are fully aware of health and safety in the environment” “I think it’s the future way for colleges and universities to reach a wider student base” “useful tool for distance learning”													
	0	0	2	7	3															
Graphical representation	<table border="1"> <caption>Data for Graphical Representation</caption> <thead> <tr> <th>Option</th> <th>Count</th> </tr> </thead> <tbody> <tr> <td>VL</td> <td>0</td> </tr> <tr> <td>L</td> <td>0</td> </tr> <tr> <td>U</td> <td>2</td> </tr> <tr> <td>H</td> <td>7</td> </tr> <tr> <td>VH</td> <td>3</td> </tr> </tbody> </table>					Option	Count	VL	0	L	0	U	2	H	7	VH	3			
Option	Count																			
VL	0																			
L	0																			
U	2																			
H	7																			
VH	3																			

Two others mentioned that this could be the future in college and university teaching in acquiring a wider student base and pointed out that it would be a more useful tool for distance learners. The mode value of four suggests that majority of the experts “highly” considered use of the proposed system in their respective domains.

When asked whether they enjoyed using the system and would like to know more about it, a majority of seven out of the twelve “agreed” and the rest “strongly agreed” that they enjoyed learning how to use the system and wanted to know more about it (Table 5.17).

Table 5.17: Results and interpreted comments for question seventeen

(Option 1 = strongly disagree (SD) to Option 5 = strongly agree (SA)), n= 12

Question No 17	Options & Results (n = 12)					Mode	Commented Statement													
							Validity	Changes	Future direction											
Raw data	SD	D	U	A	SA	4 (Agree)	“it is great to find out about the capturing of results and learning outcomes. Also, as a student, experiencing what they go through” “I would like to know more about the learning structure” “the interaction between the virtual world and the encoded knowledge”													
	0	0	0	7	5															
Graphical representation	<table border="1"> <caption>Data for Graphical Representation</caption> <thead> <tr> <th>Option</th> <th>Count</th> </tr> </thead> <tbody> <tr> <td>SD</td> <td>0</td> </tr> <tr> <td>D</td> <td>0</td> </tr> <tr> <td>U</td> <td>0</td> </tr> <tr> <td>A</td> <td>7</td> </tr> <tr> <td>SA</td> <td>5</td> </tr> </tbody> </table>					Option	Count	SD	0	D	0	U	0	A	7	SA	5			
Option	Count																			
SD	0																			
D	0																			
U	0																			
A	7																			
SA	5																			

The experts who “strongly agreed” also commented on a specific area that they were interested in knowing more about. One of the experts wanted to know more about the learning structures, how they were broken down and how the knowledge was mapped to each of these structures. Another expert wanted to know more about how the interaction takes place between the virtual environment and the encoded knowledge. The other comment was more of a knowledge statement, stating that it was great for teachers and students to see what had gone wrong while performing the task.

When asked about their overall opinion of the proposed system, seven answered “very good” and the remainder said “good”. The comments provided were all validity and future direction statements, one of the experts insisting again that this should be introduced at the early stage of college or university education and that it would be valuable to know students’ need in order to build knowledge for it (Table 5.18). The other experts commented that it would increase the scope of distance learners by providing flexibility in starting from any point and being able to practise using the tool whenever you wanted. In addition, one expert commented by acknowledging the research and saying that it was an excellent piece of work combining teaching and learning knowledge to their full advantage by using the artificial intelligence and ontology relationship. The determined mode value was five, suggesting that the majority of experts’ opinions were “very good” with regard to the proposed KBEd system. The section below summarises the results and discusses the changes that were made by analyzing all the feedback gathered from the experts.

Table 5.18: Results and interpreted comments for question eighteen

(Option 1 = very bad (VB) to Option 5 = very good (VG)), n= 12

Question No 17	Options & Results (n = 12)					Mode	Commented Statement										
	VB	B	U	G	VG		Validity	Changes	Future direction								
Raw data	0	0	0	5	7	5 (Very good)	“very new method of learning for me – useful” “increases the scope of distance learning” “it gives the flexibility to students to start from any part of the learning materials and have a go with the tools whenever they want” “an excellent piece of research that links teaching and learning knowledge to its advantage with the use of the AI and ontology relationship”		“it would be useful at a college/university level to introduce students to this process early. It could be valuable in recognising students’ needs and building the knowledge of learners” “it opens up many possibilities”								
Graphical representation	<table border="1"> <caption>Data for Graphical Representation</caption> <thead> <tr> <th>Option</th> <th>Frequency</th> </tr> </thead> <tbody> <tr> <td>VB</td> <td>0</td> </tr> <tr> <td>B</td> <td>0</td> </tr> <tr> <td>U</td> <td>0</td> </tr> <tr> <td>G</td> <td>5</td> </tr> <tr> <td>VG</td> <td>7</td> </tr> </tbody> </table>									Option	Frequency	VB	0	B	0	U	0
Option	Frequency																
VB	0																
B	0																
U	0																
G	5																
VG	7																

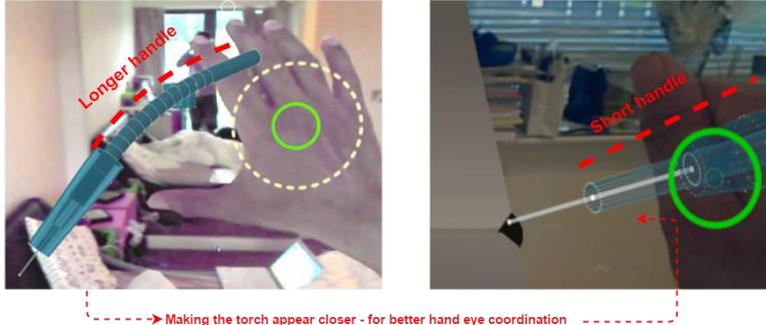
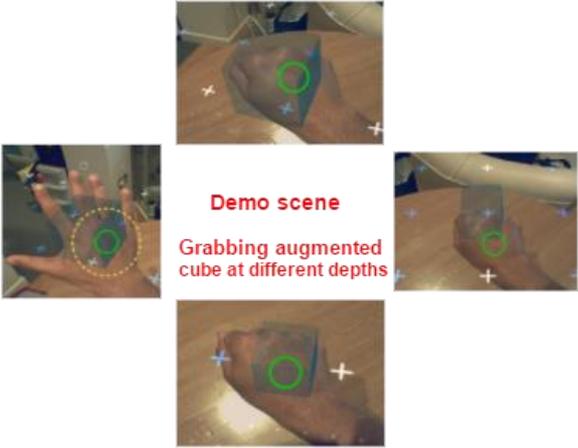
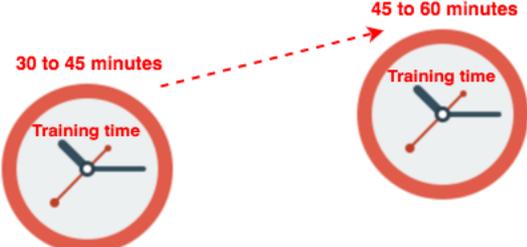
5.4 Discussion

With the face validity assessment, we were able to acquire the required data to fulfil the set objective, that is, to test the readiness and usability of the proposed KBEd system to learn practical skills in an augmented reality environment. This validation, along with the capturing of the experts' acceptance or non-acceptance of the readiness and usability of the proposed system, has also provided their suggestions about the possible changes and future development that need to be made before validating the system with the students. Moreover, having experts with mixed experience in AR and welding has provided wider feedback and made the analysis more generic in addition to task-specific.

The 12 experts who participated in the session reported that the use of the KBEd system was acceptable, the realism was high, as was the interaction/immersion and level of confidence when training through the AR environment, leading to positive overall evaluation of the realism and usability of the system. However, by analyzing the comments provided by the experts under each of the realism and usability questions, three important issues were identified: lack of realism and difficulty in handling the torch; the depth factor; and requests for more practice time. Changes were made to address these issues individually (see Table 5.19). First, the torch model was made to appear closer to the AR glass by eliminating the long handle, which made the torch grabbing much easier. In addition, the whole torch was rendered with single transparent material to provide a better view of the nozzle edges.

Second, to increase the accuracy in judging the right depth while interacting with the augmented objects, a demo scene with a simple cube to grab and move at different depths was created to provide a clearer and better understating of the depth factor for the students before they start to execute the welding task.

Table 5.19: Changes made with respect to comments provided in the realism and usability validity questions.

Description	Changes made
Altering the torch handle size	 <p>→ Making the torch appear closer - for better hand eye coordination</p>
Simple demo scene to practise grabbing at different depths	 <p>Demo scene</p> <p>Grabbing augmented cube at different depths</p>
Time scale for AR training	 <p>30 to 45 minutes</p> <p>Training time</p> <p>45 to 60 minutes</p> <p>Training time</p>

However, this does not solve the whole issue of depth judgment, as the hardware used was a development kit with limitations with respect to the minimum and maximum distance and angle at which an object is interactable. By exceeding or dropping out of range, the object handling becomes tougher, which was one of the limitations of the AR prototype used in the system. Having said that, more enhancements in future prototype hardware and software will eventually make the depth perception easier by increasing

the interaction accuracy with the augmented object. Finally, the time allowed for AR training for each individual was extended from 30-45 minutes to 45-60 minutes to provide enough time for each individual to become accustomed to the environment and to practice more.

Almost 80% of the experts found the proposed method for capturing and modelling the on-campus tutor's knowledge into the AI tutor and the augmented knowledge was robust and high in quality. In addition, the level of acceptance of the chosen semantic technology in modelling the knowledge was also high, as the semantic method not only demonstrated the use for the current task, but was also adaptable to other tasks with more complex knowledge modelling. All of the experts appreciated the adaptability of the system to teach and assess different learning needs by allowing the learners to construct their preferred way of learning. Even though 90% of the experts judged that the system was effective and efficient in training hands-on practical skills anywhere and anytime and by reducing the cost, there were contradictions in the comments provided about its usability in different domain levels. We cannot particularly judge which domain level (undergraduate/postgraduate/industry) will benefit more, since the current research focuses on evaluating the effectiveness of the proposed system only with first year undergraduates. In the future, by extending the evaluation with the same learners, or by developing other suitable tasks for each of the domain level learners, the usability with respect to each level could probably be measured.

The experts judged the developed KBEd system to be very useful for training practical skills in engineering distance learners and some of them also considered that the addition of the proposed system into conventional teaching methods could improve learners' performance by allowing them to practise more without using real resources. In response to other general validity questions, 90% of the experts considered the

diagnosis provided by the AI tutor to be very useful and appreciated the clear visualization of internal process simulated while performing the task. Moreover, the majority of the experts highly considered using the system in their respective domains to train wider audiences, and some also mentioned specific tasks that they would make use of. Among these a three-axis milling machine task was suggested by a number of experts, which could be considered as one of the practical tasks for future development.

5.5 Chapter summary and conclusions

This chapter described the validation method and techniques that were used to examine the usability and readiness of the developed KBEd prototype. The chapter also presented the data collected from experts and the analysed results. The chapter concluded by discussing the gathered evidence, the results have shown that majority of the experts agreed that the presented prototype was capable in training engineering practical skill for distance learners. However, experts pointed out some training difficulties while performing the modelled task through the prototype. Further, these suggested changes were presented and the methods adopted in addressing and refining them was also explained in detail.

Although the face validity with the expert group has demonstrated the feasibility of the proposed KBEd system in training laboratory skills through an AR environment, some research has pointed out the lack of depth, precision and rigour of inquiry using face validity. For this reason, it cannot be a standalone assessment tool in concluding the research findings (Anastasi, 1976; Nunnally, 1978 and Li, 1995). With that in mind, the study went on to test the proposed KBEd system with the student groups using concurrent validity. The next chapter provides the concurrent validity assessment and results involving two student groups, one learning in the proposed AR environment,

and the other in a conventional environment, and the testing of their learning outcome by a common experimental task.

Chapter 6 Validation with students

“Real education enhances the dignity of a human being and increases his or her self-respect. If only the real sense of education could be realized by each individual and carried forward in every field of human activity, the world will be so much a better place to live in”

- **A.P.J Abdul Kalam**

6.1 Introduction

The objective of this chapter is to validate whether the skills acquired in the AR-based training environment are transferable to the real environment and also to investigate the same practical task taught in a conventional environment. After comparing the performance of the AR-based learners and the on-campus based ones by measuring their practical learning outcome with respect to the fundamental, procedural, preparation and executional skills, we present the analysis and results of our experimentation.

The validation process started by identifying two groups of students with equal abilities in the selected practical subject. Forty-six students with no previous experience in welding from the case organisation's first year engineering undergraduates were randomly selected as participants (Figure 6.1). They were then further randomized into two groups using sealed envelopes. The first group received training in the proposed AR environment and the other group went on to train in the conventional environment. The training in the conventional environment consisted of an on-campus tutor explaining and demonstrating the welding task. The same task was performed in the AR environment with an AI tutor for teaching and guiding purposes. To establish concurrent validity, an experiment was conducted to compare the performance of the students who learned in the AR environment using augmented objects with the AI tutor,

and the students who learned in the conventional environment using real objects with an on-campus tutor.

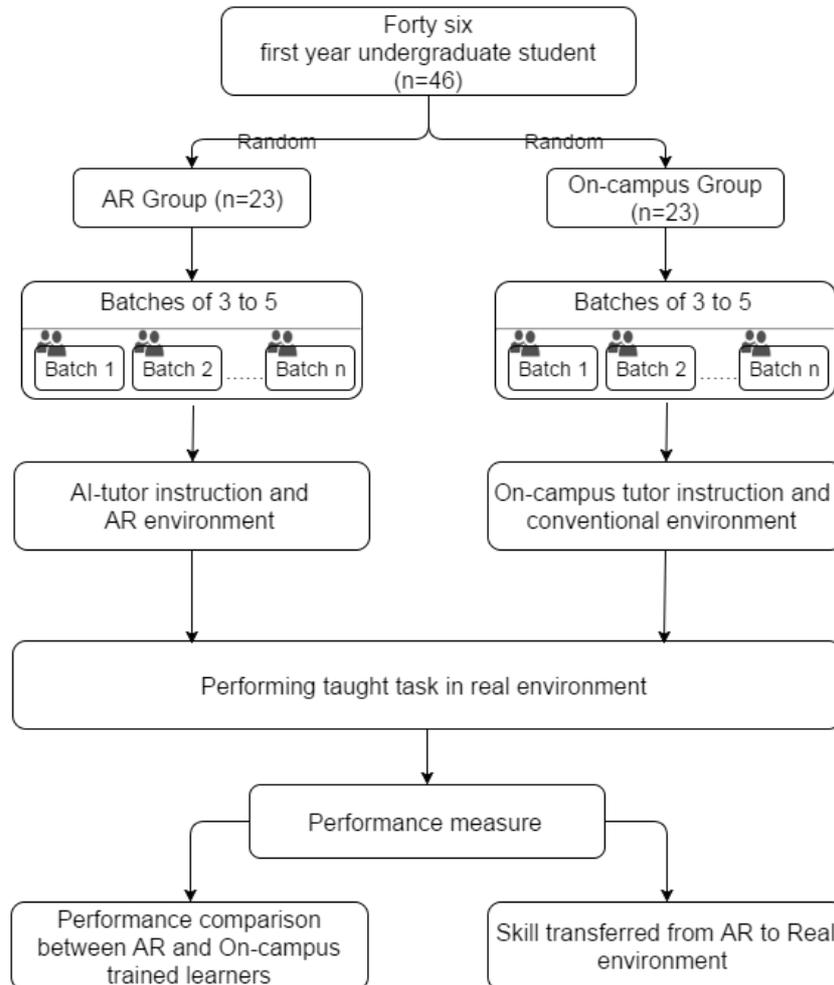


Figure 6.1: Concurrent validity with two groups of students

After the training, all the participants from both groups individually performed the same welding task in the real environment without any help. During this, their performances were measured by two laboratory tutors by detecting errors and their task outcome. Furthermore, all the AR participants' experience of and suggestions about the proposed KBEd system were collected. The students in both training environments had the same learning content and learning mission; therefore, the amount of knowledge made available for students in both groups did not significantly differ. However, the limitations and benefits of the AR and conventional on-campus environments had an

influence on the learning process. The following section explains in brief the learning processes involved in each environment and compares their advantages and disadvantages.

6.2 Learning processes involved in the AR and conventional environments

All the participants from both groups were separately sub-divided into batches of three to five; the AR participants were then given a demonstration of the developed KBEd system and how to use it. In addition, each participant subsequently completed a simple grabbing and moving exercise over an augmented cube, which ensured basic understanding of how to interact in an AR environment before starting the main task. The learning process started with an introduction to the practical task, which involved basic safety protocol that the students needed to be aware of and the fundamental principles involved in basic welding.

In the conventional environment the on-campus tutor explained and demonstrated the introduction and answered any queries that were raised by the students (Figure 6.2). On the other hand, in the AR environment students were allowed to construct their own learning objects, involving their choices on where they wanted to start and how they wanted to learn (Figure 6.3). For instance, students who preferred more visual or audio input for learning chose to see video or listen to audio about the introduction, while students who were more kinaesthetic chose to do some activities to learn about the introduction; whenever they needed help, the AI tutor assessed them by correcting their mistakes.

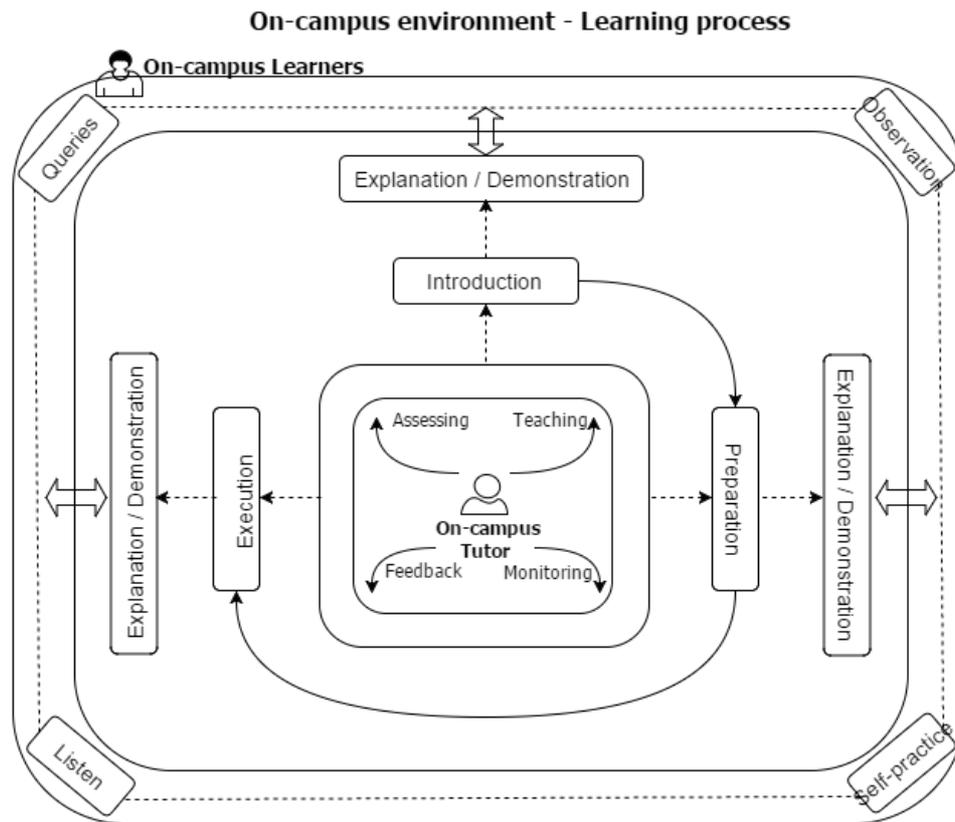


Figure 6.2: On-campus environment learning process

After the introduction, the students were taught about preparation, which involved setting up the welding equipment. In the on-campus environment the tutor used the physical equipment and demonstrated how to set it up, whereas in the AR environment, as in the introduction, the learners constructed their own learning object depending on their preferred learning style in learning the preparation skills. Finally, the students learned how to execute the welding through a step by step procedure. In the on-campus environment the tutor physically demonstrated how to execute the welding and provided feedback on any doubts that were raised. In the AR environment, in addition to the AI tutor's explanation of the execution through audio and video source, the learners were also allowed to train by themselves by using the augmented welding torch and the metal plate over the real environment. Their actions were constantly monitored by the AI tutor in order to detect errors and provide them with feedback. The AR

learners were asked to perform consecutive successful welding to acquire the rigour (optimal performance) for welding. As for the conventional environment, the students were not given the liberty of having several tries during training, as the time and cost involved were longer and more expensive. However, the on-campus learners were allowed to practise their technique with the welding torch without switching the welding console.

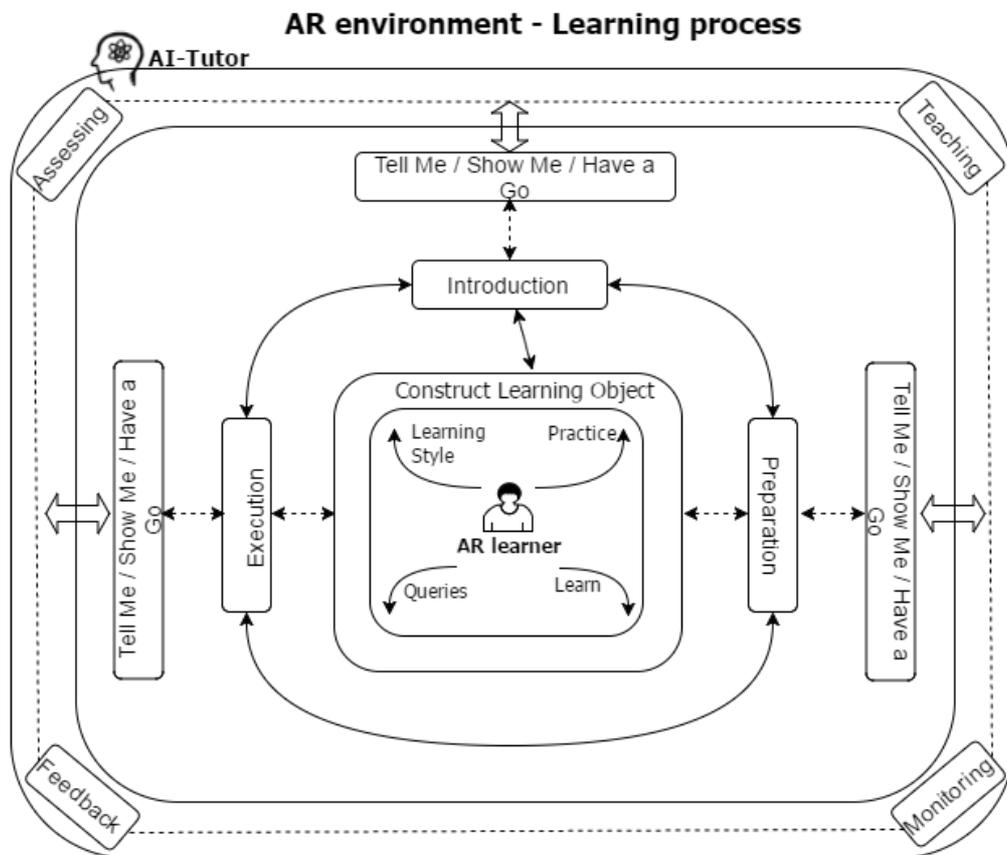


Figure 6.3: AR environment learning process

The AR learners had some advantages over the on-campus learners in terms of constructing their own learning objective with their preferred leaning style (Figure 6.4) and individually practising the welding skills in the AR environment using augmented objects and feedback from the AI-tutor. However, whether the AR learners would be able to transfer the acquired practical skills from an augmented world to a real one remains the hypothetical question of this study. To validate the hypothesis, the

concurrent validity method was adopted to measure the performance of the AR learners when they were asked to perform the welding task in real environment, by comparing them to the performance and learning outcome of the on-campus trained learners. The following section provides a detailed explanation of the parameters that were used to measure the performance and gives the results measured from these parameters.

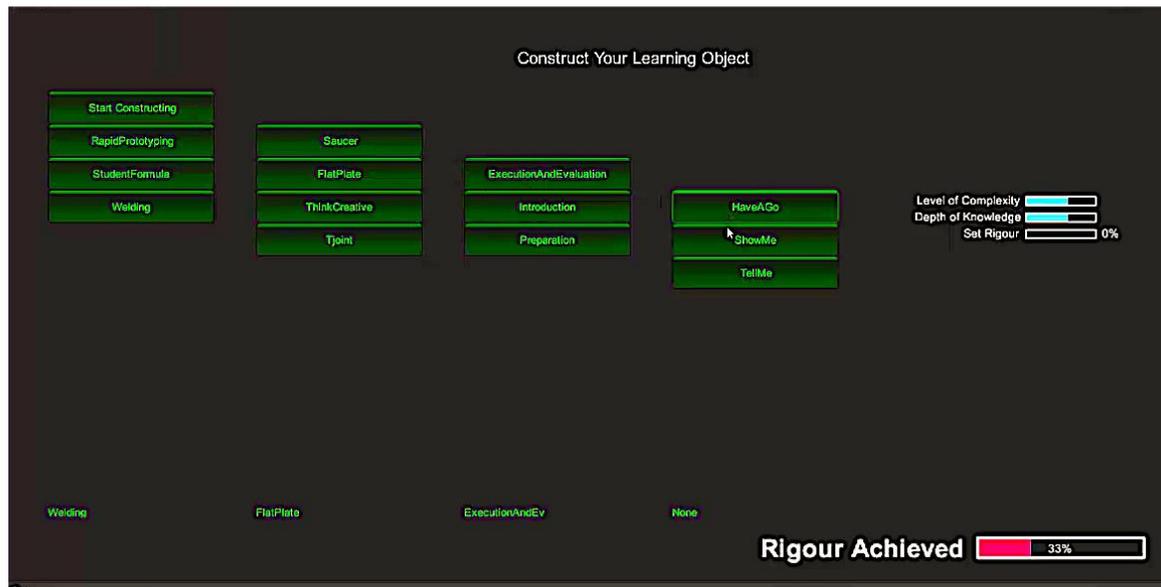


Figure 6.4: AR learners constructing their own learning objects

6.3 Concurrent validity measuring parameters

Each of the participants from both groups was asked to perform the taught welding task in the real environment without any help. They executed the practical subtask sequentially, first by satisfying the fundamental safety protocol, then by preparing the equipment needed, and finally by executing the welding task procedurally. Practical skill is not only about executional skill, but also incorporates skill acquisition involving understanding, relating and patterning of activities. This way of executing the practical task mirrors one of the important theories of skill acquisition in the work of Fitts (1954), who suggested a three stage development process. In this, students initially learn the fundamental procedures and properties related to the practical task, which is known as

the cognitive stage. Secondly, they relate the learned procedure into a sequence of action known as the associative stage and finally they combine the sequence of actions into a smooth pattern of activity known as the skilled activity stage. This theory not only provides understanding of how the skill acquisition takes place, but also enables us to determine the critical aspects that need to be observed when measuring practical skills. This study on measuring learners' performance over the given practical activity not only measures the skilled activity but also the fundamental, procedural and preparation skills involved with it.

Furthermore, the study explores appropriate techniques for measuring these skills levels, for which the studies of Boud *et al.* (1999); Wang (2005), Sturm *et al.* (2008) and Ramos *et al.* (2014) have used error detection, time scale and a scoring system to measure the practical skill performance. Table 6.1 provides a summary of the measuring techniques that have been used in other similar studies to measure performance. Most of these can be grouped into three major categories; time scale, error detection and scoring system. This study proposes a parametric assessment method which uses two of the above techniques to measure the assigned parameters under each of the skills. The parametric assessment method uses all the critical elements involved in each of the fundamental, procedural, preparational and executional skills as parameters to measure the respective skill level. Each of these parameters is then measured through one of the measuring techniques depending upon the nature of the skill. The parameters for measuring fundamental skills involve all the safety protocols that need to be satisfied, which include wearing of a safety mask, gloves, coat and closing of the curtain. These fundamental parameters were measured by the error detection technique by checking whether all the parameters were satisfied or not. Very

minor or major mistakes in satisfying any of the safety parameters were all considered as errors.

Table 6.1: Performance measuring techniques used in similar studies

Studies	Parameters	Measuring Technique	Sample size involved
Boud <i>et al.</i> (1999)	Task completion and time involved	- Error detection - Time scale	20
Ramos <i>et al.</i> (2014)	Time of completion and error avoidance	- Scoring system - Error detection	36
Windsor <i>et al.</i> (2008)	Quality of the task performed	- Scoring system	20
Wang (2005)	Time of completion and errors made	- Time scale - Error detection	16
Seymour <i>et al.</i> (2012)	Timing of procedure completion and errors made	- Time scale - Error detection	16
Exner and Rainer (2015)	Task completion	- Error detection	12
Others: Tuggy (1998); Scott <i>et al.</i> (1999) and (2000); Cohen <i>et al.</i> (2000); Gerson and van Dam (2003); Grantcharov <i>et al.</i> (2004); Sedlack <i>et al.</i> (2004) and Ahlberg <i>et al.</i> (2005)	Task completion time. Overall performance. Ability to complete procedure. Performance errors. Flow of procedure. Time and motion. Increase in productivity. Confidence factor.	- Scoring system - Error detection - Time scale	Minimum of 12

The parameters for measuring the preparation skill involved setting up the earth strap, amperage, wire-fed speed and level, and switching the welding console on, all of which were also measured through the error detection technique. Similarly, even slight deviations from accurate setting values were considered as errors. The parameter for measuring procedural skill involved two procedural tasks; degreasing the plate and placing magnets on a specific location of the plate. These procedural parameters were also measured through the error detection technique, in which only exact procedural execution was not considered as an error; any deviations in the procedure were all considered as errors.

The executional skills were measured against seven executional parameters involving torch holding, hand speed, penetration, technique, tack weld, 20mm weld and the main weld. These parameters were measured through the scoring system technique, which gave an insight into how good or bad the executional parameters were. The scoring system used a five point scale to rate each of the executional parameters, from poor to excellent. This validation also measured the final outcome of the practical task (Table 6.2), where the students tested their welded plate by placing it on the vice and hitting it with a hammer. The welds that stayed unbroken even when the plate bent when applying external force by the hammer were considered to be a pass, while the remainder were considered as fails.

In addition, the study also measured the number of attempts that it took for the students who failed at the first attempt to acquire the desired learning outcome. During the concurrent validation experiment it was made clear to all participants that speed was not a measuring parameter; instead, emphasis was placed on safety and tool handling. The following section provides a comparative analysis of the performance results of the two groups measured using the parametric assessment method.

Table 6.2: Description of measuring parameters

Measure	Parameters	Description
Fundamental skill	<ul style="list-style-type: none"> - Safety protocol 	All the safety measures that needed to be satisfied before starting the welding task. These included wearing an appropriate mask, gloves, safety coat and shoes, and finally ensuring the safety curtains were closed.
Preparation skill	<ul style="list-style-type: none"> - Earth strap - Amperage (Amp) - Wire-fed speed (WFS) - Gas level - Switching the machine on 	All these are the critical preparation tasks involved in setting up the welding bay and the equipment needed for the main welding task.
Procedural skill	<ul style="list-style-type: none"> - Plate degreasing - Magnet positioning 	These two pre-executional tasks required procedural knowledge to produce smooth plate edges with appropriate tools and in aligning them by positioning the magnet in the right location.
Executional skill	<ul style="list-style-type: none"> - Torch holding - Hand speed - Penetration - Technique - Tack weld - 20mm weld - Main weld 	Each of these executional parameters had a direct effect on the final welding outcome. Torch holding represents the position and angle of the welding torch that is being held. Hand speed represents the hand movement and technique represents the torch manoeuvre over the edges. Penetration, tack, 20mm and main represent the visual outcome.

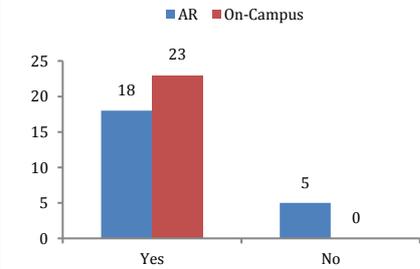
6.4 Concurrent validity results and analysis

6.4.1 Fundamental skill

Out of the 23 students who learned through the AR environment, in the final actual assessment only 18 were able to satisfy all the safety measures that were required for the practical task, while the remaining 5 committed one or more errors, which gave a

completion rate of approximately 79%. On the other hand, all 23 who learned in the on-campus environment were able to satisfy all the safety measures without any errors, giving them a 100% completion rate in satisfying all the fundamental safety protocols (Table 6.3). However, the experiment involved no tutor intervention; except all five students who committed errors by failing to satisfy any of the safety measures were eventually stopped by the on-campus tutor before being allowed to proceed to the next task. The tutor then went on to explain what safety measures they had missed out and the injuries this might have caused them. Only after satisfying all the safety measures were they allowed to proceed with the task, but they were marked down as incomplete because of their errors.

Table 6.3: Concurrent validity results of fundamental and procedural skills of AR learners (n=23) vs on-campus learners (n=23)

Measure (Error detection)			AR learners (n = 23)	On-campus learners (n= 23)	Raw data plot
Fundamental skill	Health and safety protocol	Yes	18	23	
		No	5	0	

*Raw data with bar charts comparing fundamental skill performance between AR vs on-campus learners

As can be seen, there is a substantial difference in the errors committed between the two groups in terms of demonstrated fundamental skill. When analysing what might have caused the AR trained students to have a lower completion rate in satisfying all the safety measures, there seems to be one major reason. In the on-campus environment the tutor strongly insists on the seriousness of safety measures and makes students more cautious, as they would get hurt if they made mistakes. On the other hand, even though

in the AR environment the AI tutor does not allow the students to progress to executing the other tasks before satisfying all the safety measures, the AR learners tend to satisfy the safety measures without realising the seriousness of the dangers that they might face if they fail. This made them less careful compared to the on-campus trained learners. Further, when asked, all five of the AR trained learners who failed to satisfy the safety measures in the real environment gave a similar reason. Most of them felt it was difficult to reconstruct the simulated AR safety equipment in reality, and moreover, mapping the seriousness with respect to the safety measures from an AR environment to a real environment was not clear. On the other hand, the students who learnt in the on-campus environment were more cautious, as they were able to instantly map the seriousness of the injury in reality compared to the AR trained learners.

6.4.2 Procedural skill

When it came to procedural skill performance, out of the 23 AR trained learners 22 of them were able to degrease the plate properly using the appropriate method and tools, and all 23 kept the plates edges aligned properly by placing a magnet in the right position. On the other hand, 20 of the on-campus learners were able to successfully complete the degreasing of the plate, and 22 could place the magnet in the right position (Table 6.4). As can be seen, the error rate in the first procedural task for the AR trained learners was 4% and for the on-campus trained learners it was 13%, while for the second procedural task it was 0% for the AR trained students, and 4% for the on-campus trained ones. Overall there is little difference in the procedural skill performance between the two groups.

Although in both the procedural tasks the AR learners showed an error rate of no more than 4%, when analysing why they were slightly more precise in their procedural

memory than the on-campus learners after training in the AR environment, we established the following reasons. The mistakes and forgetfulness in degreasing the plate among the on-campus learners were directly related to the group size. The groups with a maximum of three students were able to see and listen to the tutor easily while he was demonstrating, whereas larger groups had difficulty in having a clear picture of what was being taught and demonstrated. All three who failed to degrease the plate were from one of the larger groups. Apart from that, the sequential way of executing the procedure was less apparent among the on-campus trained learners, as they rushed on to next sequence before finishing the previous one. The AR trained learners, on the other hand, irrespective of the group size, were individually taught and trained by the AI tutor in the AR environment.

Table 6.4: Concurrent validity results offundamental and procedural skill of AR learners (n=23) vs On-campus learners (n=23)

Measure (Error detection)			AR learners (n = 23)	On-campus learners (n= 23)	Raw data plot
Procedural skill	Degreasing the plate	Yes	22	20	
		No	1	3	
Procedural skill	Placing the magnet	Yes	23	22	
		No	0	1	

*Raw data with bar charts comparing fundamental and procedural skill performance between AR vs on-campus learners

In addition, they remembered the sequence better, as this information was augmented in front of them on request while performing the procedural task, without having to refer to separate media or a laboratory manual. Moreover, when the on-campus trained learners who did not degrease the plate were questioned, one of them answered that he did not forget, but decided to carry on to the next procedure as the plate edges were smooth enough. The errors made by both groups in placing the magnet in the right location were almost null; only one of the on-campus trained learners did not place the magnet on top of the plate before executing the tack weld. When asked, the student replied he was confident enough to weld without the help of a magnet to hold the plates together, and the same student went on to produce a quality weld and pass the test at the first attempt. In summary, although there is little difference in the procedural errors made by the two groups, on investigation it is clear that the errors made by on-campus learners were mainly down to group size and individual judgment, rather than the taught process involved in the environment.

6.4.3 Preparation skill

The overall performance measurements of the preparation skill of the AR and on-campus learners were similar (Table 6.5). Out of 23 on-campus trained learners, two made errors setting up the correct wire feed speed and gas levels, which led them to produce a weaker weld with less penetration. This demonstrated the importance of understanding the taught fundamentals and relating them to the preparation task. When asked, one said she had completely forgotten the setting value that was taught, while the other replied that he had not thought about relating the wire feed out from the nozzle to the known setting value.

Table 6.5: Concurrent validity of preparation skill of AR learners (n=23) vs on-campus learners (n=23)

Measure (Error detection)			AR learners (n = 23)	On-campus learners (n = 23)	Raw data plot
Preparation skill for setting-up:	Earth strap (ES)	Yes	22	22	
		No	1	1	
	Amperage (Amp)	Yes	23	23	
		No	0	0	
	Wire fed speed (WFS)	Yes	23	21	
		No	0	2	
Gas level (GL)	Yes	23	21		
	No	0	2		
Switching welding console on (SW)	Yes	21	23		
	No	2	0		

* Raw data with bar charts comparing preparation skill performance between AR vs on-campus learners

On the other hand, the AR trained learners had a 9% higher error rate in switching the welding console on compared to that of the on-campus trained ones. When analysed, the two learners who committed errors were more kinaesthetic while training in the AR environment; they skipped the AI tutor’s explanation and went on to execute the tasks straightway. This type of learner relies heavily on the AI tutor’s feedback system to

point out mistakes, rather than being self-aware; when asked to perform the task in the real laboratory environment they committed several minor errors.

6.4.4 Executional skill

(a) Torch holding

When it came to executional skill, out of the 23 AR trained learners 10 of them achieved a score of excellent, whereas only one on-campus trained student was able to score the same in torch holding. Moreover, a total of four of the on-campus trained learners exhibited either below average or poor torch holding skills, while none of the AR trained learners showed this level (Figure 6.5). Overall, there was a substantial performance difference in the torch handling skill between the AR and on-campus learners, as the calculated z-value (3.624915) exceeds the critical range (-1.96 to 1.96), with the p-value (0.000289) lesser than 0.05. So the medians are eventually different, with the AR learners having a higher torch holding score than the on-campus trained ones (Table 6.6).

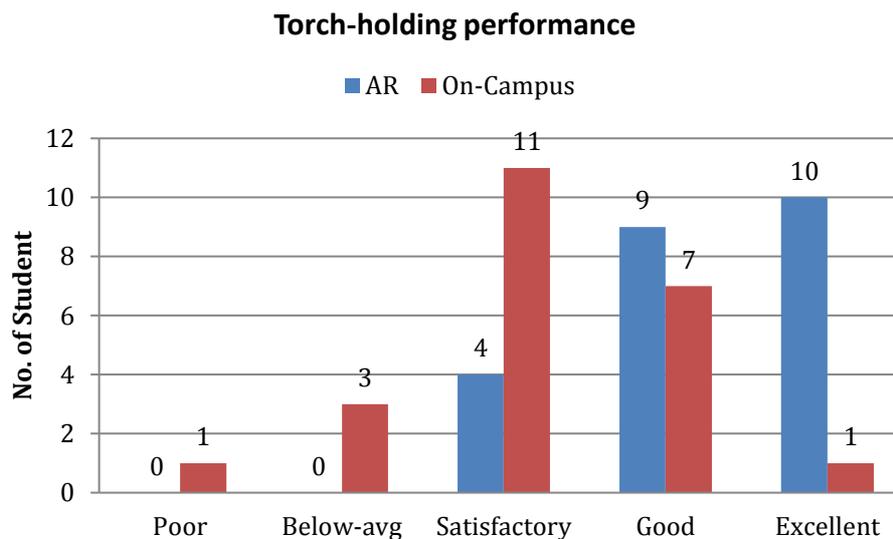


Figure 6.5: Torch holding performance comparison chart between AR and on-campus trained learners. (Total number of participants 46: AR (23) and on-campus (23))

When analysis was made to interpret the reasons, the following causes were identified. The AR training provided a deeper insight into the torch holding technique through better visuals and by allowing the students to simulate their real hand position over the augmented welding torch. On the other hand, the on-campus learners were allowed to hold the real torch and practise the torch angle. The feedback provided in this case was not instant and repetitive compared to that of the AR environment.

Table 6.6: Torch holding results for torch holding skill between AR and on-campus learners

(Poor = 1 to Excellent = 5)

Measure Of torch holding skill (Scoring system)	Sample 1	Sample 2	Result	
	AR Learners	On-campus learners	Hypothesis to prove (p-value ≥ 0.05)	
			z-score	p-value
Poor	0	1	3.624915	0.000289
Below Avg	0	3	Rejects null hypothesis as p-value < 0.05 , i.e. result is significant	
Satisfactory	4	11		
Good	9	7		
Excellent	10	1		
Count (n)	23	23		
95% CI (α)	0.05	0.05		

*If the z-score is less than -1.96, or greater than 1.96, reject the null hypothesis

Moreover, the AR trained learners were more confident, one of them mentioning that he knew how to hold the torch when asked to perform with the real one, as he was able to transfer the practised hand position over the augmented object to the real one. This was one of the initial proofs of the transfer of AR trained skills to the real environment; moreover, in this scenario it also outperformed the conventional training method. In summary, the AR trained learners outperformed the on-campus trained ones in their torch holding skill.

(b) Hand speed

The AR-trained learners continued to show better results with hand speed compared to the on-campus learners. Out of the 23 AR-trained learners, 4 scored excellent and 10 scored good, giving 14 students in total scoring above the satisfactory level. On the other hand, out of the on-campus trained learners, only 1 managed to score excellent, with 6 scoring good, giving a total of 7 students above the satisfactory level (Figure 6.6). But the number of students who scored satisfactory was higher among the on-campus learners, which made the difference less significant. Which is evident from the z-value (1.592766) being within the the critical range (-1.96 to 1.96), with a p-value (0.111213) greater than 0.05, with the AR learners' median value for hand speed being quite close to that of the median value of the on-campus learners (Table 6.7).

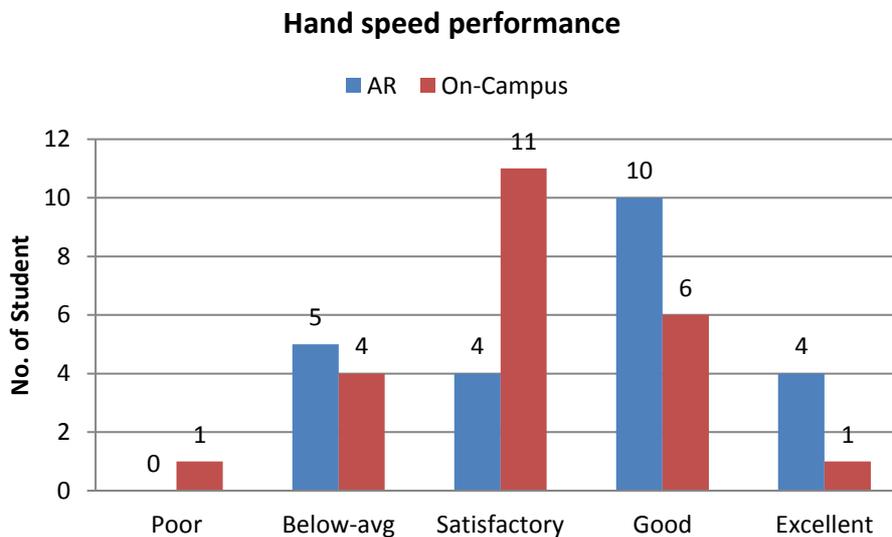


Figure 6.6: Hand speed performance comparison chart between AR and on-campus trained learners. (Total number of participants 46: AR (23) and on-campus (23))

On further investigation of the students who scored higher after being trained in the AR environment, most of them mentioned that the instant feedback that was provided by the AI tutor while training in the AR system helped them to have a steady and controlled

hand speed. In addition, some mentioned that the augmented torch with welding characteristics gave them a good understanding of relating their hand speed to the welding sound, which made them adjust the speed by listening to the welding sound and figuring out whether they were too fast, too slow or just right. In summary, the number of underperforming learners scoring below the satisfactory level remained the same in both groups and there was no significant difference between hand speed performance, although the AR-trained learners achieved more above satisfactory scores and demonstrated steadier hand movement and less panic during execution than the on-campus trained students.

Table 6.7: Hand speed results for hand speed skill between AR and on-campus learners

(Poor = 1 to Excellent = 5)

Measure Of torch holding skill (Scoring system)	Sample1	Sample2	Result	
	AR Learners	On-campus learners	Hypothesis to prove (p-value ≥ 0.05) Confidence level = 95% ($\alpha = 0.05$)	
			z-score	p-value
Poor	0	1	1.592766	0.111213
Below Avg	5	4	Accepts null hypothesis as p-value ≥ 0.05 i.e. result is non-significant	
Satisfactory	4	11		
Good	10	6		
Excellent	4	1		
Count (n)	23	23		
95% CI (α)	0.05	0.05		

*If the z-score is less than -1.96, or greater than 1.96, reject the null hypothesis

(c) Technique

When it came to welding executional technique, out of the 23 AR-trained students 4 scored excellent and 10 scored good. On the other hand, only 7 of the on-campus trained learners managed to score good, with none scoring excellent. Learners from both groups with below satisfactory levels in hand speed showed improvement in executional technique; none of them scored poor and just 3 of the learners from each group scored below average (Figure 6.7). Overall, the AR-trained learners' technique

in keeping the torch precisely over the edges of the plate was very similar to that of the on-campus trained learners. This made the z-value (1.845411) within than the critical range (-1.96 to 1.96), with the p-value (0.064978) greater than 0.05, in determining non-significance between both groups (Table 6.8).

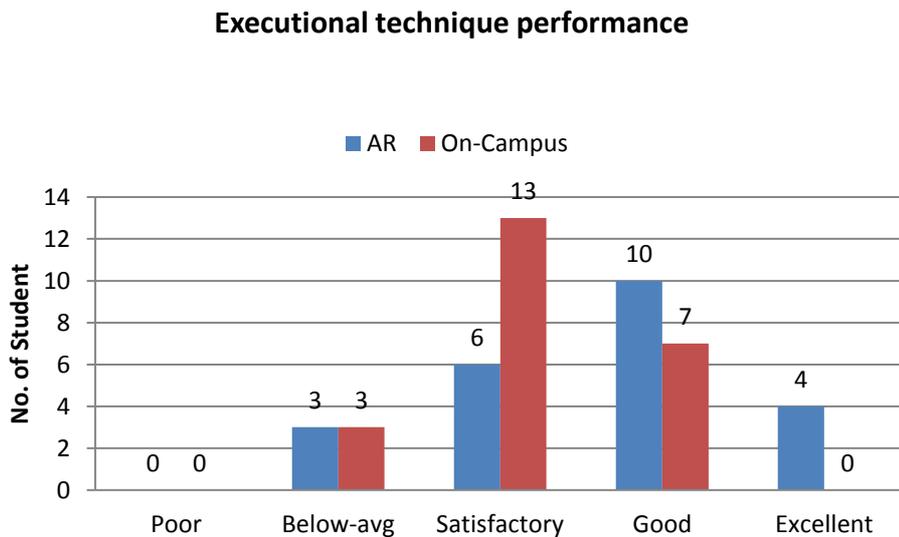


Figure 6.7: Technique performance comparison chart between AR and on-campus trained learners. (Total number of participants 46: AR (23) and On-campus (23))

Similar to the hand speed performance graph, more of the AR-trained learners scored above the satisfactory level compared to the on-campus trained learners, by demonstrating better technique when welding over the edges. When analysing the feedback provided by the learners from both groups, the following reasons were interpreted. In the real situation, the welding mask blocks out the view before and after the welding arc, meaning most of the on-campus learners failed to achieve a higher technique score by keeping the torch steady in-tacks over the edges of the plate. On the other hand, most of the AR-trained learners had a better technique when welding over the edges, as they were able to judge properly. This was because the AR learners knew the internal process that takes place when the welding arc appeared.

Table 6.8: Technique results for executorial technique between AR and on-campus learners

(Poor = 1 to Excellent = 5)

Measure of torch holding skill (Scoring system)	Sample 1	Sample 2	Result	
	AR Learners	On-campus learners	Hypothesis to prove (p-value ≥ 0.05)	
			Confidence level = 95% ($\alpha = 0.05$)	
			z-score	p-value
Poor	0	0	1.845411	0.064978
Below Avg	3	3	Accepts null hypothesis as p-value ≥ 0.05 i.e. result is non-significant	
Satisfactory	6	13		
Good	10	7		
Excellent	4	0		
Count (n)	23	23		
95% CI (α)	0.05	0.05		

*If the z-score is less than -1.96, or greater than 1.96, reject the null hypothesis

Although the AR environment replicated the real welding scenario, the AR learners had the advantage of looking through the internal process that takes place in parallel when the welding arc appeared. This made them understand and develop the technique faster and more rigorously by relating the actions to the underlying principles. In summary, the significance in the performance difference continued to be minimal between the two groups, as the same number of AR and on-campus trained learners who demonstrated excellent and good hand speed skill also exhibited a high executorial technique level.

(d) Penetration

The way the torch was held and the speed of the hand movement, along with the technique in executing the weld over the edges of the plate, influenced the outcome of the weld penetration. The penetration outcomes produced by both groups were similar, with minimal differences. Since the AR-trained learners demonstrated more accuracy in torch holding than the on-campus trained ones, they managed to dominate, with high scores (Figure 6.8). In total, 11 of the AR-trained learners produced either good or excellent weld penetration, compared to the on-campus trained learners, with a total of

7, although the on-campus learners, by increasing their hand speed and executional performance to that of the AR learners, overall were able to produce a similar penetration outcome.

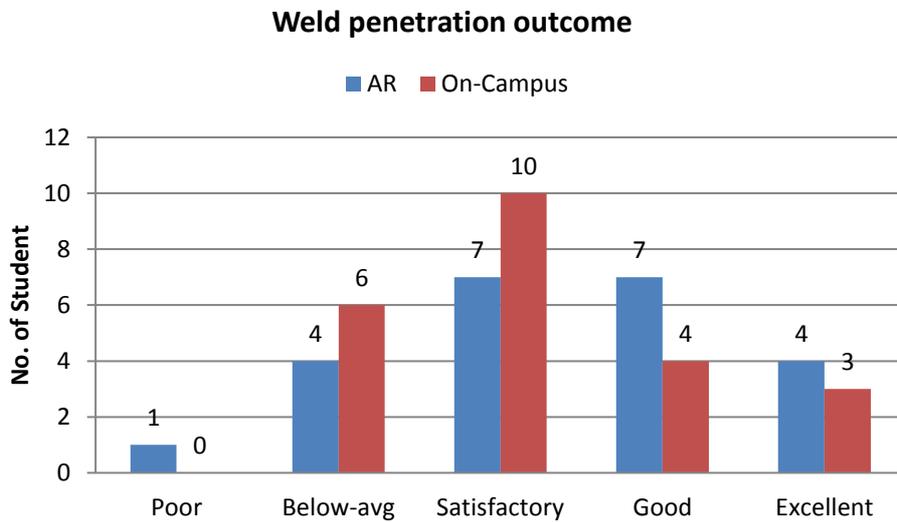


Figure 6.8: Weld penetration outcome comparison chart between AR and on-campus trained learners. (Total number of participants 46: AR (23) and on-campus (23))

As can be seen, the calculated means of the two groups are not significantly different, with the AR learners' median value on the quality of penetration being same to that of the on-campus learners' median value. This makes the z-value (0.801875) within the critical range (-1.96 to 1.96), and the p-value (0.422625) greater than 0.05 so proving the non-significance (Table 6.9). In summary, the scores given for the previous skills also reflect the physical outcome; overall, the AR and on-campus trained learners produced a similar weld penetration outcome.

Table 6.9: Weld penetration results for executional technique between AR and on-campus learners

(Poor = 1 to Excellent = 5)

Measure of torch holding skill (Scoring system)	Sample 1	Sample 2	Result	
	AR Learners	On-campus learners	Hypothesis to prove (p-value ≥ 0.05)	
			Confidence level = 95% ($\alpha = 0.05$)	
			z-score	p-value
Poor	1	0	0.801875	0.422625
Below Avg	4	6	Accepts null hypothesis as p-value ≥ 0.05 i.e. result is non-significant	
Satisfactory	7	10		
Good	7	4		
Excellent	4	3		
Count (n)	23	23		
95% CI (α)	0.05	0.05		

*If the z-score is less than -1.96, or greater than 1.96, reject the null hypothesis

(e) Tack weld

Although the AR-trained learners performed better than the on-campus learners with respect to holding the torch at the right angle, they struggled when starting to tack weld the corners. This was reflected in the tack weld outcome, as in total only three of the AR-trained learners managed to produce a good tack weld, and none was excellent (Figure 6.9). On the other hand, six of the on-campus trained learners were able to produce good tack welds and two others finished with excellent tacked corners. When the reasons for the sudden shift in the performance between the two groups were analysed, the following key factors emerged. In the real world, when executing the tack welding the AR-trained learners experienced the intensity and real feel of molten iron with flying sparks for the first time, which made them a little scared. The other major factor that heavily influenced on the AR trained learners performance was relating the depth factor from an AR based trained environment to a real environment execution

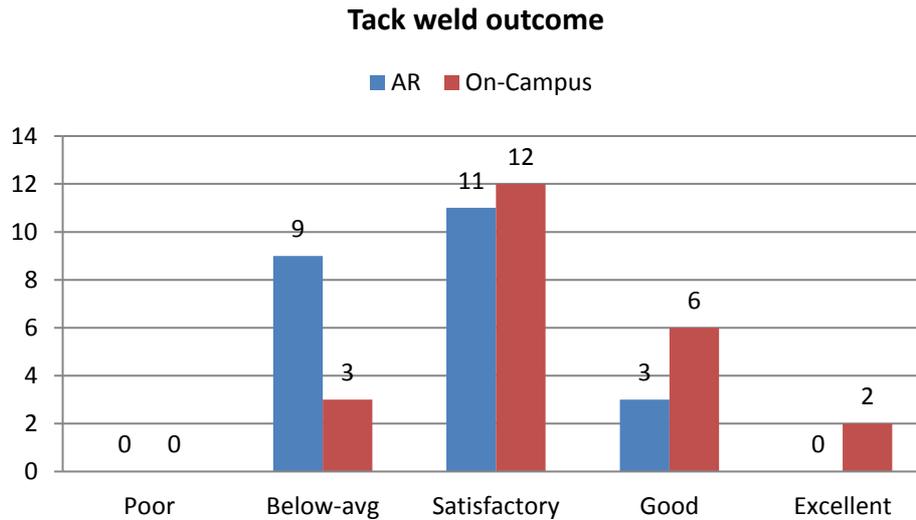


Figure 6.9: Tack weld outcome comparison chart between AR and on-campus trained learners. (Total number of participants 46: AR (23) and on-campus (23))

Although the AR environment augmented the virtual objects referenced over the real environment, the depth involved in handling the objects differed with respect to that of the real world scenario. This was down to the hardware and software that was used in developing the AR system, although the research used some of the latest hardware and software technology. This is one of major challenges the AR domain is experiencing at the moment. By improving the depth factor with an increase in the efficiency of object handling in the AR environment and thereby closing the gap between AR and the real environment, the performance of AR-trained learners should improve. This is echoed in the feedback gathered from the AR-trained learners after completing the welding task in the real environment.

The number of satisfactory welding outcomes was similar in both groups, but the number of learners with below satisfactory outcomes was higher among the AR learners than the on-campus ones (Table 6.10).

Table 6.10: Tack weld results for executional technique for AR and on-campus learners

(Poor = 1 to Excellent = 5)

Measure Of torch holding skill (Scoring system)	Sample1	Sample2	Result	
	AR learners	On-campus learners	Hypothesis to prove (p-value ≥ 0.05) Confidence level = 95% ($\alpha = 0.05$)	
			z-score	p-value
Poor	0	0	-2.152980	0.031320
Below Avg	9	3	Rejects null hypothesis as p-value < 0.05, i.e. result is significant	
Satisfactory	11	12		
Good	3	6		
Excellent	0	2		
Count (n)	23	23		
95% CI (α)	0.05	0.05		

*If the z-score is less than -1.96, or greater than 1.96, reject the null hypothesis

As can be seen, the scores of the two groups are significantly different, with the AR learners' average quality of tacked corners being lower than the average quality produced by the on-campus learners. The difference in performance output was further proved by the calculated z-value (-2.152980) exceeds the critical range (-1.96 to 1.96), and the p-value (0.031320) being lower than 0.05. In summary, the on-campus trained learners outperformed the AR learners in the tack weld output.

(f) 20mm weld

The overall performance of the AR-trained learners for the 20mm weld was almost the same as the tack weld. But the performance of the on-campus trainer learners was lower, as half the students who produced a satisfactory tack weld were not able to perform a satisfactory or good 20mm weld. This made the performance difference less significant, as the average quality of the 20mm weld produced by the on-campus learners was similar to that of the AR-trained learners (Figure 6.10), although the performance gap for learners who produced high quality weld remained the same for both groups.

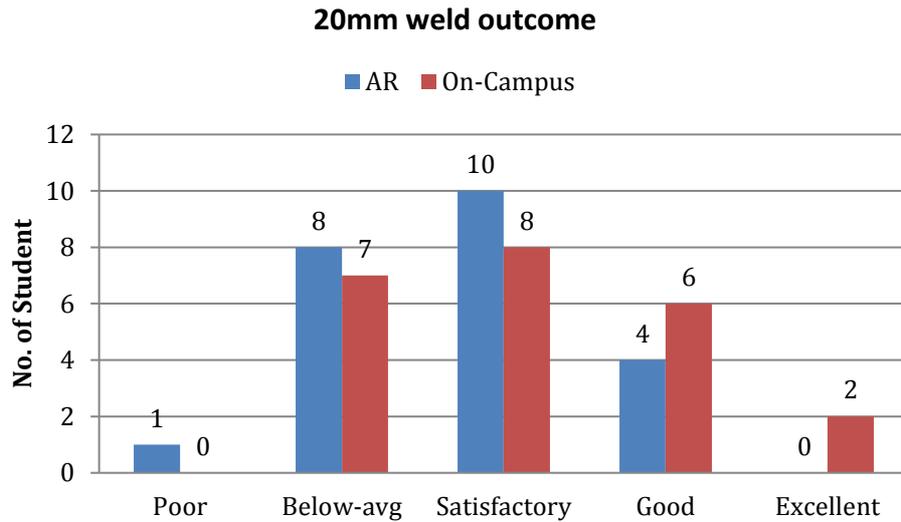


Figure 6.10: 20mm weld outcome comparison chart between AR and on-campus trained learners. (Total number of participants 46: AR (23) and on-campus (23))

The number of students that produced below and above satisfactory 20mm welds was similar in both groups, which made the calculated z-value is within the critical range (-1.96 to 1.96), and the p-value (0.231182) greater than 0.05, therefore proving the non-significance (Table 6.11). In summary, the average quality of the 20mm weld produced by both groups was similar.

Table 6.11: 20mm weld results for executional technique of AR and on-campus learners

(Poor = 1 to Excellent = 5)

Measure of torch holding skill (Scoring system)	Sample1	Sample2	Result	
	AR learners	On-campus learners	Hypothesis to prove (p-value ≥ 0.05)	
			Confidence level = 95% ($\alpha = 0.05$)	
			z-score	p-value
Poor	1	0	-1.197320	0.231182
Below Avg	8	7	Accepts null hypothesis as p-value ≥ 0.05 i.e. result is non-significant	
Satisfactory	10	8		
Good	4	6		
Excellent	0	2		
Count (n)	23	23		
95% CI (α)	0.05	0.05		

*If the z-score is less than -1.96, or greater than 1.96, reject the null hypothesis

(g) Main weld

Although the tack weld and 20mm weld are important for the assigned welding task, the most critical for the two metal plates to stay intact relies heavily on the main weld that is performed along the major portion of the edges. The performance of the AR-trained learners continued to improve while they were executing the two tack welds on the corners and the two 20mm welds on? each of the tacked corners. Out of the 23 AR-trained learners, three of them produced an excellent main weld, 10 were good and four others achieved satisfactory main welds (Figure 6.11). On the other hand, out of the 23 on-campus trained learners, four demonstrated an excellent main weld, eight were good and six had a satisfactory outcome.

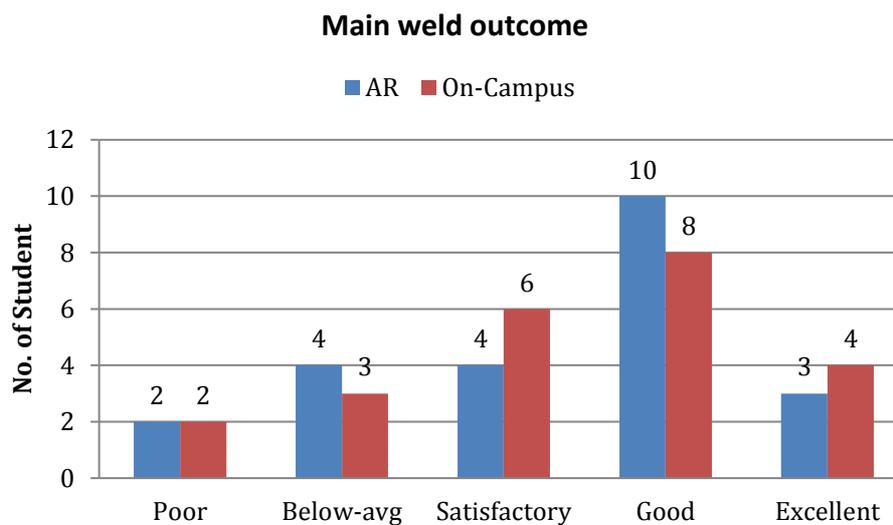


Figure 6.11: Main weld outcome comparison chart between AR and on-campus trained learners. (Total number of participant 46: AR (23) and on-campus (23))

The average quality of the main weld produced by both groups was quite similar, since the performance of the AR learner improved as they were able to relate the depth of the real torch with respect to the edges of the solid plate. Non-significance was further proved by the calculated z-value is within the critical range (-1.96 to 1.96), with the p-value (0.938709) greater than 0.05 (Table 6.12). In summary, the average quality of the

main weld produced by the AR learners was similar to that of the on-campus learners. By raising their main weld performance to that on the on-campus learners in the real welding task, when asked to test their welding outcome 18 out of 23 of the AR-trained learners were able to pass the test by having an unbroken weld when tested with the hammer (Figure 6.12). The final testing outcome was the same for the on-campus trained learners, with five failing the test on their first attempt.

Table 6.12: Main weld results for executional technique of AR and on-campus learners

(Poor = 1 to Excellent = 5)

Measure Of torch holding skill (Scoring system)	Sample1	Sample2	Result Hypothesis (d=0) Confidence level = 95% ($\alpha = 0.05$)	
	AR learners	On-campus learners	z-score	p-value
Poor	2	2	-0.076892	0.938709
Below Avg	4	3	Accepts null hypothesis as p-value ≥ 0.05 i.e. result is non-significant	
Satisfactory	4	6		
Good	10	8		
Excellent	3	4		
Count (n)	23	23		
95% CI (α)	0.05	0.05		

*If the z-score is less than -1.96, or greater than 1.96, reject the null hypothesis

The five failed students from each group were provided feedback by the on-campus tutor, who pointed out the mistakes that had been committed, and they were asked to make a second attempt. Out of five AR-trained learners who failed on the first attempt, one passed with just one repetition, three with two, and one with three repetitions. On the other hand, out of the five on-campus training learners, four passed on their second repetition and one on the third repetition. In comparison, there is little difference in performance between the two groups in the second cycle (Table 6.13).

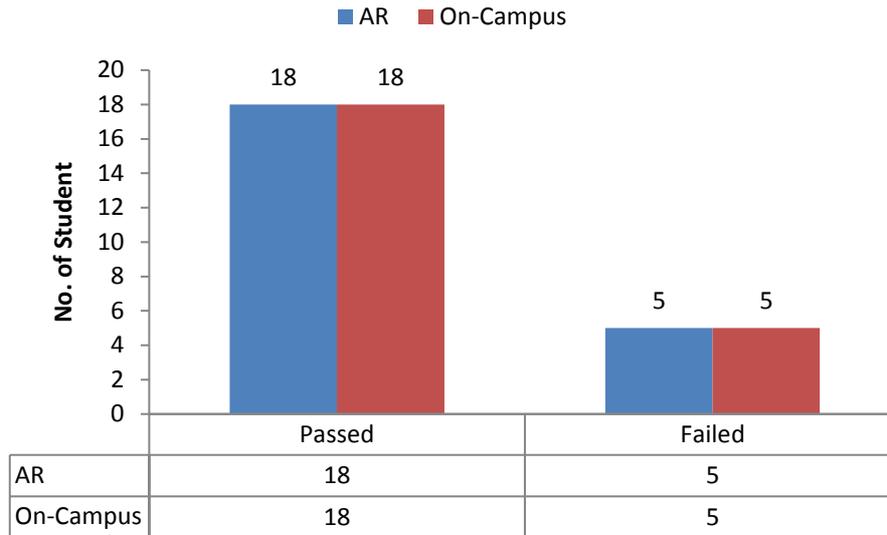


Figure 6.12: Welding test outcome comparison chart between AR and on-campus trained learners

The comments provided by the on-campus tutor on teaching the students from both groups pointed out that the AR-trained students were quicker in reflecting on the technique changes than the conventional group. When each of the AR-trained students who had failed to pass the test at the first attempt were questioned, most replied that it was down to the difficulty in adjusting to the real world depth and feel.

In summary, although the proposed KBEd system has proved the possibility of transformation of hands on practical skills from the AR environment to a real environment, the results achieved in the study also rely on the adaptability of the students; as can be seen, the AR learners with the ability to quickly adapt to the real world were able to achieve better result. The section below summarizes the results, discusses the obtained validity in addressing the research question and explores future directions of study.

Table 6.13: Number of attempts made by the learners who failed at the first attempt to pass the test

Number of attempts	AR learners (n = 5)	On-campus learners (n =5)
Attempt 1	1	
Attempt 2	3	4
Attempt 3	1	1

Comparison Chart

Attempt	AR Learners	On-Campus Learners
A-1	1	0
A-2	3	4
A-3	1	1

6.5 Discussion

The objective of the concurrent validity was to evaluate whether there is any significance in the practical outcome of the AR and on-campus trained learners for a common practical task. The concurrent validity assessment in total involved 46 participants; 23 of them trained in the proposed KBEd system with the help of an AI tutor. The other 23 trained in the conventional environment with a real tutor. Their performance and task outcomes were measured through a parametric assessment method involving critical elements such as fundamental, procedural, preparation and executional skills as measurement parameters. It was found that after training in the AR environment, the students made more errors (27.74%) and were less careful compared to the on-campus trained learners, who had 0% error when satisfying the safety protocols. This demonstrated the proposed system’s limitation in communicating the

seriousness of the health and safety issues, which made the AR learners less careful than the on-campus ones. Fundamental safety is of the highest priority in any laboratory task, so this should be addressed in making the AR learners aware of its seriousness and being more careful, so reducing the errors committed. The use of sensors in the AR environment to stimulate physical pain could be an additional aspect of future development, as this could help the proposed system to teach more critical tasks by increasing the safety skills in the AR learners.

On the other hand, the procedural performance of the AR and on-campus trained learners showed similar results. In the AR method, students were more enthusiastic in learning and practising the procedural skills compared to those using the conventional method; in addition, they showed better procedural memory with less errors (4%) in both procedural tasks. It was also found that the on-campus learners being trained in larger groups had difficulties in grasping the taught procedures. All three students who made errors in the procedural task were from one of the larger groups; on the other hand, in the AR environment, irrespective of group size, each student was individually taught and trained by the AI tutor. Unfortunately, the time and cost involved in the conventional environment to provide such a learning experience is prohibitive. Although the addition of the proposed AR system to the existing conventional training could solve the problem, this needs to be tested to explore the hypothesis whether increases in flexibility and decreased resources, along with the on-campus tutor's involvement, benefits the conventional learning process.

The overall performance of the AR and on-campus learners in preparing the required equipment for the task was similar. The errors made by both groups were minimal (8.7%), although some learning attitudes of the AR-trained learners caused preparation errors. It was found that some of the AR learners relied heavily on the AI tutor's

feedback rather than being self-aware when executing the preparation task, as the AI tutor was constantly monitoring the users' actions; any mistakes committed were automatically pointed out and appropriate answers provided. When performing the real world task, some of the AR-trained learners still expected someone to verify the setting value, which caused them to make errors when setting up the equipment. To address this problem, further development could include two modes for training; one with AI tutor feedback and the other without feedback. By asking the AR learners to train in both modes, a better balance could be achieved.

After practising the executional skill in the AR environment, AR learners scored higher in the torch holding performance than the on-campus learners. From the U-test result (Table 6.6) it can be seen that the AR learners' performance in torch holding was significantly higher (z-value 3.624915) than the on-campus learners' performance. Further, the analysis showed the cause was mainly the advantage that the AR learners had by practising longer and also by having a deeper insight of the visualisation of the torch holding technique. This showcases the limitation in the concurrence between the learning processes involved in each of the environments, but on the other hand it demonstrates the advantages that the proposed AR-based system could provide. Moreover, this performance result has been the opening proof in answering the main research objective by validating the transferability of hands-on skills acquired in the AR environment to the real environment. However, there was no significant difference in the demonstrated hand speed, technique and weld penetration outcome between both groups ($p > 0.05$). The learners who scored above satisfactory level were predominantly AR trained learners. They proved skill transferability to the real environment and the effectiveness of the system in training practical skills anywhere without a physical tutor or equipment.

The AR trained learners were able to successfully transfer most of the fundamental, procedural and preparation skills to the real environment, but not all the executional skills were instantly transferable. The AR-trained learners performed lower quality tack welds compared to those of the on-campus learners. This was due to the difficulty in relating the depth factor from an AR-based training environment involving floating objects to a real world environment with physical objects. Although the depth involved in practising tack welds in the AR environment was different to the real environment, most of the AR learners quickly adapted to the real world depth and demonstrated equivalent performance in producing quality 20mm welds (z-value -1.197320) and main welds (z-value -0.076892). The final testing further validated the non-significance in the practical learning outcome, as an equal number of students (18:18) produced non-breakable welded plates; this non-significance remained valid, as the students who failed to produce a quality weld at the first attempt (5:5) went on to produce good welds the second time (Table 6.13). The issues with depth factor could be addressed by improving the hardware and software of the AR device and also by integrating haptic feedback to provide a real world feel. However, this would increase the cost and reduce the portability that facilitates training at home, although this would be dependent upon the complexity of the training task. The proposed KBEd system has proved the transferability of basic welding techniques from an AR environment to a real one; further employment of the proposed system in other practical tasks could validate the usefulness of the system in enhancing practical skills for distance learners.

In general, the proposed KBEd system has been more effective and efficient than the conventional system, by providing more flexibility in students constructing their own learning objects with their preferred learning structure and style, and also allowing the learners to practise more with less use of physical resources. From the above summary

of the discussions it can be concluded that the skills that were acquired by the AR learners from the proposed KBEd environment were transferable to the real environment. In addition, these transferred skills and physical outcomes achieved in the AR environment when compared to those of the on-campus trained learners in a common experimental task have shown a non-significant difference. Although there was little performance variation between the two groups, the variation was rooted in the limitations of the system's hardware and the limitations of the teacher-centric conventional teaching process. Moreover, the learning outcomes achieved by the AR learners have also validated the use of an AI tutor that is automated by the knowledge captured from real tutors and also the modelling method has proved to be efficient in transforming the knowledge from the real tutor to the AI tutor for teaching and assessing the practical skills of learners in the AR environment. The following chapter provides the conclusion of the research and suggests some future directions while addressing some of the research limitations.

6.6 Chapter summary and conclusions

Following the validation of the developed KBEd system with expert group in Chapter 5, this chapter focused in addressing the ultimate research question 'Can engineering learners acquire practical skills in an augmented reality environment?' The chapter presented the experimental results and analysed the research hypotheses by testing whether there was significant difference or not between the skills acquired and the final task outcome by learners who practised in an AR environment with an AI tutor to those of learners who practised in an on-campus environment with a real tutor. The findings suggested that the student who practised in the KBEd prototype were able to transfer their skills on to real laboratory environment and further achieved results similar to that of the on-campus trained students. The next chapter summarised the whole thesis and

re-visits the objectives of the study to ensure that the objectives of the study are achieved.

Chapter 7 Conclusion and recommendations

“The purpose of education is to make good human beings with skill and expertise... Enlightened human beings can be created by teachers”
- A.P.J Abdul Kalam

This chapter consists of six main sections. The first and second sections provide a summary of the research, including the identified research problem, research questions and objectives. The third section highlights the overall outcomes and addresses each of the research questions. The remaining three sections detail the research contributions and limitations, and also present possible directions for future research.

7.1 Summary

The purpose of the study was to determine whether practical engineering skills could be achieved through an augmented reality (AR) environment with an artificial intelligence (AI) tutor, by capturing, modelling and automating on-campus tutors' knowledge into a knowledge-based education (KBEd) framework. Research was conducted to determine whether skills acquired using the KBEd system were transferable to a real laboratory environment. The practical skills were broken down into fundamental, preparational, procedural and executional ones and used to evaluate the welding task.

7.1.1 Problem statement

The effectiveness of using a virtual laboratory to teach distance learners has been extensively developed for disciplines such as management and computer science, but is relatively underdeveloped in engineering science disciplines (Murphy and Manzanares, 2008; Rajaei and Aldhalaan, 2011). Teaching practical skills is different from teaching theory, especially in an engineering educational domain, and is often

associated with a lab instructor and workshop equipped with special equipment, involving long periods of time to practise or rehearse the technique (Ma and Nickerson, 2006) The knowledge of the laboratory instructor plays an integral part in developing and assessing the practical skills of the learner.

Current distance learning technologies such as virtual and augmented reality have been applied in various fields of education such as medicine, construction, engineering and aviation (Lee and Wong, 2008; Santana *et al.*, 2010; Lee, 2012; Wang *et al.*, 2013; Ong and Andrew, 2013). However, very little attention has been paid to aspects of the method and approach for capturing and modelling tutors' knowledge in order to automate these technologies in teaching and assessing practical skills for engineering distance learners (Sottolare *et al.*, 2013; Li and Zhou, 2015). This study designed and developed a knowledge-based education (KBEd) framework that captured and modelled the on-campus tutors' knowledge with the aim of automating laboratory teaching and assessment processes through current distance learning technology.

Furthermore, a direct comparison between the practical skills transferred from the augmented reality environment and those of the real environment was conducted. This was accomplished using an experimental comparison (concurrent validity) of the two groups of students subjected to the different learning environments, using a parametric assessment method to measure the errors and accuracy in executing the welding task.

7.2 Findings for the research questions and their objectives

The study sought to address the following research questions and objectives:

7.2.1 Research questions

- Can the principles and practice of knowledge-based engineering be applied to acquire the knowledge of a tutor to create a knowledge-based educational framework?
- Can this framework be embodied into an augmented reality environment that would allow study by distance learners?
- Can engineering learners acquire practical skills in an augmented reality environment?

7.2.2 Research objectives

1. To establish a research landscape by identifying and reviewing the ‘best practices’ and issues in delivering practical skills for engineering distance learners.
2. To capture, model and automate on-campus tutor knowledge for teaching and assessing practical skills.
3. To design and develop an augmented reality environment for learning.
4. To validate the performance of the augmented reality environment.

7.3 Research outcomes and findings

The following sub-section provides the conclusions by summarising the results of the overall study. For this purpose, each of the objectives outlines how it was achieved in addressing the related research question:

(a) Research Objective 1:

This was addressed by exploring and reviewing the state of the art of engineering distance learning. The literature review conducted revealed various methods in delivering laboratory activities for distance learners (see Sections 2.3.1, 2.3.2, 2.3.3 and 2.4.1) and further exposed the current challenges faced by the universities offering them (see Sections 2.5 and 2.6). While a number of studies have looked at addressing these challenges from a technological point of view (see Sections 2.4.2 and 2.4.3), very little attention has been paid from an instructional design point of view by capturing and embedding on-campus tutors' knowledge into current distance learning technologies for teaching and assessing practical skills (Sottolare *et al.*, 2013; Li and Zhou, 2015). This was further explored in the latter part of the literature review, where the domain of knowledge-based engineering (KBE) principles and its techniques were explored to understand how to capture, model and codify human knowledge into a system for automation (see Sections 2.7.1, 2.7.2 and 2.7.3). The findings from the literature helped in establishing the research landscape and provided concrete understanding related to current engineering distance learning challenges.

(b) Research Objective 2:

This was addressed by adopting industrial-based techniques such as knowledge-based engineering (KBE), ontology and artificial intelligence (AI) to fit the educational domain (see Section 3.2.2). The study presented a simple three-column approach consisting of procedure, product and diagnostics to capture on-campus tutors' tacit knowledge with respect to the engineering practical task

(see Section 4.1). The captured knowledge was modelled through a modelling structure involving the learning object at the core, encapsulated by its sub-learning objects, learning structure and learning mode (see Section 4.2). Finally, by feeding the modelled knowledge into artificial intelligence with the use of state machines, the process of teaching and assessing practical skills was automated (see Section 4.3).

(c) Research Objective 3:

This was addressed by using state of the art augmented reality technology to allow students to practise hands-on engineering skills by interacting with augmented objects (see Section 4.4). The study used a gaming engine to develop the virtual equipment and its behavioural intelligence to teach the welding (see Sections 4.4.2 and 4.4.4). The developed AR environment was further refined through the face validity method involving internal and external experts' suggestions (see Sections 4.4.5 and 5.2).

(d) Research Objective 4:

This was addressed by conducting concurrent validity on two groups of novice students (N=46); one group trained in the proposed AR laboratory and the other in the existing real laboratory (see Sections 6.1 and 6.2). Their performance was measured on a common on-campus based welding task, which allowed the testing of whether the skills acquired by the AR-trained students were transferable to a real environment task and comparison with the results achieved by the on-campus trained students (see Section 6.3). This tested the two hypotheses.

(i) ***Null hypothesis 1:***

The first hypothesis of the evaluation was “*There is no significant difference between the basic welding skills acquired by learners who practised in an AR environment with an AI tutor and those of learners who practised in an on-campus environment with a real tutor*”. This was retained, as there was no significant difference ($p > 0.05$) in the overall welding skills scores between the AR-trained and on-campus trained groups (see Section 6.4). The AR-trained learners showed more accuracy (avg. 4.26) in the torch handling skill, but were vulnerable when satisfying all the health and safety protocols (see Sections 6.4.1 and 6.4.4).

(ii) ***Null hypothesis 2:***

The second hypothesis of the evaluation was “*There is no significant difference between the final welding task outcomes achieved by learners who practised in an AR environment with an AI tutor and those of learners who practised in an on-campus environment with a real tutor*”. This was also retained, as there was no significant difference ($p = 0.45113$) in the final practical task outcome between the AR-trained and on-campus trained groups (see Section 6.5). The same number of students from each of the groups (18:18) produced a non-breakable welded plate and the non-significance remained valid, as those who failed made the same number of subsequent attempts before producing a good weld (on average, two attempts).

(e) Research questions:

Finally, the following conclusions are drawn from the above findings for the research questions identified (see Section 7.2.1):

- Yes, the principles and practice of knowledge-based engineering can be applied to acquire the knowledge of a tutor to create a knowledge-based educational (KBEd) framework. The performance results have answered this research question by successfully capturing, modelling and automating an on-campus tutor's knowledge.
- Yes, the KBEd framework was successfully embodied into an augmented reality environment to allow the learning of practical skills by the use of ontology, artificial intelligence (AI), a unity gaming engine and a state of the art augmented reality (AR) head mounted display META.
- Yes, the engineering learners were able to acquire practical skills in an augmented reality environment, as there was no significant difference ($p > 0.05$) in the demonstrated practical skills and final task outcome between the learners who trained in the AR environment with the AI tutor and those who trained in the on-campus environment with the real tutor. This has answered the final research question 'Can engineering learners acquire practical skills in an augmented reality environment?' by proving the effectiveness of the AI tutor through the proposed capturing, modelling and automating technique in training practical skills anywhere, without a physical tutor or equipment.

(f) Conclusions:

The following conclusions are drawn from the findings:

1. Learning the practical task through the KBEd system provided greater flexibility for the learners.

Learners who practised in the AR environment were able to construct their own learning objects with their preferred learning structure and style. This allowed the learners to practise more with less use of physical resources. Further the data analysis showed that on-campus learners being trained in larger groups had difficulties in grasping the taught procedures. Unfortunately, the time and cost involved in providing a KBEd equivalent learning experience in the conventional environment is prohibitive. The addition of the proposed AR system to the existing conventional training could solve the problem; however this needs to be tested to explore the hypothesis as to whether increases in flexibility and decreased resources, along with the on-campus tutor's involvement, benefit the conventional learning process.

2. Practising welding task through the KBEd system positively improved learner's practical skills.

The combined results from the parametric assessment method show that even through the AR-trained learners were less careful in satisfying the safety protocol, they exhibited more enthusiasm and better procedural memory and preparation skills compared to those using the conventional method. Moreover, they demonstrated similar executional skills compared to that of the on-campus trained learners. There was one significant difference in performance between the two groups, which was that the AR trained learners initially found it more difficult to judge the depth factor accurately.

- 3. Practicing welding tasks through the KBEd system using the AR environment, the learners were successfully able to transfer the practical skills to the real environment.**

From the data analysis, it was evident that the skills that were acquired by the learners from the AR environment were transferable to the real laboratory environment. In addition, these transferred skills and physical outcomes achieved by the AR environment when compared to those of the on-campus trained learners in a common experimental task have shown slightly better torch holding technique.

- 4. The principle of KBE is adaptable from a *product design automations* perspective to *instructional design automation*.**

The learning outcomes achieved by the AR learners have also validated the use of an AI tutor that is automated by the knowledge captured from real tutors. The modelling method has also proved to be efficient in transforming the knowledge from the real tutor to the AI tutor for teaching and assessing the practical skills of learners in the AR environment. Further the data analysis has shown its potential to be extendable to other taught distance-learning courses involving practical skills.

7.4 Contribution to theory and practice

The study makes a noteworthy contribution to theory and practice in the domain of engineering distance learning, as outlined in the following subsections.

7.4.1 Knowledge capturing method for gathering on-campus tutor knowledge

The focus of this study was to contribute to the challenges faced by engineering education providers in delivering practical skills to their learners while they are away from the physical laboratory. As this required the capture of tutors' knowledge of how the practical laboratory task is taught and assessed in an on-campus environment (see Section 4.1), the study adopted knowledge-based engineering (KBE) techniques that have been applied in design and manufacturing industries to capture complex knowledge from experts in automating product design into the educational domain in automating instructional design. It presented a three-column approach (see Table 4.3) to establish this knowledge, which consisted of procedure, product and diagnostic to identify and structure the procedural sequence, intermediate checks and the diagnostics ('why') knowledge required for automation (see Section 4.1.3). This three-column approach is a significant contributor to the theory.

7.4.2 Knowledge modelling structure

Figure 4.8 in Chapter 4 presents the procedure for modelling the instructional knowledge, whose knowledge structure consists of the learning object as the core and its sub-learning objects around it; these sub-learning objects were then encapsulated by the learning structure and each of the learning structures is further encapsulated by learning modes (see Section 4.2.2). The learning structure referred to the different learning levels under each of the sub-learning objects; the study presented three levels

in the learning structure, namely Introduction, Preparation and Execution, in which learners were able to start from any of the preferred levels, depending upon their previous knowledge and experience with respect to the learning task. The learning mode referred to the preferred way of learning these different levels through different modes by providing the learners with audio content (tell me) to listen to, video visuals (show me) to see, or an AR environment (have a go) in which to practise their laboratory skills. This knowledge modelling structure is another significant contributor to the theory.

7.4.3 Assessment automation

The learning outcomes of the learner were measured through the Level, Depth and Rigour axis (see Figure 4.17). Level represents the complexity of the task that the learner is performing, Depth the depth of knowledge that the learner needs to execute the task, and Rigour represents the measure of successful completion (see Section 4.3.5). This concept of measuring the learning outcome is an extension of the “Hess cognitive rigor matrix” principle, which suggests two axes, level and depth, to measure a learner’s performance (see Section 2.3.3 (c)). In the course of automating the assessment process for practical skills, this study has integrated rigour as a third axis to measure learners’ confidence in executing the task, which is also one of the significant contributors to the theory.

7.4.4 Knowledge-Based Educational (KBEd) framework

The KBEd framework developed for the study (see Figure 3.6) incorporated the above mentioned key contributions in a single framework to achieve the overall research goal in practice. The framework was then developed as a system and its readiness and usability in training practical skills was refined through domain experts (see Section

5.3). This refined framework was then successfully tested with a student group to determine its efficiency and effectiveness in facilitating the learning of engineering practical skills (see Section 6.3). Therefore, the presented KBEd framework introduces a novel concept for the delivery of practical skills to engineering distance learners, which is influenced by existing educational and industrial principles within the context of hands-on practical tasks, and the challenges in delivering them when the learner is away from the actual facility. The presented framework can, therefore, act as a useful tool for training other practical tasks in educational and industrial domains, which is a significant contributor to practice.

7.5 Limitations of the study

As encouraging as the findings of this research appear, caution must be taken on the scope and context to which such results are applicable. The following are some of the limitations of the research.

The focus of the study is limited to engineering practical skills. This was intentional due to the objectives of the study and the importance of them among current engineering employers (see Section 1.1). Moreover, the study only tested one use-case, ‘basic welding’, to prove the transferability of the practical skill from an AR environment to a real one (see Section 4.1.1). However, this limitation is acceptable, as the system has demonstrated its overall effectiveness and efficiency in training practical skills. Further, by employing the KBEd system for other engineering practical tasks and also in the industrial domain to train employees while away from training facilities, the approach could be generalized in order to enhance practical skills in distance learners.

Although the study persuaded in capturing complete knowledge from the experts for teaching and assessing the welding task (see Section 4.1 and 4.2), it is not possible to

capture all of them (Lynch *et al.*, 2015). With that in mind, the study presented the knowledge modelling through ontology, which allows easy integration of uncaptured or new knowledge into the system. Moreover, the sample size involved in the evaluation was small (n=46). However, by restricting the selection of students to first year engineering undergraduates with no experience of welding, the sample size adequately addressed the objectives of the study (see Section 6.1). Further, the results could be tested with a larger sample size or different groups to confirm the non-significance in the two groups subjected to the different training environments.

In the on-campus environment, students were taught in groups, whereas in the AR environment each student was individually taught and trained by the AI tutor (see Section 6.2). This highlighted the limitation in the concurrence between the learning processes involved in each of the environments. Unfortunately, the time and costs involved in the conventional environment to provide such a learning experience are prohibitive. In the future, with provision of one-on-one training with the real tutor the result could be reassessed.

7.6 Recommendations for further research

Based on the findings of the study several recommendations can be made for delivering engineering practical tasks for distance learners, as follows.

7.6.1 Enhancing safety practices in the AR environment

It was found that after training in the AR environment, the students were less careful than the on-campus trained ones when satisfying the safety protocol (see Section 6.4.1). This demonstrates the KBEd system's limitation in relating the real seriousness of the dangers when performing a real laboratory task. Fundamental safety is of highest priority in any laboratory task, so this should be addressed by making the AR learners

aware of the seriousness and that they should be more vigilant in protecting themselves and others around them. The use of sensors in the AR environment to stimulate physical pain could be an additional aspect of future development, as this could help the system to teach more critical tasks by increasing the safety skills in the AR learners.

7.6.2 Improving the accuracy of the depth factor

The majority of the experts experienced difficulty in judging the right depth while interacting with the augmented objects and called for enhancement of this aspect (see Table 5.7). The study attempted to address this by developing a demo scene to master the object grabbing and moving in the AR environment (see Table 5.19). However, this did not solve the whole issue of depth judgment, as the hardware used was a development kit with its own limitations with respect to the minimum and maximum distance and angle at which an object is intractable. It should be understood that the AR field is still in its infancy when used for training practical tasks, yet this study has demonstrated the evident usability of AR for such training. Future AR hardware and software developments could eventually make depth perception easier, thus increasing the transferability of the practical skills gained to a real environment.

7.6.3 Implementing the framework for practical tasks in other domains

The findings of the study reveal that the implemented KBEd system is capable of transferring practical skills from augmented reality (AR) environment to a real one (see Section 6.5). However, the study was focused on one practical task, 'basic welding'. Therefore, the need to testing these in training other practical tasks would be crucial in future research. This was also evident from the experts' validation; the majority of the experts seriously considered using the KBEd system in their respective domains to train practical skills in their employees or students, and some also mentioned specific tasks

that they would make use of (see Table 5.16). Among these, a three-axis milling machine task was suggested by a number of experts, which could be considered as one of the practical tasks for future development. Further, the framework could be adapted to industrial needs for training complex practical skills by capturing knowledge from domain experts and feeding this back into the system.

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Appendix 1: List of Publications

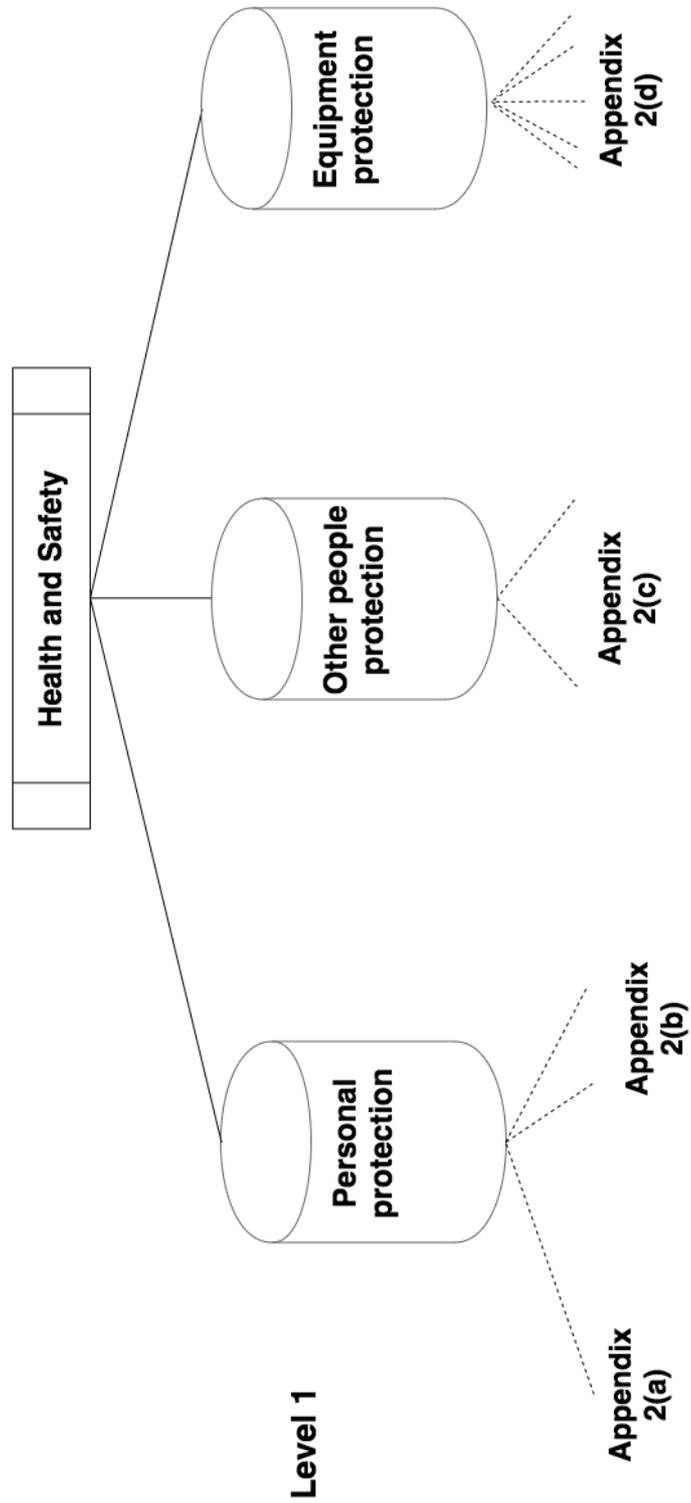
Journal Articles

Andrew M.T.; **Chennam Vijay, V.**; Raju, P., Chapman, C.; Chima, P.; Alok, M.; Adel, C., "Parametric virtual laboratory development: A hydropower case study with student perspectives." *Advances in Engineering Software* 64 (2013): 62-70.
Url: <http://www.sciencedirect.com/science/article/pii/S0965997813000392>

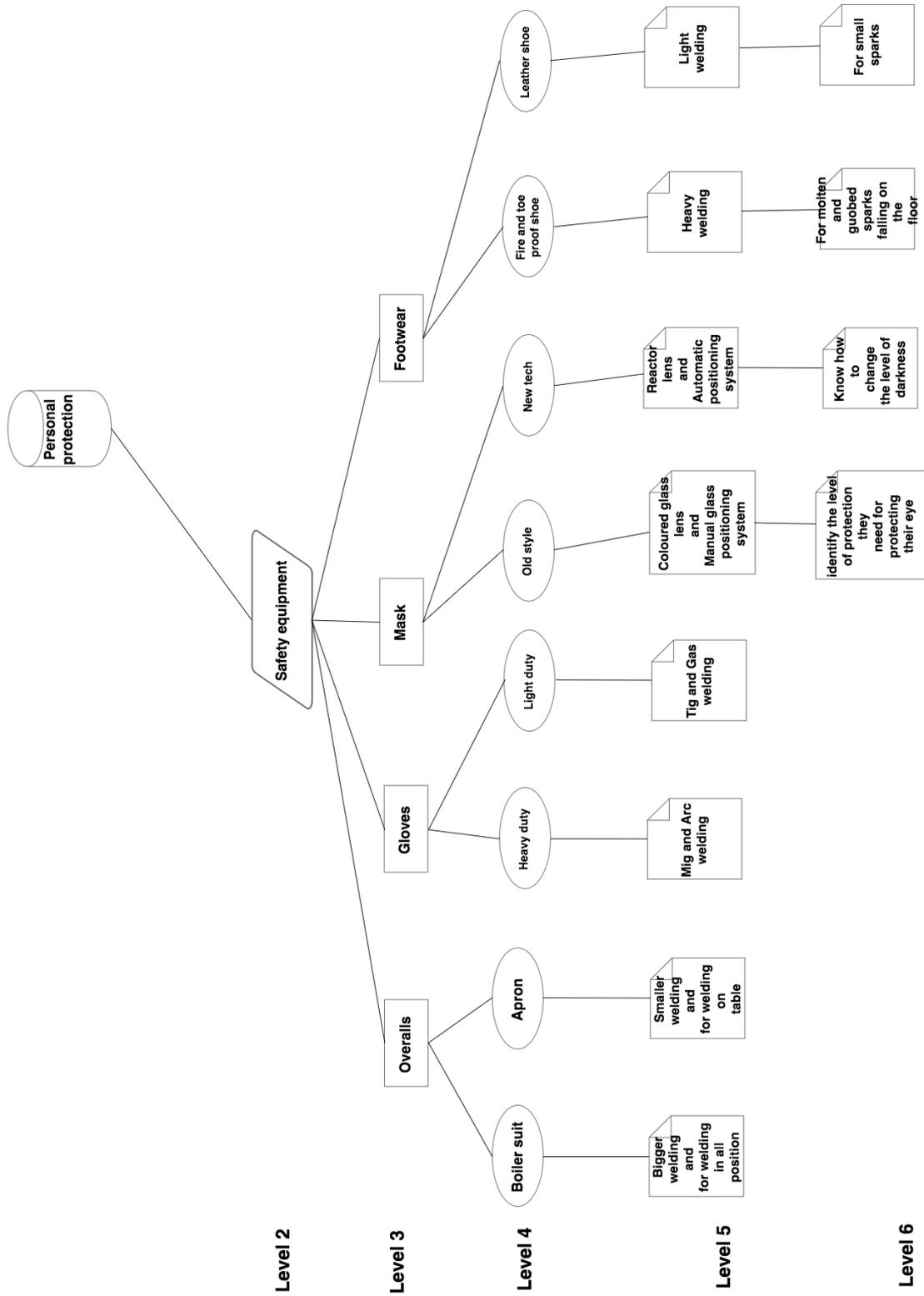
Conference Articles

- **Chennam Vijay, V.**; Lees, M.; Chima, P.; Chapman, C., "Augmented Reality Environment for Engineering Distance Learners to Acquire Practical Skills" in *13th International Conference on Remote Engineering and Virtual Instrumentation (REV), 2016 IEEE*, 24th – 27th February 2016 Madrid's University City.
Url: <https://www.conftool.com/rev-conference/sessions.php>
- **Chennam Vijay, V.**; Lees, M.; Chima, P.; Chapman, C.; Raju, P., "Knowledge based educational framework for enhancing practical skills in engineering distance learners," in *Global Engineering Education Conference (EDUCON), 2015 IEEE*, vol., no., pp.124-131, 18-20 March 2015.
Url: <http://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=7095961&isnumber=7095933>
- **Chennam Vijay, V.**; Lees, M.; Chima, P.; Chapman., "Knowledge Based Educational Framework for capturing, mapping and automating oncampus laboratory instructor knowledge for enhancing practical skills in engineering distance learners, " in *iBEE The Annual Conference of The Council of Heads of the Built Environment (CHOBE), 2015 IBEE*, 2nd – 4th September 2015 University of Bath.
URL:[http://ibee-conference.com/cms/resources/uploads/files/iBEE%20Conference%20Programme%20September%202015%20web%20version%20final\(1\).pdf](http://ibee-conference.com/cms/resources/uploads/files/iBEE%20Conference%20Programme%20September%202015%20web%20version%20final(1).pdf)

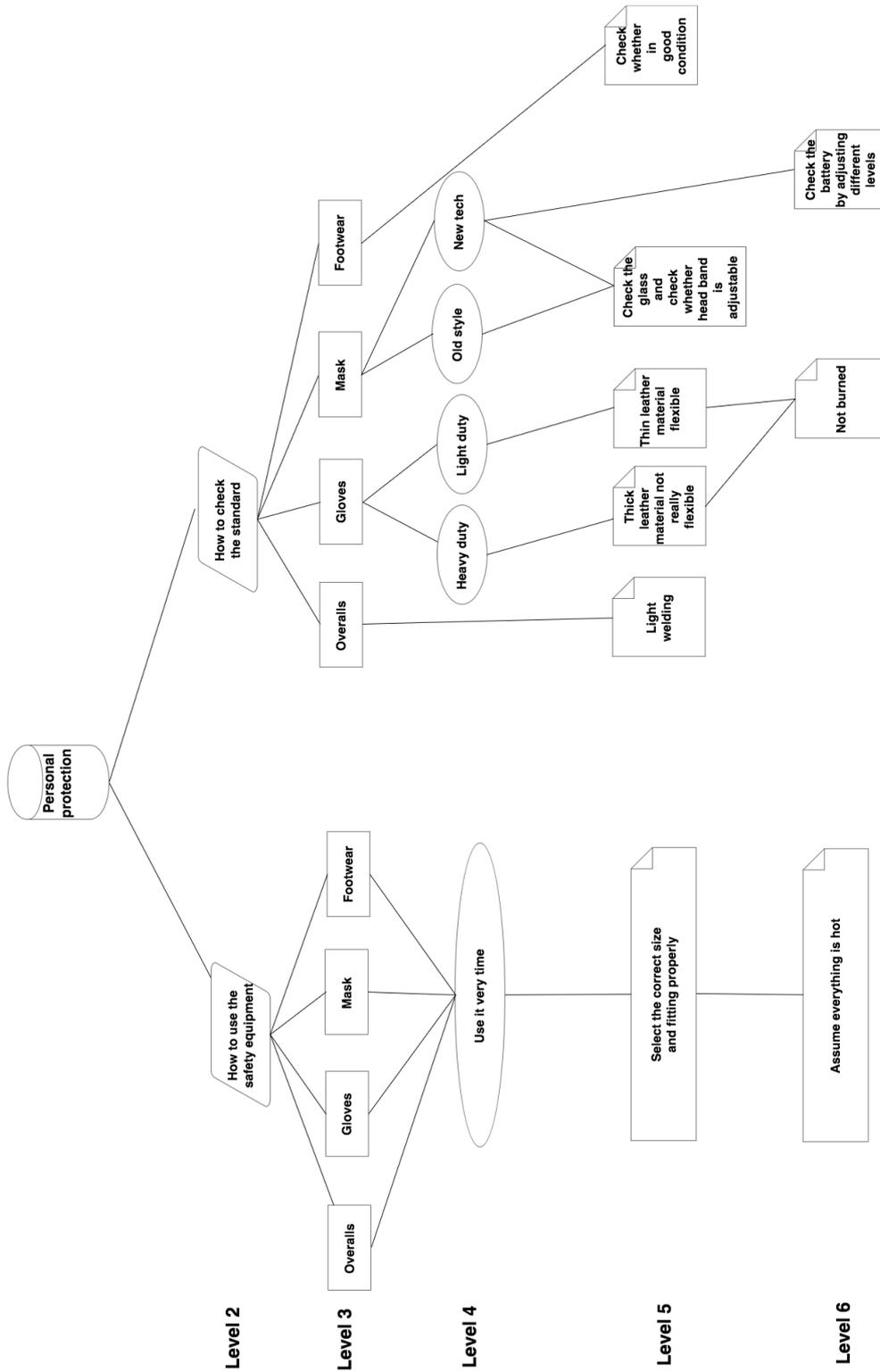
Appendix 2: Health and safety hierarchical structure



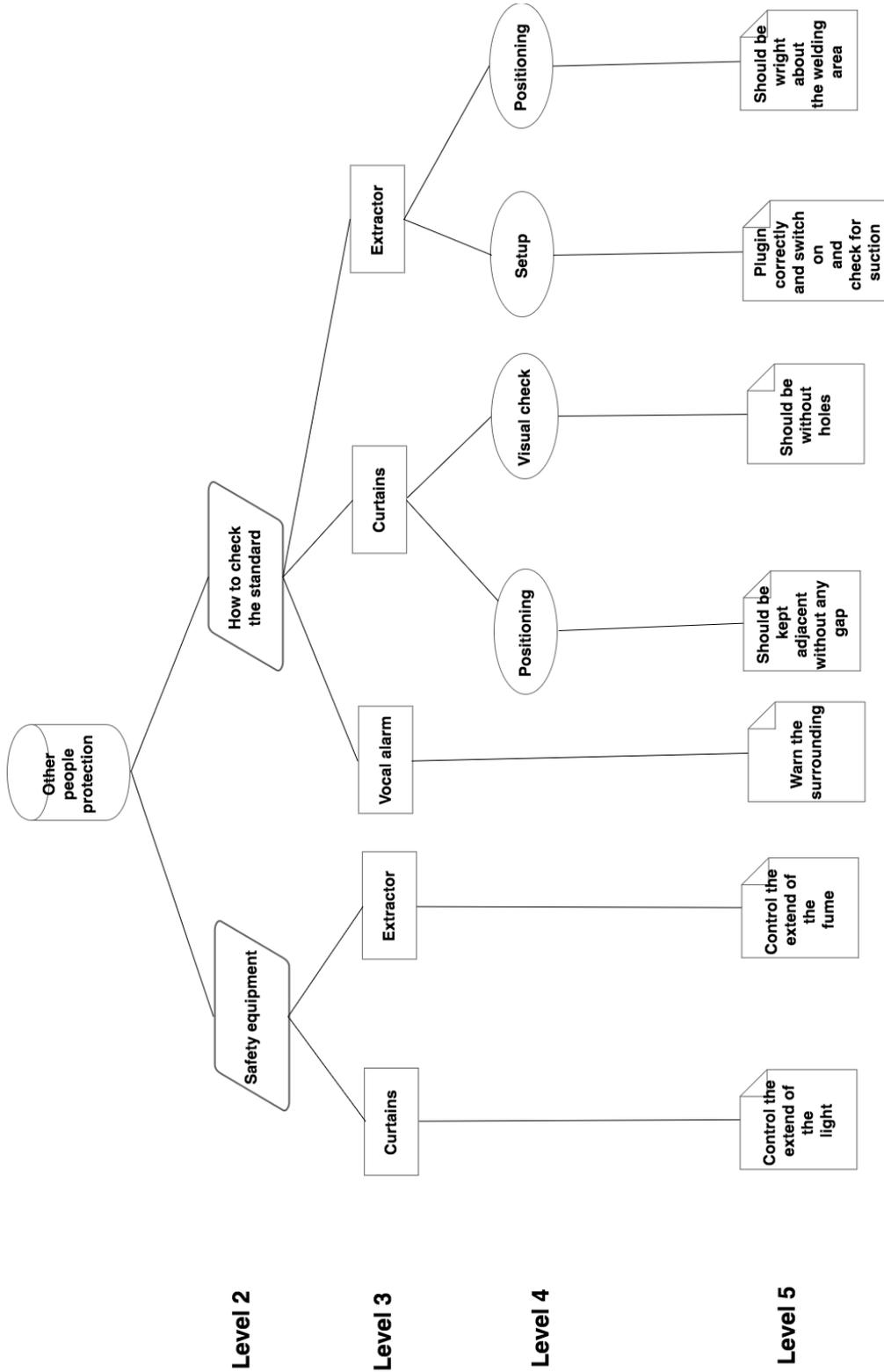
Appendix 2(a)



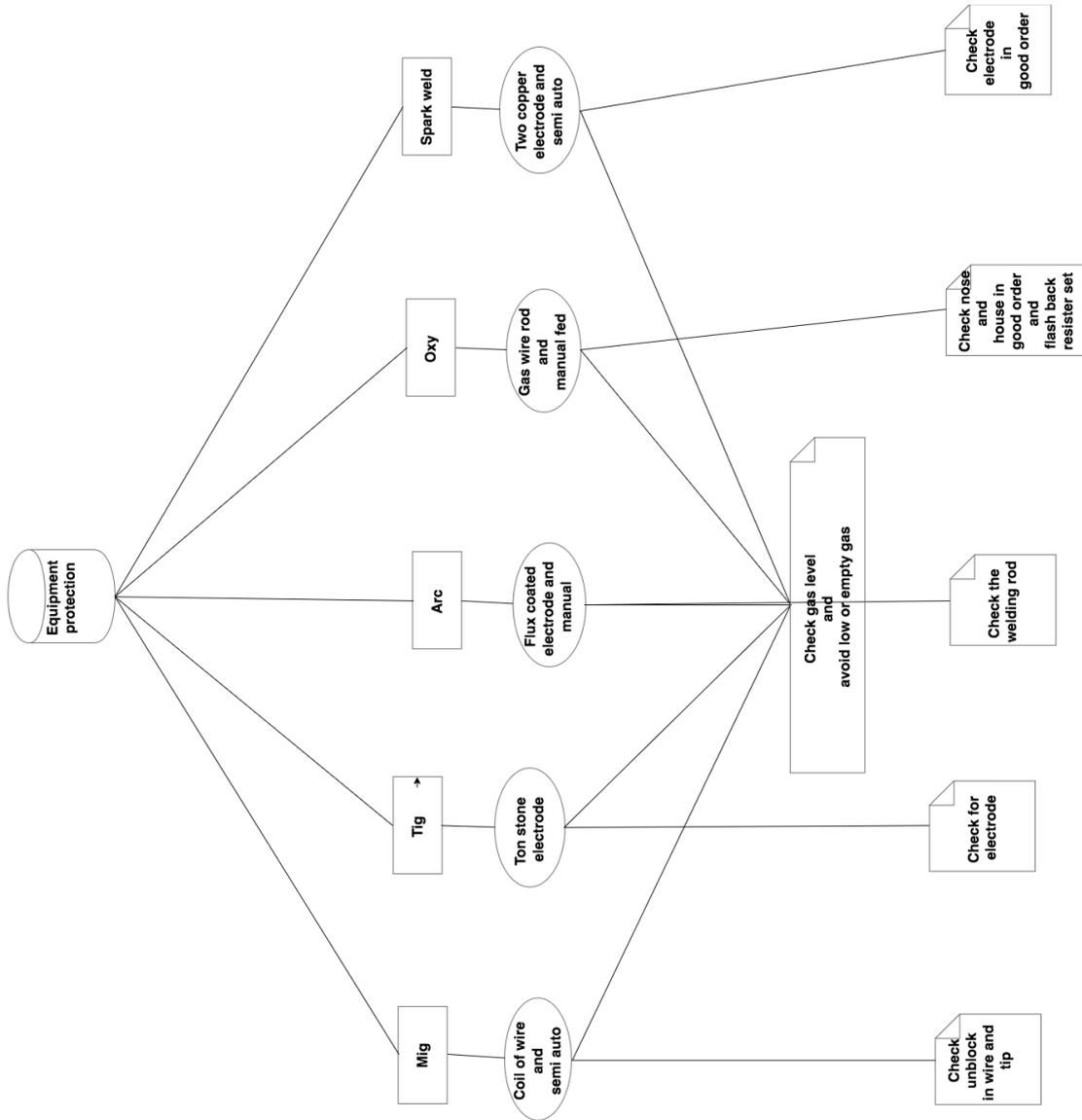
Appendix 2(b)



Appendix 2(c)



Appendix 2(d)



Appendix 3: Knowledge captured using procedural, product and diagnostics (three) columns

(i) Three columns capture for flat plate welding

Procedural	Product	Diagnostics
<p>Health and Safety protocol</p> <p>Personal protection: Select your safety equipment: ->Mask -> Overall -> Gloves -> Footwear</p> <p>Other people protection: Close the curtain</p>	<p>Check for if all appropriate personal and other people protection is satisfied.</p>	<p>Problem pointed: <i>Could be because of ignorance or unaware of danger with respect to welding. Could be wrong amps or wfs level setup or both</i></p> <p>Lack of: <i>fundamental knowledge.</i></p> <p>Learning needed: <i>Learning or revision on importance of safety protocol and detail insight on how to use safety gears and how to use them.</i></p>
<p>Select two metal plate</p> <p>Degrees the plate</p> <p>Remove any burns</p>	<p>Check the selection of plate and whether the plate has a cleaned edges and surface</p>	<p>Problem pointed: <i>Could be because of wrong procedure involved in selection of plate or appropriate tool in degreasing them.</i></p> <p>Lack of: <i>Preparation knowledge</i></p> <p>Learning needed: <i>Learning or revision in procedure involved in selecting right plate, tools and how to perform degreasing.</i></p>
<p>Position the plate</p> <p>Hold it with magnets</p> <p>Connect the earth wire to the welding platform</p> <p>Setup the amps and wire-fed-speed (wfs)</p>	<p>Check whether the plates and magnet were positioned proper, so that the plates are intact.</p> <p>Check whether the earth wire is connected to the welding platform</p> <p>Check for selected plate thickness</p> <p>- If 1.5mm wfs should be level 6 and amp should be at level 3</p>	<p>Problem pointed: <i>Could be because of misalignment between two plates and the magnet. Could be wrong amps or wfs level setup or both</i></p> <p>Lack of: <i>knowledge is relating the thickness of the plate and welding console setup.</i></p> <p>Learning needed: <i>Learning or revision in orienting the plate and magnet in right place.</i></p>

	- If 3mm wfs should be between level 8 and 9 and amp should be at level 6	<i>Understanding on calculation involved in amp and wfs setup with respect to the plate thickness.</i>
Tack weld both the corner Remove the magnet	Check whether the corners are tacked properly. When picked up after removing the magnet, the two plates should stay together.	<p><i>Problem pointed: Could be because of wrong angle of torch, hand and eye coordination. Causing improper weld failing to keep plates together.</i></p> <p><i>Lack of: executional knowledge skill.</i></p> <p><i>Learning needed: more practice in holding the torch in the right angle to have clear hand eye coordination. Revision on procedure in learning how to execute a proper tack weld.</i></p>
Weld 20mm inside from each tacked corners	Check if any gap between weld beads or bend on the plate. Check whether weld penetrated to the rear side of the plate.	<p><i>Problem pointed: Could be because of wrong hand speed and orientation. Causing improper weld to have less weld penetration to the rear.</i></p> <p><i>Lack of: executional knowledge skill.</i></p> <p><i>Learning needed: more practice in having right hand orientation and speed. Revision on procedure in learning how to execute a 20mm weld from tacked corners.</i></p>
Weld in the middle Scrape the excess	Check for a nice and flat welded plate. Check for the enough depth in penetration on the rear side.	<p><i>Problem pointed: Could be because of imprecise hand speed and orientation. Causing bad weld with gaps between weld beads and less penetration.</i></p> <p><i>Lack of: executional knowledge skill.</i></p> <p><i>Learning needed: more practice in having steady and precise hand speed. Revision</i></p>

		<i>on procedure in learning how to execute a main weld.</i>
Put into vice and hit it with hammer	Check if the metal bend or the weld breaks.	<i>Learning needed: more revision and practice on the errors made in preoperational procedure and executional skills.</i>

(ii) Three columns capture for T-joint plate welding

Procedural	Product	Diagnostics
Health and Safety protocol Personal protection: Select your safety equipment: ->Mask -> Overall -> Gloves -> Footwear Other people protection: Close the curtain	Check for if all appropriate personal and other people protection is satisfied.	Problem pointed: <i>Could be because of ignorance or unaware of danger with respect to welding.</i> Lack of: <i>fundamental knowledge.</i> Learning needed: <i>Learning or revision on importance of safety protocol and detail insight on how to use safety gears and how to use them.</i>
Select two metal plate Degrease the plate Remove any burns	Check the selection of plate and whether the plate has a cleaned edges and surface	Problem pointed: <i>Could be because of wrong procedure involved in selection of plate or appropriate tool in degreasing them.</i> Lack of: <i>Preparation knowledge</i> Learning needed: <i>Learning or revision in procedure involved in selecting right plate, tools and how to perform degreasing.</i>
Position the plate Hold it with jig Connect the earth wire to the welding platform Setup the amps and wire-fed-speed (wfs)	Check whether the plates angled to 90° by positioning them properly on to the jig. Check whether the earth wire is connected to the welding platform	Problem pointed: <i>Could be because of misalignment between two plates and the magnet.</i> <i>Could be wrong amps or wfs level setup or both</i>

	<p>Check for selected plate thickness</p> <ul style="list-style-type: none"> - If 1.5mm wfs should be level 6 and amp should be at level 3 - If 3mm wfs should be between level 8 and 9 and amp should be at level 6 	<p>Lack of: <i>knowledge is relating the thickness of the plate and welding console setup.</i></p> <p>Learning needed: <i>Learning or revision in orienting the plate and magnet in right place. Understanding on calculation involved in amp and wfs setup with respect to the plate thickness.</i></p>
<p>Tack weld both the corner</p> <p>Remove the jig</p>	<p>Check whether the corners are tacked properly. When picked up after removed from the jig, the two plates should stay together.</p>	<p>Problem pointed: <i>Could be because of wrong angle of torch, hand and eye coordination. Causing improper weld failing to keep plates together.</i></p> <p>Lack of: <i>executorial knowledge skill.</i></p> <p>Learning needed: <i>more practice in holding the torch in the right angle to have clear hand eye coordination. Revision on procedure in learning how to execute a proper tack weld.</i></p>
<p>Weld 20mm inside from each tacked corners</p>	<p>Check if the plate still at 90° and any gap between weld beads. Check whether weld penetrated to the rear side of the plate.</p>	<p>Problem pointed: <i>Could be because of wrong hand speed and orientation. Causing improper weld to have less weld penetration to the rear.</i></p> <p>Lack of: <i>executorial knowledge skill.</i></p> <p>Learning needed: <i>more practice in having right hand orientation and speed. Revision on procedure in learning how to execute a 20mm weld from tacked corners.</i></p>
<p>Weld in the middle</p> <p>Scrape the excess</p>	<p>Check for a nice and 45° welded on a 90° angled plate. Check for the enough depth in penetration on the rear side.</p>	<p>Problem pointed: <i>Could be because of imprecise hand speed and orientation. Causing bad weld with gaps between weld beads and less penetration.</i></p>

		<p>Lack of: <i>executional knowledge skill.</i></p> <p>Learning needed: <i>more practice in having steady and precise hand speed. Revision on procedure in learning how to execute a main weld.</i></p>
Put into vice and hit it with hammer	Check if the metal bend or the weld breaks.	<p>Learning needed: <i>more revision and practice on the errors made in preoperational procedure and executional skills.</i></p>

(iii) Three columns capture for saucer plate welding

Procedural	Product	Diagnostics
<p>Health and Safety protocol</p> <p>Personal protection: Select your safety equipment: ->Mask -> Overall -> Gloves -> Footwear</p> <p>Other people protection: Close the curtain</p>	<p>Check for if all appropriate personal and other people protection is satisfied.</p>	<p>Problem pointed: <i>Could be because of ignorance or unaware of danger with respect to welding. Could be wrong amps or wfs level setup or both</i></p> <p>Lack of: <i>fundamental knowledge.</i></p> <p>Learning needed: <i>Learning or revision on importance of safety protocol and detail insight on how to use safety gears and how to use them.</i></p>
<p>Select three metal plate</p> <p>Degrees the plate</p> <p>Remove any burns</p>	<p>Check the selection of plate and whether the plate has a cleaned edges and surface</p>	<p>Problem pointed: <i>Could be because of wrong procedure involved in selection of plate or appropriate tool in degreasing them.</i></p> <p>Lack of: <i>Preparation knowledge</i></p> <p>Learning needed: <i>Learning or revision in procedure involved in selecting right plate, tools</i></p>

		<i>and how to perform degreasing.</i>
Position the plate	Check whether the plates angled to 90° by positioning them properly on to the jig. Check whether the earth wire is connected to the welding platform Check for selected plate thickness - If 1.5mm wfs should be level 6 and amp should be at level 3 - If 3mm wfs should be between level 8 and 9 and amp should be at level 6	Problem pointed: <i>Could be because of misalignment between two plates and the magnet.</i> <i>Could be wrong amps or wfs level setup or both</i> <i>Lack of: knowledge is relating the thickness of the plate and welding console setup.</i> <i>Learning needed: Learning or revision in orienting the plate and magnet in right place. Understanding on calculation involved in amp and wfs setup with respect to the plate thickness.</i>
Hold it with jig		
Connect the earth wire to the welding platform		
Setup the amps and wire-fed-speed (wfs)s		
Bend the first plate 6mm of two edge to approximately 90° using vice and hammer	Check whether the plate clips together properly.	Problem pointed: <i>Could be because of misalignment of 6mm bend lip.</i> <i>Could be uneven in plate shape.</i> <i>Lack of: executional knowledge skill.</i> <i>Learning needed: more practice in making the proper bends to have a precise lap lock.</i>
Bends the second plate into a circular shape		
Bends third plate it into a 'V' shape		
Lap lock them together		
Tack weld the lip together and tack weld on the base	Check whether the corners are tacked properly when picked up plates should stay together.	Problem pointed: <i>Could be because of wrong angle of torch, hand and eye coordination.</i> <i>Causing improper weld failing to keep plates together.</i> <i>Lack of: executional knowledge skill.</i> <i>Learning needed: more practice in holding the torch in the right angle to have clear hand eye coordination. Revision on procedure in learning how to execute a proper tack weld.</i>
Weld in the bottom	Check if any gap between welds beads. Check whether	Problem pointed: <i>Could be because of wrong hand speed and orientation.</i>
Weld all the sides		
Scrape the excess		

	weld penetrated to the rear side of the plate.	<p><i>Causing improper weld to have less weld penetration to the rear.</i></p> <p><i>Lack of: executional knowledge skill.</i></p> <p><i>Learning needed: more practice in having right hand orientation and speed. Revision on procedure in learning how to execute a 20mm weld from tacked corners.</i></p>
Pour water into the welded saucer	Check for non-leaking of water.	<p><i>Learning needed: more revision and practice on the errors made in preoperational procedure and executional skills.</i></p>

Appendix 4: Scripts used in codifying Interactivity characteristics

(i) Interaction script for GUI in constructing learning objects

```
using UnityEngine;
using System.Collections;
using System.Collections.Generic;
using LitJson;
using System.Net;
using System.IO;
namespace AssemblyCSharp
{
    public class WeldingTest : MonoBehaviour
    {
        public string[] items;
        public Rect Box;
        public Rect Boxone;
        public Rect Boxtwo;
        public Rect Boxthree;
        public string clickButtonName = "Start Constructing";
        public string slectedLearningObject = "None";
        public string slectedSubLearningObject = "None";
        public string slectedLearningStructure = "None";
        public string slectedLearningMode = "None";

        //public string sLO = "Welding";

        public string tURL;

        private bool editing = false;
        private bool GUIEnabled = false;
        GetJson slectedLearningObjectData = new GetJson();
        GetJson subLearningObjectData = new GetJson();
        GetJson learningStructureData = new GetJson();
        GetJson learningModeData = new GetJson();

        void Start(){

        }

        private void OnGUI()
        {
            GUI.color = Color.green;
            if (GUI.Button(Box, clickButtonName))
            {
```

```

        editing = true;
    }

    if (editing)
    {
        MapList mlist = slectedLearningObjectData.Jsonget2("http://virtuallabmel.x10host.com/tutorial/RunTest/LearningObject.json");
        for (int x = 0; x < mlist.value.Count; x++)
        {
            if (GUI.Button(new Rect(Box.x, (Box.height * x) + Box.y + Box.height, Box.width, Box.height), mlist.value[x]))
            {
                slectedLearningObject = mlist.value[x];
                Debug.Log(slectedLearningObject);
            }
        }
        if (slectedLearningObject != "None")
        {
            // MapList mlistlo = subLearningObjectData.Jsonget2("http://localhost:8083/kbed/sub-classes?input="+slectedLearningObject);
            MapList mlistlo = subLearningObjectData.Jsonget2("http://virtuallabmel.x10host.com/tutorial/RunTest/input="+slectedLearningObject+".json");
            for (int x = 0; x < mlistlo.value.Count; x++)
            {
                if (GUI.Button(new Rect(Boxone.x, (Boxone.height * x) + Boxone.y + Boxone.height, Boxone.width, Boxone.height), mlistlo.value[x]))
                {
                    slectedSubLearningObject = mlistlo.value[x];
                    Debug.Log(slectedSubLearningObject);
                }
            }
        }
        if (slectedSubLearningObject != "None")
        {
            // MapList mlistls = learningStructureData.Jsonget2("http://localhost:8083/kbed/learning-structures?input="+slectedSubLearningObject);
            MapList mlistls = learningStructureData.Jsonget2("http://virtuallabmel.x10host.com/tutorial/RunTest/input="+slectedSubLearningObject+".json");
            for (int x = 0; x < mlistls.value.Count; x++)
            {
                if (GUI.Button(new Rect(Boxtwo.x, (Boxtwo.height * x) + Boxtwo.y + Boxtwo.height, Boxtwo.width, Boxtwo.height), mlistls.value[x]))
                {
                    slectedLearningStructure = mlistls.value[x];
                    Debug.Log(slectedLearningStructure);
                    //editing = false;
                }
            }
        }
    }

    if (slectedLearningStructure != "None")
    {
        //editing = true;
    }

```

```

//      MapList mlistm = learningModeData.Jsonget2("http://localhost:8083/kbed/learn
ning-mode?input="+slectedSubLearningObject);
      MapList mlistm = learningModeData.Jsonget2("http://virtuallabmel.x10host.co
m/tutorial/RunTest/input="+slectedLearningStructure+".json");
      for (int x = 0; x < mlistm.value.Count; x++)
      {
          if (GUI.Button(new Rect(Boxthree.x, (Boxthree.height * x) + Boxthree.y
+ Boxthree.height, Boxthree.width, Boxthree.height), mlistm.value[x]))
          {
              slectedLearningMode = mlistm.value[x];
              Debug.Log(slectedLearningMode);
              editing = false;
              senarioFinder();
          }
      }

//GUILayout.Label(slectedLearningObject);
GUI.Label(new Rect(50,600,100,20), slectedLearningObject);

//GUILayout.Label(slectedSubLearningObject)
GUI.Label(new Rect(300,600,100,20), slectedSubLearningObject);

//GUILayout.Label(slectedLearningStructure);
GUI.Label(new Rect(550,600,100,20), slectedLearningStructure);

//GUILayout.Label(slectedLearningObject);
GUI.Label(new Rect(800,600,100,20), slectedLearningMode);

}

}

private void senarioFinder()
{
    //Tell Me Finder
    if (slectedLearningMode == "TellMe" & slectedLearningStructure == "Introduction"
& slectedSubLearningObject == "FlatplateWeld")
    {
        Debug.Log("test");
        Application.LoadLevel("introOneTS");
    }
    if (slectedLearningMode == "TellMe" & slectedLearningStructure == "Preparation" &
slectedSubLearningObject == "FlatplateWeld")
    {
        Application.LoadLevel("PreparOneTS");
    }
    if (slectedLearningMode == "TellMe" & slectedLearningStructure == "Executionand
Evaluation" & slectedSubLearningObject == "FlatplateWeld")
    {

```

```

        Application.LoadLevel("Scenario1TS");
    }

    //Show Me Finder
    if (slectedLearningMode == "ShowMe" & slectedLearningStructure == "Introduction"
    & slectedSubLearningObject == "FlatplateWeld")
    {

        Application.LoadLevel("IntroductionPartOne");

    }

    if (slectedLearningMode == "ShowMe" & slectedLearningStructure == "Preparation"
    & slectedSubLearningObject == "FlatplateWeld")
    {

        Application.LoadLevel("PreparationOne");

    }

    if (slectedLearningMode == "ShowMe" & slectedLearningStructure == "Executionan
    dEvaluation" & slectedSubLearningObject == "FlatplateWeld")
    {

        Application.LoadLevel("ScenarioOne");

    }

    //Have A Go Finder
    if (slectedLearningMode == "HaveAGo" & slectedLearningStructure == "Introduction
    " & slectedSubLearningObject == "FlatplateWeld")
    {

        Application.LoadLevel("HealthandSafety");

    }

    if (slectedLearningMode == "HaveAGo" & slectedLearningStructure == "Preparation
    " & slectedSubLearningObject == "FlatplateWeld")
    {

        Application.LoadLevel("GlowingComponents");

    }

    if (slectedLearningMode == "HaveAGo" & slectedLearningStructure == "Executiona
    ndEvaluation" & slectedSubLearningObject == "FlatplateWeld")
    {

        Application.LoadLevel("");

    }

    }
}

```

(ii) Interaction Script for welding torch

```
using UnityEngine;
using System.Collections;

public class HandMove : MonoBehaviour
{
    private Vector3 screenPoint;
    private Vector3 offset;

    void OnMouseDown()
    {
        screenPoint = Camera.main.WorldToScreenPoint(gameObject.transform.position);
        offset = gameObject.transform.position - Camera.main.ScreenToWorldPoint(new Vector
3(Input.mousePosition.x, Input.mousePosition.y, screenPoint.z));
    }

    void OnMouseDrag()
    {
        Vector3 cursorPoint = new Vector3(Input.mousePosition.x, Input.mousePosition.y, scree
nPoint.z);
        //Debug.Log (cursorPoint);
        Vector3 cursorPosition = Camera.main.ScreenToWorldPoint(cursorPoint) + offset;
        transform.position = cursorPosition;
    }
}
```

(iii) Script for Collision detection when the torch nozzle touches the plate edge

```
using UnityEngine;
using System.Collections;
using System.Collections.Generic;
namespace vijaytest{
    public class WeldingTriggerOBandSparksRight : MonoBehaviour
    {

        private bool _enteredWeldingZone;

        void Start(){

        }

        void OnTriggerEnter(Collider other)
        {
            if (other.tag == "Player")
            {
                _enteredWeldingZone = true;
                OMT_CS omtcs = GameObject.Find ("OMT").GetComponent<OMT_CS> ();
                ArcLauncher2 arclauncher = GameObject.Find("Nozzle").GetComponent<ArcLaun
cher2>();
                omtcs.trackingActive = true;
                arclauncher.LaunchRay();

            }

        }

        void OnTriggerExit(Collider other)
        {
            if (other.tag == "Player")
            {
                _enteredWeldingZone = false;
                OMT_CS omtcs = GameObject.Find ("OMT").GetComponent<OMT_CS> ();
                omtcs.trackingActive = false;

            }

        }

    }
}
```

Appendix 5: Scripts used in creating welding characteristics

(i) Script that initiates the entire welding characteristics

```
using UnityEngine;
using System.Collections;
using System.Collections.Generic;
namespace vijaytest{
    public class WeldingTriggerOBandSparks : MonoBehaviour
    {

        private bool _enteredWeldingZone;

        void Start(){

        }

        void OnTriggerStay(Collider other)
        {
            if (other.tag == "Player")
            {
                _enteredWeldingZone = true;
                OMT_CS omtcs = GameObject.Find ("OMT").GetComponent<OMT_CS> ();
                ArcLauncher2 arclauncher = GameObject.Find("Nozzle").GetComponent<ArcLaun
cher2>();
                omtcs.trackingActive = true;
                arclauncher.LaunchRay();
            }
        }

        void OnTriggerExit(Collider other)
        {
            if (other.tag == "Player")
            {
                _enteredWeldingZone = false;
                OMT_CS omtcs = GameObject.Find ("OMT").GetComponent<OMT_CS> ();
                omtcs.trackingActive = false;
            }
        }
    }
}
```

(ii) Script used to produce the weld bead

```
using UnityEngine;
using System.Collections;
using System.Collections.Generic;

namespace vijaytest{
    public class WeldingTrigger20mmLeft2 : MonoBehaviour
    {

        public GameObject weldingBead20mm2Holder;
        public int countForBeadToAppear20mm2 = 0;

        void Start(){

            weldingBead20mm2Holder = GameObject.FindGameObjectWithTag("ContinuesWeldingBead20mm2");
            weldingBead20mm2Holder.SetActive (false);

        }

        void OnTriggerEnter(Collider other)
        {
            if (other.tag == "Player")
            {

                countForBeadToAppear20mm2++;

            }
            if (countForBeadToAppear20mm2 >= 100)
                weldingBead20mm2Holder.SetActive (true);
        }

        void OnTriggerExit(Collider other)
        {
            if (other.tag == "Player")
            {
                //Debug.Log ("Lost Contact");
            }

        }

    }
}
```

Appendix 6: Scripts used in creating welding arc and sound

```
using UnityEngine;
using System.Collections;
using System.Collections.Generic;
namespace vijaytest{

    public class ArcLauncher2 : MonoBehaviour {

        public GameObject arcPrefab;
        public GameObject helperPrefab;
        public LaunchMethod launchMethod = LaunchMethod.forward_raycast;
        public float Distance = 100;
        public LayerMask layers;
        public RayTransformBehaviour startBehaviour = RayTransformBehaviour.stick;
        public RayTransformBehaviour endBehaviour = RayTransformBehaviour.follow_raycas
t;
        public InertialSettings rayInertiaSettings;
        public Transform globalSpaceTransform;

        private List<RayInfo> rays;

        public List<RayInfo> Rays
        {
            get
            {
                return rays;
            }
        }

        public class RayInfo
        {
            public ArcReactor_Arc arc;
            public Transform[] shape;
            public GameObject startObject;
            public GameObject endObject;
        }

        [System.Serializable]
        public class InertialSettings
        {
            public InertiaMethod type = InertiaMethod.none;
            public float speed;
            public float detalization = 10;
            public bool localDetalization = true;
            public AnimationCurve snapbackForceCurve;
            public float maxSnapBackDistance = 100;
        }
    }
}
```

```

public enum InertiaMethod
{
    none = 0,
    linespeed = 1
}

public enum LaunchMethod
{
    forward_raycast = 0,
    double_raycast = 1
}

public enum RayTransformBehaviour
{
    immobile = 0,
    stick = 1,
    follow_raycast = 2
}

void Start ()
{
    rays = new List<RayInfo>();
}

public void LaunchRay()
{
    if (launchMethod == LaunchMethod.forward_raycast && startBehaviour == RayTransformBehaviour.follow_raycast)
    {
        Debug.LogError("Launch method 'forward_raycast' and start behaviour 'follow_raycast' are incompatible. Change one of the settings.");
        return;
    }

    if (arcPrefab == null)
    {
        Debug.LogError("No arc prefab set.");
        return;
    }

    Transform start = transform;
    Transform end;
    GameObject startObj;
    GameObject endObj;
    GameObject tmpobj = new GameObject("rayEndPoint");
    RaycastHit hit = new RaycastHit();

    //End position will be raycasted in any case
    end = tmpobj.transform;
    if (Physics.Raycast(transform.position,transform.forward,out hit,Distance,layers.value
))
    {

```

```

        end.position = hit.point;
        endObj = hit.transform.gameObject;
    }
    else
        end.position = transform.position + transform.forward * Distance;
    if (endBehaviour == RayTransformBehaviour.stick && hit.transform != null)
    {
        end.parent = hit.transform;
    }
    else
    {
        end.parent = globalSpaceTransform;
    }

//Start position will depend on launch method
switch (launchMethod)
{
case LaunchMethod.double_raycast:
    tmpobj = new GameObject("rayStartPoint");
    start = tmpobj.transform;
    if (Physics.Raycast(transform.position,-
transform.forward,out hit,Distance,layers.value))
    {
        start.position = hit.point;
        startObj = hit.transform.gameObject;
    }
    else
        start.position = transform.position - transform.forward * Distance;
    if (startBehaviour == RayTransformBehaviour.stick && hit.transform != null)
    {
        start.parent = hit.transform;
    }
    break;
case LaunchMethod.forward_raycast:
    tmpobj = new GameObject("rayStartPoint");
    start = tmpobj.transform;
    start.position = transform.position;
    if (startBehaviour == RayTransformBehaviour.stick)
    {
        start.parent = transform;
        start.rotation = transform.rotation;
        if (helperPrefab != null)
        {
            tmpobj = (GameObject)Instantiate(helperPrefab);
            tmpobj.transform.parent = start;
            tmpobj.transform.position = start.transform.position;
            tmpobj.transform.rotation = start.transform.rotation;
        }
    }
    else
    {
        start.parent = globalSpaceTransform;
    }
    break;

```

```

}

RayInfo rinfo = new RayInfo();
tmpobj = (GameObject)Instantiate(arcPrefab);
tmpobj.transform.parent = globalSpaceTransform;
rinfo.arc = tmpobj.GetComponent<ArcReactor_Arc>();
bool[] destrFlags = new bool[0];

switch (rayInertiaSettings.type)
{
case InertiaMethod.none:
    rinfo.shape = new Transform[2];
    rinfo.shape[0] = start;
    rinfo.shape[1] = end;
    rinfo.arc.shapeTransforms = rinfo.shape;
    destrFlags = new bool[2];
    break;
case InertiaMethod.linespeed:
    int transformCount = 0;
    if (rayInertiaSettings.localDetalization)
    {
        transformCount = Mathf.CeilToInt(rayInertiaSettings.detalization) + 2;
    }
    else
    {
        transformCount = Mathf.CeilToInt(Vector3.Distance(start.position,end.position)/
rayInertiaSettings.detalization) + 2;
    }
    rinfo.shape = new Transform[transformCount];
    destrFlags = new bool[transformCount];
    rinfo.shape[0] = start;
    rinfo.shape[transformCount-1] = end;
    for (int i = 1; i < transformCount-1; i++)
    {
        tmpobj = new GameObject("rayInertiaPoint");
        tmpobj.transform.position = Vector3.Lerp(start.position,end.position,(float)i/(tra
nsformCount-1));
        tmpobj.transform.parent = globalSpaceTransform;
        rinfo.shape[i] = tmpobj.transform;
    }
    break;
}

for(int i = 0; i <= destrFlags.Length-1; i++)
    destrFlags[i] = true;

rinfo.arc.shapeTransforms = rinfo.shape;
rinfo.arc.transformsDestructionFlags = destrFlags;
rays.Add(rinfo);
}

// Update is called once per frame
void LateUpdate ()
{

```

```

RaycastHit hit = new RaycastHit();
List<RayInfo> destrArr = new List<RayInfo>();
foreach (RayInfo rinfo in rays)
{
    if (rinfo.arc == null)
    {
        destrArr.Add(rinfo);
    }
    else
    {
        Vector3 endPos = Vector3.zero;
        if (startBehaviour == RayTransformBehaviour.follow_raycast)
        {
            if (Physics.Raycast(transform.position,-
transform.forward,out hit,Distance,layers.value))
            {
                rinfo.startObject = hit.transform.gameObject;
                rinfo.shape[0].position = hit.point;
            }
            else
            {
                rinfo.startObject = null;
                rinfo.shape[0].position = transform.position - transform.forward * Distance;
            }
        }
        if (endBehaviour == RayTransformBehaviour.follow_raycast)
        {
            if (Physics.Raycast(transform.position,transform.forward,out hit,Distance,layers.value))
            {
                rinfo.endObject = hit.transform.gameObject;
                endPos = hit.point;
            }
            else
            {
                rinfo.endObject = null;
                endPos = transform.position + transform.forward * Distance;
            }
        }
        else
        {
            endPos = rinfo.shape[rinfo.shape.Length-1].position;
        }
        switch (rayInertiaSettings.type)
        {
            case InertiaMethod.none:
                rinfo.shape[rinfo.shape.Length-1].position = endPos;
                break;
            case InertiaMethod.linespeed:
                int transformCount = rinfo.shape.Length;
                Vector3 targetPos;
                for (int i = 1; i < transformCount; i++)
                {
                    targetPos = Vector3.Lerp(rinfo.shape[0].position,endPos,(float)i/(transform
Count-1));

```

```

        rinfo.shape[i].position = Vector3.MoveTowards(rinfo.shape[i].position,target
tPos,
        rayInertiaSettings.speed * rayInertiaSettings.sn
apbackForceCurve.Evaluate(Vector3.Distance(rinfo.shape[i].position,targetPos) / rayInertiaS
ettings.maxSnapBackDistance) * Time.deltaTime);
    }
    break;
}

}
}
foreach(RayInfo rinfo in destrArr)
{
    rays.Remove(rinfo);
}
}
}
}
}

```

Appendix 7: Script used in measuring the hand movement and speed

(i) Capturing hand movements through wave points

```
using UnityEngine;
using System.Collections;
using System.Collections.Generic;
using System.IO;

[ExecuteInEditMode]
public class OMTSaveWaypointData_CSV_CS : MonoBehaviour {

    public OMT_CS omtComponent;           // OMT Component that data will be saved from
    public bool saveDataNOW;              // Set to true to save data. Will revert back to false automatically
    public enum DataSaveOptions { All, OMTSettings, WaypointData }
    public DataSaveOptions dataToSave;    // Specify what data is to be saved
    public string fileName = "Waypoint Data"; // File name to apply
    public string fileExtension = ".csv"; // File extension to apply
    string finalFileName;                 // The final filename that will be used when saving the file
    //public string filePath = "C:/Test";
    public string filePath = "C:/Test";   // The path to the folder in which the data will be saved
    public bool prefixFileNameWithDateAndTime; // If set to true the date and time will be added on to the file name
    public bool reverseWaypointGroupOrder; // If you would like the data to be in time order
    public bool stopIfFileExists;        // If file exists then the save function will abort saving
    string dataToWrite;                   // String to be saved to SaveWaypointData
    string omtSettingsToWrite;           // String to save the current settings of OMT

    void Update () {

        //If saveDataNow true start saving
        if(saveDataNOW == true)
        {
            //Reset saveDataNow switch
            saveDataNOW = false;

            //Start saving waypoint data
            if(dataToSave == DataSaveOptions.All || dataToSave == DataSaveOptions.OMTSettings)
            {
```

```

        StartCoroutine(SaveOMTSettings());
    }

    if(dataToSave == DataSaveOptions.All || dataToSave == DataSaveOptions.Waypoint
Data)
    {
        StartCoroutine(SaveWaypointData(omtComponent.waypointGroups));
    }
}

public IEnumerator SaveOMTSettings () {

    omtSettingsToWrite = "trackingActive;" +
        "trackThis (Transform Name);" +
        "autoAssigntrackThis;" +
        "waypointPlottingModes (0=Groups 1=Continuous);" +
        "waypointsIDPrefix;" +
        "waypointIntervalModes (0=Distance 1=Seconds 2=Both);" +
        "waypointIntervalDistance;" +
        "waypointIntervalSeconds;" +
        "maxNumberOfwaypointsGroupPlottingModeRemoval (0=None 1=Activ
e 2=Extreme);" +
        "maxNumberOfwaypoints;" +
        "storeRotations;" +
        "storeTimeStamp;" +
        "showGizmos;" +
        "absoluteWaypoint;" +

        "absoluteWayPointOffset.x;" +
        "absoluteWayPointOffset.y;" +
        "absoluteWayPointOffset.z;" +

        "offsetWaypointPlottingMethod (0=Manual 1=Percentage 2=Actual);" +

        "offsetManualAmount.x;" +
        "offsetManualAmount.y;" +
        "offsetManualAmount.z;" +

        "offsetMinPosition.x;" +
        "offsetMinPosition.y;" +
        "offsetMinPosition.z;" +

        "offsetMaxPosition.x;" +
        "offsetMaxPosition.y;" +
        "offsetMaxPosition.z;" +

        "offsetWithThisObjectPosition;" +
        "mergeActiveWaypointGroup;" +
        "activeWaypointGroupMergeSpeed;" +
        "adjustMergingSpeedWithMergeRatePercentage;" +
        "activeMergeRatePercentage;" +
        "nonActiveWaypointMergeModes;" +
        "mergeNonActiveWaypointGroups;" +
        "nonActiveWaypointGroupMergeSpeed;" +

```

```

        "notes;" +
        "#\n";

//Enable tracking - Primes the tracker ready to do stuff.
omtSettingsToWrite += omtComponent.trackingActive + ";";

//Clear or add and object for the offset waypoint to match. In this case we clear it just to
provide an example of it's usage
if(omtComponent.trackThis == true)
{
    omtSettingsToWrite += omtComponent.trackThis.transform.name + ";";
} else {
    omtSettingsToWrite += "null;";
}

omtSettingsToWrite += omtComponent.autoAssigntrackThis + ";";

omtSettingsToWrite += (int)omtComponent.waypointPlottingModes + ";";

omtSettingsToWrite += omtComponent.waypointsIDPrefix + ";";

omtSettingsToWrite += (int)omtComponent.waypointIntervalModes + ";";

omtSettingsToWrite += omtComponent.waypointIntervalDistance.ToString("G") + ";";

omtSettingsToWrite += omtComponent.waypointIntervalSeconds.ToString("G") + ";";

omtSettingsToWrite += (int)omtComponent.maxNumberOfwaypointsGroupPlottingMo
deRemoval + ";";

omtSettingsToWrite += omtComponent.maxNumberOfwaypoints + ";";

omtSettingsToWrite += omtComponent.storeRotations + ";";

omtSettingsToWrite += omtComponent.storeTimeStamp + ";";

omtSettingsToWrite += omtComponent.showGizmos + ";";

omtSettingsToWrite += omtComponent.absoluteWaypoint + ";";

omtSettingsToWrite += omtComponent.absoluteWayPointOffset.x.ToString("G") + ";";
omtSettingsToWrite += omtComponent.absoluteWayPointOffset.y.ToString("G") + ";";
omtSettingsToWrite += omtComponent.absoluteWayPointOffset.z.ToString("G") + ";";

omtSettingsToWrite += (int)omtComponent.offsetWaypointPlottingMethod + ";";

omtSettingsToWrite += omtComponent.offsetManualAmount.x.ToString("G") + ";";
omtSettingsToWrite += omtComponent.offsetManualAmount.y.ToString("G") + ";";
omtSettingsToWrite += omtComponent.offsetManualAmount.z.ToString("G") + ";";

omtSettingsToWrite += omtComponent.offsetMinPosition.x.ToString("G") + ";";
omtSettingsToWrite += omtComponent.offsetMinPosition.y.ToString("G") + ";";
omtSettingsToWrite += omtComponent.offsetMinPosition.z.ToString("G") + ";";

```

```

omtSettingsToWrite += omtComponent.offsetMaxPosition.x.ToString("G") + ",";
omtSettingsToWrite += omtComponent.offsetMaxPosition.y.ToString("G") + ",";
omtSettingsToWrite += omtComponent.offsetMaxPosition.z.ToString("G") + ",";

if(omtComponent.offsetWithThisObjectPosition == true)
{
    omtSettingsToWrite += omtComponent.offsetWithThisObjectPosition.transform.nam
e + ",";
} else {
    omtSettingsToWrite += "null;";
}

omtSettingsToWrite += omtComponent.mergeActiveWaypointGroup + ",";

omtSettingsToWrite += omtComponent.activeWaypointGroupMergeSpeed.ToString("G
") + ",";

omtSettingsToWrite += omtComponent.adjustMergingSpeedWithMergeRatePercentage
+ ",";

omtSettingsToWrite += omtComponent.activeMergeRatePercentage.ToString("G") + ","
;

omtSettingsToWrite += (int)omtComponent.nonActiveWaypointMergeModes + ",";

omtSettingsToWrite += omtComponent.mergeNonActiveWaypointGroups + ",";

omtSettingsToWrite += omtComponent.nonActiveWaypointGroupMergeSpeed.ToStrin
g("G") + ",";

omtSettingsToWrite += omtComponent.notes + ",";

omtSettingsToWrite += "#\n\n\n\n";

yield return null;
}

// This function can also be called remotely
public IEnumerator SaveWaypointData (List<OMT_CS.WayPointsClass> waypointGroup
s) {

    //Reversing the group order means the waypoint data will be in true time order
    if(reverseWaypointGroupOrder)
    {
        waypointGroups.Reverse();
    }

    //Apply data and time information to the filename if selected
    if(prefixFileNameWithDateAndTime == true)
    {
        finalFileName = fileName + " - " + System.DateTime.Now.ToString("MM-dd-
yyyy - HH-mm-ss") + "." + fileExtension;
    } else {
        finalFileName = fileName + "." + fileExtension;
    }
}

```

```

}

//File exists check
if (stopIfFileExists == true && System.IO.File.Exists(filePath + "/" + finalFileName))
{
    //File exists so give warning and break out of the function
    Debug.LogWarning("File Exists! - " + filePath + "/" + finalFileName);
    yield break;
}

//Start the dataToWrite container that will hold everything that will be written to file
dataToWrite = "Waypoint Group ID;" +
    "Waypoint Group Is Active;" +
    "Waypoint Total;" +
    "Waypoint Position (X);" +
    "Waypoint Position (Y);" +
    "Waypoint Position (Z);" +
    "Waypoint Rotation (X);" +
    "Waypoint Rotation (Y);" +
    "Waypoint Rotation (Z);" +
    "Waypoint Rotation (W);" +
    "Waypoint Scale (X);" +
    "Waypoint Scale (Y);" +
    "Waypoint Scale (Z);" +
    "Waypoint Time Stamp (Seconds)";

//Iterate through the waypointGroups List
for(int i = 0; i < waypointGroups.Count; i++)
{
    //Mark end of group with * - This is used as a marker for the importing data back into
    //Unity - It's also usefull in CSV files
    dataToWrite += "*";

    //Iterate through the array and add to the dataToWrite container
    for(int w = 0; w < waypointGroups[i].waypointTotal; w++)
    {
        dataToWrite += "\n" +
            waypointGroups[i].id + ";" +
            waypointGroups[i].activeWaypointGroup.ToString() + ";" +
            waypointGroups[i].waypointTotal.ToString("G") + ";" +

            waypointGroups[i].waypointPosition[w].x.ToString("G") + ";" +
            waypointGroups[i].waypointPosition[w].y.ToString("G") + ";" +
            waypointGroups[i].waypointPosition[w].z.ToString("G") + ";" +

            waypointGroups[i].waypointRotation[w].x.ToString("G") + ";" +
            waypointGroups[i].waypointRotation[w].y.ToString("G") + ";" +
            waypointGroups[i].waypointRotation[w].z.ToString("G") + ";" +
            waypointGroups[i].waypointRotation[w].w.ToString("G") + ";" +

            waypointGroups[i].waypointScale[w].x.ToString("G") + ";" +
            waypointGroups[i].waypointScale[w].y.ToString("G") + ";" +
            waypointGroups[i].waypointScale[w].z.ToString("G") + ";" +

            waypointGroups[i].waypointTimeStamp[w].ToString("G") + ";";
    }
}

```

```
    }  
  }  
  
  //Save the dataToWrite to file  
  File.WriteAllText(filePath + "/" + finalFileName, omtSettingsToWrite + dataToWrite);  
  
  //Output location that the file was saved at  
  Debug.Log("Your file was saved here: " + filePath + "/" + finalFileName);  
  
  yield return null;  
  }  
}
```

(ii) Computing the hand speed from the captured wave points

```
using UnityEngine;
using System.Collections;
using System.Collections.Generic;
using System.IO;
namespace vijaytest{
public class TimeFactor : MonoBehaviour
{
    private int _lastCount=0;
    private bool _enableFast;
    private bool _enableSlow;
    private bool _enableKeepGoing;

    //Warning-Texture
    public Texture2D Fast;
    public Texture2D Right;
    public Texture2D Slow;

    //Feedback text
    // public Camera cameraSeeningNozle;
    // public Vector3 nozelPosition;
    // public Transform nozelTransformHolder;
    // public Rect warningTextBox;
    // private string warningTextForSlow = "Hand Speed is Slow";
    // private string warningTextForFast = "Hand Speed is Fast";

    //Welding sounds
    public AudioSource WeldingSoundSource;
    public AudioClip WeldingSoundRightSpeed;
    public AudioClip WeldingSoundSlowSpeed;
    public AudioClip weldingSoundFastSpeed;

    //Going wrong count
    public int goingWrongCount = 0;

    //Continue-Button
    public Rect main2ResultBox;
    private string main2ResultString = "Done";

    //BRK storing variable and file location
    private string filePath = "C:/Users/venkatesh/Documents/Vijay_programFiles/BRK/BRKFile.txt";

    //WelBead Count Variable
    private int _weldBeadCount = 0;

    //Bolean for Weldbead
    public bool instanceForWeldBead1;
    private bool _enableCountWeldBead1;
    private int _countForBead1;
    public bool instanceForWeldBead2;
```

```
private bool _enableCountWeldBead2;
private int _countForBead2;
public bool instanceForWeldBead3;
private bool _enableCountWeldBead3;
private int _countForBead3;
public bool instanceForWeldBead4;
private bool _enableCountWeldBead4;
private int _countForBead4;
public bool instanceForWeldBead5;
private bool _enableCountWeldBead5;
private int _countForBead5;
public bool instanceForWeldBead6;
private bool _enableCountWeldBead6;
private int _countForBead6;
public bool instanceForWeldBead7;
private bool _enableCountWeldBead7;
private int _countForBead7;
public bool instanceForWeldBead8;
private bool _enableCountWeldBead8;
private int _countForBead8;
public bool instanceForWeldBead9;
private bool _enableCountWeldBead9;
private int _countForBead9;
public bool instanceForWeldBead10;
private bool _enableCountWeldBead10;
private int _countForBead10;
public bool instanceForWeldBead11;
private bool _enableCountWeldBead11;
public bool instanceForWeldBead12;
private bool _enableCountWeldBead12;
public bool instanceForWeldBead13;
private bool _enableCountWeldBead13;
public bool instanceForWeldBead14;
private bool _enableCountWeldBead14;
public bool instanceForWeldBead15;
private bool _enableCountWeldBead15;
public bool instanceForWeldBead16;
private bool _enableCountWeldBead16;
public bool instanceForWeldBead17;
private bool _enableCountWeldBead17;
public bool instanceForWeldBead18;
private bool _enableCountWeldBead18;
public bool instanceForWeldBead19;
private bool _enableCountWeldBead19;
public bool instanceForWeldBead20;
private bool _enableCountWeldBead20;
public bool instanceForWeldBead21;
private bool _enableCountWeldBead21;
public bool instanceForWeldBead22;
private bool _enableCountWeldBead22;
public bool instanceForWeldBead23;
private bool _enableCountWeldBead23;
public bool instanceForWeldBead24;
private bool _enableCountWeldBead24;
public bool instanceForWeldBead25;
```

```
private bool _enableCountWeldBead25;
public bool instanceForWeldBead26;
private bool _enableCountWeldBead26;
public bool instanceForWeldBead27;
private bool _enableCountWeldBead27;
public bool instanceForWeldBead28;
private bool _enableCountWeldBead28;
public bool instanceForWeldBead29;
private bool _enableCountWeldBead29;
public bool instanceForWeldBead30;
private bool _enableCountWeldBead30;
public bool instanceForWeldBead31;
private bool _enableCountWeldBead31;
public bool instanceForWeldBead32;
private bool _enableCountWeldBead32;
public bool instanceForWeldBead33;
private bool _enableCountWeldBead33;
public bool instanceForWeldBead34;
private bool _enableCountWeldBead34;
public bool instanceForWeldBead35;
private bool _enableCountWeldBead35;
public bool instanceForWeldBead36;
private bool _enableCountWeldBead36;
public bool instanceForWeldBead37;
private bool _enableCountWeldBead37;
public bool instanceForWeldBead38;
private bool _enableCountWeldBead38;
public bool instanceForWeldBead39;
private bool _enableCountWeldBead39;
public bool instanceForWeldBead40;
private bool _enableCountWeldBead40;
public bool instanceForWeldBead41;
private bool _enableCountWeldBead41;
public bool instanceForWeldBead42;
private bool _enableCountWeldBead42;
public bool instanceForWeldBead43;
private bool _enableCountWeldBead43;
public bool instanceForWeldBead44;
private bool _enableCountWeldBead44;
public bool instanceForWeldBead45;
private bool _enableCountWeldBead45;
public bool instanceForWeldBead46;
private bool _enableCountWeldBead46;
public bool instanceForWeldBead47;
private bool _enableCountWeldBead47;
public bool instanceForWeldBead48;
private bool _enableCountWeldBead48;
public bool instanceForWeldBead49;
private bool _enableCountWeldBead49;
public bool instanceForWeldBead50;
private bool _enableCountWeldBead50;
public bool instanceForWeldBead51;
public bool instanceForWeldBead52;
public bool instanceForWeldBead53;
public bool instanceForWeldBead54;
```

```

public bool instanceForWeldBead55;
public bool instanceForWeldBead56;
public bool instanceForWeldBead57;
public bool instanceForWeldBead58;
public bool instanceForWeldBead59;
public bool instanceForWeldBead60;

//Total WeldBead Count
private int _totalWeldBeadCount = 0;

//To be deleted
public int weldBeadCount = 0;

void Start(){

    //Initiates the feedback bollean
    _enableFast = false;
    _enableSlow = false;
    _enableKeepGoing = false;
    //Intiating the sound
    WeldingSoundSource = gameObject.GetComponentInChildren<AudioSource>();
}

void OnGUI(){

    if(_enableFast){
        GUI.DrawTexture(new Rect(10,10,60,60), Fast);
        WeldingSoundSource.clip = weldingSoundFastSpeed; // sound relavent to the speed
        WeldingSoundSource.Play ();

    }

    if(_enableSlow){

        GUI.DrawTexture(new Rect(10,10,60,60), Slow);
//        WeldingSoundSource.clip = WeldingSoundSlowSpeed; // sound relavent to the speed
//        WeldingSoundSource.Play ();

    }

    if(_enableKeepGoing){
//GUI.Label(new Rect(10,10,100,100), "You are on the right speed");
        GUI.DrawTexture(new Rect(10,10,60,60), Right);
        WeldingSoundSource.clip = WeldingSoundRightSpeed; // sound relavent to the speed
        WeldingSoundSource.Play ();
    }

    if(GUI.Button(main2ResultBox,main2ResultString)){

        WriteBRKFile(filePath);
    }
}

```

```

    Debug.Log(weldBeadCount);
    CalculatingAllTheWeldBead ();
    Debug.Log ("Total:"+_totalWeldBeadCount);

    Application.LoadLevel ("HitItWithVice");

}

}

public void speedMeasure(){

    OMT_CS omtcs = GameObject.Find ("OMT").GetComponent<OMT_CS> ();

    //omtcs.storeTimeStamp = true;
    if (omtcs.trackingActive) {

        //Stack<float> timeF = new Stack<float> ();
        float activeWpgIndex = omtcs.activeWaypointGroupIndexNumber; //Taking t
he active Index number of each active wavepoints.

        OMT_CS.WayPointsClass wpc = omtcs.waypointGroups [(int)activeWpgInde
x]; //Storing them in 'wpc' [] an array of wavepoints.
        if (wpc.waypointPosition.Count > _lastCount) {           // If this is the current
wavepoint count is greater than the last then - execute the following

            _lastCount = wpc.waypointPosition.Count;           //Making the current
wave point as the lastone
            Debug.Log (wpc.waypointPosition.Count + ", " + wpc.waypointTimeSta
mp.Count);
            if (wpc.waypointTimeStamp.Count > 1) {

                //for (int i = 0; i< wpc.waypointTimeStamp.Count; i++)
                //Debug.Log(i+": "+wpc.waypointTimeStamp[i]);
                //int lastIndex = wpc.waypointPosition.Count - 1;
                float currentTimestamp = wpc.waypointTimeStamp [0];//Current tim
e of the wavepoint
                float lastTimestamp = wpc.waypointTimeStamp [1]; //Previous time
of the wavepoint

                //Debug.Log (currentTimestamp+", "+lastTimestamp);
                float _diff = currentTimestamp - lastTimestamp;
                Debug.Log ("DIFF IS " + _diff);
                if (_diff > 0.1f && _diff < 0.7f) {           //Right speed

                    _enableKeepGoing = true;
                    _enableFast = false;
                    _enableSlow = false;
                    Debug.Log ("Right speed");
                }

                if (_diff > 0.01f && _diff < 0.1f) {           //Too fast

                    goingWrongCount ++;
                    _enableFast = true;
                    _enableKeepGoing = false;

```

```

        _enableSlow = false;
        Debug.Log ("Too Fast");
    }

    if (_diff > 0.7f && _diff < 10.0f) { //Too slow

        goingWrongCount ++;
        _enableFast = false;
        _enableKeepGoing = false;
        _enableSlow = true;
        Debug.Log ("Too slow");
    }

    }

}

if(omtcs.trackingActive == false){

    _enableFast = false;
    _enableKeepGoing = false;
    _enableSlow = false;
    WeldingSoundSource.Stop ();
}

}

// void StopWeldingSoundClip1(){
//
//     WeldingSoundSource.clip = WeldingSoundClip1; // Stop sound
//     WeldingSoundSource.Stop ();
//
// }
//
// void StopWeldingSoundClip2(){
//
//     WeldingSoundSource.clip = WeldingSoundClip2; // Stop sound
//     WeldingSoundSource.Stop ();
//
// }

void WriteBRKFile(string filePath){

    StreamWriter sw = new StreamWriter (filePath);

    if(goingWrongCount >= 30){
        Debug.Log(goingWrongCount);
        sw.WriteLine ("True");
        sw.Flush();
    }
}

```

```

    sw.Close ();
}

if(goingWrongCount < 30){
    Debug.Log(goingWrongCount);
    sw.WriteLine ("False");
    sw.Flush();
    sw.Close();
}
}
}

void CountingTheWeldBead(){

    if(_enableCountWeldBead1 == true){
        if(instanceForWeldBead1 == true){

            _countForBead1 = 1;
            _enableCountWeldBead1 = false;
        }
    }

    if(_enableCountWeldBead2 == true){
        if(instanceForWeldBead2 == true){

            _countForBead2= 1;
            _enableCountWeldBead2 = false;
        }
    }

    if(_enableCountWeldBead3 == true){
        if(instanceForWeldBead3 == true){

            _countForBead3= 1;
            _enableCountWeldBead3 = false;
        }
    }

    if(_enableCountWeldBead4 == true){
        if(instanceForWeldBead4 == true){

            _countForBead4= 1;
            _enableCountWeldBead4 = false;
        }
    }

    if(_enableCountWeldBead5 == true){
        if(instanceForWeldBead5 == true){

            _countForBead5= 1;
            _enableCountWeldBead5 = false;
        }
    }

    if(_enableCountWeldBead6 == true){

```

```

    if(instanceForWeldBead6 == true){
        _countForBead6= 1;
        _enableCountWeldBead6 = false;
    }
}

if(_enableCountWeldBead7 == true){
    if(instanceForWeldBead7 == true){

        _countForBead7= 1;
        _enableCountWeldBead7 = false;
    }
}

if(_enableCountWeldBead8 == true){
    if(instanceForWeldBead8 == true){

        _countForBead8= 1;
        _enableCountWeldBead8 = false;
    }
}

if(_enableCountWeldBead9 == true){
    if(instanceForWeldBead9 == true){

        _countForBead9= 1;
        _enableCountWeldBead9 = false;
    }
}

if(_enableCountWeldBead10 == true){
    if(instanceForWeldBead10 == true){

        _countForBead10= 1;
        _enableCountWeldBead10 = false;
    }
}

if(_enableCountWeldBead11 == true){
    if(instanceForWeldBead11 == true){

        _weldBeadCount = +1;
        _enableCountWeldBead11 = false;
    }
}

if(_enableCountWeldBead12 == true){
    if(instanceForWeldBead12 == true){

        _weldBeadCount = +1;
        _enableCountWeldBead12 = false;
    }
}

```

```

if(_enableCountWeldBead13 == true){
    if(instanceForWeldBead13 == true){

        _weldBeadCount = +1;
        _enableCountWeldBead13 = false;
    }
}

if(_enableCountWeldBead14 == true){
    if(instanceForWeldBead14 == true){

        _weldBeadCount = +1;
        _enableCountWeldBead14 = false;
    }
}

if(_enableCountWeldBead15 == true){
    if(instanceForWeldBead15 == true){

        _weldBeadCount = +1;
        _enableCountWeldBead15 = false;
    }
}

if(_enableCountWeldBead16 == true){
    if(instanceForWeldBead16 == true){

        _weldBeadCount = +1;
        _enableCountWeldBead16 = false;
    }
}

if(_enableCountWeldBead17 == true){
    if(instanceForWeldBead17 == true){

        _weldBeadCount = +1;
        _enableCountWeldBead17 = false;
    }
}

if(_enableCountWeldBead18 == true){
    if(instanceForWeldBead18 == true){

        _weldBeadCount = +1;
        _enableCountWeldBead18 = false;
    }
}

if(_enableCountWeldBead19 == true){
    if(instanceForWeldBead19 == true){

        _weldBeadCount = +1;
        _enableCountWeldBead19 = false;
    }
}

```

```

if(_enableCountWeldBead20 == true){
    if(instanceForWeldBead20 == true){

        _weldBeadCount = +1;
        _enableCountWeldBead20 = false;
    }
}

if(_enableCountWeldBead21 == true){
    if(instanceForWeldBead21 == true){

        _weldBeadCount = +1;
        _enableCountWeldBead21 = false;
    }
}

if(_enableCountWeldBead22 == true){
    if(instanceForWeldBead22 == true){

        _weldBeadCount = +1;
        _enableCountWeldBead22 = false;
    }
}

if(_enableCountWeldBead23 == true){
    if(instanceForWeldBead23 == true){

        _weldBeadCount = +1;
        _enableCountWeldBead23 = false;
    }
}

if(_enableCountWeldBead24 == true){
    if(instanceForWeldBead24 == true){

        _weldBeadCount = +1;
        _enableCountWeldBead24 = false;
    }
}

if(_enableCountWeldBead25 == true){
    if(instanceForWeldBead25 == true){

        _weldBeadCount = +1;
        _enableCountWeldBead25 = false;
    }
}

if(_enableCountWeldBead26 == true){
    if(instanceForWeldBead26 == true){

        _weldBeadCount = +1;
        _enableCountWeldBead26 = false;
    }
}

```

```

}

if(_enableCountWeldBead27 == true){
    if(instanceForWeldBead27 == true){

        _weldBeadCount = +1;
        _enableCountWeldBead27 = false;
    }
}

if(_enableCountWeldBead28 == true){
    if(instanceForWeldBead28 == true){

        _weldBeadCount = +1;
        _enableCountWeldBead28 = false;
    }
}

if(_enableCountWeldBead29 == true){
    if(instanceForWeldBead29 == true){

        _weldBeadCount = +1;
        _enableCountWeldBead29 = false;
    }
}

if(_enableCountWeldBead30 == true){
    if(instanceForWeldBead30 == true){

        _weldBeadCount = +1;
        _enableCountWeldBead30 = false;
    }
}

if(_enableCountWeldBead31 == true){
    if(instanceForWeldBead31 == true){

        _weldBeadCount = +1;
        _enableCountWeldBead31 = false;
    }
}

if(_enableCountWeldBead32 == true){
    if(instanceForWeldBead32 == true){

        _weldBeadCount = +1;
        _enableCountWeldBead32 = false;
    }
}

if(_enableCountWeldBead33 == true){
    if(instanceForWeldBead33 == true){

        _weldBeadCount = +1;
        _enableCountWeldBead33 = false;
    }
}

```

```

    }
}

if(_enableCountWeldBead34 == true){
    if(instanceForWeldBead34 == true){

        _weldBeadCount = +1;
        _enableCountWeldBead34 = false;
    }
}

if(_enableCountWeldBead35 == true){
    if(instanceForWeldBead35 == true){

        _weldBeadCount = +1;
        _enableCountWeldBead35 = false;
    }
}

if(_enableCountWeldBead36 == true){
    if(instanceForWeldBead36 == true){

        _weldBeadCount = +1;
        _enableCountWeldBead36 = false;
    }
}

if(_enableCountWeldBead37 == true){
    if(instanceForWeldBead37 == true){

        _weldBeadCount = +1;
        _enableCountWeldBead37 = false;
    }
}

if(_enableCountWeldBead38 == true){
    if(instanceForWeldBead38 == true){

        _weldBeadCount = +1;
        _enableCountWeldBead38 = false;
    }
}

if(_enableCountWeldBead39 == true){
    if(instanceForWeldBead39 == true){

        _weldBeadCount = +1;
        _enableCountWeldBead39 = false;
    }
}

if(_enableCountWeldBead40 == true){
    if(instanceForWeldBead40 == true){

        _weldBeadCount = +1;

```

```

        _enableCountWeldBead40 = false;
    }
}

if(_enableCountWeldBead41 == true){
    if(instanceForWeldBead41 == true){

        _weldBeadCount = +1;
        _enableCountWeldBead41 = false;
    }
}

if(_enableCountWeldBead42 == true){
    if(instanceForWeldBead42 == true){

        _weldBeadCount = +1;
        _enableCountWeldBead42 = false;
    }
}

if(_enableCountWeldBead43 == true){
    if(instanceForWeldBead43 == true){

        _weldBeadCount = +1;
        _enableCountWeldBead43 = false;
    }
}

if(_enableCountWeldBead44 == true){
    if(instanceForWeldBead44 == true){

        _weldBeadCount = +1;
        _enableCountWeldBead44 = false;
    }
}

if(_enableCountWeldBead45 == true){
    if(instanceForWeldBead45 == true){

        _weldBeadCount = +1;
        _enableCountWeldBead45 = false;
    }
}

if(_enableCountWeldBead46 == true){
    if(instanceForWeldBead46 == true){

        _weldBeadCount = +1;
        _enableCountWeldBead46 = false;
    }
}

if(_enableCountWeldBead47 == true){
    if(instanceForWeldBead47 == true){

```

```

        _weldBeadCount = +1;
        _enableCountWeldBead47 = false;
    }
}

if(_enableCountWeldBead48 == true){
    if(instanceForWeldBead48 == true){

        _weldBeadCount = +1;
        _enableCountWeldBead48 = false;
    }
}

if(_enableCountWeldBead49 == true){
    if(instanceForWeldBead49 == true){

        _weldBeadCount = +1;
        _enableCountWeldBead49 = false;
    }
}

if(_enableCountWeldBead50 == true){
    if(instanceForWeldBead50 == true){

        _weldBeadCount = +1;
        _enableCountWeldBead50 = false;
    }
}

}

void CalculatingAllTheWeldBead(){

    _totalWeldBeadCount += (_countForBead1 + _countForBead2 + _countForBead3 + _countForBead4 + _countForBead5 + _countForBead6 + _countForBead7 + _countForBead8 + _countForBead9 + _countForBead10);

}

void Update(){
    speedMeasure ();
    CountingTheWeldBead ();
}

}
}

```

Appendix 8: KBEd system demo CD

Folder 1: Video demonstration of the developed systems

Folder 2: Experts' validation recording and improved versions of different scenarios

Folder 3: All the images, video and audio recordings gathered during knowledge capturing phase.