A FRAMEWORK FOR KNOWLEDGE AS A SERVICE IN THE SUPPORT OF MOBILE INTERFACE AMBIENT LEARNING.

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THIS DISSERTATION IS SUBMITTED IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE AWARD OF MASTERS OF SCIENCE IN INFORMATION SYSTEMS MANAGEMENT IN THE FACULTY OF COMPUTING AND INFORMATION MANAGEMENT AT KCA UNIVERSITY.

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DECLARATION

I declare that this dissertation is my original work and has not been previously published or submitted elsewhere for award of a degree. I also declare that this contains no material written or published by other people except where due reference is made and author duly acknowledged.

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ABSTRACT

Knowledge as a Service (KaaS) has been a promising computing paradigm in the circles of cloud computing environments. In recent times there has been a growing need for access to knowledge on demand that is fully aligned with the cloud computing paradigm which derives from the idea that users will be able to access on- demand to any application from any location in the world. In KaaS, knowledge is considered an understanding of information based on its relevance on a problem area and is perceived as a precious resource essential in decision making. This research paper has developed a framework hinged on this technology that can be used to utilize knowledge from ambient learning systems in regard to sustainable development goals with a specific approach to the fourth goal targeting inclusive and equitable quality education through open education resources for lifelong learning. The main aim was to provide a platform for dissemination and exploitation of available knowledge that will help improve the quality of education on the ambient learning system. The research also involved a look at different ambient learning projects that aim to meet this SDG goal and helped come up with a KaaS model that can be implemented alongside an ambient learning system. This has helped find out how a collaborative effort can be approached in order to form a knowledge network that can allow access to heterogeneous sources of knowledge which can in turn be of benefit to the knowledge consumers i.e. ambient learning system developers.

Keywords: Cloud computing, Actionable Knowledge, TEL, and Multi-modal devices.

DEDICATION

I dedicate this dissertation to my parents and all my family members, your prayers and support have brought me to this moment and to my friends and workmates who have given me full support to engage this work.

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I am truly grateful to God the Almighty for His grace and this far He has brought me. Special thanks to my supervisor for the constructive advice, professional guidance and support offered during this research study. The knowledge imparted was not only practical but quite invaluable.

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LIST OF ABBREVIATIONS

KaaS – Knowledge as a Service.

IaaS- Infrastructure as a Service.

PaaS- Platform as a Service.

SaaS – Software as a Service.

DBMS- Database Management System.

KM- Knowledge Management.

ICT – Information and Communication Technology.

SDG – Sustainable Development Goals.

TEL – Technology Enhanced Learning.

LAN – Local Area Network.

WLAN – Wireless Local Area Network.

UMTS – Universal Mobile Telecommunication Service.

GPRS – General Packet Radio Service.

LMS – Learning Management System.

PLE – Personal Learning Environment.

MOOCs – Massive Open Online Courses.

RFID – Radio Frequency Identifier.

AKaaS- Actionable Knowledge as a Service

CKaaS- Collaborative Knowledge as a Service

COP- Community of Practice

MIAL – Mobile Interface Ambient Learning

FIAL – Fixed Interface Ambient Learning

HIAL – Hybrid Interface Ambient Learning

CHAPTER ONE

INTRODUCTION

1.1 Background of the Study

Knowledge as a Service (KaaS) has been hailed as the new paradigm for acquiring knowledge via the cloud as far as knowledge management is concerned (Bothun, G.2016). Old knowledge management technology cannot cut it in this new age of open data and big data environments. Traditional stand-alone platforms of client and server architecture are too rigid to keep pace with changes. Cloud computing solves this challenge efficiently and effectively (Armbrust, M. et al, 2012). Cloud computing by definition is a three layer model of distributed computing namely: the SaaS (Software as a Service) which provides the interface and top-level functionality, the Paas (Platform as a Service) which handles the processing necessary for applications to work and the IaaS (infrastructure as a Service) layer which handles low level services like database administration (Smith, 2009). KaaS on the other hand refers to a platform for providing the best knowledge, leveraging it from anywhere, anything and anyone in a distributed computing model (Ssekakubo et al, 2013). Ambient learning is a highly innovative integrated knowledge and learning management system which merges the e-learning provision with context-based knowledge management (Al-Busaidi, 2013). The approach of this research is to see how this knowledge can be harnessed through ICT to realize knowledge gaps in the realization of inclusive and equitable quality education while promoting lifelong learning which is the 4th goal in light of approach of vision 2030 and achievement of SDG goals. The 2030 agenda for sustainable development which was adopted by the United Nations General Assembly on 25 September 2015 seeks to leave no one behind as it aspires to transform the world we live in. KaaS is not a software package but a framework of a collection of lessons learned, best practices, proven workflows and case studies from developed countries that allow the diffusion of knowledge in an open cloud platform. With these SDGs, global development has entered a new stage with clearer focus on current challenges and key means to counter them. This invariably puts knowledge in the center of how development can be achieved. Moreover, a major factor in the huge proliferation of information which includes documents, data, government records, multimedia and tacit knowledge such as blogs can be made available in digital formats. With this in mind it is clear data is experiencing exponential growth with 90% of the world's stored data created in the last two years alone. The implications of this is that the potential for the availability of knowledge for development is huge with the only questions being who owns this knowledge and how it is shared. The idea therefore is to look at the vast data and see how a conceptual framework can be used to focus on inclusive and equitable education while leveraging ambient learning to help improve the livelihoods of the general population.

1.2 Problem Statement

Education is a major contributor to the sustainability transformation. Goal 4 from the list of SDG goals aims to ensure that all people have access to quality education and lifelong learning opportunities. This goal focuses on the acquisition of foundational and higher order skills at all stages of education and development with greater and more equitable access to quality education. Today, this goal is not fully realized given the revelation from the Kenya National Adult Literacy Survey which shows that only 61.5% of the adult and out-of-school youth above 15 years have attained minimum literacy level leaving 38.5% (7.8 million) adults illiterate (UNESCO, 2015). A majority of them are individuals from less fortunate backgrounds who are left out of a chance to attain quality education either due to lack of resources or reading material. With the prevalence of mobile phones where Kenya has a national coverage of about 77% of the population, the mobile industry covers over 31 million people and is therefore the ideal platform that can be leveraged to bridge this gap to help enhance accessibility of learning materials (Oteri O. et al 2015). Ambient learning is an example of technology enhanced learning approaches that aims at enhancing access to quality education (Mwendia et al., 2014, 2016). However initial observation indicates that little or no research has been conducted to evaluate its effectiveness to achieve this goal. As a result, there is lack of theoretical models that describes how knowledge regarding education quality can be extracted from ambient learning systems.

1.3 Purpose of Study/Objectives

Main Objective.

The main objective of the study is to discover how knowledge can be used to bridge gaps in the realization of inclusive and quality education through the leveraging of an ambient learning system and make available opportunities for lifelong learning.

Specific Objectives.

1. To review the current state of ambient learning.
2. To analyze and establish an appropriate Knowledge as a Service model for the ambient learning applications.
3. To evaluate the effectiveness of the established model with one of the reviewed technology enhanced learning cases.

1.4 Research Questions

The fundamental research questions of this study will focus on:

1. What is the general overview and current state of ambient learning?
2. Which are the existing KaaS Models that can be integrated in technology enhanced learning (TEL) approaches like ambient learning?
3. How can knowledge as a service be utilized to realize gaps in ambient learning systems?
4. How can the results from a conceptual framework be best implemented?

CHAPTER TWO

2.0 LITERATURE REVIEW

2.1 Introduction

Ambient learning refers to using modern means of ICTs through the effective integration of information technology and a curriculum to enhance and support teaching and learning activities (E. Lwoga, 2012). Ambient learning could also be defined as an area that combines mobile learning, situated learning and context awareness, where the learners wish to learn anytime, anywhere and anyhow (Kofod-Petersen et al, 2011).

Ambient learning has five main characteristics:

1. Learning is not restricted to a classroom as it takes place anytime and anywhere.
2. Learners take on the role of organizers whereas instructors serve as both the distributors of educational content and facilitators of the learning process.
3. Learning is a lifelong process and is therefore not solely linked to educational institutions.
4. Learning takes place in communities of learning or communities of practice where learners participate in formal and informal discussions.
5. Learning is informal and non-formal whereby it takes place at home, in the workplace and during leisure time thus not centered on teachers or institutions.

An ambient learning system will provide multi-modal, multiligual, personalised and context-sensitive access to learning material from anywhere. Multimodal broadband access allows the user to access content anytime anywhere anyhow through the broadband network access i.e. Local Area Network LAN, Wireless Local Area Network (WLAN), General Packet Radio Service (GPRS), Universal Mobile Telecommunications System (UMTS), Bluetooth , Satellite etc.

Multilingual access allows the learner to define the language in which he wishes to receive the content. Context management allows the delivery of ambient services in a personalised way by taking into account the learner's profile, role, interests, available device, preferences, network access and much more (Kolmel B., Rinshe, A. 2012).

The Mobile Africa 2015 study conducted by GeoPoll and World Wide Worx surveyed 3500 mobile phone users in five major markets namely South Africa, Nigeria, Kenya, Ghana and Uganda. The survey revealed that Internet browsing via phones stands at 40%, across these markets with 51% of respondents in Ghana and 47% in Nigeria with South Africa pulling in 40% and Kenya at 34% and Uganda at 29%. However South Africa leads in app downloads which was an indication of higher smartphone adoption, with 34% of phone users downloading apps from app stores which compared to 31% in Ghana, 28% in Nigeria, 19% in Kenya and 18% in Uganda.

The truth in the statement the cellphone is poised to become the PC of Africa, (Ford,M. 2009) is slowly but gradually becoming a reality.

By July 2013, there were 44 mobile learning products in Africa. South Africa and Kenya led the region with eight and five mobile learning products respectively. (Ambient Insight, 2013)

Mobile learning is now the most advanced learning technology in the world. The worldwide market for Mobile Learning products and services reached $8.4 billion in 2014. Projected revenues show the Mobile learning industry will triple if not double in countries that have embraced this mode of learning to $14.5 billion by 2019. (S. Adkins, 2015)

The growing adoption of mobile technologies accompanied by ubiquitous connectivity as well as the increasing pervasiveness of information technology are changing the conditions for lifelong learning.

In addition to this mobile learning has been found to have multiple benefits like:

- Ease of use - Since mobile owning learners know how to use their devices there is no training necessary when it comes to using mobile educational technology.
- Ease of access – Learners can access lessons and feedback from virtually anywhere.
- Instant feedback – Learners get access to instant feedback without having to rely on instructors.

On a global stage, Africa, Latin America and Asia are expected to have the highest growth rates in mobile learning. From a research done by Ambient insight team 15 of the 20 countries analyzed in Asia, 14 of the 15 countries analyzed in Latin America, 12 of the 14 countries analyzed in Africa, and 9 0f the 12 countries analyzed in the Middle East all have growth rates above an aggregate of 18.2%. In Africa, 11 countries have growth rates above 30% while 6 countries in the Middle East have growth rates above 50% as depicted in the graph in figure 2.1 below.

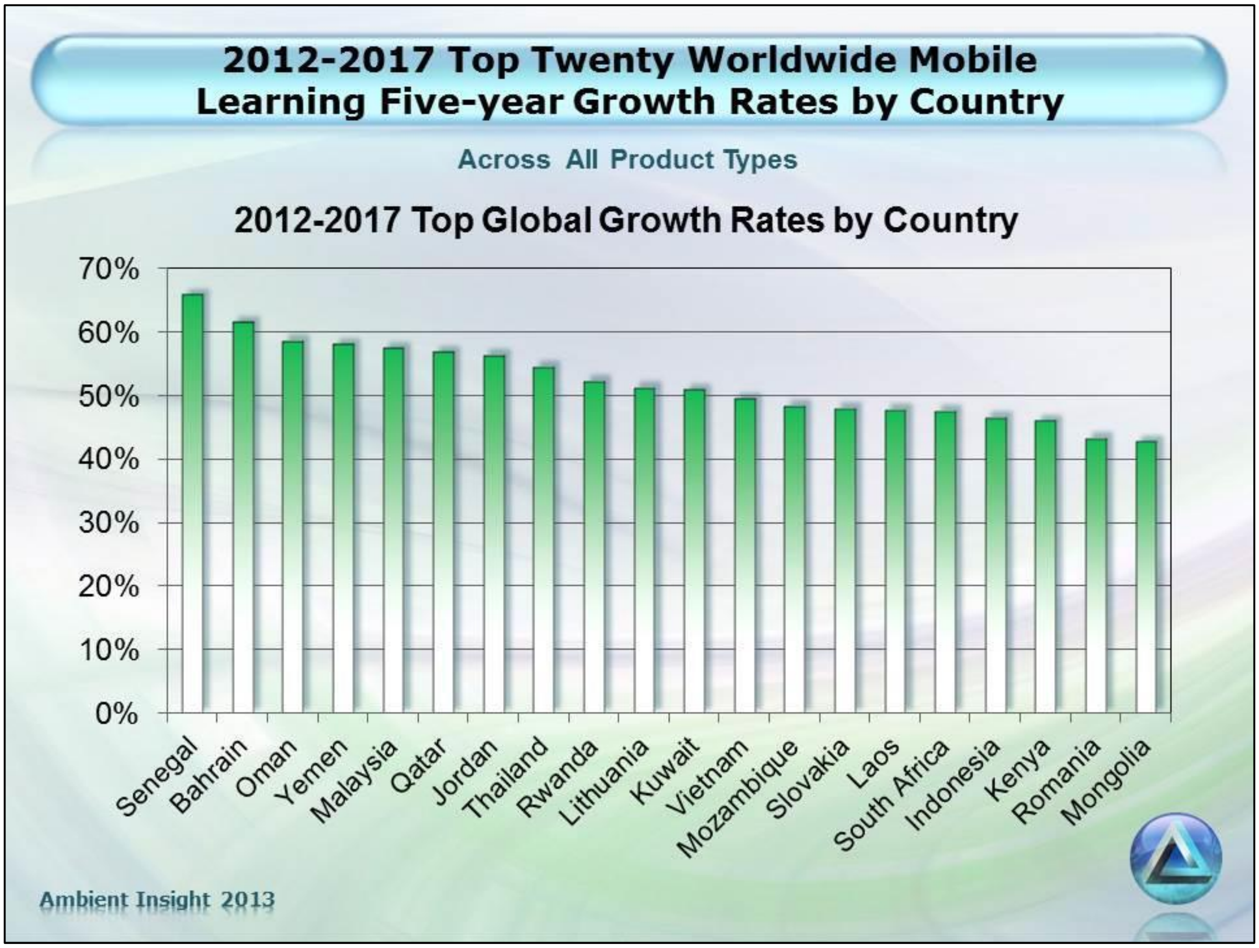


Figure 2. 1: Ambient Learning Overview 2012-2017

(Source: Ambient Insight)

The graph shows that six of the top twenty growth rates are in Asia, six in the Middle East and five are in Africa. It is therefore evident that mobile learning is quickly being embraced as an essential strategy to improve education in these dynamic economies.

2.2 State of Ambient Learning

Ambient learning which is viewed as the next generation of technology enhanced learning in mobile learning seeks to enable anytime, anywhere and anyhow access to customized and high quality E-learning material (Mwendia&Buchem, 2014). Ambient learning focuses on the mobility of the learner, the design of learning spaces, lifelong learning and informal learning. Mobile phones are the most preferred choice for an ambient learning platform for the simple reason that they are mostly available at almost every place and people move around with them most of the time. Ambient intelligence on the other hand is a type of intelligence that embeds intelligence to our environment thus making it sensitive to us (Sharma & Jain, 2013). It describes a world in which technology is both implicit and anticipatory (Olson et al., 2014). One of the technologies that make this possible are sensors and actuators which are also known as ambient intelligence applications (AmI). Sensors are used for interacting between the user and input devices while actuators are used for manipulating and controlling a device or equipment (Kim & Kim, 2013). Devices used in ambient environments will mainly have state-change sensors or actuators that can obtrusively observe the state change of a device or application thereby influencing how a user will interact with the environment. There are three categories of ambient learning as discussed by (Mwendia, 2013) which interact with learners in an ambient intelligence environment. These include:

1) **Mobile Interface Ambient Learning (MIAL)**

MIAL is where learners are restricted to accessing contextually relevant learning material sent by trainers through mobile devices only. This category is appropriate for contexts with high prevalence of mobile devices but low prevalence of location dependent devices. (Mwendia&Wagacha, 2013).

Examples of this include:

i. **Open Mobile Ambient Learning (OMAL) in Kenya. (Mwendia & Wagacha, 2013).**

The ambient learning approach is used to research supervision services. Learners use an intelligent mobile application installed on their smartphones to download relevant open educational resources (OER) hosted on cloud based repositories like Google drive and Dropbox. The learner logs in to the OMAL app and through the context manager checks the context database and figures the education level of the learner as well as preferences of learning material. The system also through use of an accelerometer determines if the user is on the move or not. If the learner is not moving, OMAL searches the beginners topics in case the learner is a beginner from the OER cloud and determines from data obtained from other stationary users that text format is the majority download format. Once the user starts moving OMAL brings up a screen on the user interface that prompts the learner to download the most popular format for learners on the move which is the mp3 file which can be listened to through earphones while walking. In case the learner gets into a vehicle or other means of transport the system using the accelerometer detects an accelerated change in location which brings up a prompt screen allowing to choose the preferred format or if none is selected the most popular format which is the mp4 format for beginners is downloaded and the learner will now watch a video instead. When the user is done with the introductory files, OMAL searches for a list of research groups for beginners from the OER cloud and the user is prompted to send a request to join one of them and interact with other online members.

Figure 2.2 shows the OMAL system and how the components are interconnected.

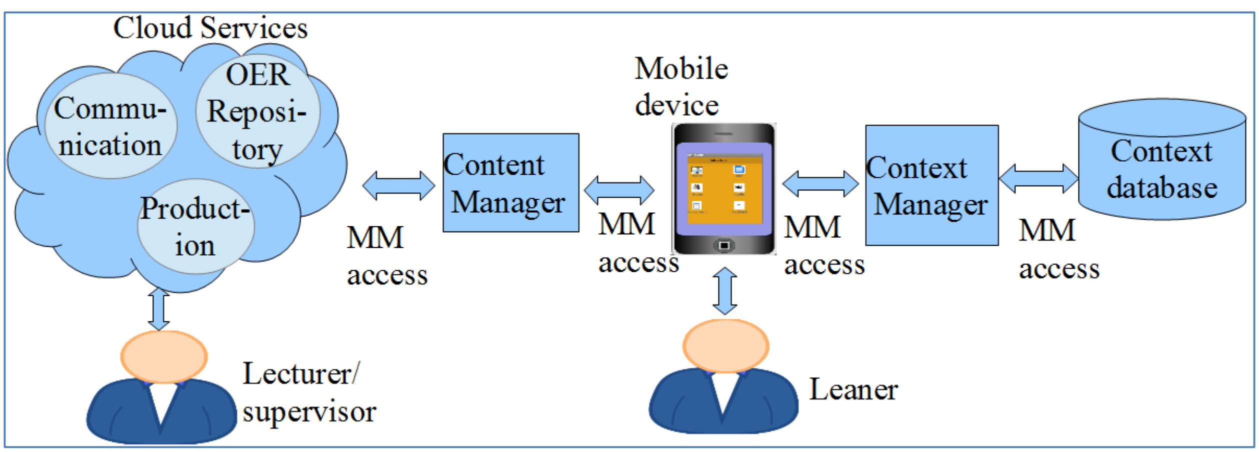


Figure 2. 2: OMAL System Architecture

Source: (Mwendia et al., 2014).

The focus of this study will be to improve this system by adding a KaaS component and to propose a model that will help manage and facilitate the knowledge in cloud computing using the techniques of KMS.

ii. The Australian National University Project (Beckmann, 2010)

This mobile learning project was implemented for Master of Applied Anthropology and Participatory Development students who were enrolled in distance learning and offered downloadable resources e.g., readings, audio, or video lectures and opportunities to interact with others in online discussion. Authoring tools were also utilized to help lecturers build this media rich content. This allowed students to download relevant content and learn at their preferred places or times.

iii. Clinical Training at Remote Sites Project in India. (Vyas et al., 2010)

This mobile learning project was implemented for students undergoing clinical training in remote secondary hospital sites in India. It was designed to enable students to access a knowledge repository known as the Tufts University Sciences Knowledgebase (TUSK) through their mobile phones and fulfill their learning needs using other mobile applications. TUSK entails a comprehensive suite of tools that enables the delivery of course content to students while serving as a curriculum and content repository, and management system for faculty and school administrators.

iv. Alfabeto Project in Latin America. (Kim, 2009).

The mobile learning project was designed for underserved migrant indigenous children in Latin America where it was used to develop their literacy due to the fact that they live far away from town centers thus formal education not easily accessible. The lesson displays alphabet letters and sample words starting with each letter, delivers a voice recording of the letters and words and provides short stories with sequenced animations show casing the portability and multimedia features of mobile technology that can be made readily available anywhere.

v. Mobile Assisted Language Learning Project (Chen and Li, 2010).

This project provides a function of context-awareness whereby individual learners discover and learn new English vocabulary by logging in to personalized context-aware ubiquitous learning system (PCULS). The system retrieves learners' personal portfolios, their English level while automatically sensing their location, and provides the appropriate vocabulary material from the database.

vi. Context-aware Dynamic learning environment for Multiple Objectives Project (Min Chen et al., 2014) (CDLEMO)

Mobile-centric ambient intelligence technologies feature prominently in this project as they support the mobile learning platform by allowing access to dynamically organized resources based on the learners' current situation and location. The context aware system uses the learner's context to deliver corresponding digital learning resources that include pictures and information of flowers in the learner's immediate neighborhood.

vii. Mobilogue Project in Germany (Giezma et al., 2013).

This is a location-aware mobile learning that enables educators and learners to author and deploy learning support through the use of mobile devices. The aim of the project is to enhance the simplicity and flexibility of content deployment and authoring.

viii. Nursery Plants Classifier Project in China. (2006).

The project involves using 2D dimension barcode that is captured by a mobile phone to classify nursery plants on learners' phones through a translated web link that appears on the learner's screen. The learner can however only access information about the nursery plants that are tagged with the barcodes which means learning is dependent on the location and barcodes.

2) Fixed Interface Ambient Learning (FIAL)

FIAL is a type of ambient learning that relies on location dependent devices that are embedded to physical environments surrounding learners (Mwendia&Wagacha, 2013). Learning therefore is informal and lifelong and can take place outside a dedicated learning environment like in a smart classroom where remote learners can get interact with lecturers via cameras, microphones, media boards and students' board over the internet. FIAL is highly dependent on good infrastructure especially electricity and internet. Examples of this kind of ambient learning include:

i. German University in Cairo iclass

This project is an ambient intelligence environment test bed. The iclass looks like any other classroom containing normal features like desks, chairs and a white smart board. It is defined as a multiuser space that can be used through different teaching activities (Mowafet, S. et al, 2009). The unusual features of the iclass include a standard multimedia PC that combines a projector with a flat-screen monitor and another digital monitor which is placed outside the class to inform students with the starting and ending time, name of lecture topic and any other announcements regarding the lecture. The iclass is able to take the automatic attendance of students through the use of a Radio Frequency Identification (RFID) reader which can read the IDs of the students without having to swipe them The RFID also detects when the lecturer enters the class and checks the automatic timetable to upload the slides and lecture material for the particular lecture. An empty notepad is also opened on the smart board which the lecturer can use and edit during the lecture. The notepad file is saved together with lecture notes in the course intranet which can be accessed by students later at will. The iclass has various sensors and actuators which provide temperature and other internal control features like time of the day and date, internal and external light level sensor, internal and external temperature sensor, humidity sensor and presence sensor. Any networked computer that can run a standard Java process can access whereby the multimedia PC can act as an interface controlling the devices in the classroom which may include wireless devices like mobile phones. . Fixed microphones are also embedded in this environment that allow for the room to recognize the speaker from a saved wave file that make the system aware of who is using the room which in turn loads the users preferred settings of the environment conditions that are detected by other embedded agents e.g. light level or temperature.

ii. Augmented School Desk in Greece (Leonidis et al,. 2012)

The augmented school desk is literally an additional piece of furniture that has been designed to fit typical school desk standard dimensions while almost invisibly embedding itself to all devices required for the ambient intelligence environment. It integrates on its front side a camera that captures images of the conventional desk and a smart pen while behind the screen two cameras implement a vision-based back projection multi-touch that ensures gesture interaction quality under variable lighting conditions. This allows for ambient interaction as well as digital augmentation of physical paper by supporting paper-based learning materials and the use of handwriting. The augmented school desk uses two middleware infrastructure technologies namely ClassMATE and PUPIL. ClassMATE monitors the ambient environment and makes context-aware decisions in order to assist the student in conducting learning activities, and the teacher with administrative activities. PUPIL on the other hand facilitates design, development and deployment of pervasive educational applications within the intelligent classroom.

Figure 2. 3: Augmented School Desk in Greece

Source: (Leonidis et al., 2012)

iii. SESIL system in Greece (Margetis et al,. 2012)

This project introduces an augmented reality environment that provides a seamless, contex-aware support to students by unobtrusive monitoring their natural reading and writing process. This environment does not require any special writing devices to monitor student gestures and handwriting as it is able to perceive interaction with actual books and pens through the cameras setup in the environment. The system enhances learning by naturally providing additional information related to current student's activity on interactive screens.

Figure 2. 4: SESIL system in Greece

Source: (Margetis et al., 2012)

iv. Smart Classroom in China (Shi et al., 2010)

The smart classroom project presents a key multimodal interface and context-awareness technology that merges speech, handwriting, gestures, location tracking, direct manipulation, large projected touch-sensitive displays and laser pointer tracking which aims to provide enhanced experience for both teachers and students. Video cameras, microphone arrays are installed to sense human gestures, motion and utterance.

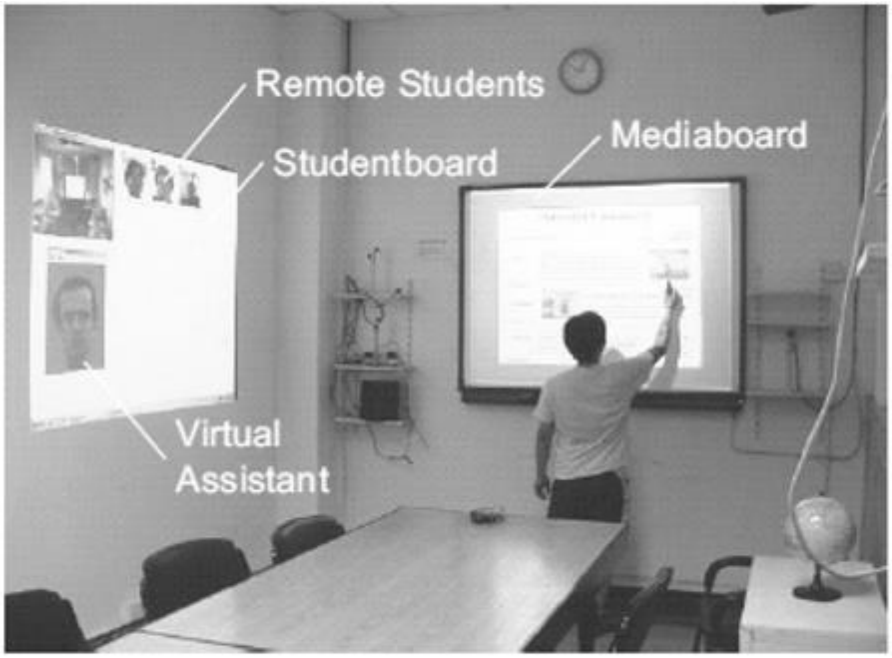


Figure 2. 5: Smart Classroom in China.

Source: (Shi et al., 2010)

3) Hybrid Interface Ambient Learning (HIAL)

This type of ambient learning is characterized by use of both location dependent devices and mobile devices. It also supports lifelong and informal pedagogy allowing learning to take place outside a dedicated learning environment (Mwendia&Wagacha 2013).

i. Stellenbosch University in South Africa

This is a high-tech teaching space that was launched to encourage social learning among students and stimulate brain functioning using new ways of teaching and presenting information. The teaching space is equipped with the latest audio and visual technology in the form of projection facilities, equipment for hearing-impaired students, a television screen, wireless internet, a touch screen presentation computer and tablets which students can use to participate in active learning exercises. Students entering the class interact with the faculty smart board which identifies the student's identification number, name, research interests, impairment if any, and education level. Contextualized content is then downloaded onto the student's tablet which comes with the course syllabus, lecturer contacts and information on how to access the study. An animated hand sign image is included for students with hearing impairment. This contextualized information can be accessed from anywhere once the student has registered for the course.

ii. Digital Lecture Hall (Hover et al., 2010).

The DLH project mainly aims at supporting lecturers in their presentation activities during lectures through adding functionalities such as extended annotation of lecture material and slide history with several projectors. The project also employs mobile devices such as smart phones, pen-based notebooks, talking assistant headset, PDAs and computers Lectures can also be recorded and shared so as to make them readily available for students who could not be physically available for the class.

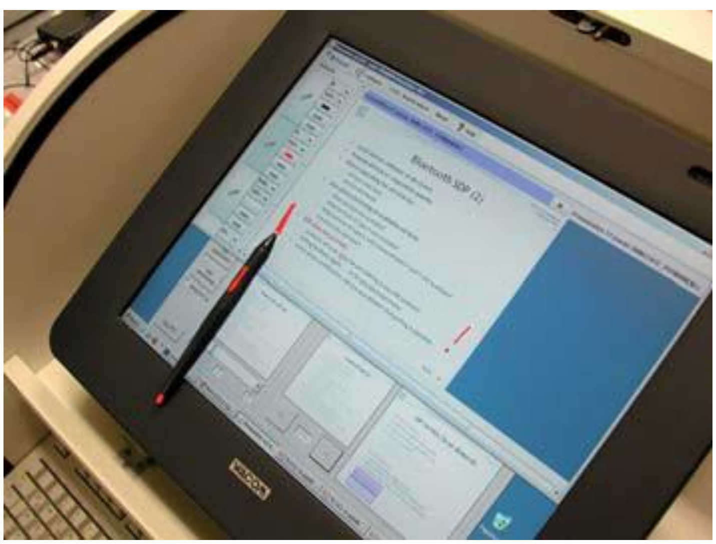


Figure 2. 6: Digital Lecture Hall

Source: (Hover et al., 2010).

iii. Smart Classroom(Shi et al., 2010)

This is the same smart classroom project I analyzed in the FIAL projects. It features in this category as well since it showed features of a HIAL in that apart from the media board which is used as the lecturer's blackboard, on which prepared electronic courseware and lectures' annotation are displayed, there is also a student board that is used for displaying the status and information of remote students, who are part of the class via the internet.

Conclusion

The above ambient learning systems can be enhanced and made more reliable with the use of a Knowledge as a Service component to enable the actors involved i.e the lecturers, learners or context providers to be able to enhance the learners' learning experience. The (KaaS) would be best implemented through a Knowledge Management System (KMS) in the cloud computing environment based on the knowledge life cycle. Managing knowledge requires focusing on the aspects of creating, storing, structuring, codifying, sharing, controlling, transferring, using and utilizing the knowledge (Sagsan, 2006).

2.3 Existing Knowledge as a Service Models

i. Actionable Knowledge as a Service model

The need for knowledge that is discoverable on demand is part of the knowledge discovery paradigms that greatly impacts the nature, structure and security parameters of data necessary to provide contextualized and real time analytics. Cloud computing paradigms are becoming increasingly popular due to decrease in terms of costs, efforts and resources to deploy solutions in line with knowledge consumers' needs. According to (Khoshnevis and Rabeifar, 2012) the deployment of knowledge management (KM) in cloud environments is to enable storage of knowledge in great sizes for learning and inference requirements for computational capacity.

Actionable knowledge as a service (AKaaS) is a knowledge management system deployed in the cloud computing environments that seeks to enable available knowledge assets to be gathered, and customized according to the knowledge consumer's context and needs. This brings about an evolution from traditional KM that is oriented towards a global knowledge delivery to a model that emphasizes a personalized knowledge acquisition by users. By seeking to ensure the actionability of this knowledge specific data-based inputs are required and preferably real time overview of user's interactions with the system in place. This will allow for systematic ways of handling the data such as knowledge analytics (K-analytics) techniques i.e data mining in order to identify the knowledge consumer's needs in terms of knowledge which does not only depend on maintenance and case resolutions but also on the ability to gain useful knowledge and make effective and informed decisions in their context of use. Figure 2.7 below shows the AKAAS model.

Figure 2. 7: AKaaS model

Source: (Depeige&Doyecourt, 2015).

More advanced methods to analyze data such as predictive modelling can be applied through machine learning and the results interpreted and evaluated as to whether the knowledge gained has the potential to satisfy the end user's needs. Decision support in the cloud has been found to be feasible and helps in better decision making (Dixon et al, 2013). This model can be applied in an ambient learning system like OMAL which at the moment does not give this actionable knowledge aspect on data gathered and analyzed from users since its evident that cloud infrastructure indeed delivers the potential of having a vast amount of devices that are interconnected and this provides efficiency in that knowledge is accessible from any kind of device or platform used by the knowledge consumer, in any location and at any time which means that information is not processed on the client side but on the cloud side.

ii. Collaborative Knowledge as a Service model

The Collaborative Knowledge as a Service (CKaaS) model is a generic architecture that integrates disparate cloud knowledge through collaboration among distributed KaaS entities with the goal of satisfying consumer knowledge needs (Krolinger et al., 2015). The CKaaS is involved in storing large amounts of data from diverse sources, supporting interoperability and integration and offering a scalable reconfigurable cloud solution for efficient resource consumption. Storage of large amounts of heterogenous data is achieved by using relational databases and NoSQL data stores in the cloud environment.As the word suggests, NoSQL is a database management system (DBMS) that explicitly avoids SQL as its querying language although it is still based on a relational model (Zollman J., 2012). In contrast to relational DBMS most NoSQL databases are designed to scale well in the horizontal direction and not rely on readily available hardware (Strauch C., 2009). This falls in line with the two major requirements of data stores in cloud computing environments which are scalability and low administration overhead. This particular CKaaS is also not applied to an ambient learning system but rather a disaster management domain which enhances the knowledge management solutions given that disaster related data is massive, heterogeneous and complex. The main objective of KaaS is to generate knowledge from heterogeneous data located in a cloud environment and make it available as a knowledge service (Krolinger et al., 2015). The CKaaS in this context facilitates better decision making by integrating distributed disaster related information and providing knowledge as a service from the data. In the ambient learning system a collaborative feature would come in handy by integrating a NoSQL approach given the characteristic horizontal scalability and excellent performance with simple read and write operations. The CKaaS uses a distributed cloud architecture in which several cloud providers contain a complementary domain-dependent knowledge. The main advantages of this being:

- Interconnecting of several KaaS entities helps facilitate collaboration and organize knowledge sources.
- KaaS services can be efficiently managed by the distributed cloud architecture to provide quality of service from both inter and intra cloud environment.

Actors involved in this model include the cloud consumer, the cloud broker and the cloud provider. The figure 2.8 below shows the CKaaS system model.

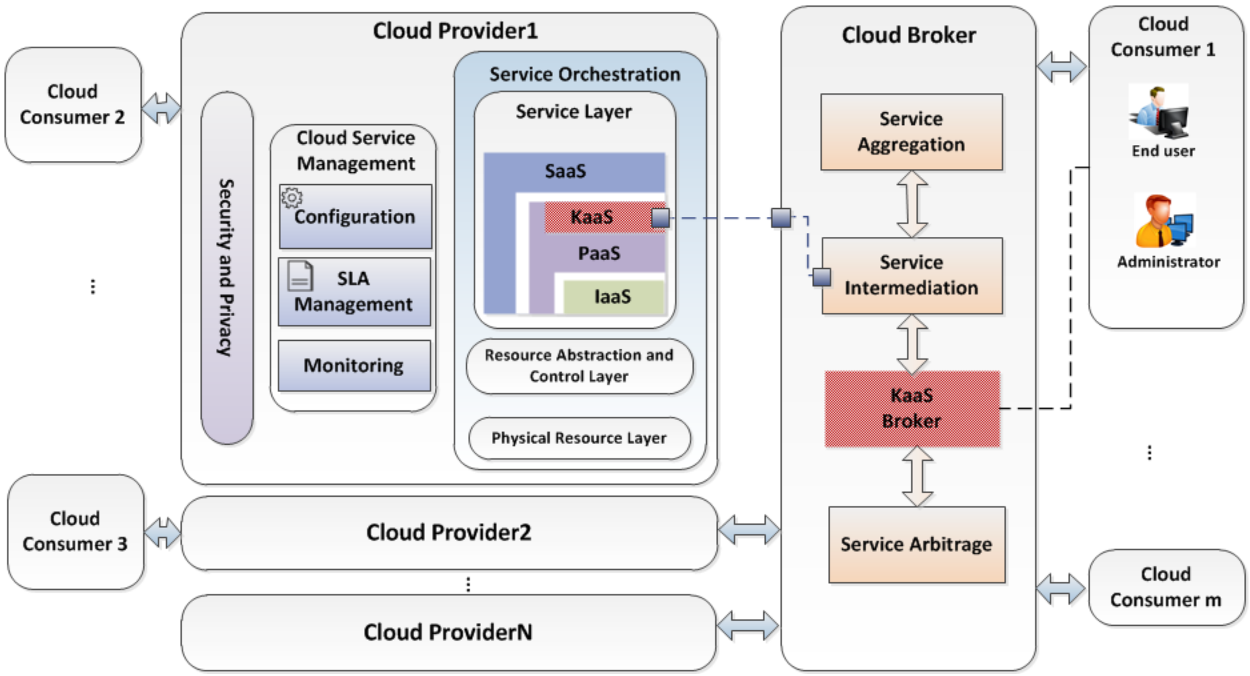


Figure 2. 8: CKaaS system architecture

Source: (Krolinger et al., 2015).

From the model above the cloud consumer is any entity that consumes the services offered by the KaaS cloud provider under specific service level agreements (SLA). The cloud broker is a mediator between the cloud consumers and the KaaS services provided and provides efficient access to the appropriate KaaS knowledge providers. The KaaS broker on the other hand provides a knowledge based cache that is built from previous requests or responses to improve the cloud consumer's experience. The knowledge gathered in this cache allows the KaaS broker to refer to it and know whether it can directly respond to the cloud consumer's request without forwarding requests to the KaaS cloud providers. The cloud broker is also engaged three fundamental services i.e service intermediation which facilitates communication between cloud consumers and KaaS cloud providers, service aggregation which combines multiple responses from the KaaS cloud providers into a final integrated response and lastly the service arbitrage which handles the learning strategies to help the KaaS broker select the best KaaS cloud provider for future requests.

Conclusion

Ambient systems sense their environment providing a lot of context related data that is gathered and provided to other application systems. This data could be used to support and tailor knowledge and learning processes directly to the individual's context e.g. place and time (Bick &Pawlowski, 2009).

When learning individually learning resources are put into relation through a personal knowledge graph. Manual construction and maintenance of a personal knowledge graph is limited by the human cognitive and mental limits which means these knowledge graphs exist only in implicit form therefore sharing this knowledge with others would mean individuals have to externalize their personal knowledge graphs. Through a cloud based architecture, computer aided construction, and maintenance of this knowledge using suitable tools an ambient learning system gains the needed support that entails acquiring, aggregating and processing data from learners so as to use this knowledge for a truly collaborative knowledge environment that improves individual user interactions and learning experience. The tools in question in this case are data mining tools and artificial intelligence languages like Prolog that can work together to give the expected results. Data mining is concerned with discovering new meaningful information so that decision makers can learn as much as they can from valuable data sets (Gargano & Raggad, 1999). It is a valuable tool for extending human knowledge. As an artificial intelligence programming language Prolog which is short for programming logic, is essentially a statement of a problem in formal logic. Prolog makes use of an interpreter that follows facts or rules stored in a knowledge base and answers queries through a sophisticated search. For the purposes of this study the data mining platform to be used will be Weka. Weka is a machine learning workbench that provides an extensive collection of machine learning algorithms (e.g classification and association rules) and data pre-processing methods complemented by graphical user interfaces for data exploration and the experimental comparison of different machine learning techniques on the same data set. Classification rule mining is a data mining technique used to predict group membership for data instances (Phyu, T. 2009). Weka uses the J48 algorithm to classify data and come up with decision trees that help make predictions on new data. Decision trees are the most powerful approaches in knowledge discovery and data mining in that it allows for the use of bulky data in order to discover useful patterns which are easy to understand. Association rule mining on the other hand is also a data mining technique that aims to extract interesting correlations, frequent patterns, associations or casual structures among sets of items in data repositories (Kotsiantis & Kanellopoulos, 2006). For association rule learning, Weka uses the Apriori algorithm which is used to find frequent patterns given the number of transactions.

2.4 Conceptual Framework

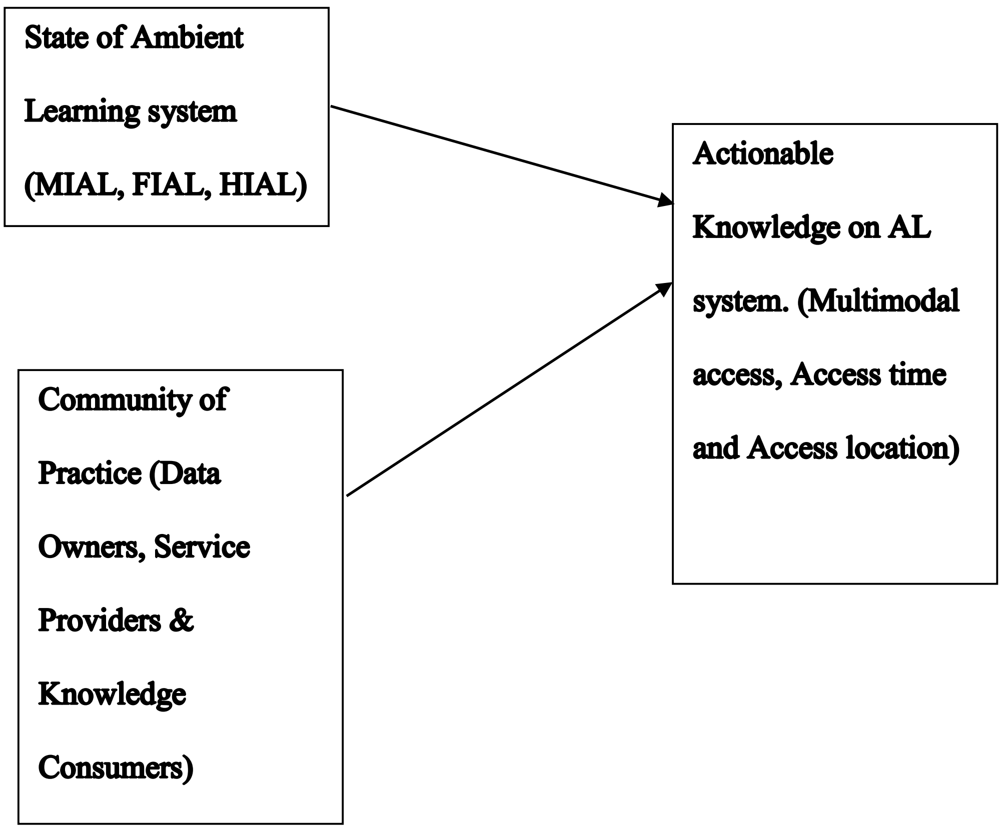


Figure 2. 9 : Conceptual Framework

2.5 Operationalization of Variables

For this project a cloud based knowledge sharing system will involve resources from learning objects, open educational resources and mobile education. Learning analytics which correlate to patterns of student activity with learning outcomes will be derived to support students to reach their potential and the delivery of personalized learning. The table below represents the operationalization of variables.

Variable	**Sub variable**	**Indicators**	**Values**
State of Ambient learning systems	MIAL	Mobile devices	-smart phone
		-M-AmI Sensors	- AmI app -Mobile RFID -mobile screen
		M-AmI Actuators	AmI app
		Multimodal Access	A mixture of content representation modes
	FIAL	Fixed Devices	Board,Desktop
		F-AmI Sensors	Fixed microphone , Fixed RFID Fixed screen
		F-AmI Actuators	AmI app

		Multimodal Access	A mixture of content representation modes
	HIAL	-Mobile & Fixed devices	smart phones, desktops, boards etc.
		Both M-AmI & I-AmI Sensors and Actuators	M-AmI app, Fixed RFID, Fixed. -Microphone -Mobile & Screens
		Multimodal Access	A mixture of content representation modes.
COP	Data Owners	Protects data Decides data usage	Yes/No
	Service providers	KAAS Experts and tools	- Knowledge engineer - Weka app - Prolog app
	Knowledge consumer	- Users that consult and Query knowledge	- Prolog users

Actionable Knowledge	Multimodal access Knowledge	Models for multimodal access	Decision trees rules, clusters for multimodal access
	Access time knowledge	Models for Access times	Decision trees rules, clusters for access times
	Access location Knowledge	Models for Access place	Decision trees association rules, clusters for access place

Table 2. 1: Operationalization of Variables

Table 2.1 above illustrates the variables, sub variables, indicators and values that identify the different aspects of this research. The state of ambient learning involves an in-depth look at the three categories of ambient learning i.e Mobile Interface Ambient Learning, Fixed Interface Ambient Learning and Hybrid Interface Ambient Learning. These three categories each have different forms of indicators and sensors that help contextualize a learner's environment. Radio Frequency Identifier (RFID) readers are examples of sensors whereas the ambient Intelligence app (AmI) are applications on devices act as actuators that enable an action to be performed by the learner. The community of practice represents the data owners, service providers and knowledge consumers who all interact together in an ambient learning environment. Actionable knowledge is thereby termed actionable through the multimodal access to knowledge which is expressed in models and rules such as decision trees and association rules respectively.

CHAPTER 3

METHODOLOGY

3.1 Introduction

This chapter helped describe in detail the methods that were used by the researcher in carrying out the research. It included the research design, data collection and procedure, target group, sample design, data processing and analysis, research schedule and research budget.

3.2 Research Design

The research design for this study took on a two pronged approach i.e. the content analysis method and the creative process for service development method.

3.2.1 Content Analysis Method

The content analysis method was used to address objective one and answer research questions one and two. Content analysis falls in the interface of observation and document analysis. It is a research technique for objective, systematic and quantitative description of the given content of communication by asking important questions that will help describe characteristics of content and make inferences on the causes of the content through questions like what, why, who, and with what effect to comprehensively be able to make valid and replicable inferences from data to its context (Prasad B., 2004).

3.2.2 Creative Process for Service Development Method

The creative process for service development method on the other hand helped address objectives 2 and 3. Just as it is important to promote technical solutions that bring about service innovations, human factors must also be taken into account. Novelty is a prerequisite of creativity whereby to be identified as creative, a service idea must be appropriate, valuable and actionable (Zeng et al., 2009). This method enabled out of the box thinking which is also known as ideation. The process of ideation facilitated strategies like conceptual expansion where I as the researcher looked at an existing concept and try find a way to better it. In this case the system in question is the OMAL ambient learning system that has been discussed. Another strategy used was conceptual combination which involved analyzing different KaaS concepts and combining the desired features that helped come up with the new novel system as shown in the figure 3.1 below.

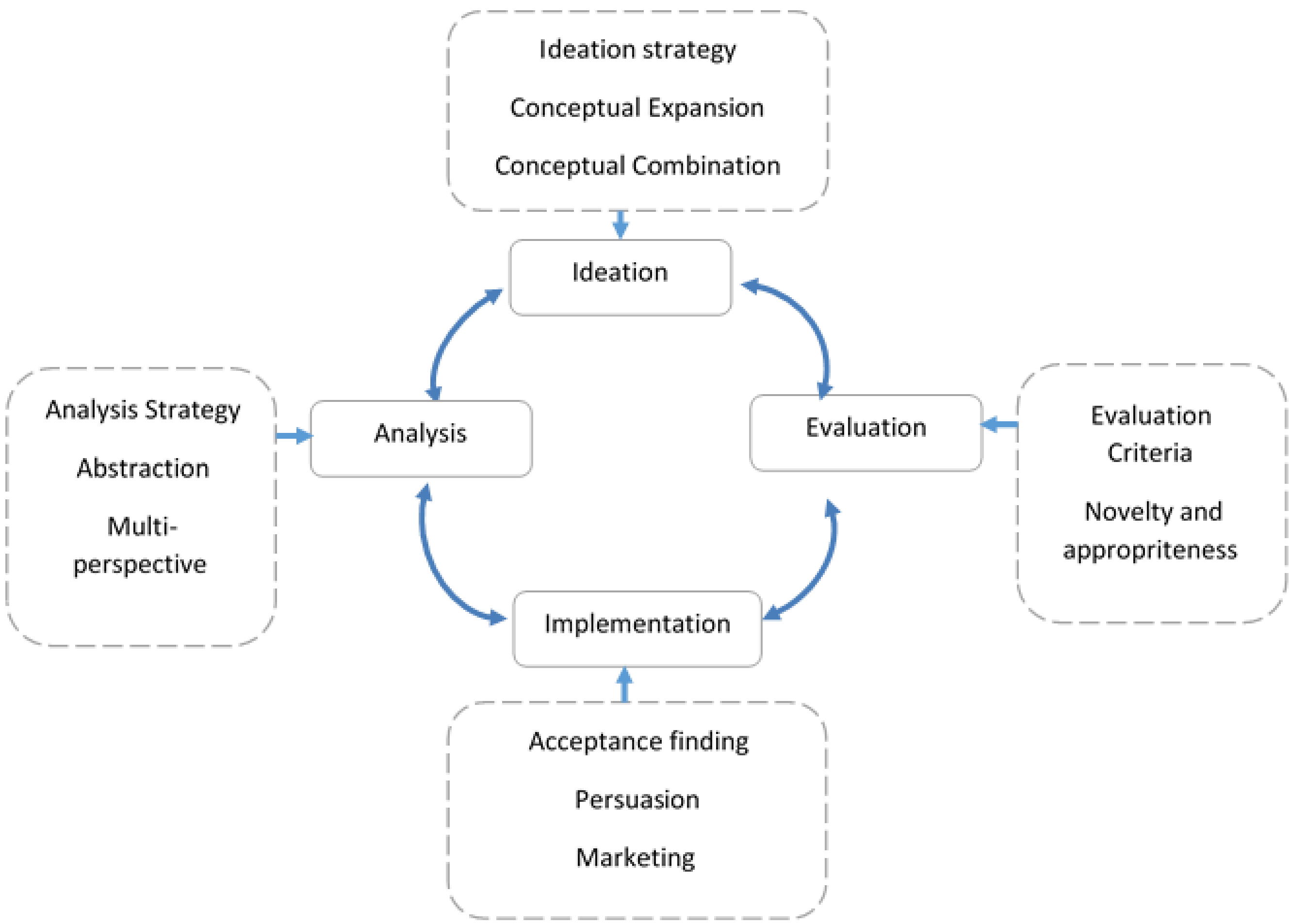


Figure 3. 1: Creative Process for Service Development

Source: (Zeng et al., 2009)

3.3 Data Collection and Procedure

The documentation review from case studies that meet the scope of the research was analyzed objectively and systematically to help convert recorded raw data into information that can be treated in essentially a scientific manner to build up a body of knowledge. This was followed by using data from an ambient learning system that was used to capture knowledge through a knowledge discovery process known as Knowledge Discovery from Data which involves the extraction of information through an iterative sequence from large databases as shown in the figure 3.2 below:

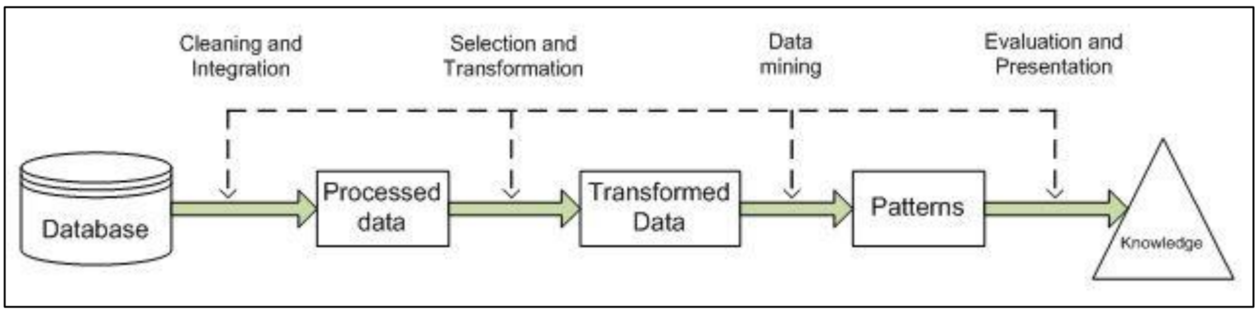


Figure 3. 2: Knowledge Discovery from Data Process

Source: Changala et al., 2015.

This iterative process involves:

- Data cleaning and integration – to remove noise or inconsistent data and combination of multiple data sources
- Data selection – data relevant to the analysis task is retrieved from the database.
- Data transformation – data is transformed onto forms appropriate for mining.
- Data mining – Intelligent methods are applied in order to extract data patterns.
- Pattern evaluation- Identifying interesting patterns representing knowledge based on interesting measures.

- Knowledge presentation – Visualization and knowledge presentation techniques are used to present the mined knowledge to the user.

3.4 Target Group

A target group is defined as persons or groups in society who are to be directly affected by the impact of a project (Forster R., Osterhaus J., 2010). The target group of this research included case studies of ambient learning systems and KaaS systems that would provide for documentation review to meet the objectives of the research. Community of practice members i.e system developers and learners of one of the ambient learning systems reviewed in the documentation, the OMAL system that is piloted at KCA university higher learning institution in Kenya was the target group during implementation and evaluation stages of the creative process.

3.5 Sample Design

The samples collected during this study included publications that were reviewed against the objectives and research questions. I reviewed a total of 20 publications that will be the basis for understanding and reviewing the objectives with emphasis placed on the three types of ambient learning available. The sampling method used to retrieve the publications followed with location of relevant literature and related studies through analysis of this textual content. The other sampling involved the finding of cognitive creative service development through problem analysis of the ambient system OMAL which helped identify new service opportunities. The methods used therefore include content analysis method and creative process for service development method.

3.6 Data Analysis

Descriptive techniques were used to analyze data collected from documentation review highlighting patterns to be examined and relationships to be explored within given content. Data sets from the OMAL system were analyzed using the weka software where mining took place to find new knowledge.

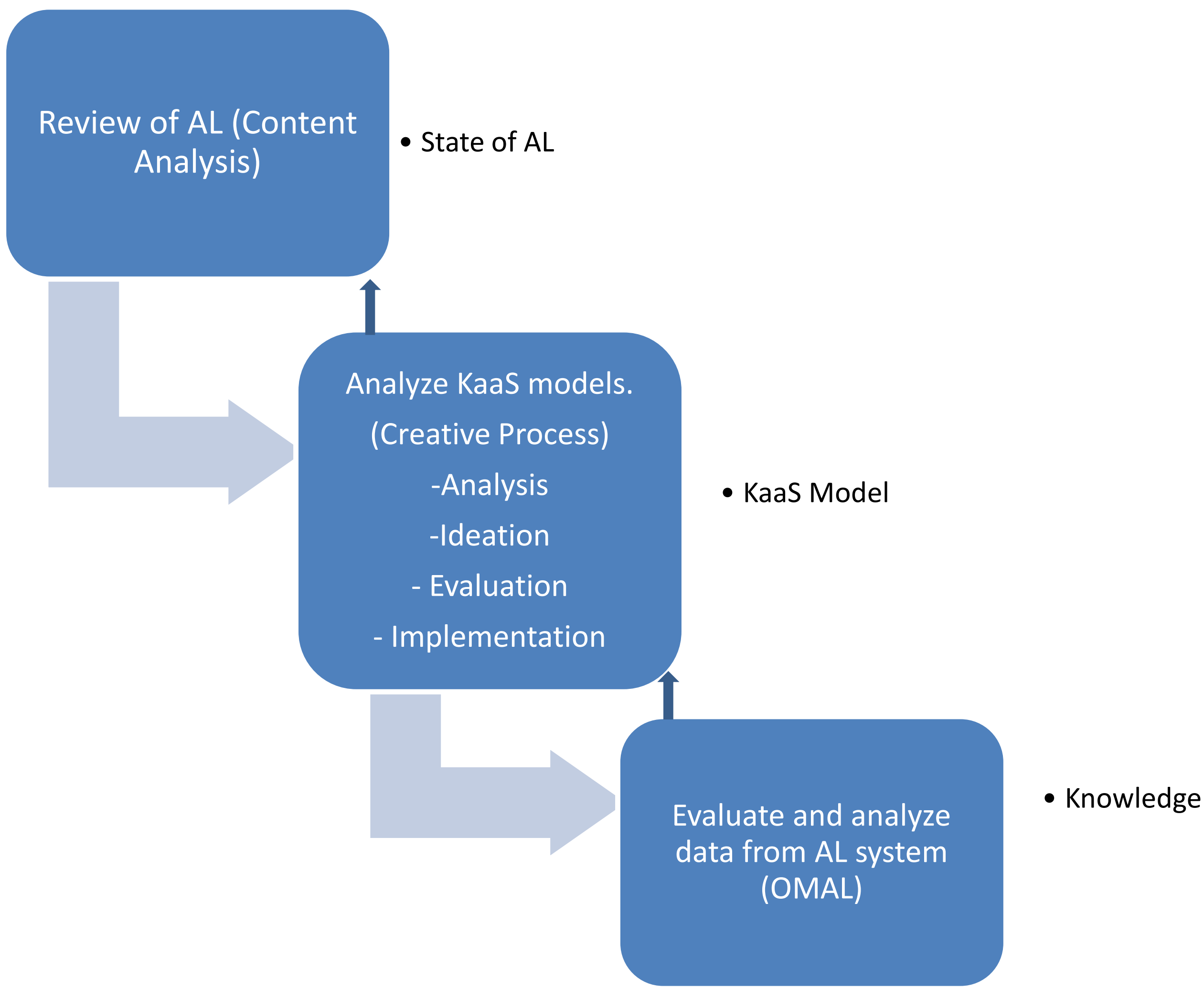


Figure 3. 3: Collaborative Research Design Methodology Process.

CHAPTER 4

RESULTS AND DISCUSSIONS

4.1 Introduction

The main objective of this research was to discover and use knowledge to bridge gaps in the realization of quality and equitable education through the leveraging of an ambient learning system and make available opportunities for lifelong learning.

4.2 Results for Objective One

This research has shown that for ambient intelligence is gradually taking root in our everyday lives and having a great impact in the society. Mobile phones are the most common choice in an ambient environment due to the fact that ambient intelligence technologies are described as technologies that provide context aware natural interfaces through mobile devices (Mwendia et al., 2016). We can however not limit our thinking to only mobile devices as an ambient intelligence environment is one that is sensitive to the users' needs whether they are using handheld devices or fixed devices thus making the places we live, work or study beneficial to us. Mobile and fixed ambient intelligence technologies are set apart from traditional e-learning by features like embedment, anticipatory, context-awareness and adaptation of learning services targeting the user's needs. As pointed out in the previous chapter, I will employ the content analysis method in this research to gather the relevant information needed for this study. I will use this method to give a clear picture on the state and general overview of ambient learning at a global level. This research will give an analysis of ambient learning projects based on the features of an ambient intelligence environment with the purpose to discover common ground and similarities along with differences, inconsistencies or contradictions within the domain of ambient intelligence. As discussed in the literature review the projects that were introduced were of interest as they met the criteria or standards of this research i.e. mode of access, availability of ambient intelligence technologies in the form of sensors and actuators and the type of devices used. I will tabulate the findings of my analysis as per every ambient learning category as follows:

4.2.1 Mobile Interface Ambient Learning Projects

MIAL Projects	**Region**	**Devices**	**M-AmI Sensors**	**M-AmI Actuators**	**Multimodal Access (Text, Audio, Video)**
Australian National University	Australia	Smart phones	Touch screen	AmI app	Yes
Open Mobile Ambient Learning	Kenya	Smart phones	Touch Screen, Accelerometer	AmI app	Yes
Synergy	India	Smart phones	Touch screen	AmI app	Yes
Alfabeto	Latin America	Phablets/Smart phones	Touch screen	AmI app	Yes
MALL	China	Smart phones	Touch screen, GPS.	AmI app (PCLUS system)	Yes

CDLEMO	China	Smart phones	Touch screen, GPS.	AmI app	Yes
Mobilogue	Germany	Smart phones	Touch screen, Mobile RFID	AmI app (QR scanner)	Yes
Nursery Plants Project	China	Smart phones	Touch screen	AmI app (Barcode reader)	Yes

Table 4. 1: Mobile Interface Ambient Learning Projects.

As indicated in table 4.1, out of the 15 publications reviewed, 8 cases of MIAL approach were observed. These represented 50% of all ambient learning cases that were found in this research. As stated earlier this came as no surprise given the high prevalence of mobile phones in most parts of the world. The Asian continent showed a high adoption of this form of pedagogy with 50% of the MIAL projects coming from member countries. Europe, the Americas, Australia and Africa each had one project.

4.2.2 Fixed Ambient Interface Learning Projects

Projects categorized under FIAL as discussed in the literature were few in number but they nevertheless captured both features of location dependent ambient intelligent learning as per the requirements of this research. The results are as shown in table 4.2 below:

FIAL Projects	**Region**	**Devices**	**Sensors**	**Actuators**	**Multimodal Access**
German University in Cairo iClass	Egypt	Smart phones, Digital monitors, RFID reader, Smart board,	Temperature sensors, Light level sensors, RFID, Microphone	F-AmI app	Yes
Augmented School Desk	Greece	Fixed Screen,Cameras, Smart pen	Touch screen,	F-AmI apps (ClassMATE and PUPIL)	Yes
SESIL	Greece	Fixed screen, Cameras	Touch screen	F-AmI app	Yes
Smart Classroom	China	Fixed microphones, Fixed media boards, Fixed screens.	Touch screen, Microphones,	F-AmI app	Yes.

Table 4. 2: Fixed Interface Ambient Learning Projects.

As indicated in table 4.2 above, the projects classified under FIAL had a majority presence in Europe with Greece having 50% of the projects observed. China's uptake on ambient intelligence was also evidenced again in this category as well through the Smart classroom project with Africa also having one project.

4.2.3 Hybrid Interface Ambient Learning Projects

HIAL Projects	Region	Devices	Sensors	Actuators	Multimodal Access
Stellenbosch University Project	South Africa	Computers, Tablets, Smartphones, Screens, Smart board	RFID, Touch screens	M-AmI &AmI app	Yes
Digital Lecture Hall	Germany	Smart phones, Pen-based notebooks, Talking Assistant headset, PDAs, Laptops/Computers	Touch screens, Microphone	M-AmI & AmI app	Yes
Smart Classroom	China	Fixed microphones, Fixed media boards, Fixed screens.	Touch screen, Microphones	M-AmI & AmI apps	Yes

Table 4. 3: Hybrid Interface Ambient Learning Projects.

HIAL projects were few with only Africa, Europe and Asia making up this part of the research. The HIAL projects are expensive to put up which in part explains the scarcity of these projects but they did show a clear leaning to the enhancement and improvement of user experience through efforts to sense, perceive, interpret, project, react to and anticipate the events of interest and offer services to users/learners accordingly.

4.3 Results for Objective Two

The novelty of this research will be determined by whether an ambient learning system can be improved by the inclusion of a knowledge based system that can deliver knowledge upon request from anywhere and anyhow. Novelty is the prerequisite of creativity (Zeng et al., 2009). My novel idea in this case is to come up with a framework for a collaborative architecture between an ambient learning system and a knowledge based KaaS system. To put it into context, a KaaS provides a collection of lessons learned, best practices, and case studies that can help systems leverage knowledge from anywhere in a distributed computing environment. The main objective therefore of the KaaS will be to generate knowledge from heterogeneous data while located in a cloud environment and make it available as a knowledge service to the community of practice. The following process diagram will show the expected interaction between an ambient learning system and the proposed KaaS.

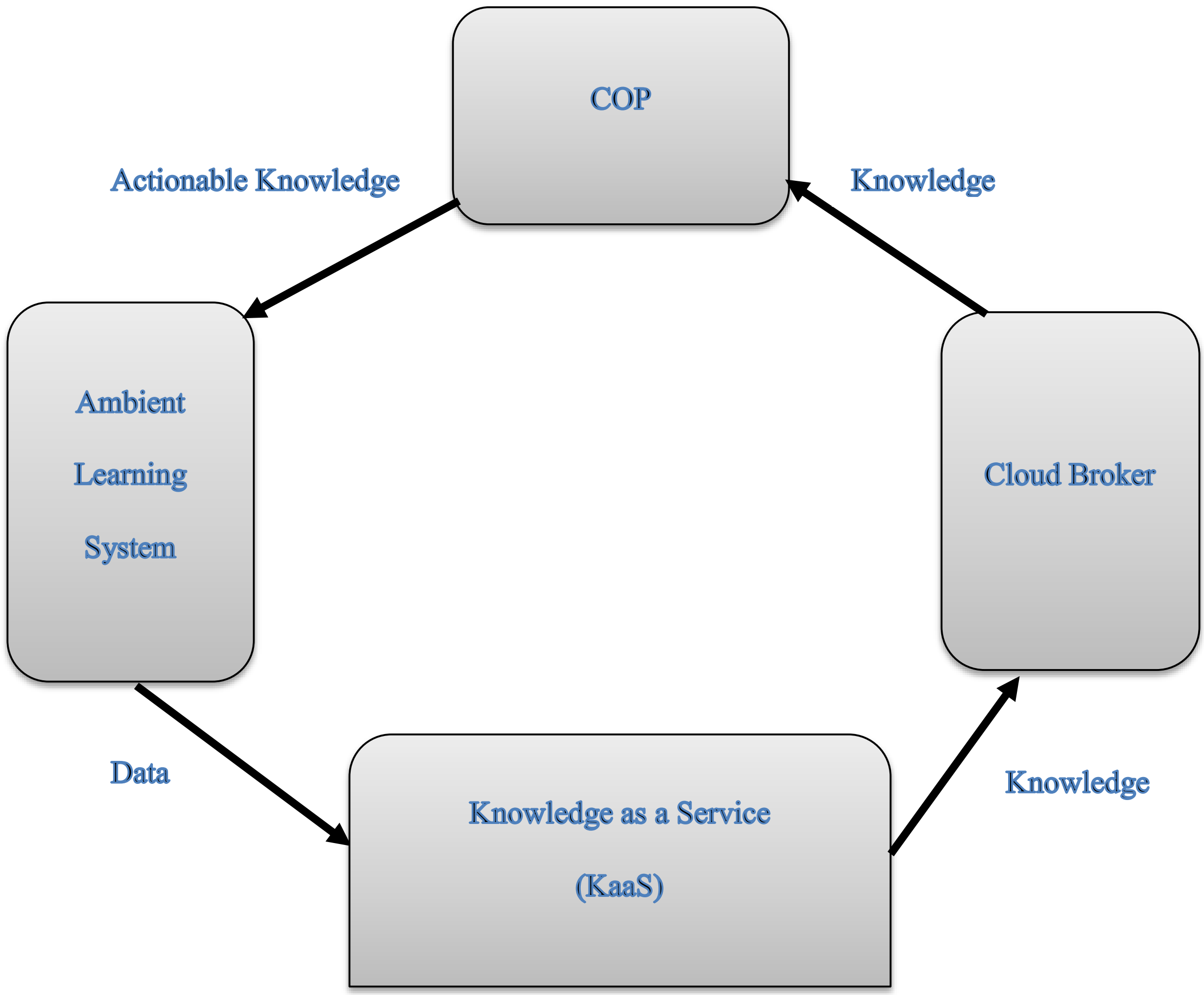


Figure 4. 1: Process diagram for a Knowledge as a Service ambient learning system.

4.3.1 The Community of Practice/ Knowledge Consumers

As illustrated in the process diagram above, the COP is made up of the knowledge engineer and the ambient learning expert (Knowledge consumer).The knowledge engineer is the KaaS expert who uses the knowledge mined to improve the knowledge base and provide the needed service to the knowledge consumer. The ambient learning expert is the person involved with improving the ambient learning system with the knowledge gained from the knowledge based system (KBS) also known as actionable knowledge. An important success factor of actionable knowledge as a service is whether knowledge discovered meets the users' requirements which constitutes the basis for decision-making and value creation outcome.

4.3.2 Ambient Learning System

The system in question is the Open Mobile Ambient Learning system (OMAL) which I have covered in detail in the previous chapters. It is represented by the figure 4.2 below.

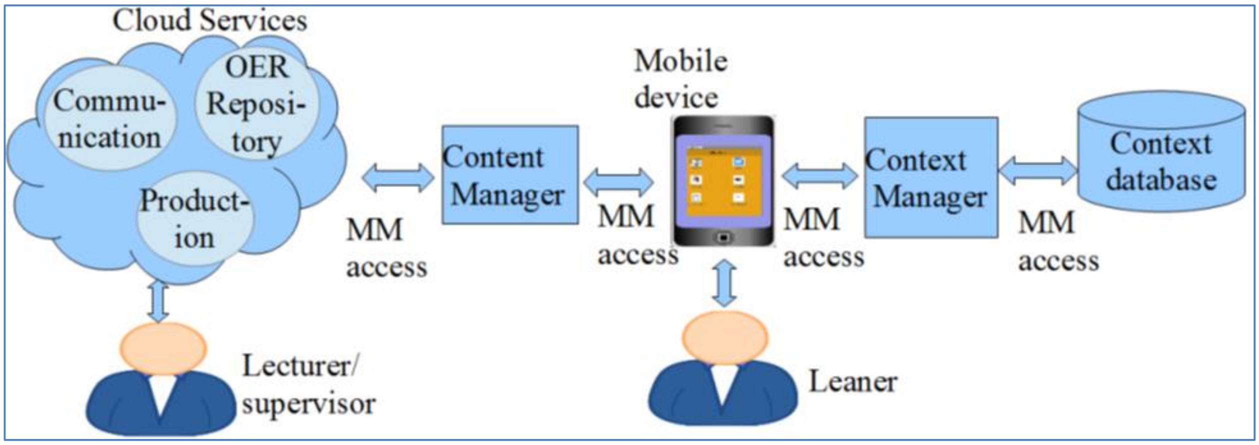


Figure 4. 2: Open Mobile Ambient Learning System (Mwendia et al., 2014).

4.3.3 The Knowledge as a Service system

The KBS is made up of the data mining algorithm that processes and transforms the data and finds the patterns hidden in the data. A rule based system is also included in the KBS that takes new found knowledge from the ambient learning system and runs it through a working knowledge base that contains facts/heuristics and rules that is interpreted by an artificial intelligence programming language known as Prolog. The knowledge base is accessed through the notepad interface where the rules are input and ran through the inference engine to come up with a solution.

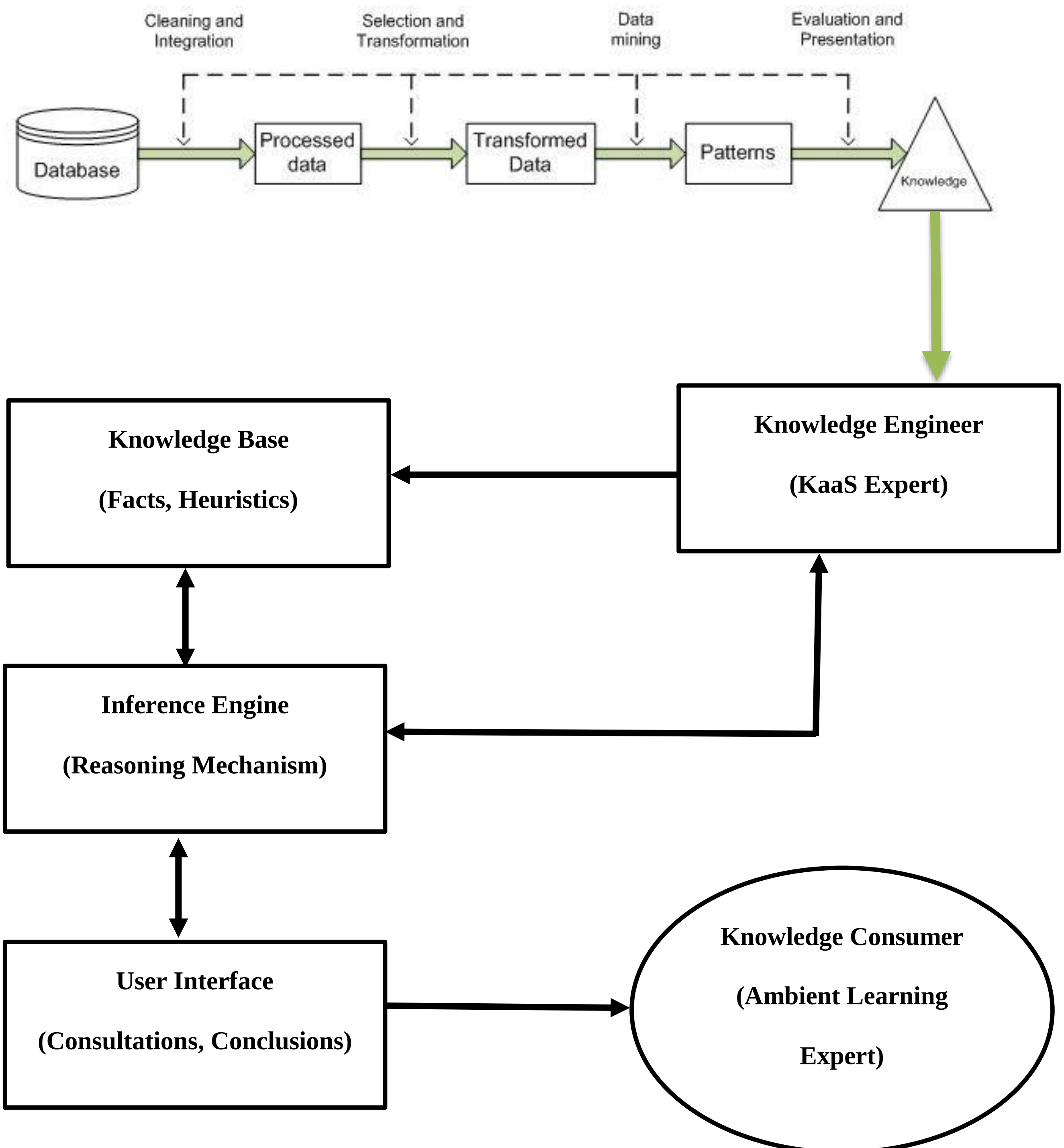


Figure 4. 3: Knowledge as a Service System

With the above system in place I was able to integrate it onto the ambient learning system and provide a way the COP can interact with it through the cloud broker to acquire the necessary knowledge needed from anywhere and at any time to improve the AL system. The cloud broker contains within it a KaaS broker which stores a knowledge cache built from previous requests or responses to the COP that allows for faster and efficient dissemination of knowledge when needed. The cloud broker provides an additional service in service intermediation which facilitates communication between the cloud consumer and the cloud provider to ensure maximum availability of the service. The system architecture is as shown in figure 4.4 below.

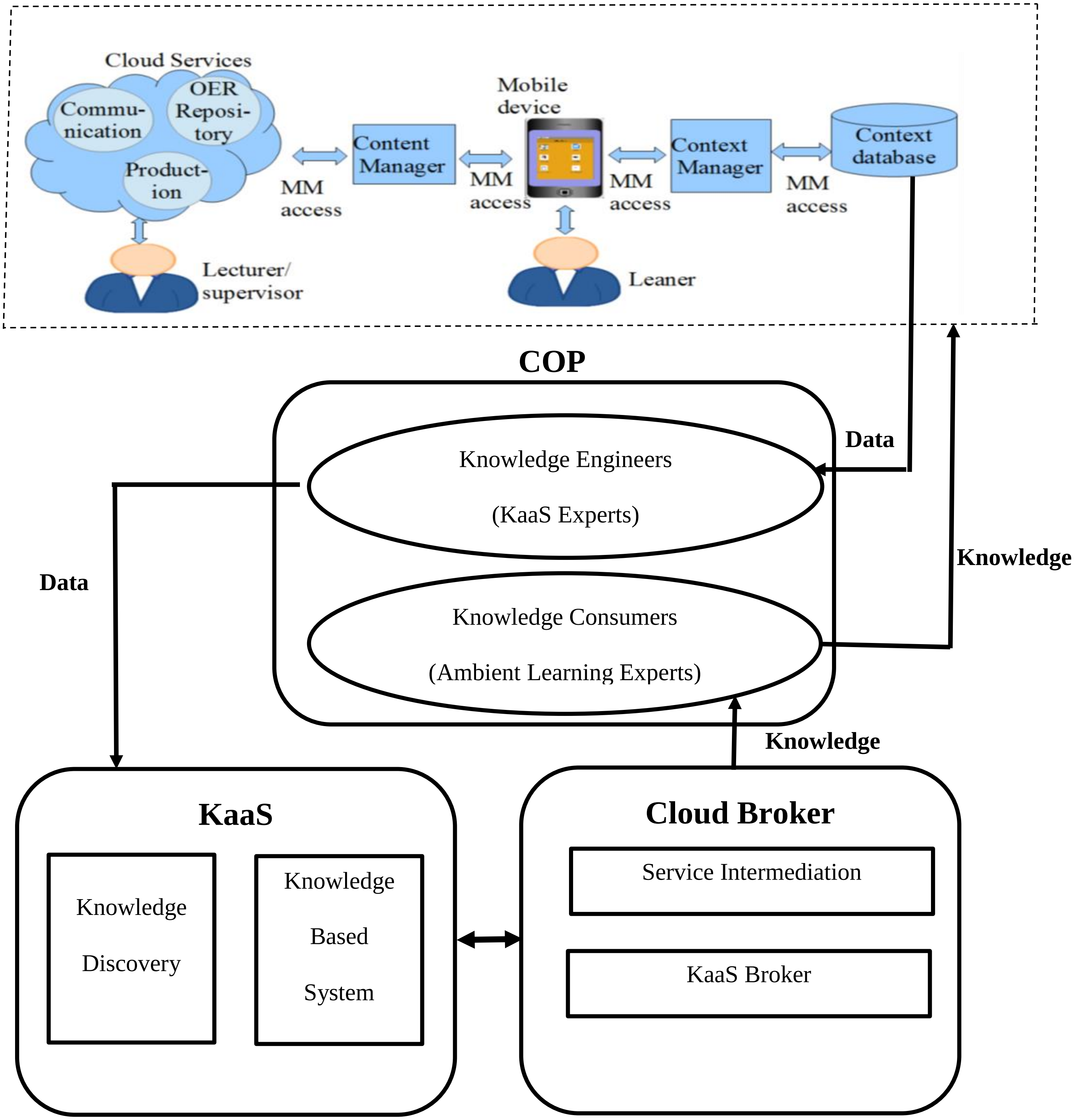
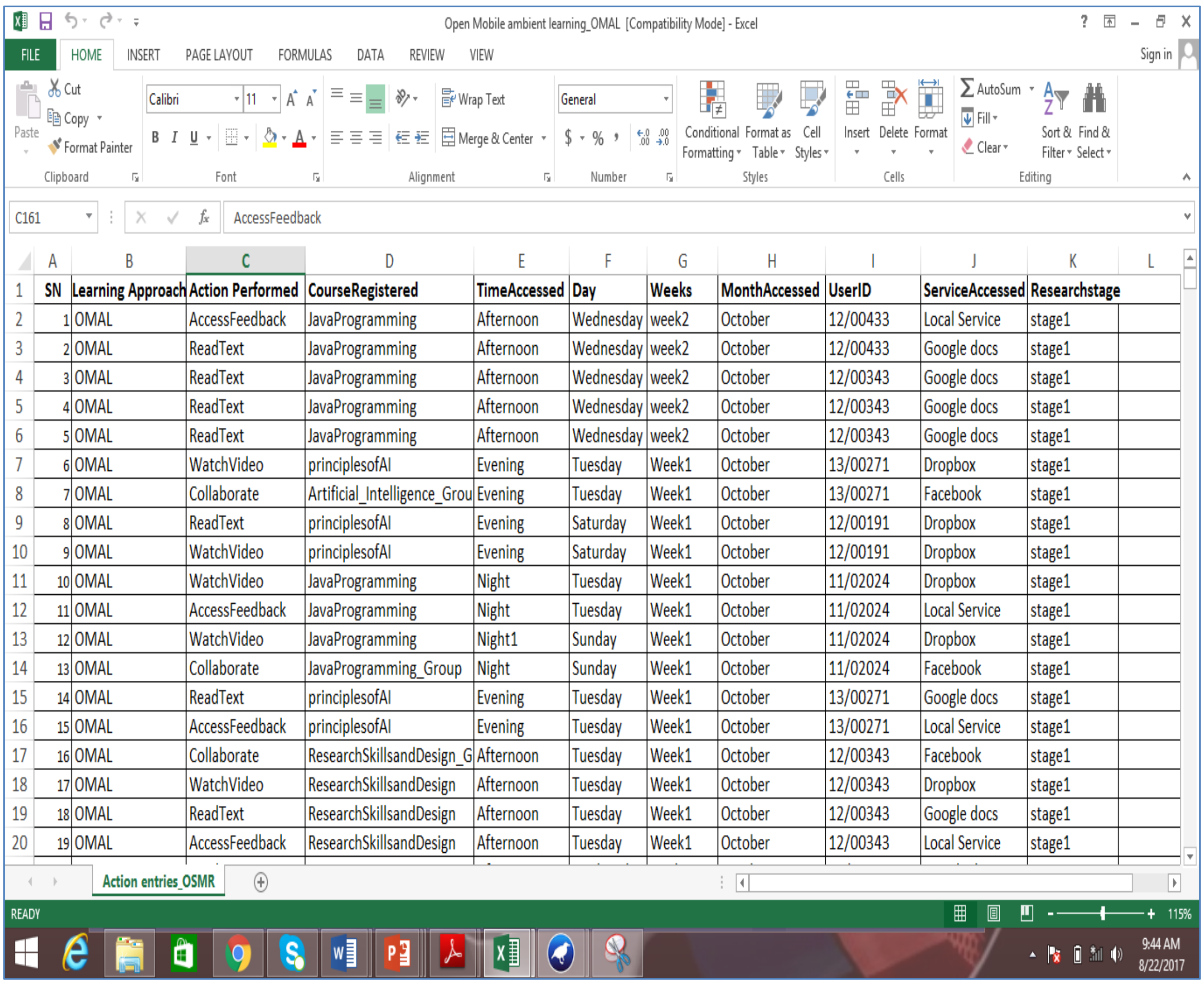


Figure 4. 4: Ambient Learning Knowledge as a Service system architecture.

4.4 Results for Objective Three

This section will involve pre mining results with a close look at objective three which focuses on an evaluation of the effectiveness of the established model with one of the reviewed technology enhanced learning cases. The OMAL system provided the needed data for mining that captured aspects of how users/students interacted with the system. They include: action performed, course registered, time and day of access, week and month accessed, user ID, service accessed and the research stage of the user. The data is as shown in figure 4.5 below.



SN	Learning Approach	Action Performed	CourseRegistered	TimeAccessed	Day	Weeks	MonthAccessed	UserID	ServiceAccessed	Researchstage
1	OMAL	AccessFeedback	JavaProgramming	Afternoon	Wednesday	week2	October	12/00433	Local Service	stage1
2	OMAL	ReadText	JavaProgramming	Afternoon	Wednesday	week2	October	12/00433	Google docs	stage1
3	OMAL	ReadText	JavaProgramming	Afternoon	Wednesday	week2	October	12/00343	Google docs	stage1
4	OMAL	ReadText	JavaProgramming	Afternoon	Wednesday	week2	October	12/00343	Google docs	stage1
5	OMAL	ReadText	JavaProgramming	Afternoon	Wednesday	week2	October	12/00343	Google docs	stage1
6	OMAL	WatchVideo	principlesofAI	Evening	Tuesday	Week1	October	13/00271	Dropbox	stage1
7	OMAL	Collaborate	Artificial_Intelligence_Grou	Evening	Tuesday	Week1	October	13/00271	Facebook	stage1
8	OMAL	ReadText	principlesofAI	Evening	Saturday	Week1	October	12/00191	Dropbox	stage1
9	OMAL	WatchVideo	principlesofAI	Evening	Saturday	Week1	October	12/00191	Dropbox	stage1
10	OMAL	WatchVideo	JavaProgramming	Night	Tuesday	Week1	October	11/02024	Dropbox	stage1
11	OMAL	AccessFeedback	JavaProgramming	Night	Tuesday	Week1	October	11/02024	Local Service	stage1
12	OMAL	WatchVideo	JavaProgramming	Night1	Sunday	Week1	October	11/02024	Dropbox	stage1
13	OMAL	Collaborate	JavaProgramming_Group	Night	Sunday	Week1	October	11/02024	Facebook	stage1
14	OMAL	ReadText	principlesofAI	Evening	Tuesday	Week1	October	13/00271	Google docs	stage1
15	OMAL	AccessFeedback	principlesofAI	Evening	Tuesday	Week1	October	13/00271	Local Service	stage1
16	OMAL	Collaborate	ResearchSkillsandDesign_G	Afternoon	Tuesday	Week1	October	12/00343	Facebook	stage1
17	OMAL	WatchVideo	ResearchSkillsandDesign	Afternoon	Tuesday	Week1	October	12/00343	Dropbox	stage1
18	OMAL	ReadText	ResearchSkillsandDesign	Afternoon	Tuesday	Week1	October	12/00343	Google docs	stage1
19	OMAL	AccessFeedback	ResearchSkillsandDesign	Afternoon	Tuesday	Week1	October	12/00343	Local Service	stage1

Figure 4. 5: OMAL dataset

As with the data mining process previously discussed, I prepared the data for mining by;

i. Cleaning and integrating the data through removing noise and inconsistencies. This involved filling in missing entries, removal of spaces, and removing values that would affect the consistency of the data.

90	OMAL	AccessExample	ManagementMathematicsI	Afternoon	Friday	week3	October	10/04000	Google docs	stage1
91	OMAL	ReadText	ManagementMathematicsI	Afternoon	Friday	week3	October	10/04000	Google docs	stage1
92	OMAL	ReadText	ManagementMathematicsI	Afternoon	Friday	week3	October	10/04000	Google docs	stage1
93	OMAL	ReadText	ManagementMathematicsI	Afternoon	Tuesday	week3	October	kca/09/03057	Google docs	stage1
94	OMAL	ReadText	ManagementMathematicsI	Afternoon	Tuesday	week3	October	kca/09/03057	Google docs	stage1
95	OMAL	AccessFeedback	JavaProgramming	Afternoon	Tuesday	week3	October	11/02024	Local Service	stage1
96	OMAL	WatchVideo	JavaProgramming	Afternoon	Tuesday	week3	October	11/02024	Google drive	stage1

90	OMAL	AccessExample	ManagementMathematicsII	Afternoon	Friday	week3	October	10/04000	Googledocs	stage1
91	OMAL	ReadText	ManagementMathematicsII	Afternoon	Friday	week3	October	10/04000	Googledocs	stage1
92	OMAL	ReadText	ManagementMathematicsII	Afternoon	Friday	week3	October	10/04000	Googledocs	stage1
93	OMAL	ReadText	ManagementMathematicsII	Afternoon	Tuesday	week3	October	09/03057	Googledocs	stage1
94	OMAL	ReadText	ManagementMathematicsII	Afternoon	Tuesday	week3	October	09/03057	Googledocs	stage1
95	OMAL	AccessFeedback	JavaProgramming	Afternoon	Tuesday	week3	October	11/02024	LocalService	stage1
96	OMAL	WatchVideo	JavaProgramming	Afternoon	Tuesday	week3	October	11/02024	Googledrive	stage1

Figure 4. 6: OMAL data cleaning

ii. Data selection which ensured I used data relevant to the analysis. This meant I had to do away with columns like serial number, learning approach, and user ID as shown in figure 4.7 below.

	A	B	C	D	E	F	G	H
1	**ActionPerformed**	**CourseRegistered**	**TimeAccessed**	**Day**	**Weeks**	**MonthAccessed**	**ServiceAccessed**	**Researchstage**
2	AccessFeedback	JavaProgramming	Afternoon	Wednesday	week2	October	LocalService	stage1
3	ReadText	JavaProgramming	Afternoon	Wednesday	week2	October	Googledocs	stage1
4	ReadText	JavaProgramming	Afternoon	Wednesday	week2	October	Googledocs	stage1
5	ReadText	JavaProgramming	Afternoon	Wednesday	week2	October	Googledocs	stage1
6	ReadText	JavaProgramming	Afternoon	Wednesday	week2	October	Googledocs	stage1
7	WatchVideo	principlesofAI	Evening	Tuesday	week1	October	Dropbox	stage1
8	Collaborate	Artificial_Intelligence_Group	Evening	Tuesday	week1	October	Facebook	stage1
9	ReadText	principlesofAI	Evening	Saturday	week1	October	Dropbox	stage1
10	WatchVideo	principlesofAI	Evening	Saturday	week1	October	Dropbox	stage1

Figure 4. 7: OMAL data selection

iii. Data transformation which involves transforming the data into an appropriate form for mining which in this case involved changing the data from an excel .xls format to a .CSV (Comma Delimited) file format. This is because WEKA the data mining tool expects the data file to be converted from the CSV format to ARFF (Attribute-Relation File Format) before any algorithm is applied to the data.

OMAL2 - Notepad

File Edit Format View Help

```
Action Performed,CourseRegistered,TimeAccessed,Day,Weeks,MonthAccessed,ServiceAccessed,Researchstage,
AccessFeedback,JavaProgramming,Afternoon,Wednesday,week2,October,LocalService,stage1,
ReadText,JavaProgramming,Afternoon,Wednesday,week2,October,Googledocs,stage1,
ReadText,JavaProgramming,Afternoon,Wednesday,week2,October,Googledocs,stage1,
ReadText,JavaProgramming,Afternoon,Wednesday,week2,October,Googledocs,stage1,
ReadText,JavaProgramming,Afternoon,Wednesday,week2,October,Googledocs,stage1,
WatchVideo,principlesofAI,Evening,Tuesday,Week1,October,Dropbox,stage1,
Collaborate,Artificial_Intelligence_Group,Evening,Tuesday,Week1,October,Facebook,stage1,
ReadText,principlesofAI,Evening,Saturday,Week1,October,Dropbox,stage1,
WatchVideo,principlesofAI,Evening,Saturday,Week1,October,Dropbox,stage1,
WatchVideo,JavaProgramming,Night,Tuesday,Week1,October,Dropbox,stage1,
AccessFeedback,JavaProgramming,Night,Tuesday,Week1,October,LocalService,stage1,
WatchVideo,JavaProgramming,Night,Sunday,Week1,October,Dropbox,stage1,
Collaborate,JavaProgramming_Group,Night,Sunday,Week1,October,Facebook,stage1,
ReadText,principlesofAI,Evening,Tuesday,Week1,October,Googledocs,stage1,
AccessFeedback,principlesofAI,Evening,Tuesday,Week1,October,LocalService,stage1,
Collaborate,ResearchSkillsandDesign_Group,Afternoon,Tuesday,Week1,October,Facebook,stage1,
WatchVideo,ResearchSkillsandDesign,Afternoon,Tuesday,Week1,October,Dropbox,stage1,
ReadText,ResearchSkillsandDesign,Afternoon,Tuesday,Week1,October,Googledocs,stage1,
AccessFeedback,ResearchSkillsandDesign,Afternoon,Tuesday,Week1,October,LocalService,stage1,
ReadText,JavaProgramming,Afternoon,Wednesday,week2,October,Googledocs,stage1,
WatchVideo,JavaProgramming,Evening,Wednesday,Week2,October,Googledrive,stage1,
AccessFeedback,JavaProgramming,Evening,Wednesday,week2,October,LocalService,stage1,
```

Figure 4. 8: OMAL .csv file

A *@relation* tag with the dataset's name, an *@ attribute* tag with the attribute information and a *@ data* tag is added to make and the file is saved as a .arff file.

OMAL3 - Notepad

File Edit Format View Help

```
@RELATION OMAL

@attribute ActionPerformed{AccessFeedback,ReadText,WatchVideo,Collaborate,AccessExample}
@attribute CourseRegistered{JavaProgramming,principlesofAI,Artificial_Intelligence_Group,Resea
@attribute TimeAccessed{Afternoon,Evening,Night,Morning}
@attribute Day{Monday,Tuesday,Wednesday,Thursday,Friday,Saturday,Sunday}
@attribute Weeks{week1,week2,week3,week4}
@attribute MonthAccessed{October,November,December}
@attribute ServiceAccessed{LocalService,Googledocs,Googledrive,Facebook,Dropbox}
@attribute Researchstage{stage1,stage2,stage3,stage4,stage5}

@DATA
AccessFeedback,JavaProgramming,Afternoon,Wednesday,week2,October,LocalService,stage1,
ReadText,JavaProgramming,Afternoon,Wednesday,week2,October,Googledocs,stage1,
ReadText,JavaProgramming,Afternoon,Wednesday,week2,October,Googledocs,stage1,
ReadText,JavaProgramming,Afternoon,Wednesday,week2,October,Googledocs,stage1,
ReadText,JavaProgramming,Afternoon,Wednesday,week2,October,Googledocs,stage1,
WatchVideo,principlesofAI,Evening,Tuesday,week1,October,Dropbox,stage1,
Collaborate,Artificial_Intelligence_Group,Evening,Tuesday,week1,October,Facebook,stage1,
ReadText,principlesofAI,Evening,Saturday,week1,October,Dropbox,stage1,
WatchVideo,principlesofAI,Evening,Saturday,week1,October,Dropbox,stage1,
WatchVideo,JavaProgramming,Night,Tuesday,week1,October,Dropbox,stage1,
AccessFeedback,JavaProgramming,Night,Tuesday,week1,October,LocalService,stage1,
```

Figure 4. 9: OMAL.arff file

The above data having gone through preprocessing and transformation to get the data ready for mining and saving it as an .arff file. I went ahead to apply intelligent methods that could extract data patterns that could give knowledge. These methods include classification and association rule mining using the J48 and Apriori algorithms respectively. The attributes picked from the OMAL context database include: Action performed, Course Registered, Time Accessed, Day, Weeks, Month Accessed, Service Accessed and Research Stage. From these the following rules were captured.

4.5 Post Mining Results

The purpose of this section is to discuss results obtained from mining of the data using classification rule mining and association rule mining to find knowledge that can be used input in the knowledge based system and used by the ambient learning expert.

4.5.1 Data Mining through Classification rule mining

Figure 4.10 below shows J48 classification algorithm was run on Weka and gave back the rules shown. It shows that from the OMAL dataset, when action performed is access feedback then local service is the mode of access that is used. The local service in this case is the web server that is only available to the students when they need to access their course marks and remarks as submitted by the lecturer. The local service is not part of the other cloud services i.e Google docs, Google drive, Drop box and Facebook in order to ensure confidentiality of students' details.

The next rule is that if action performed is read text, and month accessed is first month, where research stage is stage 1, then Google docs is the mode of access used with only one wrong classification.

```
=== Run information ===

Scheme:       weka.classifiers.trees.J48 -C 0.25 -M 2
Relation:     OMAL
Instances:    602
Attributes:   8
              ActionPerformed
              CourseRegistered
              TimeAccessed
              Day
              Weeks
              MonthAccessed
              ServiceAccessed
              Researchstage
Test mode:    10-fold cross-validation

=== Classifier model (full training set) ===

J48 pruned tree
------------------

ActionPerformed = AccessFeedback: LocalService (203.0)
ActionPerformed = ReadText
|   MonthAccessed = FirstMonth
|   |   Researchstage = stage1: Googledocs (97.0/1.0)
```

Figure 4. 10: J48 Classifier

```
ActionPerformed = WatchVideo
|   MonthAccessed = FirstMonth
|   |   Weeks = week1: Dropbox (5.0)
|   |   Weeks = week2: Googledrive (13.0)
|   |   Weeks = week3: Googledrive (16.0)
|   |   Weeks = week4: Googledrive (15.0)
|   MonthAccessed = SecondMonth: Googledrive (26.0)
|   MonthAccessed = ThirdMonth: Dropbox (1.0)
```

Figure 4. 11: J48 Classifier Watch video mode

The above rule in figure 4.11 shows that if students on the OMAL system perform the watch video action and month of access is the first month, week 1 was accessed through Dropbox while week 2 and 3 have Google drive as the service accessed.

```
|   MonthAccessed = ThirdMonth: Dropbox (1.0)
ActionPerformed = Collaborate: Facebook (34.0)
ActionPerformed = AccessExample
|   Researchstage = stage1
|   |   MonthAccessed = FirstMonth: Googledocs (36.0/5.0)
|   |   MonthAccessed = SecondMonth: Googledrive (10.0)
|   |   MonthAccessed = ThirdMonth: Googledocs (0.0)
```

Figure 4. 12: Classifier J48 Collaborate rule

The above rule in figure 4.12 states that if the students on the OMAL system access the collaborate action then the service accessed is Facebook.

```
Number of Leaves  :     56

Size of the tree :      69


Time taken to build model: 0 seconds

=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances         561               93.1894 %
Incorrectly Classified Instances        41                6.8106 %
Kappa statistic                          0.9025
Mean absolute error                      0.0369
Root mean squared error                  0.1571
Relative absolute error                 13.0381 %
Root relative squared error             41.814  %
Total Number of Instances              602
```

Figure 4. 13: J48 Summary

Figure 4.13 above validates the three rules shared above showing that there were 561 correctly classified instances translating to 93.184% and 41 incorrectly classified instances translating to 6.8106%. In other words the rules are valid and useful. When it comes to the resulting decision tree however, given the high number of leaves (56) and the large size of the tree (69) it was impossible to derive a clear pruned decision tree from it. I therefore opted to prune the decision tree by reducing the number of attributes so as to be able to accommodate a smaller, easier to understand decision tree. This meant reduction of the number of attributes to three i.e. action performed, course registered and service accessed as shown in figure 4.14 below.

```
=== Run information ===

Scheme:       weka.classifiers.trees.J48 -C 0.4 -M 2
Relation:     OMAL-weka.filters.unsupervised.attribute.Remove-R3-5-weka.
Instances:    602
Attributes:   3
              ActionPerformed
              CourseRegistered
              ServiceAccessed
Test mode:    10-fold cross-validation

=== Classifier model (full training set) ===

J48 pruned tree
------------------

ActionPerformed = AccessFeedback: LocalService (203.0)
ActionPerformed = ReadText: Googledocs (218.0/53.0)
ActionPerformed = WatchVideo: Googledrive (76.0/6.0)
ActionPerformed = Collaborate: Facebook (34.0)
ActionPerformed = AccessExample: Googledocs (71.0/25.0)

Number of Leaves  :     5

Size of the tree :      6
```

Figure 4. 14: J48 Pruned decision tree in textual form

Using three attributes i.e. Action performed, course registered and service accessed the J48 algorithm delivers the rules as shown above. When action performed is access feedback, Local service is the service accessed with all instances correctly classified. When action performed is read text, Google docs is the service accessed with 218 correctly clarified instances and 53 incorrectly classified instances. The action watch video was accessed via Google drive with 76 correctly classified instances and 6 incorrectly classified instances. Facebook was correctly classified with complete accuracy as the service accessed when collaboration was the action performed. When action performed was access example, Google docs was the service accessed with 76 correctly classified instances and 25 wrongly classified instances.

```
Time taken to build model: 0 seconds

=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances         508               84.3854 %
Incorrectly Classified Instances        94               15.6146 %
Kappa statistic                          0.7728
Mean absolute error                      0.0874
Root mean squared error                  0.2134
Relative absolute error                 30.9248 %
Root relative squared error             56.7795 %
Total Number of Instances              602
```

Figure 4. 15: J48 Summary

The rules validation shows 508 correctly classified instances translating to 84.3854% and 94 incorrectly classified instances translating to 15.6146%. Though lower than the previous run of the algorithm the rules delivered pass the statistical evaluation measures which include Kappa statistic, mean absolute error, and root mean squared error. The Kappa statistic is a statistical measure of agreement according to (Bangdiwala & Munoz, 1997) that shows how strongly data items in the same class resemble each other as shown in the guidelines of Landis and Koch in the table below

Kappa Statistic	Strength of agreement
0	Poor
0 – 0.2	Slight
0.2 – 0.4	Fair
0.4 – 0.6	Moderate
0.6 – 0.8	Substantial
0.8 – 1	Almost perfect

Table 4. 4: Kappa Statistic Levels of Agreement.

The given Kappa statistic value of 0.7728 means that the statistical significance of the model is rather high meaning the rules are valid and useful. Mean absolute error is the quantity used to measure how close forecasts or predictions are to the actual outcomes (Suman et al., 2014). It therefore goes that the smaller the value of the mean absolute error the better the prediction model. The Root Mean Square Error on the other hand is the square root of sum of squares error divided by number of prediction. It measures the values predicted by a model and the values actually observed hence the smaller the value the better the accuracy of the model. With a mean absolute error of 0.0874 and a root mean square error of 0.2134 the rules meet the evaluation measures confirming their validity and usefulness. The rules generated provided the tree in figure 4.16 below.

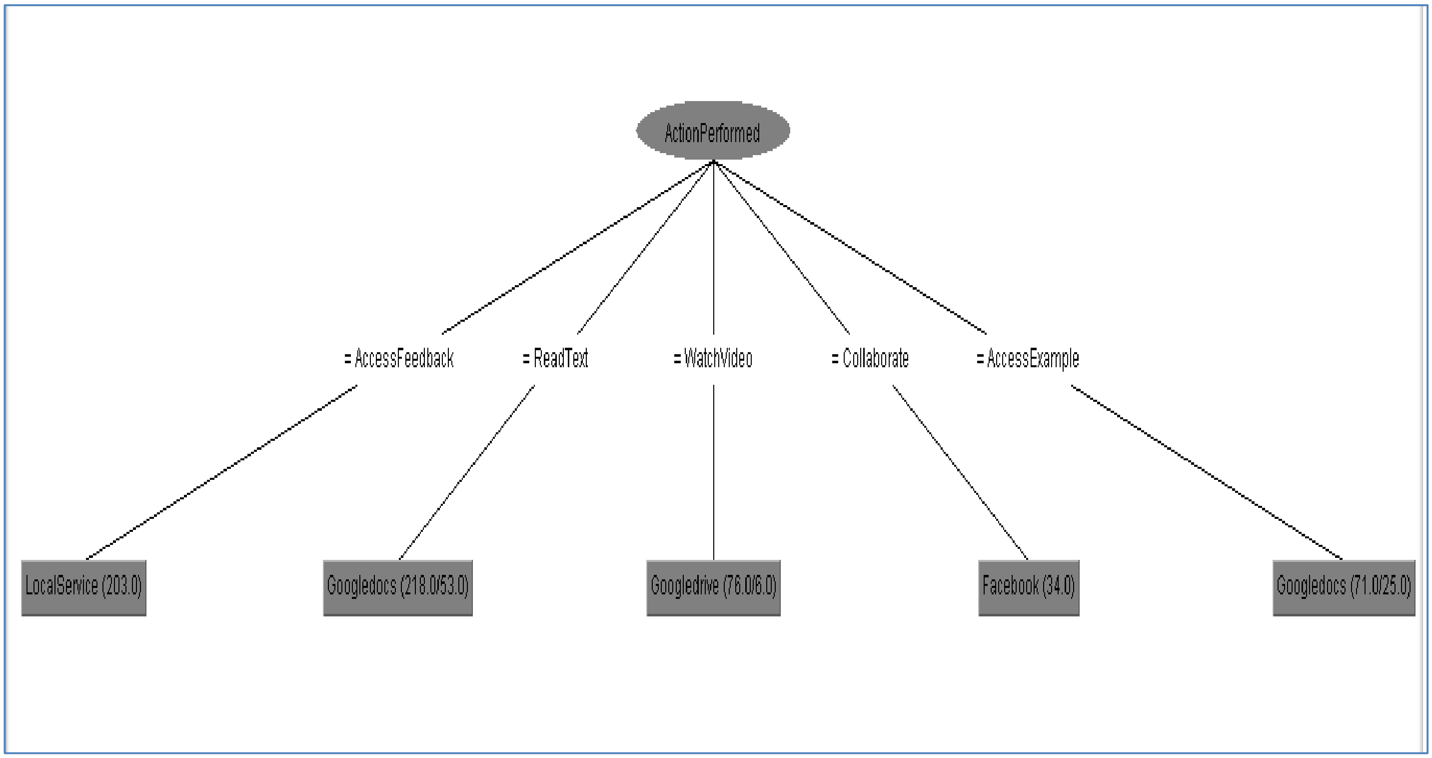


Figure 4. 16: J48 Decision Tree.

4.5.2 Data Mining through Association Rule Mining

Figure 4.17 shows the results from Weka after running the OMAL dataset through the Apriori algorithm in order to deliver association rules.

```
Apriori
=======

Minimum support: 0.1 (60 instances)
Minimum metric <confidence>: 0.8
Number of cycles performed: 18

Generated sets of large itemsets:

Size of set of large itemsets L(1): 10

Size of set of large itemsets L(2): 10

Size of set of large itemsets L(3): 3

Best rules found:

 1. ActionPerformed=AccessFeedback 203 ==> ServiceAccessed=LocalService 203    <conf:(1)> lift:(2.95) lev:(0.22) [134] conv:(134.21)
 2. ActionPerformed=AccessFeedback CourseRegistered=JavaProgramming 84 ==> ServiceAccessed=LocalService 84    <conf:(1)> lift:(2.95) lev:(0.09) [55] conv:(55.53)
 3. CourseRegistered=principlesofAI ServiceAccessed=LocalService 66 ==> ActionPerformed=AccessFeedback 66    <conf:(1)> lift:(2.97) lev:(0.07) [43] conv:(43.74)
 4. ActionPerformed=AccessFeedback CourseRegistered=principlesofAI 66 ==> ServiceAccessed=LocalService 66    <conf:(1)> lift:(2.95) lev:(0.07) [43] conv:(43.63)
 5. ServiceAccessed=LocalService 204 ==> ActionPerformed=AccessFeedback 203    <conf:(1)> lift:(2.95) lev:(0.22) [134] conv:(67.6)
 6. CourseRegistered=JavaProgramming ServiceAccessed=LocalService 85 ==> ActionPerformed=AccessFeedback 84    <conf:(0.99)> lift:(2.93) lev:(0.09) [55] conv:(28.17)
 7. ActionPerformed=WatchVideo 76 ==> ServiceAccessed=Googledrive 70    <conf:(0.92)> lift:(4.02) lev:(0.09) [52] conv:(8.37)
 8. CourseRegistered=JavaProgramming ServiceAccessed=Googledocs 133 ==> ActionPerformed=ReadText 111    <conf:(0.83)> lift:(2.3) lev:(0.1) [62] conv:(3.69)
```

Figure 4. 17: Apriori algorithm rules

The main idea of the Apriori algorithm approach is scanning the dataset repeatedly and coming up with frequent patterns that reflect the relationships according to three objectives i.e. support, confidence and interestingness (Zhang et al., 2010). This is expressed in the form, if X then Y. Support represents the fraction of transactions that contain both X and Y while confidence is the ratio of the number of transactions that contain both X and Y to the number of transactions that contain X. A rule is deemed to be interesting if it meets the evaluation metrics of lift, leverage and conviction. Lift measures how far from independence X and Y are with an unlimited range from 0.5. Values close to 1 imply that X and Y are independent thus rule is not interesting however values far from 1 indicate evidence of X provides information about Y making the rule interesting. Leverage determines the novelty of a rule by finding the co-occurrence of X and Y and expected support given that X and Y are independent. Given that the leverage range is given from -0.25 to 0.25, a high leverage implies high support which makes a rule interesting. Conviction compares the probability that X appears without Y and given from a range of 0.5, a conviction value of 1 means that X and Y are independent however conviction rules greater and further from 1 indicate interesting rules.

```
Best rules found:

 1. ActionPerformed=AccessFeedback 203 ==> ServiceAccessed=LocalService 203    <conf:(1)> lift:(2.95) lev:(0.22) [134] conv:(134.21)
 2. ActionPerformed=AccessFeedback CourseRegistered=JavaProgramming 84 ==> ServiceAccessed=LocalService 84    <conf:(1)> lift:(2.95) lev:(0.09) [55] conv:(55.53)
 3. CourseRegistered=principlesofAI ServiceAccessed=LocalService 66 ==> ActionPerformed=AccessFeedback 66    <conf:(1)> lift:(2.97) lev:(0.07) [43] conv:(43.74)
 4. ActionPerformed=AccessFeedback CourseRegistered=principlesofAI 66 ==> ServiceAccessed=LocalService 66    <conf:(1)> lift:(2.95) lev:(0.07) [43] conv:(43.63)
 5. ServiceAccessed=LocalService 204 ==> ActionPerformed=AccessFeedback 203    <conf:(1)> lift:(2.95) lev:(0.22) [134] conv:(67.6)
 6. CourseRegistered=JavaProgramming ServiceAccessed=LocalService 85 ==> ActionPerformed=AccessFeedback 84    <conf:(0.99)> lift:(2.93) lev:(0.09) [55] conv:(28.17)
 7. ActionPerformed=WatchVideo 76 ==> ServiceAccessed=Googledrive 70    <conf:(0.92)> lift:(4.02) lev:(0.09) [52] conv:(8.37)
 8. CourseRegistered=JavaProgramming ServiceAccessed=Googledocs 133 ==> ActionPerformed=ReadText 111    <conf:(0.83)> lift:(2.3) lev:(0.1) [62] conv:(3.69)
```

Figure 4. 18: Apriori algorithm rules

The rules in figure 4.18 above are derived from the same attributes used on the J48 algorithm i.e. Action Performed, Course Registered and Service accessed. For example if we take a look at the first rule which happens to be the best rule we see that when action performed is access feedback then the service accessed is local service i.e. the local web server where grades and comments are stored by the lecturer or supervisor. This rule has a confidence of 1, lift of 2.95, leverage of 0.22

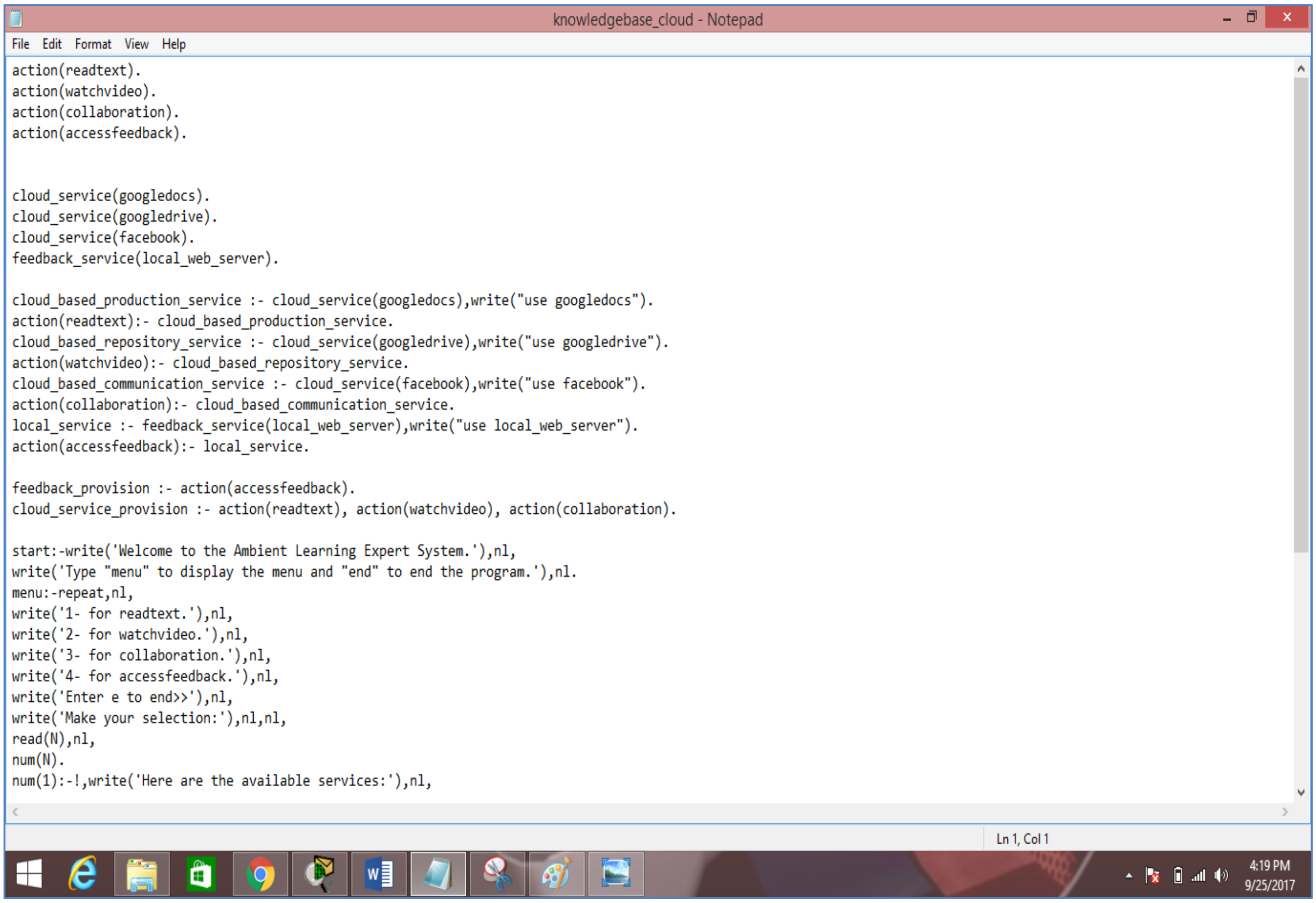
and a conviction of 134.22. With these high metrics the rule is deemed interesting and actionable. All the above rules meet the evaluation metrics standards and represent the interesting elements of the data set. A representation of the averages of the confidence, lift, leverage and conviction on the rules is tabulated below.

Confidence	**Lift**	**Leverage**	**Conviction**
0.96	3.00	0.11	48.11

Table 4. 5: Averages of Evaluation Metrics of Apriori Algorithm Rules.

As shown in table 4.5 above, the association rules meet the given evaluation metrics confirming the validity of the rules.

With the given knowledge, the next phase of achieving knowledge as a service within the knowledge based system was creating an interactive interface that would be programmed with the artificial intelligence language prolog. The knowledge is keyed in by the knowledge expert in a text editing environment which forms the knowledgebase that contains the precedents that are loaded onto SWI prolog. SWI prolog is an implementation of the programming language prolog that aims at providing a prototyping environment by facilitating good development tools, both for command line usage with graphical development tools. The knowledgebase is as shown in figure 4.19 below.



knowledgebase_cloud - Notepad

File Edit Format View Help

```
action(readtext).
action(watchvideo).
action(collaboration).
action(accessfeedback).


cloud_service(googledocs).
cloud_service(googledrive).
cloud_service(facebook).
feedback_service(local_web_server).

cloud_based_production_service :- cloud_service(googledocs),write("use googledocs").
action(readtext):- cloud_based_production_service.
cloud_based_repository_service :- cloud_service(googledrive),write("use googledrive").
action(watchvideo):- cloud_based_repository_service.
cloud_based_communication_service :- cloud_service(facebook),write("use facebook").
action(collaboration):- cloud_based_communication_service.
local_service :- feedback_service(local_web_server),write("use local_web_server").
action(accessfeedback):- local_service.

feedback_provision :- action(accessfeedback).
cloud_service_provision :- action(readtext), action(watchvideo), action(collaboration).

start:-write('Welcome to the Ambient Learning Expert System.'),nl,
write('Type "menu" to display the menu and "end" to end the program.'),nl.
menu:-repeat,nl,
write('1- for readtext.'),nl,
write('2- for watchvideo.'),nl,
write('3- for collaboration.'),nl,
write('4- for accessfeedback.'),nl,
write('Enter e to end>>'),nl,
write('Make your selection:'),nl,nl,
read(N),nl,
num(N).
num(1):-!,write('Here are the available services:'),nl,
```

Ln 1, Col 1

4:19 PM
9/25/2017

Figure 4. 19: OMAL system knowledgebase.

The knowledgebase is accessed using SWI prolog where the ambient learning expert will interact with the system by typing ‘start’. This will bring up a welcome message upon which the expert will be guided by the prompts that follow. The ambient learning expert will be able to see a menu which is repeated to allow the choosing of other options or end the program at will. The figure 4.20 below shows a screenshot of the running program.

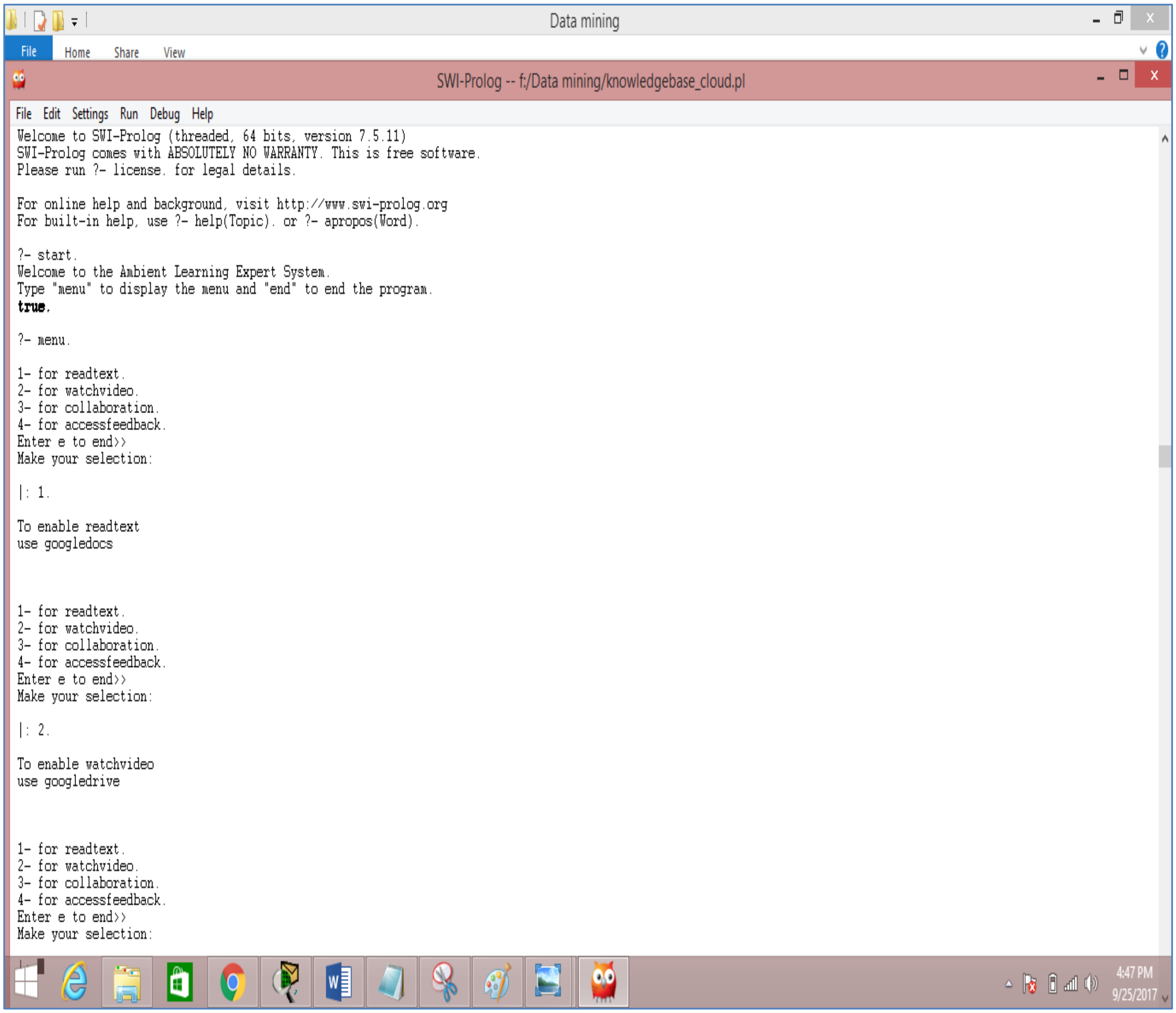


Figure 4. 20: OMAL knowledgebase system.

4.6 Discussion of Results

The purpose of this section is to discuss the results obtained during the research. To do this the main focus will be on the research questions.

RQ1. What is the general overview and current state of ambient learning?

This research took a deep look at ambient learning as a technology enhanced learning pedagogy which can address the issues facing quality and equitable lifelong learning approaches. The mobile interface ambient learning projects are spaced out across the globe with use of smartphones or tablets allowing for multimodal access to content. Fixed interface ambient learning projects which included various fixed devices that allowed for ambient learning to be experienced in specific controlled environments. Hybrid interface ambient learning projects on the other hand allowed for a combination of features involved in both mobile and fixed types of ambient learning. Though expensive to set up, it is a kind of pedagogy that enhances user experience both inside and outside the classroom through interactive sensors and actuators.

RQ2. Which are the existing KaaS models that can be integrated in technology enhanced learning (TEL) approaches like ambient learning?

The Collaborative KaaS system architecture discussed previously provided great insight in helping develop a KaaS for the ambient learning system used in this research. The reason for this is the generic nature of the collaborative KaaS system which allowed for experimentation by borrowing a component from its architecture and integrating it on the OMAL system, namely the cloud broker. The OMAL system is the main focus of this research. As Mwendia et al. 2014 showed in his research the OMAL system provides a multi modal access to students but not a way to way to gather knowledge from data generated to be able to make changes or decisions as this research has done. This in itself is a major improvement on the OMAL system architecture with enabling of the dissemination of knowledge gathered on the knowledge based system via the proposed cloud service hence making it knowledge as a service. This is actionable knowledge which the ambient learning experts will use to improve the quality of education and the system at large.

RQ3. How can knowledge as a service be utilized to realize gaps in ambient learning systems?

The knowledge as a service system involves data mining from the OMAL system database that helps realize gaps in the system. The knowledge gathered from this process is provided as a service by passing it through an inference engine that uses a user interface which the knowledge consumer will interact with. The efficiency this provides is to enable easier decision making for the ambient learning expert while improving the quality of education.

RQ4. How can the results from a conceptual framework be best implemented?

The conceptual framework in this research takes a step by step approach in meeting the objectives of the study. The first step is to assess the state of ambient learning. The next step shows the involvement of the COP who are the ambient learning experts who can also be referred to as the data owners and the knowledge experts who provide the actionable knowledge for use on the system. The ambient learning experts are responsible with deciding whether knowledge gathered is actionable or not. This makes sure the knowledge consumer gets the relevant knowledge upon implementation of the framework.

4.7 Summary of Results

The methods applied to the OMAL dataset deliver actionable knowledge which the ambient learning expert can use to improve the system. This research has shown that integrating a knowledge based system in the ambient learning system will allow an ambient learning expert to have readily accessible knowledge on how to improve it and enhance the quality of education.

Applicability of the knowledge as a service feature can improve the dissemination of the knowledge via the cloud whereby the knowledge based system interface would be made available online so that the ambient learning experts can make adjustments to the system given the dynamic nature of how users access the system. The technical focal point of the service is to use the knowledge from the knowledge based system to make informed decisions on which courses to correspond with the different multi modal forms of representation i.e. audio, video or text.

CHAPTER FIVE

CONCLUSION AND RECOMMENDATIONS

5.1 Introduction

The main objective of the research is to discover how knowledge can be used to bridge gaps in the realization of inclusive and quality education through the leveraging of an ambient learning system and make available opportunities for lifelong learning. This chapter discusses the views of the researcher that were derived from the study. It will include an overview of findings, limitations and recommendations for future study.

5.2 Overview of Findings

The first objective of this research was to find out the current state of ambient learning. It was evident from the results of this objective that the regions of the Middle East and Europe had the highest number of ambient learning projects. This could be explained by the fact that these places have better network infrastructures and computing devices like smartphones, laptops and PCs are easily available. The well laid out network infrastructure allows for fast internet connection in most if not all parts of these countries. With these convenient internet connection speeds, lifelong, quality learning is ensured and also given the advanced education systems in these countries learners are provided with the resources i.e. laptops or tablets to thrive in such an environment. Other regions like Africa and Latin America are not far behind as there were a few ambient learning projects to show but the economical aspect and poor network infrastructure put most countries in this regions at a disadvantage.

The second specific objective was to analyze and establish an appropriate knowledge as a service for an ambient learning application. The results of this objective was the novel ambient learning knowledge as a service system architecture that brings together the community of practice which involves the knowledge experts and ambient learning experts, the KaaS which includes the knowledge discovery and knowledge based system, and the cloud broker which includes the service intermediation and KaaS broker. These three are the main components in coming up with and disseminating knowledge to improve the quality of learning via the already existing OMAL ambient learning system.

The third objective was to evaluate the effectiveness of the established model with one of the reviewed technology enhanced cases. The results of this objective were conclusive in ascertaining the need for an ambient learning system that has a knowledge based system that can gather new knowledge from the data produced on the ambient learning system that can help make improvement or changes. The research proposes that the prolog interface should be available online through a link that can be hosted on a cloud server thus allowing accessibility from anywhere at any time.

5.3 Contribution of the study

The main contribution of this research was to show how the Open Mobile Ambient Learning (OMAL) system can integrate a knowledge as a service system which can use data from the OMAL system, mine it and extract knowledge that will be used by the ambient learning system developer in decision making and improvements. Apart from that, this research has also brought to light the regions that are lagging behind in ambient learning in the hope that it can arouse the interest for the development of more ambient learning systems which can integrate the knowledge as a service system for better quality education with lifelong learning opportunities.

5.4 Limitations

The limitations associated to this research are few. They include:

i. This research focused on investigating how an ambient learning system can be improved to enhance the quality of education based on the ambient learning system developer's perspective. Issues that learners may experience on the system are not featured at all.
ii. The research did not focus on the other categories of ambient learning i.e. FIAL and HIAL given that they are types of ambient learning and only the context in which the learners have access to them changes. It would therefore be a waste of time and counterproductive.
iii. The research also did not feature more advanced forms of collaboration such as Whatsapp to cater for those students who are more likely to use Whatsapp than Facebook.

5.4 Recommendations for future study

Based on the achievements on each specific objective I recommend the following research tasks to be carried out in future:

i. From objective one results I recommend a more in depth research on the state of ambient learning especially for the disadvantaged regions due to the lack of literature documenting ambient learning projects that may be in existence.
ii. From objective two results there is need to find out if other ambient learning knowledge as a service systems exist so as to be able to benchmark this research's model.
iii. From objective three results I recommend a research to find out if other artificial intelligence programming languages can be used to facilitate the knowledge based system.

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