AN ARTIFICIAL INTELLIGENCE-BASED KNOWLEDGE MANAGEMENT SYSTEM FOR OUTCOME-BASED EDUCATION IMPLEMENTING IN HIGHER EDUCATION INSTITUTIONS

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ASIA e UNIVERSITY

2025

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A Thesis Submitted to Asia e University in
Fulfilment of the Requirements for the
Degree of Doctor of Philosophy

June 2025

ABSTRACT

The main challenges faced by Higher Education Institutions (HEIs) in Indonesia in the context of Industrial Revolution (IR) 4.0 lie in the development of knowledge-intensive skills and the development of outcome-oriented curricula. This study investigates the role of Knowledge Management Systems (KMS) and artificial intelligence (AI) in facilitating the implementation of Outcome-Based Education (OBE) as a strategic approach to improve the quality of HEIs in responding to the demands of IR 4.0. Specifically, this study investigated the knowledge creation process in KMS to support the implementation of OBE in HEIs. The objectives of this study include developing relevant knowledge pool in the area informatics for KMS, to develop a learning analytics technique for KMS in order to support the implementation of OBE in HEIs, to validate the KMS developed for OBE implementation in HEIs and to evaluate its acceptance among the users. AI in KMS is used in the knowledge creation process. The Bert2Bert model is used in the multi-document summarisation of Indonesian-language knowledge in the knowledge combination process. Recommendation system on learning analysis was implemented in a hybrid algorithm combines Rule-based and Content-based filtering algorithms. KMS validation was carried out through expert assessment, and the user acceptance of the KMS was evaluated using a survey method, which adopted a questionnaire from the Technology Acceptance Model (TAM) framework. Based on the results of the knowledge creation in KMS, it succeeded in meeting learners' learning needs. The upload function represents the externalisation of knowledge. This function enables the expert to add knowledge, and followed by scraping and summarising knowledge, represented by a combination of knowledge. The scraping process extracted knowledge from online media, and knowledge from various documents or sources was then summarized. Based on the results of the evaluation of Bert2Bert model the readability for summarising 2 and 3 knowledge documents using the Flesch-Kincaid Grade Level (FKGL) showed that the average values were 20.35 and 18.1, the Gunning Fog Index (GFI) method 7.52 and 8.165, and the Dwiyanto Djoko Pranowo method 20.33 and 32.2. The evaluation explained that adults and learners at higher education levels can understand the summarized knowledge. Readability evaluation was carried out manually by Indonesian language experts. A total of 20 document knowledge was evaluated manually, and the results from document summary were understood. Internalisation of knowledge in KMS was represented through the learning analytics function, followed by an automatic recommendation system to improve knowledge. Based on the evaluation results using the confusion matrix, the Recall value was 59.1%, Precision was 100%, F1-Score was 74%, and Mean Absolute Error (MAE) of 0.97 (testing 31 data with 5 categories and target range 0-4), indicating that the recommendation system in the KMS has good classification capabilities and high accuracy in prediction. KMS also received positive validation from learning media experts, learning content, and information and communication technology (ICT) experts, with the percentage of assessment results of 79.54% and 86.1%, respectively. These results indicate the developed of KMS achieved level good and suitable for use category and does not need revision. A survey from 95 learners HEIs adopted from TAM revealed that KMS was significantly accepted for implementation of OBE via personalized learning and hence, be able to improve learners' learning. This study has significantly contributed to the development of KMS, especially in the context of personalized learning to support OBE

implementation in HEIs and the integration of AI technology in the knowledge creation process in KMS.

Keywords: KMS, personalized learning, OBE, HEI, knowledge creation, summarisation, recommendation system, validation, evaluation, and TAM Model

APPROVAL

This is to certify that this thesis conforms to acceptable standards of scholarly presentation and is fully adequate, in quality and scope, for the fulfilment of the requirements for the Degree of Doctor of Philosophy.

The student has been supervised by: **Professor Ts Dr Titik Khawa Abdul Rahman & Professor Dr Muhammad Ali Ramdhani**

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………………………………
Professor Dr Siow Heng Loke
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Chairman, Examination Committee
17 June 2025

DECLARATION

I hereby declare that the thesis submitted in fulfilment of the requirements for the Degree of Doctor of Philosophy is my own work and that all contributions from any other persons or sources are properly and duly cited. I further declare that the material has not been submitted either in whole or in part, for a degree at this or any other university. In making this declaration, I understand and acknowledge any breaches in this declaration constitute academic misconduct, which may result in my expulsion from the programme and/or exclusion from the award of the degree.

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Signature of Student: **Date**: 17 June 2025

ACKNOWLEDGEMENTS

In the name of Allah, the Most Gracious and the Most Merciful. Praise and gratitude to Allah SWT, the Most Gracious, my Sustainer, who has given me life and maintained my hopes as a thinking person. I want to thank the State Islamic University (UIN) Sunan Gunung Djati Bandung Indonesia and Asia e University (AeU) Malaysia for providing a place to conduct research. My highest appreciation goes to my main supervisor, Prof. Dr Titik Khawa Abdul Rahman, Faculty of Information and Communication Technology, Asia e University (AeU), for all her support, advice, and inspiration. Her endless patience in guiding and providing invaluable insights will always be remembered. Also, my co-supervisor, Prof. Dr H Muhammad Ali Ramdhani, STP, MT., Informatics Department, State Islamic University (UIN) Sunan Gunung Djati Bandung, has always supported my journey. Thank you to my beloved mother for her prayers and sacrifices. My beloved wife and children have been the reason for staying enthusiastic about difficulties. Father and mother-in-law, thank you for your prayers and support. Lastly, thank you to the head of the faculty of science and technology, the head of the department and friends in the Informatics Department of the State Islamic University (UIN) Sunan Gunung Djati Bandung, who have provided support for the completion of my studies.

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LIST OF ABBREVIATION

AeU	Asia e University
AI	Artificial Intelligence
BERT	Bidirectional Encoder Representations from Transformers
CLO	Course Learning Outcomes
FKGL	Flesch-Kincaid Grade Level
GFI	Gunning Fog Index
HEI	Higher Education Institutions
IR	Industrial Revolution
KM	Knowledge Management
KMS	Knowledge Management System
OBE	Outcome-Based Education
PL	Personalized Learning
PLO	Program Learning Outcomes
PS	Problem Statement
RO	Research Objective
RQ	Research Question
SECI	Socialisation, Externalisation, Combination, Internalisation
TAM	Technology Acceptance Model
TRA	Theory of Reasoned Action

CHAPTER 1

INTRODUCTION

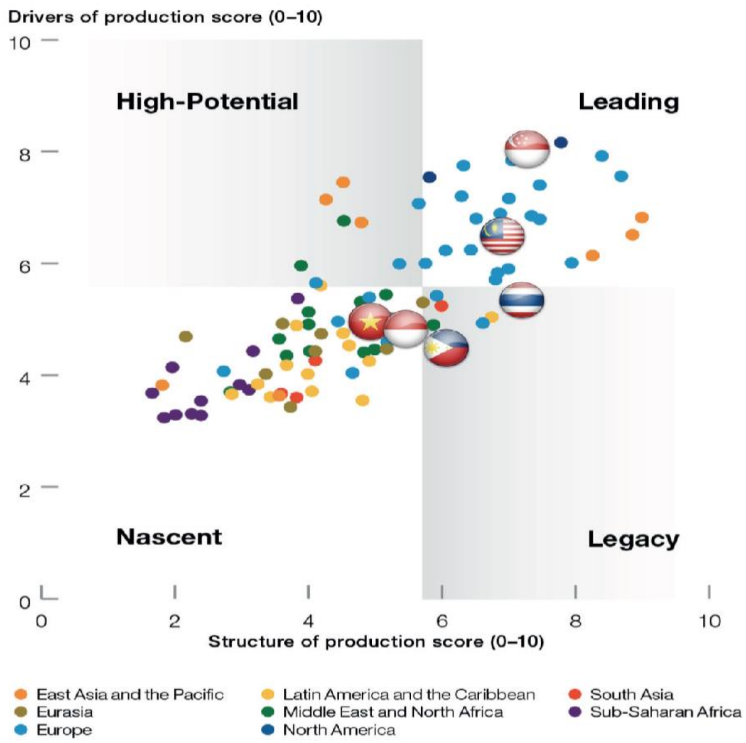
1.0 Introduction

Adapting to every change is the key to success for higher education institutions (HEIs) in facing the challenges of Industry 4.0. Adaptation to continuous scientific and technological advances is the key to success for HEIs in improving the quality of education. One of the adaptation processes involves developing a knowledge management system (KMS) to support the adaptive learning process of organisational members. Artificial intelligence (AI) technology in KMS is widely utilised in the knowledge creation process, one of which is natural language processing (NLP). Implementing NLP using the BERT2BERT model can assist in multi-document summarisation of knowledge. AI technology is also utilised to create personalised learning environments through learning analytics. Recommendation systems in learning analytics use hybrid algorithms (collaborative filtering and content-based filtering). The next adaptation is the ability of HEIs to adopt a learning outcomes-based curriculum (OBE). This study discusses the development, implementation, and evaluation of KMS in HEIs. The structure of Chapter One discusses the background of the study, including the problem statement, research objectives, research questions, justification of the research significance, and a summary of Chapter 1.

1.1 Background of Study

Based on the 2018 World Economic Forum Readiness for Future Production Report regarding the readiness of countries in the world to face Industry 4.0. According to this report, Indonesia is one of the countries considered unready to face the challenges of Industry 4.0. This unpreparedness is marked by Indonesia's production structure and drivers, which are needed to catch up to other countries in the ASEAN region. One of the production drivers is the human capital factor (Kearney, 2018).

Figure 1.1: Global Map of Readiness Assessment Results 2018



Source: Kearney, 2018

Increasing human capital is the biggest challenge for Indonesia in facing the Industrial Revolution (IR) 4.0 and developing various knowledge-intensive skills (Iswanto, 2019; Kearney, 2018, Mehralian et al., 2018). The Indonesian government has made various efforts to develop various skills that suit the needs of RI 4.0, one of which is involving higher education institutions (HEI). The government and HEIs must support the development of Education 4.0 because Industry 4.0 requires Education 4.0 (Sima et al., 2020). One of these developments is adapting the curriculum based on learning outcomes (OBE) at HEI (Jadhav et al., 2020; Kementerian Perindustrian Republik Indonesia, n.d.; Rathy et al., 2020; Sima et al., 2020).

HEI's active participation in improving various knowledge-intensive skills can be realized through efforts to become an effective learning organization. An effective learning organization can increase capacity and intellectual capital, motivate employees to learn adaptively, generatively, and continuously, learn together, and share knowledge so that each employee has high competence (Senge, 1990). In order to become an effective learning organization, HEI needs to transform continuously. One of the transformations is adopting processes in knowledge management (KM) to gain a competitive advantage in the future (Damartini & Lorenzo, 2017; Jamalzadeh, 2012; Kalsom, 2014). The processes in KM are related to how to generate value from wealth—intellectual property owned by HEI. Through the process of creating, storing, disseminating, and using knowledge, HEIs can improve innovation and organizational performance (Jones & Leonard, 2009; Nonaka & Takeuchi, 1995; Shujahat et al., 2018; Song & Sun, 2018).

Knowledge in organizations consists of tacit and explicit knowledge. Tacit knowledge is rooted in action, experience, and involvement in a specific context. The tacit knowledge dimension consists of cognitive and technical elements. Cognitive elements refer to an individual's mental model consisting of mental maps, beliefs, paradigms, and points of view. The technical component consists of knowledge, craft, and concrete skills that apply in a specific context. Meanwhile, explicit knowledge is a dimension of knowledge that can be articulated, codified, communicated, and disseminated in symbolic form and natural language (Alavi & Leidner, 2001; Jones & Leonard, 2009; Nonaka, 1994).

Knowledge in organizations is created through continuous dialogue between tacit and explicit knowledge. The socialisation process in KM converts tacit knowledge into tacit knowledge through shared experiences and daily social interactions. The externalisation process is the articulation of tacit knowledge into explicit knowledge, and it can be shared with others to become the basis of new knowledge. The combination process is creating explicit knowledge from other explicit knowledge. Explicit knowledge is collected from inside or outside the organization and then combined, edited, or processed to form more complex and systematic explicit knowledge. Meanwhile, the internalisation process in KM is explicit knowledge created and shared throughout the organization and then converted into tacit knowledge by individuals (Nonaka & Takeuchi, 1995; Nonaka & Toyama, 2003; Shujahat et al., 2018)

The process of creating knowledge in KM is a cognitive process. The knowledge environment strongly influences the creation process, both sources and technology used to obtain or process knowledge (Avdeenko et al., 2016; Cha et al., 2015; Córdova & Gutiérrez, 2018; Supic, 2018). Cognitive processes in KM must be able to provide adaptive learning spaces. Personalized learning (PL) adjusts learning needs to learners' interests, talents, and abilities. PL provides a flexible learning environment for individuals to learn under different conditions (Basham et al., 2016; Davis & Jiang, 2014). PL can utilize learning resources from online media or big data, utilizing Artificial Intelligence (AI) technology to support learning (Damartini & Lorenzo, 2017).

Paradigm changes in HEIs require the ability to adapt, collaborate, innovate, master technology, and manage intellectual assets as capital in improving the quality of education. This change is marked through the implementation of KM, the use of AI and OT technology to improve the quality of education at HEIs (Ahmed et al., 2018; Bhusry et al., 2011; Mansur et al., 2019; Kong et al., 2021; Lemay et al., 2021; Munir & Rohendi, 2012; Ouyang & Jiao, 2021; Quadir et al., 2021; Zhang & Aslan, 2021).

KMS in Indonesian HEIs has not been widely implemented. HEIs that have implemented a Knowledge Management System (KMS) include the Bandung Institute of Technology (ITB) in 2016 (Sopandi & Saud, 2016) and Bina Nusantara University (BINUS) in 2018 (Prabowo, 2010; Qisty, 2021).

The most fundamental change to HEI is HEI's ability to adapt the OBE curriculum. Through the OBE curriculum, educational success is measured by the learning success achieved by learners. Significant learning experiences reflect learners competence (Spady, 1994). OBE is a student-centered curriculum. Emphasizes assessing learners performance results, knowledge, skills, and behavior (Jadhav et al., 2020; Rathy et al., 2020). The implementation of the OBE curriculum in HEIs in Indonesia still faces various challenges. These challenges relate to the readiness of teachers who are accustomed to traditional learning methods, strategies, materials, and assessment tools (Mufanti et al., 2023; Piyasena et al., 2023; Susanti et al., 2024).

This research studies and develops a knowledge management system (KMS) at a university. The primary goal is to implement AI to provide knowledge that supports an adaptive, personalised, and results-driven learning process. The KMS implements the Bert2Bert model in the automatic summarisation of multi-document knowledge in the Indonesian language. Hybrid algorithm (Rule-based and content-based filtering algorithms) are implemented in the automatic recommendation system for learning analytics in the KMS. The rules for developing KMS at HEI refer to the SECI model. The model focuses on knowledge creation, storage, dissemination, and use (Nonaka & Takeuchi, 1995). Transformation of knowledge in the hybrid model combines the SECI model with the case-based reasoning (CBR) knowledge representation model in case solving (Avdeenko et al., 2016). The Network of Damage Adjusters (RAS) model adopts the SECI model. The RAS model facilitates employee learning to acquire higher expertise at work (Córdova & Gutiérrez, 2018). Specifically, Galeon and Palaoag (2019) developed a KMS framework to support the sustainable implementation of OBE in HEIs in the Philippines (Galeon & Palaoag, 2019). PL in KMS provides a framework for how learning processes in KMS are carried out adaptively, according to the interests and needs of learners (Basham et al., 2016; Johns & Wolking, 2016; Nitchot et al., 2019).

1.2 Problem Statement

Knowledge at HEI comes from internal and external organizations. Knowledge in KM is collecting and combining knowledge from various sources, both internal and external to the organization (Dalkir, 2005). Utilizing knowledge from various sources is one of the keys to creating an effective learning organization (Damartini & Lorenzo, 2017; Jamalzadeh, 2012; Janus, 2016). Exploring knowledge sources comprehensively and utilizing technology in presenting knowledge is a challenge for HEIs. More than efforts to explore knowledge from various sources are needed in terms of storage media (Munadi et al., 2019), HEIs need to identify knowledge sources that suit the learning needs of organizational members.

Tacit knowledge is personal, specific, and sourced from experience or work (Nonaka & Takeuchi, 1995). They are building implicit knowledge into a social context to expand knowledge. A medium is needed to articulate tacit knowledge and resolve conflicts towards a higher conceptual level (Nonaka, 1994). HEIs widely use online media and has become quite an effective medium for sharing knowledge, exchanging ideas, conveying ideas, or sharing experiences (Carvalho & Gomes, 2017; Cerchione & Esposito, 2017; Cetto et al., 2018; Córdova & Gutiérrez, 2018; He et al., 2017d; Un Jan & Contreras, 2016). Disseminating knowledge in online media (Cha et al., 2015; He et al., 2017) produces knowledge documents with many pages.

Documents with many pages require a selection process and quite a long reading time (Torres-Moreno, 2014).

Online media provides structured knowledge. Knowledge combination in KM involves knowledge sourced from internal or external organizations (Avdeenko et al., 2016; Cha et al., 2015; Córdova & Gutiérrez, 2018; He et al., 2017; Supic, 2018). The combination of knowledge gives rise to complexity and the need for classification, even additions from an expert. The contribution of an expert in the knowledge combination process is expected to produce more structured knowledge, which can be extracted into specific knowledge so that it is suitable to meet the learning needs of the organization (Celesti et al., 2019; Du, Chen, Liu, Zhang, & Zhang, 2018; Johns & Wolking, 2016; Kearney, 2018). Internalizing knowledge is not only a learning-by-doing process (Campatelli et al., 2016; Nonaka & Takeuchi, 1995). The process of internalizing knowledge is part of the learning cycle, which includes the process of assessing learning outcomes (Tsai & Lee, 2006). Assessment of learning outcomes in PL helps determine learning needs by learners characteristics (Conde & Rodríguez-Sedano, 2024; Epp & Bull, 2015; Guenaga & Garaizar, 2016; Gursoy et al., 2017; Ruipérez-Valiente et al., 2016; Oakleaf et al., 2017; Tempelaar et al., 2017). Assessment in the cognitive process consists of measuring and analyzing learning outcomes. The OBE curriculum adaptation contains two forms of assessment: course learning outcomes (CLO) and program learning outcomes (PLO) (Jadhav et al., 2020; Rathy et al., 2020; Spady, 1994). Knowing the extent of the learning outcomes achieved in the learning process will be easy with assessment. Knowledge development will be challenging to map; learners will need help to acquire knowledge in stages. They also find it challenging to adapt to developments in science and technology; what they learn does not support the development of skills to the needs of

Industry 4.0 (Celesti et al., 2019; Du et al., 2018; Johns & Wolking, 2016; Kearney, 2018).

HEI develops KM as a strategic vision to achieve the comprehensive goals of the organization's mission (Salo, 2011). This strategic vision should be the Indonesian government's vision of increasing human capital to face the challenges of Industry 4.0 (Kementerian Perindustrian Republik Indonesia, n.d.). The suitability of KMS development needs to be assessed from the system's functionality and from the perspective of learners' knowledge development needs. This assessment is carried out to ensure that the KMS development can represent the strategic vision that the organization has set.

Table 1.1: Summary of Problem Statement

PS1	Munadi et al. (2019) research explains the reality of KM in HEIs in Indonesia, from the production, storage and distribution of knowledge. The study did not explore knowledge sources comprehensively. Knowledge in the organization is explained from the storage media side. When organizations cannot identify needs and explore knowledge sources for organizational members, it is difficult for HEIs to realize an effective learning organization. As a result, it is difficult for HEIs to realize competitive advantages in the future (Demartini & Benussi, 2017; Jamalzadeh, 2012; Kalsom, 2014; Senge, 1990)
PS2	Externalisation of knowledge in online media (Cha et al., 2015; He et al., 2017) produces much knowledge in terms of the number of documents and pages. The large number of documents and pages that must be read requires a selection process and a long reading time, and sometimes, it becomes

	biased (Torres-Moreno, 2014). These documents contain the best knowledge and experience in solving problems. Research on automatic text summarisation has been widely conducted; the challenge is how to reduce the gap between the summary results and the reader's understanding (Yao, et al., 2017; Safiah et al., 2017; Munadi et al., 2019; Nurul Nazariah & Hoque, 2019). Unlike English-language documents, research on automatic text summarisation of Indonesian-language documents has not been widely conducted. This is because Indonesian is unique and different from other languages , and the available data set is relatively limited.
PS3	The knowledge combination process in several KM models (Avdeenko et al., 2016; Córdova & Gutiérrez, 2018; He et al., 2017d; Sadewa et al., 2019; Supic, 2018), does not provide a mechanism for expert contribution in adding knowledge. The contribution of an expert in KMS has a strategic role in combining knowledge. The availability of structured, valid and specific knowledge can reduce the occurrence of knowledge gaps in the industrial world.
PS4	Internalisation of knowledge in KM consists of applying knowledge and knowledge creation (Alavi & Leidner, 2001; McElroy, 2000; Nonaka & Takeuchi, 1995). Internalisation in the learning cycle perspective is when learners understand the content of knowledge and apply that knowledge in practice or the testing stage of the concepts that have been formed (Tsai & Lee, 2006). The explicit development of the KMS framework to support the implementation of OBE in HEIs was carried out by Galeon and Palaoag (2019). The model does not integrate the processes in PL and does not

	explain the assessment aspects in detail. When the assessment components in the OBE process are not fully represented, measuring the achievement of course learning (CLO) will be difficult.
PS5	Several KMS Models have been developed (Avdeenko et al., 2016a; Córdova & Gutiérrez, 2018; Paguio et al., 2016; Sadewa et al., 2019). These models are not integrated with PS and do not explain how the learning outcome assessment process is carried out, how the learning needs mechanism is carried out, and how the level of learners knowledge is determined. Internalisation of knowledge in KM should include an assessment process to measure and analyze learning outcomes. Personal learning (PL) assessment helps learners know the achievement of results and mapping of learning needs (Izmestiev, 2013; Shemshack & Spector, 2020). On the other hand, when learning is not equipped with assessment, it is difficult for learners to develop their skills in a tiered manner. They do not have a clear knowledge development roadmap. When the knowledge development roadmap is not established, it is difficult for learners to adapt to developments in science and technology. Learners do not have a level of confidence in the skills they possess because they do not have a specific skill base in accordance with the needs of RI 4.0 (Celesti et al., 2019; Du, Chen, Liu, Zhang, & Ping Zhang, 2018; Johns & Wolking, 2016; Kearney, 2018).
PS6	The OBE curriculum focuses on the knowledge, skills, and attitudes acquired from learners' learning experiences. The conventional education system, the emphasis is less on outcomes, and more on input-based (Jadhav et al., 2020). Descriptions of the perceptions and readiness of several HEIs in

	implementing the curriculum illustrate that 51.9% have poor perceptions about OBE, and 50% have poor readiness in implementing the OBE curriculum (Widyatuti & Jauhar, 2022). The implementation of OBE requires a paradigm shift and infrastructure readiness. This readiness is reflected in the quality assurance and quality improvement processes at HEIs that run effectively. When OBE is not well prepared, it is difficult for HEIs to measure the success of learning outcomes. HEIs find it difficult to obtain recognition or accreditation both nationally and internationally (Sasipraba et al., 2020).
PS7	The success of implementing Knowledge Management Systems (KMS) in Indonesian Higher Education Institutions (HEIs) depends on internal factors (leadership, culture, technology, human resources, processes) and external factors (stakeholder support) to improve knowledge productivity and academic services (Munadi et al., 2019; Nur et al., 2017). A holistic readiness model that aligns these internal and external factors has been proposed to mitigate the risk of KMS implementation failure and ensure its support for the Tri Dharma (Budianto & Sardjono, 2022). Problems arise in evaluating KMS implementation. First, Unbalanced Evaluation Focus The current evaluation of KMS implementation focuses more on management aspects (such as technical infrastructure, policies, and budget allocation) while ignoring user acceptance factors that determine the operational success of the system. Second, the impact on the sustainability of KMS, specifically the low utilisation of KMS features by end users, and the potential for long-term failure despite meeting management aspects.

1.3 Research Objectives

Based on the research problem, the main objectives of this research are as follows:

i. To develop a relevant knowledge pool in the area of informatics for the KMS in order to support the OBE implementation of in HEI.

ii. To develop a learning analytics technique for KMS in order to support the implementation of OBE in HEI.

iii. To validate KMS developed for KMS in order to support the implementation of OBE in HEI and evaluate its acceptance among the users.

1.4 Research Questions

This research will answer the following research questions:

i. How is the curriculum framework set up for KMS in order to support the implementation of OBE in HEI?

ii. What relevant knowledge in the area of informatics can be used for the development of the KMS in order to support the implementation of OBE in HEI?

iii. How is the process of combining knowledge for KMS in order to support the implementation of OBE in HEI?

iv. What is the process of summarising knowledge documents for KMS in order to support the implementation of OBE in HEI?

v. What is the process of assessing learning outcomes for KMS in order to support the implementation of OBE in HEI?

vi. What is the process of analysing learning outcomes for KMS in order to support the implementation of OBE in HEI?

vii. What instruments are used by learning and ICT experts to validate the development of KMS in order to support the implementation of OBE in HEI?

viii. What is the learners' acceptance model of the KMS and the influence of using it in order to support the implementation of OBE in HEI?

The relationship between objectives and research problems is explained in Table 1.2 as follows:

Table 1.2: Relationship between Research Problems, Research Objectives

PS1. Munadi et al. (2019) research explains the reality of KM in HEIs in Indonesia, from the production, storage and distribution of knowledge. The study did not explore knowledge sources comprehensively. Knowledge in the organization is explained from the storage media side. When organizations cannot identify needs and explore knowledge sources for organizational members, it is difficult for HEIs to realize an effective learning organization. As a result, it is difficult for HEIs to realize competitive advantages in the future (Demartini & Benussi, 2017; Jamalzadeh, 2012; Kalsom, 2014; Senge, 1990) **PS2.** Externalisation of knowledge in online media (Cha et al., 2015; He et al., 2017) produces much knowledge in terms of	**RO1.** To develop a relevant knowledge pool in the area of informatics for the KMS in order to support the OBE implementation of in HEI.	**RQ1.** How is the curriculum framework set up for KMS in order to support the implementation of OBE in HEI **RQ2.** What relevant knowledge in the area of informatics can be used for the development of the KMS in order to support the implementation of OBE in HEI?

the number of documents and pages. The large number of documents and pages that must be read requires a selection process and a long reading time, and sometimes, it becomes biased (Torres-Moreno, 2014). These documents contain the best knowledge and experience in solving problems. Research on automatic text summarisation has been widely conducted; the challenge is how to reduce the gap between the summary results and the reader's understanding (Yao et al., 2017; Safiah et al., 2017; Munadi et al., 2019; Nurul Nazariah & Hoque, 2019). Unlike English-language documents, research on automatic text summarisation of Indonesian-language documents has not been widely conducted. This is because Indonesian is unique and different from other languages , and the available data set is relatively limited.		**RQ3.** How is the process of combining knowledge for KMS in order to support the implementation of OBE in HEI? **RQ4.** What is the process of summarising knowledge documents for KMS in order to support the implementation of OBE in HEI?

PS3. The knowledge combination process in several KM models (Avdeenko et al., 2016; Córdova & Gutiérrez, 2018; He et al., 2017; Sadewa et al., 2019; Supic, 2018), does not provide a mechanism for expert contribution in adding knowledge. The contribution of an expert in KMS has a strategic role in combining knowledge. The availability of structured, valid and specific knowledge can reduce the occurrence of knowledge gaps in the industrial world. **PS6.** The OBE curriculum focuses on the knowledge, skills, and attitudes acquired from learners' learning experiences. The conventional education system, the emphasis is less on outcomes, and more on input-based (Jadhav et al., 2020). Descriptions of the perceptions and readiness of several HEIs in implementing the curriculum illustrate that 51.9% have poor		

perceptions about OBE, and 50% have poor readiness in implementing the OBE curriculum (Widyatuti & Jauhar, 2022). The implementation of OBE requires a paradigm shift and infrastructure readiness. This readiness is reflected in the quality assurance and quality improvement processes at HEIs that run effectively. When OBE is not well prepared, it is difficult for HEIs to measure the success of learning outcomes. HEIs find it difficult to obtain recognition or accreditation both nationally and internationally (Sasipraba et al., 2020).		

PS4. Internalisation of knowledge in KM consists of applying knowledge and knowledge creation (Alavi & Leidner, 2001; McElroy, 2000; Nonaka & Takeuchi, 1995). Internalisation in the learning cycle perspective is when learners understand the content of knowledge and apply that knowledge in practice or the testing stage of the concepts that have been formed (Tsai & Lee, 2006). The explicit development of the KMS framework to support the implementation of OBE in HEIs was carried out by Galeon and Palaoag (2019). The model does not integrate the processes in PL and does not explain the assessment aspects in detail. When the assessment components in the OBE process are not fully represented, measuring the achievement of course learning (CLO) will be difficult.	**RO2.** To develop a learning analytics technique for KMS in order to support the implementation of OBE in HEI.	**RQ1.** How is the curriculum framework set up for KMS in order to support the implementation of OBE in HEI

PS5. Several KMS Models have been developed (Avdeenko et al., 2016; Córdova & Gutiérrez, 2018; Paguio et al., 2016; Sadewa et al., 2019). These models are not integrated with PS and do not explain how the learning outcome assessment process is carried out, how the learning needs mechanism is carried out, and how the level of learners knowledge is determined. Internalisation of knowledge in KM should include an assessment process to measure and analyze learning outcomes. Personal learning (PL) assessment helps learners know the achievement of results and mapping of learning needs (Izmestiev, 2013; Shemshack & Spector, 2020). On the other hand, when learning is not equipped with assessment, it is difficult for learners to develop their skills in a tiered manner. They do not have a clear knowledge development roadmap.		**RQ2.** What relevant knowledge in the area of informatics can be used for the development of the KMS in order to support the implementation of OBE in HEI?

When the knowledge development roadmap is not established, it is difficult for learners to adapt to developments in science and technology. Learners do not have a level of confidence in the skills they possess because they do not have a specific skill base in accordance with the needs of RI 4.0 (Celesti et al., 2019; Du, Chen, Liu, Zhang, & Ping Zhang, 2018; Johns & Wolking, 2016; Kearney, 2018).		**RQ5.** What instruments are used by learning and ICT experts to validate the development of KMS in order to support the implementation of OBE in HEI?
PS6. The OBE curriculum focuses on the knowledge, skills, and attitudes acquired from learners' learning experiences. The conventional education system, the emphasis is less on outcomes, and more on input-based (Jadhav et al., 2020). Descriptions of the perceptions and readiness of several HEIs in implementing the curriculum illustrate that 51.9% have poor perceptions about OBE, and 50% have poor readiness in		**RQ6.** What is the process of analysing learning outcomes for KMS in order to support the implementation of OBE in HEI?

implementing the OBE curriculum (Widyatuti & Jauhar, 2022). The implementation of OBE requires a paradigm shift and infrastructure readiness. This readiness is reflected in the quality assurance and quality improvement processes at HEIs that run effectively. When OBE is not well prepared, it is difficult for HEIs to measure the success of learning outcomes. HEIs find it difficult to obtain recognition or accreditation both nationally and internationally (Sasipraba et al., 2020).		
PS7. The success of implementing Knowledge Management Systems (KMS) in Indonesian Higher Education Institutions (HEIs) depends on internal factors (leadership, culture, technology, human resources, processes) and external factors (stakeholder support) to improve knowledge productivity and	**RO3.** To validate KMS developed for KMS in order to support the implementation of OBE in HEI and evaluate its acceptance among the users.	**RQ7.** What instruments are used by learning and ICT experts to validate the development of KMS in order to support the implementation of OBE in HEI?

academic services (Munadi et al., 2019; Nur et al., 2017). A holistic readiness model that aligns these internal and external factors has been proposed to mitigate the risk of KMS implementation failure and ensure its support for the Tri Dharma (Budianto & Sardjono, 2022). Problems arise in evaluating KMS implementation. First, Unbalanced Evaluation Focus The current evaluation of KMS implementation focuses more on management aspects (such as technical infrastructure, policies, and budget allocation) while ignoring user acceptance factors that determine the operational success of the system. Second, the impact on the sustainability of KMS, specifically the low utilisation of KMS features by end users, and the potential for long-term failure despite meeting management aspects.		**RQ8.** What is the learners' acceptance model of the KMS and the influence of using it in order to support the implementation of OBE in HEI?

1.5 Contribution of the Study

The research provides both technical and theoretical significance:

i. Theoretical Significance

1. Filling the Research Gap. This research addresses the scarcity of studies on integrating Knowledge Management Systems (KMS) with personalised learning to support the implementation of Outcome-Based Education (OBE) in Indonesian higher education. Previous studies have not comprehensively discussed the synergy among these three concepts (KMS, personalised learning, and OBE).
2. Development of Conceptual Model. The research findings contribute to the development of theoretical models for managing multi-domain knowledge (curriculum, pedagogy, assessment) in OBE, as well as Adaptive learning mechanisms based on KMS that align with OBE principles. Moreover, the framework for extracting and combining knowledge from heterogeneous sources (research, practice, regulation).
3. Enriching KM Literature in Education and providing new perspectives on the role of KMS as an enabler of outcome-driven education transformation, especially in the context of developing countries such as Indonesia.

ii. Technical Significance

1. Development of Innovative KMS System. Produce a KMS prototype with technical features such as Multi-Document Automatic Summarisation of knowledge (pedagogy, teaching materials, OBE standards), Learning Analytics to map student interests/talents and recommend personalised content, and a Recommendation System based on learning pathway profiles.

2. Operational Support for OBE Implementation: KMS helps HEIs in organising knowledge related to learning outcomes, adapting learning according to individual student needs, and monitoring alignment between the learning process and targeted outcomes.
3. Technical Performance Evaluation. This research helps the implementation of OBE in HEIs. Students who use this system will be able to learn independently and evaluate their performance in achieving the learning outcomes for a particular course through the formative assessment available. Based on the results from the formative assessment, the system would be able to provide suggestions, so that the students would be able to improve their performance. The learning can also be personalised according to the students' pace and time. The system has been validated through conducting a series of trials to measure the accuracy of multi-document automatic summarisation of knowledge, the effectiveness of personalised learning recommendations, and the level of user acceptance (lecturers/students) through expert validation and user evaluation.

1.6 Operational Definition of Terms

The meaning of the terms used in this research is as follows:

i. Knowledge management system

Knowledge management systems (KMS) are information technology (IT)-based systems developed to support and improve organizational processes starting from knowledge creation, retrieval-storage, transfer, and application (Turban et al., 2002). Technology refers to IT-based knowledge management tools that support organizational actors when carrying out knowledge management process activities.

Almost the exact definition was put forward by Maier (2007): KMS is an ICT system in the sense of an application system or ICT platform that combines and integrates functions to handle the contextual nature of both explicit and tacit knowledge, throughout the organization or part of the organization that is envisioned by the initiative. The ultimate goal of KMS is to support organizational learning dynamics and organizational effectiveness (Maier, 2007).

ii. Personalized learning

A new ecosystem transforms education institutions into an innovative and integrated education-producing ecosystem (Bin, 2017). Personalized learning is adaptive, tailored to each learners's interests, strengths, and needs, and provides flexible learning time (Basham et al., 2016; Davis & Jiang, 2014). Personalized learning is recognized as a learning strategy that can meet learners' learning needs and improve academic results (Johns & Wolking, 2016).

iii. Document summarisation

Document or text summarisation is part of natural language processing developed using artificial intelligence, which allows computers to have natural language processing capabilities like humans (Alquliti and Binti, 2019). Document summarisation can automatically summarize information from multiple sources and produce text summaries that are relevant and appropriate for a particular document or collection of documents (Jin and Wan, 2020).

iv. Learning analytics

Learning analytics measures, collects, analyses, and reports learners learning outcomes (Tsai, 2018). One part of Learning Analytics is learning experience analytics. Learning experience analysis seeks to understand a particular learning activity better. Analysis of learning experiences often answers questions about usage patterns for specific activities (Rustici Mike, 2018).

v. Outcome-Based Education (OBE)

The essence of outcome-based education is the actual learning results that we desire, demonstrated by learners at the end of the learning experience with significant results (Spady, 1994). Outcome-based education focuses on what has been learned or obtained and what learners can do. In an OBE-based curriculum, educational standards are clearly defined, known, and "criteria-based" for all learners (Arifin, 2020; Shaheen, 2019).

vi. Higher Education Institution (HEI)

Higher Education is the level of Education after secondary Education, which includes diploma programs, bachelor's programs, master's programs, doctoral programs, and professional programs, as well as specialist programs, which are organized by universities based on Indonesian culture (UU No. 12, 2022).

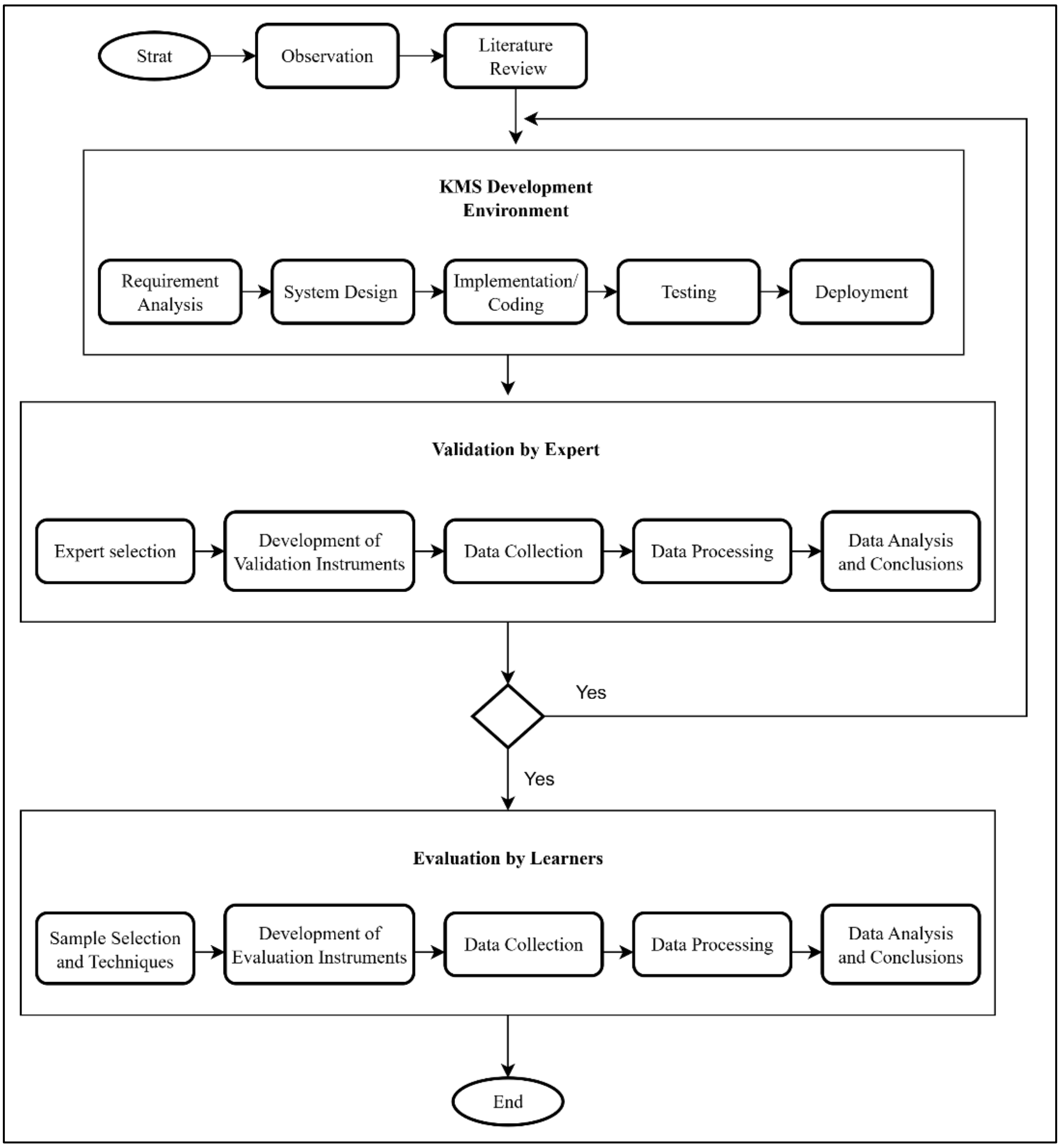
vii. Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM) provides a framework for understanding individual acceptance of technology by emphasizing the role of two primary cognitive factors: perceived usefulness and perceived ease of use (Davis, 1989). The model consists of six constructs: external variables, perceived ease of use, perceived usefulness, attitude toward use, behavioural intention to utilize the technology, and actual system use. The interactions among these constructs provide valuable insights into user behaviour and the technology adoption process.

1.7 Research Flow

Figure 1.2 shows the research flow.

Figure 1.2: Research Flow



The research flow adopted the system development steps of the Waterfall model. The developed KMS underwent a validation process by two experts: a learning content and information and communication technology expert and an instructional media expert. The evaluation was conducted by seventh-semester students in the Informatics Department of Sunan Gunung Djati State Islamic University (UIN) Bandung, who had taken the multimedia systems course. Expert assessment question items were adopted from the Gerhana YA (Indonesian Education University, 2016) dissertation research report. The student assessment adopted the Technology Acceptance Model (TAM) question instrument from research by Davis (1987), Gardner and Amoroso (2004), Kim et al. (2009), and Lee et al. (2011).

1.8 Chapter Summary

This chapter provides a comprehensive explanation of the main aspects of the research. The phenomenon is explained to understand the urgency of research and mapping research problems. The development of KMS at HEI has been discussed previously by experts. The results of this development became an initial reference and motivation to carry out further research on KMS development at HEI. KMS was developed for personalized learning, supporting OBE implementation at HEI. The KMS developed utilizes AI technology to manage knowledge from various sources, including automating knowledge document text summarisation. AI is also used in learning analytics to classify, analyse, and provide recommendations for improving learning outcomes. The assessment of learning outcomes refers to the OBE implementation framework at HEI. In summary, the development of KMS at HEI boils down to improving the quality of education to increase Indonesia's readiness to face the challenges of Industry 4.0.

CHAPTER 2

LITERATURE REVIEW

2.0 Introduction

This chapter will review the theories or concepts and previous research relevant to the research. The first part of this chapter will discuss the concept of knowledge. The second part will discuss knowledge management, knowledge management systems and artificial intelligence in knowledge management. AI-based KMS supports the implementation of OBE in HEIs. The knowledge creation process in KMS is inseparable from AI technology, one of which is natural language processing (NLP). The implementation of NLP using the BERT2BERT model can assist in multi-document knowledge summarisation. AI technology is also used to create personalised learning environments through learning analytics. Recommendation systems in learning analytics utilise hybrid algorithms (collaborative filtering and content-based filtering). The second part of this chapter will discuss the previous knowledge management system, which is the basis for developing knowledge management. The final part of this chapter discusses personalized learning and components of learning analytics.

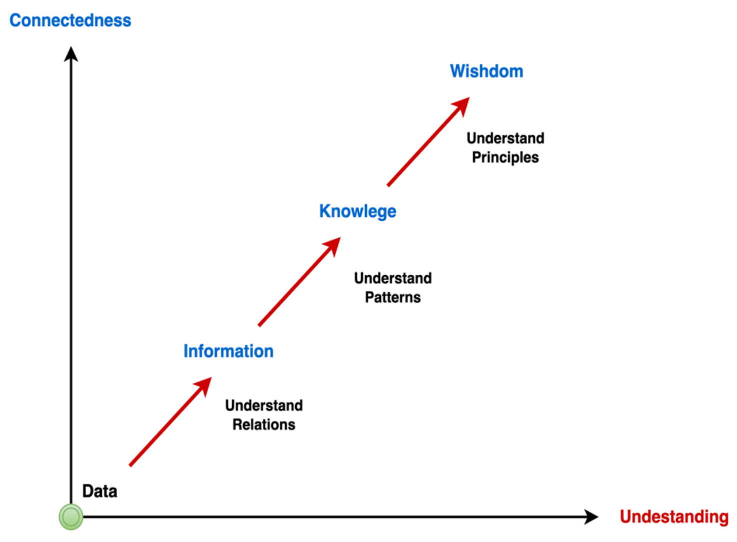
2.1 Knowledge

Knowledge is information held in the mind of an individual or personalized information related to facts, procedures, concepts, interpretations, ideas, observations, and judgments [1] Huber and Nonaka define knowledge as justified beliefs that increase an entity's capacity for effective action (Alavi & Leidner, 2001). According to Drucker (1993), knowledge is information that changes something or someone either as the basis for an action or by enabling individuals or institutions to perform different and better actions (Drucker, 1993) Knowledge by Davenport and (Davenport & Prusak, 1998) is defined as a combination of experiences, values, contextual information, and expert insights that are framed. Knowledge generation occurs when information is compared, combined, analysed, and reorganized (Maravilhas & Martins, 2019). Alkoff (1989), associates knowledge with five categories. The five categories are related to the intellectual content and human mentality (Alkoff, 1989), which can be classified as follows:

1. Data: in the form of symbols
2. Information: data that is processed so that it can be used, answering who, what, when and where
3. Knowledge: is the application of data and information and answers to how questions.
4. Understanding: appreciating the question why
5. Wisdom: evaluation of understanding

Figure 2.1 Explains the relationship between the five categories, which are depicted as a curve.

Figure 2.1: Hierarchy of Data, Information, Knowledge, and Wisdom (DIKW)



Data is a collection of transactions, a basic description of objects, events, activities, and transactions that are recorded, grouped, and stored, not yet organized to convey a certain meaning (Tiwana, 1999; Turban et al., 2002). Data can be in the form of numeric data, discrete images, or sounds that are representations of events and have no meaning. Information is data that has gone through a processing process and has meaning. Another definition of information can be defined as data that has been arranged or structured and placed in a certain context so that it has meaning (Natarajan & Shekhar, 2000). Knowledge is the basis of belief in action, containing information enriched with individual interpretation and experience. Knowledge results from dynamic social interaction and can only be obtained through communication and cooperation. Knowledge is not just a collection of data or information that is processed, but knowledge has the potential to influence an action. The implication is that KM does not only focus on providing information, but KM must also be able to build core competencies and an understanding of strategic knowledge (Alavi & Leidner, 2001; Davenport & Prusak, 1998). Understanding is how we acquire and synthesize knowledge to create new knowledge. Wisdom is defined as internalized understanding, where understanding is another layer that connects knowledge with wisdom (Bellinger et al., 2004); Wallace, 2007). Wisdom is knowledge used to make future decisions (Davenport & Prusak, 1998).

2.2 Management

The term 'management' is closely related to understanding how to organize and coordinate all available resources to achieve organizational goals. Management achieves organizational goals using resources (people, money, energy, space, time). These resources are considered inputs, and goal achievement is seen as the output of the process (Turban et al., 2002). Management is transforming an organization as a whole or part of an organization over the environment towards achieving goals (Frew, 1971). Drucker (1993) defines management as a task, discipline and people. Johannsen and Page (1986) highlight management into two angles, 1) as a useful utility and coherence of resources (capital, infrastructure, materials and labour to achieve set goals with maximum efficiency, and 2) as people in charge of organizing and operating the organization (Johannsen & Page, 1986).

Knowledge in the digital economy era is an organizational asset with infinite value. Knowledge is one of the intangible assets owned by the organization. The organization's knowledge is present due to the interaction between human capital components and information. Human capital in the organization is related to the thoughts and characters of human competence, knowledge, imagination, intuition, education, skills and experiences influenced by emotions and other attributes (Liebowitz, 1999). Management in this study's context is related to how knowledge is created in the organization.

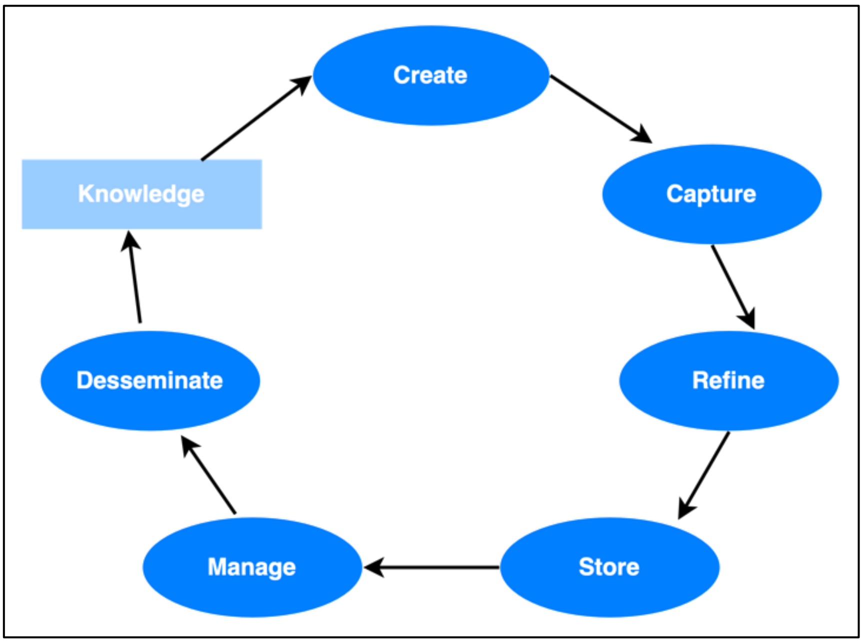
2.3 Knowledge Management (KM)

The knowledge dimension in organizations is divided into tacit and explicit knowledge. Tacit knowledge is individuals' knowledge, is difficult to articulate, communicate or reproduce, and is often related to specific circumstances (Jones & Leonard, 2009; Polanyi, 1966; Tsai & Lee, 2006). Rooted in actions, experiences, and involvement in a particular context, the tacit knowledge dimension consists of cognitive and technical elements. The cognitive element refers to an individual's mental model consisting of mental maps, beliefs, paradigms, and perspectives. The technical component consists of concrete knowledge, crafts, and skills that apply to a particular context (Nonaka & Takeuchi, 1995). In contrast, explicit knowledge refers to knowledge that can be disseminated or communicated through formal and systematic language (Polanyi, 1966). The explicit knowledge dimension is the knowledge that is articulated, codified, and communicated in symbolic form and natural language and expressed in writing, images, computer programs, patents or systems (Alavi & Leidner, 2001; Tsai & Lee, 2006). The knowledge of each member of the organization is transferred into a form that can be used to improve the capabilities and capacities of the organization through a process called knowledge management.

Knowledge management is the process of obtaining knowledge from organizations or other sources and transforming it into explicit information that employees can use to transform into their knowledge, which allows them to create and improve organizational knowledge (Jones & Leonard, 2009) Knowledge management is a conscious strategy to get the right knowledge to the right people at the right time and help people share and apply information in ways that seek to improve organizational performance (Girard et al., 2015). Shujahat et al. (2019) argue that knowledge management is a discipline and function in which knowledge is created, acquired, shared, codified, and used in an environment that allows for increased innovation and organizational performance.

According to Turban et al. (2002), the knowledge management cycle consists of six stages (Figure 2.2). The stages are as follows:

Figure 2.2: Knowledge Management Cycle



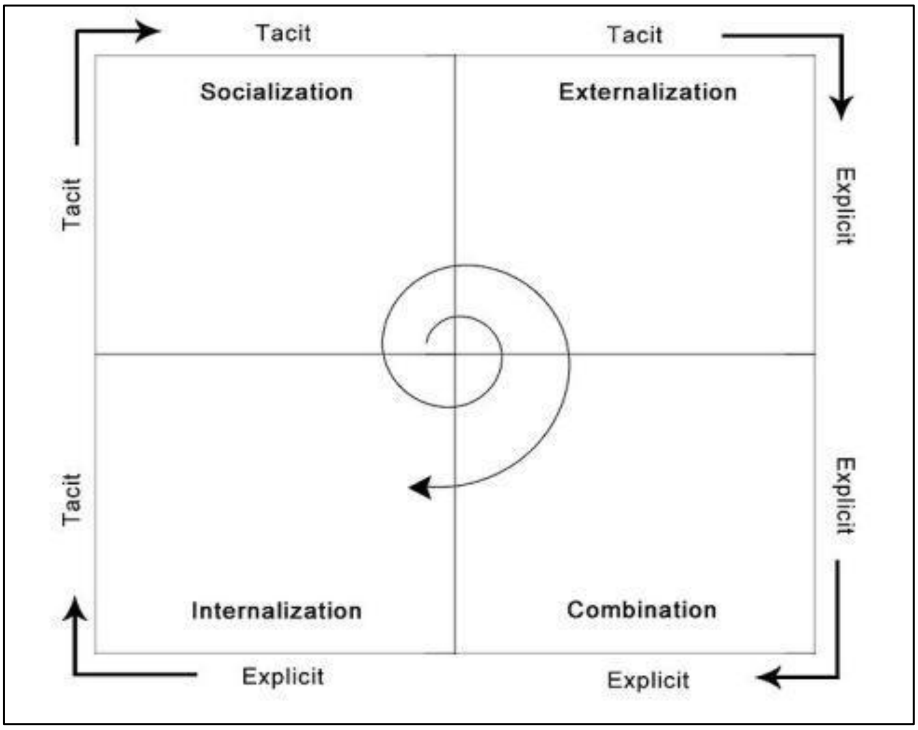
1. Create knowledge. A new way of doing something or developing knowledge know-how. Sometimes, external knowledge is brought into the organizational environment.
2. Capture knowledge: Knowledge is identified as something valuable and represented in a way that makes sense.
3. Refine knowledge: New knowledge must be placed in the context of its knowledge so that it is easy to improve or develop.
4. Store knowledge: Useful knowledge must then be stored in the right format in a knowledge repository so that it is easy for members of the organization to access it.
5. Manage knowledge: Knowledge must be continuously updated. Knowledge must be reviewed to verify and ensure it is still relevant and accurate.
6. Disseminate knowledge: Knowledge must be available in various formats, which can be used by organization members anywhere, anytime.

Knowledge management has three basic processes: creation, sharing, and application. This study will focus on the process of knowledge creation (Liebowitz, 1999) (Burgoyne, 1992). The reference model used in this research is the knowledge creation model (SECI Model) proposed by Nonaka and Takeuchi (1995).

2.3.1 Knowledge Creation

The SECI model explains how the processes of knowledge creation in organizations. How tacit knowledge is converted into explicit knowledge, and vice versa. The process of knowledge creation consists of the processes of Socialisation, externalisation, combination and internalisation. Figure 2.3 shows the process of knowledge creation in organizations.

Figure 2.3: Model of SECI



Source: Nonaka & Takeuchi (1995)

1. Socialisation

Socialisation is sharing and changing new knowledge (tacit to tacit knowledge) through shared experiences in everyday social interactions (Alavi & Leidner, 2001; Nonaka & Takeuchi, 1995; Nonaka & Toyama, 2003) Another definition, Socialisation is the process of turning explicit knowledge into tacit knowledge; through internalisation, explicit knowledge is created, shared throughout the organization and converted into tacit knowledge by individuals (Córdova & Gutiérrez, 2018; Tsai & Lee, 2006). Tacit knowledge is difficult to formalize and is often specific to time and space. Tacit knowledge can only be acquired through shared direct experience. Thus, routines are part of tacit knowledge because they are developed in close interaction over time (Nonaka & Toyama, 2003).

A more comprehensive explanation of socialisation was provided by Nonaka (1994); according to him, socialisation is a form of knowledge creation that allows us to change tacit knowledge through interaction between individuals. An individual can acquire tacit knowledge without language, including internship activities. Through internships, they work with mentors and learn skills not through language but through observation, imitation and work practice. In short, the key to acquiring tacit knowledge is through experience. Without shared experience, it is very difficult for people to share their thinking processes (Nonaka, 1994)

Socialisation is the creation of shared mental models and technical skills through various experiences. The phenomenological method effectively observes the processes that occur as they are. For example, someone can collect tacit knowledge about customers through their own experiences as customers. This allows actors to absorb knowledge in their social environment through actions and perceptions. Therefore, the dichotomy between the environment and the organization can be synthesized in the Socialisation process when organizational members accumulate and share environmental tacit knowledge through their practical awareness (Alavi & Leidner, 2001; Nonaka & Takeuchi, 1995; Nonaka & Toyama, 2003).

2. Externalisation

Tacit knowledge is articulated into explicit knowledge through externalisation (Alavi & Leidner, 2001; Nonaka, 1994) Knowledge is made explicit and shared with others to become the basis for new knowledge, such as concepts, images, and written documents (Nonaka & Takeuchi, 1995) The knowledge creation process is triggered by dialogue that can create concepts from tacit knowledge. Creating a new product concept is an example of good externalisation (Nonaka et al., 1996). Dialogue in the externalisation process is an effective method for articulating one's tacit knowledge and sharing that knowledge with others. Through dialogue between individuals, the contradictions between one's tacit knowledge and the structure are made explicit and synthesized (Lawson, 1998; Nonaka & Toyama, 2003).

Externalisation allows the conversion of tacit knowledge into explicit knowledge. Through this process, tacit knowledge is expressed and translated into concepts, hypotheses, diagrams, models, or prototypes so others can understand them (Canonico et al., 2020) In the learning process, the knowledge externalisation scale measures how a lecturer can transform teaching ideas into concrete perspectives to be shared and explained with concrete evidence. A lecturer can reflect implicit teaching experiences and effective pedagogical practices in explicit form, often in written knowledge, which can be shared with collaborating lecturers (Mendoza et al., 2022).

3. Combination

Creating explicit knowledge from explicit knowledge is called combination (Bratianu, 2010). Explicit knowledge is collected from within or outside the organization and then combined, edited, or processed to form more complex and systematic explicit knowledge through the Combination process. New explicit knowledge is then disseminated among members of the organization. Creative use of computerized communication networks and large-scale databases can facilitate this mode of knowledge creation (Alavi & Leidner, 2001; Nonaka et al., 1996) Rationalism is an effective method for combining, editing, and breaking down explicit knowledge. Information Technology plays a full role in the process of knowledge combination because most of the knowledge and information in this mode is explicit and easily processed with IT (Nonaka et al., 1996)

Combination is creating new explicit knowledge by combining and synthesizing existing explicit knowledge. Knowledge is exchanged and combined through media such as documents, meetings, or communication networks (Canonico et al., 2020). Finding knowledge combinations is an effective strategy for knowledge retrieval and discovery. Developing a knowledge combination method in a collaborative network becomes an effective approach to knowledge combination that can improve the efficiency of knowledge management (Han et al., 2020)

4. Internalisation

Explicit knowledge created and shared throughout the organization is then converted into tacit knowledge by individuals through the Internalisation process (Alavi & Leidner, 2001; Nonaka & Toyama, 2003). This stage can be understood as practical, where knowledge is applied and used in practical situations and becomes the basis for new routines. Thus, explicit knowledge, such as product concepts or manufacturing procedures, must be actualized through action, practice, and reflection to become knowledge truly. Internalisation refers to the ability to “learn by doing or using”, explicit knowledge documented in text, audio, or video formats facilitates the internalisation process. Training programs can assist in the process of internalizing knowledge. By reading and reflecting on documents, trainees can internalize the explicit knowledge written in the documents to enrich their tacit knowledge base (Nonaka et al., 1996; Adachi, 1995)

Internalisation is the conversion of explicit knowledge into individual and group-level tacit knowledge. When internalized into individual tacit knowledge through shared mental models or technical knowledge, knowledge becomes a valuable asset (Canonico et al., 2020) The challenge is determining the best method to broadly internalize explicit knowledge across the organization. The internalisation process is part of the cognitive process; knowledge internalisation is part of the learning cycle, including assessing learning outcomes. The knowledge internalisation process measures how an individual can internalize and apply collective information acquired through learning. How the knowledge gained can solve problems, the higher the score, the more they can effectively connect knowledge and use it to develop better skills (Mendoza et al., 2022).

2.3.2 Knowledge Management in Organization

Define a learning organization (LO) as an organization that facilitates learning from all its members and continuously transforms itself (Burgoyne, 1992). Organizational learning results in changes in cognitive and behavioural traits, significantly enhancing the organization's ability to innovate and improve adaptability in complex and unpredictable environments (Djonlagic & Kovacevic-rahmanovic, 2013). The knowledge gained from learning, and its application becomes capital for competitive advantage for the organization. LO strives to respond more quickly and effectively to any changes in knowledge. LO can stay ahead of the competition by presenting innovative products and services, solving problems quickly, and efficiently recruiting and retaining the best employees (Sarder, 2016)

Mutongi (2016), in the green leaf model, explains that KM in an organization must be managed properly. Good KM will make the organization stronger. Mutongi (2016) argues that human capital is very important in KM. Every part of the organization works based on KM and has a role in developing KM to become innovative, creative, responsive, and successful. According to Shujahat et al. (2019), innovation is one of the results of employee collaboration. The benefits of KM in organizations are also explained by Campatelli et al. (2016), who states that the increasing complexity of manufacturing systems requires workers to build broader and deeper skills. Applying KM practices and technologies can be a viable approach to addressing these challenges. KM is intended for training, problem-solving, and facilitating manufacturing knowledge discovery, acquisition, and sharing. Meanwhile, the key drivers of knowledge creation in the manufacturing industry, according to Campatelli et al. (2016), are influenced by four factors:

1. Culture: The purpose of the project is to introduce a new culture into the company, encourage worker empowerment and, create motivation to collaborate, share ideas and knowledge, and create a new social environment in the company.
2. Technology: New technologies will be adopted to support worker involvement in a collaborative environment. The role of software is very important in sharing knowledge.

3. Infrastructure: The infrastructure redesign will include the definition of new organizational roles and responsibilities, especially for leadership that must promote collaboration among workers and rewards for workers.
4. Measurement: To support the creation of usable technology, the system will be based on the steps' objectives, which workers can obtain and verify. The system will measure and monitor the quality of worker knowledge.

Worker productivity affects the process of knowledge management and innovation. A study of 369 employees in Pakistan showed that the productivity of skilled workers significantly affects the process of knowledge management and innovation. However, it is different from the relationship between knowledge sharing and innovation because knowledge sharing does not significantly affect the productivity of skilled workers. Innovation is generated from collaboration in KM practices, affecting knowledge sharing in the company. Innovation in KM is shown through cloud computing technology (Shujahat et al., 2019). The use of cloud computing has impacted the way knowledge is managed, and the transformation of KMS in a cloud environment has resulted in various benefits, such as cost savings, better business processes, customer satisfaction and better representation and management of knowledge, including collaboration in KMS (Rafiq et al., 2014). While the use of Web 2.0 and Big Data technologies to find, collect, manage and apply knowledge makes the KMS implementation process faster and simpler (Orenga-Roglá & Chalmeta, 2017).

2.3.3 Knowledge Management System (KMS)

A Knowledge Management System (KMS) constitutes a structured framework or platform designed to facilitate an organization's collection, storage, management, and dissemination of knowledge. The primary objective of such a system is to enhance operational efficiency, foster innovation, and improve productivity by leveraging the collective knowledge possessed by individuals and groups within the organizational context (Alavi & Leidner, 2001; Nonaka, 1994).

KMS is an information technology (IT)--based system developed to support and improve organizational processes of knowledge creation, retrieval-storage, transfer, and application (Turban et al., 2002). Technology refers to IT-based knowledge management tools that support organizational actors when carrying out knowledge management process activities. Maier (2007) put forward a similar definition: KMS is an ICT system in the sense of an application system or ICT platform that combines and integrates functions for contextual handling of explicit and tacit knowledge across the organization or part of the organization targeted by the initiative. The ultimate goal of KMS is to support the dynamics of organizational learning and organizational effectiveness (Maier, 2007)

Zouari & Dakhli (2018) define KMS as a combination of four interacting components: technology, knowledge management processes, people, and organizational context. Technology refers to IT-based knowledge management tools used to support organizational members when carrying out knowledge management process activities. Organizational context refers to organizational characteristics that influence knowledge management, such as organizational culture, national culture of organizational members, organizational structure and management style. The people component of the knowledge management strategy determines the incentives, communication, and training resources needed to implement the knowledge management process. Likewise, implementing the knowledge management process is a learning tool for the individuals involved.

2.3.4 Component of KMS

The constituents of a Knowledge Management System (KMS) are pivotal for effectively managing and retrieving knowledge within organizational settings. These components can differ across various applications, including but not limited to quantum key distribution, semantic knowledge retrieval, and collaborative software maintenance. The following delineates the fundamental aspects of KMS components:

1. Knowledge Base (KB): The Knowledge Base serves as the cornerstone of the KMS, where symbolic knowledge structures are stored. Such structures are frequently represented through ontologies that articulate concepts and their interrelations (Chakraborty et al., 2011).
2. User Interface: A user-centric interface facilitates direct manipulation of knowledge items and enhances user interaction and accessibility (Akscyn et al., 1987).
3. Retrieval Technologies: Semantic knowledge retrieval technologies are fundamental for enabling efficient access to stored knowledge, thus ensuring that users can locate pertinent information promptly (Umar et al., 2017).
4. Collaboration Tools: Within collaborative environments, KMS components facilitate knowledge sharing and maintenance among diverse stakeholders, which is vital for software maintenance activities (Mohd Zali et al., 2010)
5. APIs and Standards: Integrating standardized Application Programming Interfaces (APIs) is imperative for ensuring interoperability between various KMS instances and other systems, especially in sophisticated applications such as quantum key distribution (James et al., 2023).

While the design of KMS components aims to augment knowledge management efficacy, notable challenges persist, including the assurance of data reliability and the resolution of complexities associated with user interface design, both of which remain significant considerations in their implementation.

The development and implementation of KMS are key success factors for organizations in automatically managing knowledge (Alavi & Leidner, 2001). KMS has three general applications: (a) to codify and share best practices to transfer them internally; (b) to create a corporate knowledge directory by identifying, classifying and codifying existing internal capabilities since organizations have much knowledge that remains hidden and uncoded; and (c) to create a knowledge network that allows users to communicate in a fast and simple way (Alavi & Leidner, 2001)

The knowledge process is a major research area in management studies, especially regarding the tools and methods that facilitate knowledge creation and innovation in organizations. Automotive companies have used the SECI framework to measure the alignment of the use of Obeye KMS in the knowledge creation process. The main objective is to empirically test how Obeye in the automotive company is used to create knowledge based on the SECI model. The study's results explain that obeying can create knowledge effectively in certain empirical settings. Second, obeya is an interactive and dynamic tool based on the SECI model (Canonico et al., 2020)

2.4 Artificial Intelligence (AI)

Artificial Intelligence (AI) can be defined as the endeavour to enable computers to perform tasks that, when executed by humans, exhibit characteristics of human-like understanding or even exceed human capabilities. According to Simon, AI encompasses a domain of research, application, and instruction about computer programming to enable tasks deemed intelligent from a human perspective. From a cognitive standpoint, Bellman (Russel & Norving, 2010) posits that AI involves automating activities connected with human cognitive functions, such as decision-making, problem-solving, and learning. Furthermore, Russell and Norvig (2010) articulate that AI, through the lens of cognitive approaches, seeks to amalgamate computer models of AI with experimental methodologies from cognitive psychology, aspiring to construct theoretical frameworks that can effectively test human cognitive processes.

The essence of intelligence is thus embedded into machines (computers), allowing them to replicate human functionality. Initially, computers served merely as computational tools; however, they have evolved to occupy a pivotal role across diverse areas of human existence, transforming from mere calculation devices to entities expected to perform a wide array of tasks typically associated with human intelligence.

Kusrini (2006) delineates several foundational concepts integral to the understanding of artificial intelligence, including:

1. Turing Test - Intelligence Testing Method

The Turing Test, formulated by Alan Turing, is a method for evaluating machine intelligence. The testing protocol involves a questioner (human) and two subjects—one human and one machine—without the questioner having direct visual access to either entity. The questioner's objective is to discern the responder's identity based solely on the replies provided. Turing asserts that if the questioner cannot differentiate between the responses of the human and the machine, the machine may be regarded as possessing intelligence.

2. Symbolic Processing

Initially, computers were engineered for numerical processing; however, humans engage in problem-solving through symbolic reasoning rather than exclusively mathematical computations. A quintessential characteristic of artificial intelligence resides in its ability to execute symbolic and non-algorithmic processes in addressing problems.

3. Heuristic

The term 'heuristic' is derived from the Greek meaning "to find." Heuristics refers to strategies employed in selectively navigating the problem space, thereby directing the search process towards paths most likely to yield successful outcomes.

4. Drawing Conclusions (Inferencing)

AI endeavours to endow machines with reasoning capabilities, including concluding (inferencing) based on facts and rules and utilizing heuristic methods or other searching techniques.

5. Pattern Matching

AI employs pattern-matching methodologies to elucidate objects, events, or processes through logical or computational relationships.

The interplay between the capabilities of artificial intelligence and the simulation of human activities is elucidated by Schunk (2012), who notes that the domain of artificial intelligence is fundamentally concerned with the programming of computers to partake in human-like activities, such as cognitive thought, language utilization, and problem-solving.

2.4.1 Data Mining

Integrating data mining techniques into knowledge management practices enables organizations to leverage their data more effectively, transforming information into actionable insights. In doing so, they can enhance collaboration, improve decision-making processes, and ultimately drive organizational innovation and competitiveness (Duque, 2024). The application of data mining techniques in knowledge management systems (KMS) aims to improve the efficiency and effectiveness of organizational knowledge management. Able to support strategic and operational goals in the organization by providing deeper insights into data and improvements in organizational knowledge processes (Duque, 2024)

Research using data mining techniques to improve knowledge management systems (KMS) in higher education institutions (HEIs). The goal is to predict learners success rates and optimize educational processes by analysing learners data. The study results explain that implementing data mining into KMS in HEIs can significantly improve the ability to predict and improve learners success rates, making this tool valuable for educational administrators and policymakers (Natek & Zwilling, 2014).

2.4.2 Machine Learning (ML)

Machine learning represents a pivotal subset of artificial intelligence, facilitating computers' capacity to autonomously learn from data and generate predictions without explicit programming directives. This field encompasses various algorithms, primarily classified into three categories: supervised, unsupervised, and reinforcement learning. Notably, the efficacy of these algorithms is intricately linked to the quality of the training data utilized, as the data significantly influences the outcomes and decision-making processes across various applications.

1. Supervised Learning: This approach entails training models on labelled datasets to yield predictive outcomes, employing linear regression and decision trees (Kapoor et al., 2024).
2. Unsupervised Learning: This category concentrates on identifying patterns within unlabeled data, utilizing methodologies such as clustering techniques to extract meaningful insights (Jain & Tiwari, 2024)
3. Reinforcement Learning: This paradigm harnesses feedback from actions taken to enhance decision-making processes over time, exemplifying a dynamic learning approach (Kapoor et al., 2024)

The applications of machine learning span a multitude of industries. In healthcare, machine learning facilitates predictive analyses pertinent to patient outcomes and disease diagnoses (Kapoor et al., 2024). Within the financial sector, these algorithms contribute to automating processes and optimising decision-making in financial management (Bejjar & Siala, 2024). In agriculture, methodologies such as Random Forests play a critical role in crop forecasting and pest identification (Saini et al., 2024).

Despite the significant advancements by machine learning, it concomitantly engenders various ethical considerations, particularly in terms of algorithmic transparency and data privacy. Addressing these ethical dilemmas is imperative to responsibly harness the full potential of machine learning technologies (Bejjar & Siala, 2024)

Recent developments in machine learning have introduced many techniques and applications that fundamentally reshape multiple fields. Among the most notable advancements are the emergence of generative adversarial networks (GANs) and transformer models. These innovations have markedly enhanced capabilities in generative tasks and natural language processing (Rane et al., 2024a) Furthermore, tools such as AlphaFold have made significant strides in protein structure prediction within structural biology, facilitating access to ML methodologies for non-experts via interpretable outcomes (Vecchietti et al., 2024)

The versatility and efficiency of ML are also evident in its applications across computational electromagnetics, remote sensing, and medical diagnostics, underscoring its broad applicability (Notaroš et al., 2024) Concurrently, emerging trends like federated learning and explainable AI (XAI) address crucial privacy issues and the growing demand for transparency within ML models (Rane et al., 2024a)

Moreover, rigorous performance evaluation techniques—such as cross-validation and hyperparameter optimization—are essential for evaluating model efficacy and ensuring the robustness of applications (Raja et al., 2024). Collectively, these advancements underscore the transformative potential of machine learning across diverse sectors, indicating a profound impact on future research and application paradigms.

The implementation of machine learning (ML) encounters many challenges across diverse sectors, encompassing issues related to data quality, ethical considerations, and technical complexities. These obstacles may impede the effective deployment of ML solutions, necessitating a thorough understanding of the underlying issues:

1. Data Quality and Quantity

ML models necessitate substantial volumes of high-quality, labelled data, which can often be challenging and financially burdensome to procure (Rane et al., 2024b). Additionally, complications arise from class imbalance and data representativeness, which further hinder model training and validation (Ostojic et al., 2024).

2. Ethical and Security Concerns

The potential for algorithmic bias introduces critical ethical dilemmas, as ML models may inadvertently perpetuate preexisting biases found within the training data (Rane et al., 2024b; Yadav & Gaurav, 2023). Moreover, data privacy and security are paramount, particularly in sensitive domains such as healthcare, where breaches may lead to dire consequences (Yadav & Gaurav, 2023).

3. Technical and Organizational Challenges

The opaque "black box" nature of ML models can contribute to a lack of transparency, thereby engendering stakeholders' scepticism regarding the outcomes' reliability (Ostojic et al., 2024). Furthermore, integrating ML within existing systems frequently demands specialized expertise and alignment with overarching business objectives, which can be a significant barrier to implementation (Iyelolu & Paul, 2024).

While these challenges are considerable, they present critical opportunities for innovation and advancement in ML practices. Addressing these multifaceted issues can lead to developing more robust, ethical, and effective ML applications across various domains. Focus on data quality over quantity by combining cleaning, augmentation, and transfer learning techniques to address data limitations. Continuously evaluate the impact of each step on model performance through measurable experiments. Combining technical, governance, and regulatory approaches can be used to build safe, fair, and accountable ML systems, addressing ethics and security in ML.

2.4.3 Natural Language Processing (NLP)

NLP constitutes a pivotal domain within artificial intelligence, facilitating the capacity of machines to understand, interpret, and generate human language. The evolution of this field has progressed markedly from rudimentary rule-based systems to sophisticated machine learning and deep learning methodologies, thus enabling more nuanced and effective interactions between humans and computational systems. The subsequent sections delineate the fundamental aspects of NLP.

1. Key Concepts of NLP

   a) Understanding Language: The principal objective of NLP lies in imparting comprehension of human language to computers, thus enabling a diverse range of tasks such as reading, writing, and translating text.

   b) Applications: NLP finds extensive application across various sectors, including, but not limited to, chatbots, predictive text generation, sentiment analysis, and the mining of social media data (Boucheham, 2023; Geetha et al., 2023).

   c) Multidisciplinary Approach: The discipline of NLP adopts a multidisciplinary framework, integrating insights from linguistics, computer science, mathematics, and psychology to construct advanced computational models and algorithms (Kwong, 2023).

2. Challenges in NLP

   a) Contextual Understanding: A significant challenge within this field is the capacity to accurately interpret the meanings of words as influenced by contextual cues and cultural subtleties (Yadav & Gaurav, 2023)

b) Data Processing: The immense volume of data generated across social media platforms presents substantial challenges in effectively analyzing and deriving meaningful insights (Boucheham, 2023)

Despite the noteworthy advancements achieved in NLP, the field continues to confront a range of challenges that necessitate ongoing research and development efforts aimed at augmenting its capabilities and enhancing its applicability within real-world contexts.

Key Applications of Natural Language Processing (NLP):

1. Machine Translation: Natural Language Processing (NLP) facilitates the real-time translation of languages, enhancing global communication and accessibility (Arısoy, 2024; Kumari et al., 2024)
2. Sentiment Analysis: Organizations leverage NLP to analyze public sentiment derived from social media platforms and customer reviews. This analysis supports informed decision-making and the development of effective marketing strategies (Ghosh, 2024; Kumari et al., 2024)
3. Chatbots and Virtual Assistants: NLP serves as the foundational technology for conversational agents, which provide customer support and assist in information retrieval, ultimately enriching the user experience (Chinnaiyan et al., 2025; Kumari et al., 2024).
4. Speech Recognition: NLP underpins voice-activated systems that interpret and process spoken language, a critical development for enhancing accessibility and facilitating user interaction (Ghosh, 2024; Kumari et al., 2024)

5. Text Classification and Summarisation: NLP algorithms categorize and succinctly summarize extensive textual datasets, streamlining information processing across diverse sectors (Kumari et al., 2024; Zhou, 2024).

Despite its transformative potential, NLP confronts notable challenges such as linguistic ambiguity, data bias, and ethical considerations. Addressing these issues is essential for promoting responsible artificial intelligence development (Chinnaiyan et al., 2025; Zhou, 2024).

2.4.4 Text Summarization

Text summarisation is important for text mining and natural language processing (NLP). NLP is the convergence of linguistics and artificial intelligence that facilitates the ability of computers to understand and interact with human language substantively (Jain et al., 2018; Supriyono et al., 2024). The development of NLP has shifted from rule-based and statistical methodologies to more complex machine learning and deep learning frameworks. This technology is applied in various contexts, including chatbots, search engines, content recommendation systems, and automatic translation services.

The biggest challenges of NLP include language ambiguity, polysemy phenomena, and the diverse nature of natural language (Supriyono et al., 2024). Text mining refers to methods used to automatically or semi-automatically derive new knowledge from textual data, where the extracted knowledge is relevant and comes from a large amount of text (Singh et al., 2003; Torres-Moreno, 2014). Data handled through text mining techniques mainly consists of unstructured text. The fundamental difference between data mining and text mining lies in the data from which features or patterns are extracted. Feature extraction is paramount in the text mining framework

(Jiawei Han et al., 2000; Weiss et al., 2005) The stages of text mining can be categorized into text preprocessing, text transformation (feature generation), feature selection, data mining (or pattern discovery), and evaluation (Aksoy et al., 2020).

The first stage, text preprocessing, involves data cleaning, which includes identifying word types and performing syntactic parsing. This process allows the representation of sentences as independent graphs, thus facilitating further analysis. Next, features are extracted from the structured text during the text transformation or feature generation stage. These features can be represented in various formats, such as individual words, word sets, or combinations. After text transformation, the feature selection stage is crucial to identifying and retaining only the most relevant and non-redundant features, thereby increasing the efficiency of further analysis. Finally, the data mining stage aims to extract meaningful insights from the textual data using methodologies such as clustering, classification, and association, along with specific algorithms and techniques tailored for data mining.

Automatic text summarisation is used in Single knowledge document summarisation using the EdgeSumm framework. The test results show good performance improvement in text summarisation (El-Kassas et al., 2020). Research Automatic text summarisation is used for Urdu documents (Nawaz et al., 2020). Automatic text summarisation is also used in biomedical and healthcare domains, helping researchers and medical professionals save their time, access more information quickly, and increase the accessibility of information for researchers and medical professionals (Rohil & Magotra, 2022).

1. **Transformer Model**

The Transformer model, introduced by Vaswani et al. (2017) in their landmark paper titled "Attention is All You Need," has established itself as a cornerstone for numerous advancements in natural language processing (NLP) and other related fields. This architecture employs an attention mechanism, which empowers the model to selectively focus on specific segments of the input data while generating output. This approach marks a significant shift from prior models that primarily relied on the sequential order of input data (Vaswani, 2017).

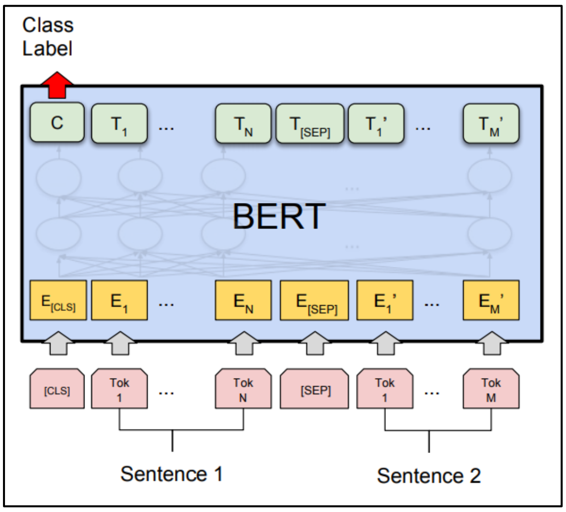
A pivotal component of the Transformer architecture is self-attention, which allows the model to evaluate the relationships between words in a given sentence, thereby enhancing contextual understanding. Furthermore, Transformers facilitate parallel data processing, in contrast to Recurrent Neural Networks (RNNs), which enhances both the efficiency of training and the speed of inference. The Transformer architecture consists of two principal components: the encoder, responsible for processing the input, and the decoder, which generates the output. Each component is composed of multiple layers that implement both the attention mechanism and feed-forward neural networks.

Transformers have found successful applications across diverse domains, including language translation. Models such as BERT and GPT, which are grounded in the Transformer architecture, have demonstrated outstanding performance. Additionally, Transformers are utilized in language modeling to facilitate a more natural understanding and generation of text, as well as in various NLP tasks such as sentiment analysis and named entity recognition.

A. Bidirectional Encoder Representations from Transformers (BERT)

BERT is a machine learning model developed by Google that aims to achieve a deeper comprehension of the contextual relationships between words in sentences, surpassing the capabilities of previous models (Devlin et al., 2019). BERT employs a bidirectional approach, analyzing context from both preceding and succeeding words during text processing. This methodology represents a departure from earlier models, which typically considered context in a unidirectional manner. The training process for BERT consists of two stages: pre-training and fine-tuning. During the pre-training phase, the model learns generalized representations of language by leveraging extensive corpora of text. In the subsequent fine-tuning phase, the model is tailored for specific tasks, such as sentiment analysis or language translation (Devlin et al., 2018). Notably, BERT employs masked language modeling (MLM) techniques during pre-training to predict missing words in sentences based on contextual clues, as well as next-sentence prediction (NSP) to ascertain the interrelation between consecutive sentences (Devlin et al., 2019).

Figure 2.4: BERT Architecture



BERT has been effectively leveraged in a variety of natural language processing applications, yielding significant advancements in fields such as language translation, sentiment analysis, and named entity recognition. Its capacity for profound contextual understanding has markedly improved accuracy in these tasks, positioning BERT as one of the most influential models in contemporary NLP. The achievements of BERT have catalyzed further research and development in natural language processing technologies, including its notable impact on the externalisation of tacit knowledge among history educators (Li et al., 2024).

1) BERT2BERT Model

Pretrained models such as BERT (Devlin et al., 2019) are a crucial part of AI advancements in the field of NLP. BERT's rich contextual representations make it widely used in various NLP fields. BERT2BERT is a sequence-to-sequence (Seq2Seq) architecture that utilises pre-trained BERT as both an encoder and a decoder. First introduced by Rothe et al. (2020), this model overcomes the limitations of the BERT model to support understanding tasks by adapting text generation tasks (summarisation, translation, etc.). The BERT2BERT model achieved competitive performance on the XSum and CNN/DailyMail datasets, with 30% better data efficiency than the scratch-built model. The BERT2BERT model addresses these gaps by:

a. Using the BERT encoder for feature extraction.
b. Modifying the BERT decoder with causal masking and cross-attention mechanisms.
c. Adopting transfer learning for data efficiency (Rothe et al., 2020)

The BERT2BERT model supports implementation in the following applications abstract summarisation, question generation and machine translation.

The BERT2BERT model has the advantage of data efficiency. The BERT2BERT model achieves sufficient accuracy with 30% less training data. Another advantage is knowledge transfer. The use of pretrained weights reduces overfitting. However, the BERT2BERT model has disadvantages, including its computational intensity due to the decoder being the same size as the encoder, and it inherits BERT's pre-training bias.

2) BERT2BERT+Extrem Model

The BERT2BERT+Extreme model builds on the original BERT2BERT framework, specifically tailored for extreme summarization. It is capable of condensing lengthy documents into just one or two concise sentences. The 'Extreme' element enhances the model's efficiency and scalability, especially beneficial for pre-training and multi-label classification tasks. By utilizing advanced techniques, it optimizes the BERT architecture, making it suitable for various applications, particularly in environments with limited resources.

a. Pre-training Speedup

1. The ExtremeBERT toolkit substantially shortens the time needed for pre-training BERT models, achieving training speeds that are 6 times faster for Basic BERT and 9 times for Large BERT compared to conventional methods (Pan et al., 2022)
2. This speedup allows researchers and practitioners to tailor BERT to specific datasets without the need for extensive computational power, thereby expanding its usability.

b. Improved Multi-Label Classification

1. The Extreme components enhance BERT’s performance in extreme multi-label classification (XMC) situations, where the model must efficiently process very large label sets (Chang et al., 2019).
2. By creating semantic clusters for labels and recognizing dependencies among them, the model excels in tasks with expansive output spaces, achieving leading results in precision metrics.

c. Compression Techniques

1. Methods for extreme compression, like ultra-low bit quantization, are incorporated to make large models manageable on smaller devices while preserving accuracy (Wu et al., 2022).
2. This strategy allows for considerable reduction in model size, enabling BERT-based models to be applied in practical scenarios.

d. Applications and Implementation

1. Generation of Headlines: Automating the creation of news headlines from extensive articles.
2. Compression of Scientific Abstracts: Providing a summarized version of an academic paper in a single paragraph.
3. Condensing Chatbot Responses.

While the Extreme components enhance efficiency and scalability, it’s essential to remember that aggressive compression and acceleration may occasionally affect model performance or increase implementation complexity. Achieving a balance between these elements is vital for success in real-world applications.

2. Text Readability Evaluation Methode

Evaluating the readability of text summarisation results can be done using several methods, both automatically through the system and manually. Gunning Fog Index (GFI), the Flesch-Kincaid Grade Level (FKGL), and Pranowo (2011) are methods for measuring the readability of summarised text processed by the system. In addition to using the system, the readability evaluation of the results can be done manually. An expert in the Indonesian language conducts manual testing. The following are several methods for evaluating the readability of text summarisation results.

a) Gunning Fog Index (GFI)

The Gunning Fog Index (GFI) operates as a readability metric aimed at evaluating textual complexity, particularly within English-language materials (Djaber et al., 2023; Yaffe, 2022). GFI assesses the readability of text based on the average number of words per sentence juxtaposed with the percentage of complex words present. Although it was initially conceived for English, considerable efforts have been undertaken to adapt the GFI for other languages, including Indonesian. The calculation of the GFI value adheres to a specific formula, which facilitates the quantification of text complexity and comprehensibility.

$$\text{Fog Indeks} = 0.4 \times \left[\left(\frac{total\ words}{total\ sentence}\right) + 100\ \left(\frac{total\ komplex\ words}{total\ words}\right)\right] \qquad (2.1)$$

GFI scores serve as a benchmark for assessing the minimum educational attainment required for proficient reading comprehension, as detailed in Table 2.1 A decrease in GFI scores corresponds to text that is more transparent and accessible, thereby facilitating reader understanding.

Table 2.1: GFI Readability Level Range

Fog Index	Readability Level by Educational Grade
17	College Graduate
16	Final year learners
15	Junior learners
14	Sophomore learners
13	Freshman
12	Final year high school
11	Senior high school
10	Final year junior high school
9	Junior high school
8	Eighth grade
7	Seventh grade
6	Sixth grade

b) The Flesch-Kincaid Grade Level (FKGL)

The Flesch-Kincaid Grade Level (FKGL) is a widely utilized metric that assesses the readability of written text, allowing educators, researchers, and writers to gauge the comprehensibility of their material. Formulated by Rudolph Flesch in 1948 and subsequently named in collaboration with education specialist Kincaid, the FKGL is anchored in linguistic analysis, taking into account the structural components of a text. The FKGL calculation is based on a formula that incorporates the total number of words, sentences, and syllables within a given passage, yielding a quantitative score that correlates with a specific educational grade level. The formula is expressed as follows:

$$\text{Skor FKGL} = 0.39\left(\frac{total\ words}{total\ sentence}\right) + 11.8\left(\frac{total\ syllabus}{total\ words}\right) - 15.59 \qquad (2.2)$$

This score is indicative of the text's readability, with lower FKGL scores signifying that the material is more accessible to readers at lower grade levels, while higher scores reflect increased complexity suitable for advanced learners. For instance, a score of 7.1 suggests that the text is appropriate for seventh-grade readers, whereas a score of 11.6 denotes suitability for twelfth-grade learners (Onwuegbuzie et al., 2013; Salihah et al., 2020). The FKGL is particularly valuable in educational contexts, enabling educators to tailor reading materials to the appropriate comprehension levels of their learners. By utilizing this tool, one can ensure that texts are both engaging and accessible, fostering an environment conducive to learning and literacy development.

Table 2.2: FKG Readability

Score	Range Reading	Level Education	Level Age Range
0-3	Elementary	Kindergarten	5-8
3-6	Elementary	Primary School	8-11
6-9	Middle	Middle School	11-14
9-12	Middle	High School	14-17
12-15	Advanced	University	17-20
>15	Advanced	Postgraduate	20+

c) Dwiyanto Djoko Pranowo

Dwiyanto Djoko Pranowo has made notable contributions to the field of readability assessment in the Indonesian language by developing a robust set of metrics to evaluate the complexity of texts. His framework consists of three fundamental components: paragraphs, phrases, and words, as elucidated by Maylawati et al. (2019a). This metric is based on thirteen indicators systematically categorized into three levels of reading ease: easy, medium, and difficult. Such a structured approach allows for a comprehensive assessment of Indonesian texts by aggregating these indicators.

The specific indicators used to gauge readability encompass the following: the total number of paragraphs, the number of sentences, the average length of sentences, the complexity and length of sentence structures, the proportion of compound sentences, the presence of words with multiple meanings, the count of passive constructions, the frequency of rarely used words, the occurrence of abstract or complex vocabulary, the use of technical or specialized terminology, the number of conjunctions, the incidence of loanwords from foreign languages, and the number of phrasal constructs within the text (Pranowo, 2011).These indicators provide a multifaceted evaluation of text readability, considering various linguistic and structural dimensions. Together, these indicators provide a multifaceted evaluation of text readability, taking into account various linguistic and structural dimensions.

Moreover, Table 2.3 further clarifies the categorization of readability, delineating the specific ranges associated with the readability levels proposed by Pranowo (2011). This framework not only enhances the understanding of textual accessibility in Indonesian but also serves as a vital resource for educators, researchers, and linguists engaged in analyzing and enhancing Indonesian texts.

Table 2.3: Dwiyanto's Readability Range

Score	**Category**
13,0 - 21,7	Easy
21,8 - 30,5	Moderate
30,6 - 39,0	Difficult

d) Human Readability Evaluation

Human readability evaluation is a crucial component in assessing the effectiveness of summary generation. This process involves the participation of experts, native speakers, or advanced readers who systematically evaluate the readability of the resulting summaries. In this study, one Indonesian language expert was involved to assess the readability of each summary generated by the system. The evaluation framework utilises a rating scale comprising three categories: readable, partially readable, and unreadable. This classification relies on several established criteria (DuBay, 2004; Verma & Om, 2019):

a) The summary must be coherent, devoid of redundancy, and focused on the central theme.
b) The sentences within the summary should be complete and coherently related to one another.
c) The summary should be free from complex sentence structures.

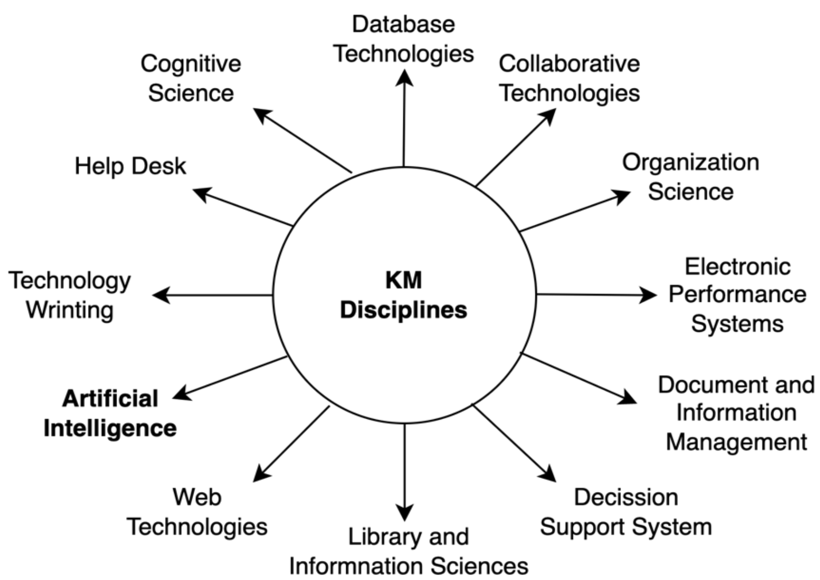
A summary will be classified as readable if it meets all specified criteria. Conversely, it will be designated partially readable if it fulfils only half of these conditions. The summary will be deemed non-readable if none of the criteria are satisfied.

2.4.5 Artificial Intelligence (AI) in Knowledge Management System

In simple terms, AI is how a computer acts or does something like a human or even exceeds it. AI from a human thinking perspective in a cognitive approach, the field of cognitive science discipline unites computer models of AI and experimental techniques from cognitive psychology, trying to build appropriate theories that can test how the human mind works (Russel & Norving, 2010).

Dalkir (2005) explains that KM has a relationship with various disciplines. Information technology contributes to the development of KM, one of which is artificial intelligence technology. Figure 2.5 illustrates several diverse disciplines that have contributed to KM. In addition to cognitive science, in general, the discipline of knowledge management is heavily influenced by information technology.

Figure 2.5: Multidisciplinary Science in KM



Digital transformation significantly impacts the knowledge creation process (SECI model), especially the knowledge combination process (Chen et al., 2024). One of these transformations is the use of AI technology in KM. AI is closely related to knowledge management; AI provides a knowledge-learning machine, while KM provides a knowledge-creation platform (Pai et al., 2022). Dohn et al. (2013), implemented an expert system in mechanical engineering enterprises. The study's rule-based expert system (RES) was used to find solutions for early warning systems and risk management. The implementation of an expert system in KM was used by Naser and Mushtaha (2010) in a prototype expert system for disease diagnostic assistance (ESMDA). Production rules are used to capture knowledge. The expert system provides good results in analyzing and diagnosing all disease cases. Research by Nisar et al. (2018) compared the effect of the Knowledge Management Discussion Group (KMDG) on increasing the richness of information in KMS and on increasing informal and social communication in KMS. The correlation test results showed that the application of KMDG was positively correlated with the richness of information, and the application of KMDG increased labour productivity. At the same time, Avdeenko et al. (2016) utilize AI to support models of knowledge transformation processes in the SECI model, while knowledge representation techniques use rule-based representation. Case-based reasoning (CBR) in KM is used by (Wichawong & Chongstitvatana, 2017) for hard disk failure analysis.

AI technology is used in several KMS development models. The Knowledge Management Collaborative System (CKMS) Framework developed by Cha et al. (2015) utilizes AI technology to combine knowledge and recommendation systems. Córdova and Gutiérrez (2018) utilize AI technology in the KMS model to measure employee skill levels. AI technology is used by He et al. (2017) in the VOZIQ

Framework model for sentiment analysis on social media. These models are reference models that will be discussed in the next chapter.

AI technology can manage knowledge in large, complex amounts of big data. Big data-based and traditional knowledge management differ in how each approach operates in the context of people, processes, and technology. While traditional knowledge management focuses on human involvement and formal processes, big data-based knowledge management offers a more dynamic and technologically advanced way to handle knowledge, making it more responsive to today's organizational needs (Sumbal et al., 2021).

2.4.6 The Integration AI into KMS

The integration of Artificial Intelligence (AI) into Knowledge Management Systems (KMS) represents a transformative development in organizational knowledge management practices, particularly in enhancing operational efficiency, fostering innovation, and promoting continuous learning. This convergence is increasingly acknowledged as a critical factor for achieving organizational success, prompting an upsurge in both research and practical applications of AI technologies within KMS frameworks. The ensuing sections elaborately discuss the salient trends and implications arising from this integration.

1. AI Enhancements in Knowledge Management

    a) Automation of Processes: AI empowers the automation of various facets of knowledge management, including acquisition, documentation, dissemination, and application. This streamlining of operations can significantly enhance the efficacy of KMS (Bolisani & Nakash, 2024)

b) Data Management: The implementation of AI technologies, especially machine learning and deep learning paradigms, has substantially improved data management capabilities. This augmentation facilitates improved decision-making processes and optimizes knowledge utilization (Arsenijević & Arsenijević, 2024)

c) Innovation Catalyst: The incorporation of AI into KMS acts as a catalyst for innovation by generating insights that drive organizational learning and adaptability, thereby enhancing overall institutional responsiveness to changing environments (Prihandoko et al., 2024).

2. Challenges and Future Directions

a) Implementation Barriers: Notwithstanding the myriad benefits, organizations frequently encounter obstacles in the integration of AI within existing KMS. Notable challenges include resistance to change among staff and a lack of requisite technical expertise (Bolisani & Nakash, 2024).

b) Need for Intelligent KMS: There is an escalating demand for Intelligent Knowledge Management Systems (IKMS) that effectively leverage AI to satisfy the unique requirements of professional service organizations, particularly concerning the onboarding and integration of new employees (Gan & Sundaram, 2023).

While the integration of AI into KMS heralds substantial opportunities for organizational advancement, it concurrently engenders concerns related to data privacy and the risk of excessive dependence on technological solutions. Consequently, a judicious and balanced approach to implementation is imperative to mitigate potential drawbacks while capitalizing on the benefits of this technological evolution.

2.5 Personalized Learning (PL)

Education 4.0 represents a transformative approach to learning characterized by the ubiquitous connectivity of individuals, objects, and machines, facilitating personalized educational experiences. This emerging ecosystem redefines educational institutions as smart and integrated environments dedicated to fostering individualized learning opportunities (Bin, 2017). Personalized learning is defined as an adaptive educational framework that is tailored to align with the distinctive interests, strengths, and needs of each learner, thereby enabling a flexible approach to the timing and space of learning activities (Basham et al., 2016; Davis & Jiang, 2014). It is increasingly recognized as a viable learning strategy capable of addressing diverse learners needs while enhancing overall academic outcomes (Johns & Wolking, 2016).

The framework of personalized learning encompasses four principal elements (Johns & Wolking, 2016):

1. Flexible Content and Tools: Instructional resources are designed to accommodate varied educational pathways, pacing, and performance tasks. Educators are trained to utilize foundational, adaptive, and highly customizable digital content and tools to differentiate learning experiences.
2. These resources do not supplant the educator's role; rather, they complement and enhance instructional efforts by providing remediation, practice, extension, and authentic assessment opportunities.
3. Targeted Instruction: Instruction is meticulously aligned with learners' specific needs and learning objectives. Through data-driven analysis, educators can identify particular learners requirements and subsequently tailor their instructional approaches to address these needs. This may involve the formation of small groups, individualized strategy sessions, or other

modes of targeted instruction, thereby cultivating a supportive learning environment conducive to the success of all learners.

4. Learners Reflection and Ownership: Continuous opportunities for learners reflection are instrumental in fostering a sense of ownership over the learning process. Learners are encouraged to regularly contemplate their progress and achievements, set improvement goals, and engage in authentic decision-making regarding their educational pursuits. This emphasis on reflection promotes genuine autonomy in the learning journey.
5. Data-Driven Decisions: Systematic data collection plays a critical role in informing instructional choices and learners groupings. Educators leverage data insights to refine their teaching strategies, while learners are afforded opportunities to analyse their performance data, empowering them to make informed decisions about their learning pathways.

The application of personalized learning is evident in the healthcare sector, particularly in the domain of surgical education for the placement of central venous catheters (CVC) among medical learners. Research utilizing a Dynamic Haptic Robotic Trainer for Central Venous Catheterization has demonstrated that personalized learning significantly enhances the competencies of medical learners in CVC procedures (Yovanoff et al., 2017). Additionally, a conceptual model for personalized learning was developed in the context of a health information system aimed at preventing type 2 diabetes mellitus (T2DM). Employing a User-Centered Design (UCD) methodology, researchers successfully established a framework for a T2DM prevention information system (Davis & Jiang, 2014).

2.5.1 Learning Analytics

The integration of learning analytics with self-regulation theory presents a valuable approach for lecturers in higher education institutions (HEIs) to enhance learners learning outcomes (Tiukhova et al., 2024). A recent study employing a temporal model of learning analytics investigated the relationship between pre-class video engagement and academic motivation. Findings indicated that learners who consistently engaged with video content exhibited a significant correlation with their weekly motivation and overall academic performance (Wu et al., 2024). Furthermore, research conducted on postgraduate learners in Taiwan utilized learning analytics to identify the impact of digital distractions and peer engagement on learning outcomes. The results revealed that higher levels of self-reported digital distractions were associated with diminished academic performance, while a stronger orientation toward peer learning correlated positively with higher grades (Liao & Wu, 2022). This indicates the critical role of both digital engagement and collaborative learning environments in fostering academic success.

2.5.2 Recommendation System

The recommendation system is the most important part of personalized learning. It is a roadmap that provides guidance in developing knowledge for employees. Nitchot et al., (2019) conducted a study on the development of a personalized learning system to describe the structure of knowledge and recommendation links or links to teaching materials.

1. **Collaborative Filtering (CF)/Rule-Based Filtering (RBF)**

Collaborative Filtering (CF) represents a prominent methodology within Recommendation Systems that leverages user assessment patterns to predict preferences, thereby facilitating tailored item recommendations (Koren et al., 2021). This methodology conducts an analysis of the relationships and similarities among various users or items. The foundational premise of this approach is that if User A exhibits preferences akin to those of User B across multiple items, then User A is likely to appreciate items that User B has rated favorably, even if these items have not been previously evaluated by User.

2. Content-Based Filtering (CBF)

Content-based filtering (CBF) is a technique employed within Recommendation Systems that leverages item-specific information (Van Meteren & Van Someren, 2000) alongside user preferences to generate recommendations (Son & Kim, 2017). This methodology operates by comprehensively analysing the various attributes and features of items that users have positively evaluated, enabling the system to recommend other items with comparable qualities. Each item is systematically characterized by a set of descriptive features or attributes in this framework. A user profile is constructed based on the salient features of items that the user has rated favorably. Numerous techniques may be employed in the processing of attributes and features in CBF, with one prominent approach being the Term Frequency-Inverse Document Frequency (TF-IDF).

3. Cosine Similarity

Cosine Similarity is a widely utilized technique for assessing similarity between feature vectors. This method quantifies the degree of similarity by calculating the cosine of the angle between two vectors (Ariantini et al., 2016). In recommendation systems, the feature vector representing the items a user prefers is compared against the feature vectors of other potential items. Items that exhibit a high Cosine Similarity score with the user's preference vector are identified as similar to the user's interests.

Consequently, these items, characterized by their elevated similarity values, are prioritized for recommendation to the user. The degree of similarity can be computed using an established formula.

$$cos(\theta) = \frac{A \,.\, B}{||A||\,||B||} \tag{2.3}$$

In this context, A, B is the dot product of vectors A and B, which produces a scalar value. The length or magnitude of vector A is expressed as $||A||$, while the length or magnitude of vector B is written as $||B||$.

The application of Cosine Similarity necessitates the input of numeric vectors; therefore, it is imperative to utilize Term Frequency-Inverse Document Frequency (TF-IDF) to convert textual data into a numeric vector format. The integration of TF-IDF with Cosine Similarity enables a recommendation system to proficiently analyze and prioritize items that are most pertinent and engaging for users based on their historical preferences.

4. Hybrid Approach

The hybrid approach refers to enhancing system performance by amalgamating multiple methodologies rather than relying solely on singular techniques (Burke, 2002). Various methodologies can be employed within this framework, among which the switching technique is particularly noteworthy in developing hybrid recommendation systems.

The switching technique is an adaptive mechanism utilized in recommender systems that enhances the accuracy of recommendations by transitioning between different recommendation methodologies contingent upon specific conditions or criteria (Burke, 2002; Sridevi et al., 2016). This technique fosters a higher degree of adaptability to fluctuations in data availability. For instance, when sufficient interaction or rating data is present, the system may leverage Collaborative Filtering. In contrast, it may pivot to Content-Based Filtering in scenarios characterized by limited interaction data. Consequently, the switching technique affords substantial flexibility in addressing a diverse array of recommendation contexts.

5. Evaluation using Confusion Matrix and Mean Absolute Error (MAE)

The confusion matrix and mean absolute error (MAE) are pivotal instruments in machine learning, serving as a visual apparatus for evaluating model performance. It encapsulates the results of predictions about actual values, facilitating a comprehensive assessment of classification accuracy. Recent advancements have broadened the scope of confusion matrices, introducing hierarchical structures and specialised frameworks for evaluating feature attribution methodologies.

a) Precision, Recall, and F1-Score

Precision, recall, and F1-score are pivotal metrics in evaluating classification model performance, particularly in scenarios characterized by imbalanced datasets. These metrics provide comprehensive insights into a model's capability to identify relevant instances while effectively managing the trade-off between false positives and false negatives. Subsequent sections delineate the significance and applicability of each metric.

1. Precision

Precision quantifies the accuracy of positive predictions and is calculated as the ratio of true positives to the total of true and false positives. In the domain of car damage classification, observed precision values ranged from 94.34% to 95.59%, signifying a high level of accuracy in the identification of various damage types (Midha et al., 2024) In the context of weapon detection, precision attained 96% for one specific class, thereby illustrating the model's efficacy in minimizing false positives (Suryavanshi et al., 2024).

2. Recall

Recall, often called sensitivity, evaluates the model's proficiency in identifying all relevant instances. It is the ratio of true positives to the sum of true positives and false negatives. The car damage classification model demonstrated recall rates exceeding 94%, illustrating its competence in detecting pertinent instances across multiple categories (Midha et al., 2024). Conversely, recall values exhibited variability in weapon detection, with one class achieving a recall of 93.17%, which underscores the model's ability to capture true positives (Suryavanshi et al., 2024).

3. F1-Score

The F1 Score is the harmonic mean of precision and recall, yielding a metric encapsulating both dimensions. The car damage classification model consistently recorded F1 scores surpassing 95%, indicating a robust balance between precision and recall (Midha et al., 2024) In weapon detection, the F1 Score reached 91.92%, reflecting commendable performance across various classes (Suryavanshi et al., 2024).

While precision, recall, and F1-score metrics are fundamental to evaluating model performance, it is crucial to account for the underlying context and specific application requirements. In certain instances, alternative metrics, such as accuracy or area under the curve (AUC), may provide supplementary insights, especially in situations characterized by diverse class distributions (Naidu et al., 2023).

b) The Mean Absolute Error (MAE)

The mean absolute error (MAE) is a widely recognized metric utilized for evaluating quantitative models. It is particularly esteemed for its interpretability in comparison to alternative error metrics such as mean squared error (MSE). The MAE effectively quantifies the average magnitude of errors derived from a set of predictions while intentionally ignoring their directional bias. This characteristic renders MAE a straightforward yet robust measure of model performance. The ensuing sections will elaborate on its defining characteristics, practical applications, and comparative advantages.

a. Characteristics of MAE

1) Interpretability: The MAE offers clear and comprehensible insights into the average magnitude of errors, making it accessible to many stakeholders (Robeson & Willmott, 2023).
2) Decomposition: The MAE can be systematically decomposed into three fundamental components: bias error, proportionality error, and unsystematic error. This decomposition provides valuable insights into the nature and sources of model errors (Robeson & Willmott, 2023).

b. Applications of MAE

1) Model Evaluation: The MAE is particularly effective in contexts where the error distribution adheres to a Laplacian form, making it applicable across diverse fields, including meteorology and finance (Hodson, 2022).
2) Comparison with RMSE: While the MAE is optimal for certain error distributions, the root mean squared error (RMSE) is generally preferred for error terms that are normally distributed. This distinction underscores

the importance of contextual factors in selecting appropriate evaluation metrics (Hodson, 2022).

Despite its advantages, a growing body of research suggests that an exclusive reliance on MAE may obscure critical aspects of model performance, particularly in scenarios where error distributions deviate significantly from established norms. As such, a thorough evaluation of model accuracy typically necessitates using multiple metrics, including RMSE, to achieve a more comprehensive understanding of model efficacy (Hodson, 2022).

2.6 Outcome-Based Education (OBE)

Education serves as a fundamental pillar in the development of a nation. In the context of rapid global changes, education systems must be designed to cultivate graduates with knowledge and pertinent skills that align with societal and labour market demands. The Outcome-Based Education (OBE) approach is increasingly recognized as a relevant framework. OBE is an educational paradigm that prioritizes learners learning outcomes as the principal aim. This approach emphasizes the learning process and the specific competencies that learners must attain (Spady, 1994). This theoretical framework will explore the definition, principles, supporting theories, curricular structure, implementation strategies, advantages, and challenges associated with the OBE approach.

Outcome-based education (OBE) is a systematic educational framework that positions learning outcomes as the focal point of all educational activities. Spady (1994), a seminal figure in the formulation of OBE, defines the approach as an educational process designed to align the entire educational framework with attaining specific and measurable outcomes. According to Spady (1994), OBE is predicated on the principle that all learners must achieve the necessary competencies for future success.

OBE strongly emphasizes content delivery and applying knowledge and skills in practical, real-world contexts. (Biggs & Tang, 2011) assert that OBE centralizes learning outcomes within the design of the curriculum, pedagogical strategies, and assessment methodologies.

Spady (1994) delineates four foundational principles underpinning OBE:

1. Clarity of Focus: OBE necessitates precision in defining learning outcomes, which should be specific, measurable, relevant, and attainable. Examples of such outcomes include, but are not limited to, problem-solving capabilities, critical thinking skills, and collaborative teamwork.
2. Design Down, Deliver Up: The OBE curriculum adheres to a "backward design" methodology, wherein learning outcomes are established prior to determining the learning and assessment processes. This approach ensures that every educational activity is conducive to achieving the intended outcomes.
3. High Expectations: OBE advocates for elevated standards for all learners, positing that every learners has the potential to meet specified learning outcomes if provided with appropriate support and resources.
4. Expanded Opportunity: OBE facilitates an environment in which learners are afforded significant opportunities to learn and achieve learning outcomes, encompassing flexibility in teaching methodologies and the temporal allowances granted for the learning process.

2.6.1 OBE Curriculum Structure and Framework

Outcome-Based Education (OBE) represents an educational paradigm that prioritizes a learners-centred approach to learning, assessing learners performance through clearly defined outcomes. These outcomes encompass the essential skills and knowledge learners are expected to acquire by the culmination of a course or program. OBE is structured around various hierarchical levels of outcomes, including Course Outcomes (COs), Program Outcomes (POs), and Graduate Attributes, all aimed at equipping learners with the requisite competencies to thrive professionally and personally.

1. Course Outcomes (COs) are articulated as specific skills and knowledge that learners are anticipated to achieve by the end of an individual course. The assessment of COs employs both direct and indirect evaluative methods, such as Continuous Internal Evaluations (CIEs), assignments, quizzes, and seminars (Balaji & Pai, 2020). The calculation of CO attainment integrates scores from internal and external assessments, providing a comprehensive evaluation framework (Balaji & Pai, 2020).
2. Program Outcomes (POs), in contrast, delineate broader competencies that learners are expected to demonstrate upon completing a degree program. These outcomes align with industry standards and accreditation guidelines, particularly those established by the National Board of Accreditation (NBA) (Saha et al., 2023) Assessment of POs typically involves an analysis of course outcomes alongside feedback derived from course exit surveys (Balaji & Pai, 2020).
3. Graduate Attributes, refer to the high-level qualities and skills learners should cultivate throughout their educational journey, including problem-solving

abilities, effective communication, and ethical principles (Saha et al., 2023). These attributes are interconnected across multiple courses and evaluated through a comprehensive assessment framework (Mahrishi et al., 2023). The attainment of graduate attributes is critical to ensuring that graduates are adeptly prepared for the complexities and demands of the real world (Mahrishi et al., 2023).

While OBE is increasingly recognized and implemented in fields such as engineering and business education, its successful adoption necessitates a significant shift in instructional and assessment methodologies. The outcome-focused framework inherently requires a precise delineation of learning objectives and a robust assessment strategy to guarantee that learners meet these articulated goals. This modern approach starkly contrasts traditional educational models, which frequently place greater emphasis on content delivery than on the measurement of tangible (Saha et al., 2023).

2.6.2 Theoretical Basis for OBE Implementation

Several key theoretical frameworks underscore the implementation of outcome-based education (OBE) within educational settings, emphasizing the importance of explicit learning outcomes, systematic curriculum design, and robust evaluation mechanisms. These frameworks align educational programs with the skills and competencies necessary for success in professional domains, particularly engineering and vocational education. The ensuing discussion delineates the primary theoretical frameworks that support the effective execution of OBE.

1. Defining Learning Outcomes

Outcome-based education prioritizes articulating clearly defined learning outcomes that learners are expected to achieve upon completing a course or program.

This process necessitates the establishment of explicit, measurable objectives that inform both curriculum development and pedagogical approaches (Hongyan Liu, 2019; Syeed et al., 2022). Moreover, these learning outcomes are strategically aligned with industry standards, thereby ensuring that learners acquire pertinent skills essential for their subsequent careers (Sun & Xu, 2024; Wang, 2024).

2. Curriculum Design and Flexibility

In the context of OBE, curriculum design is characterized by its inherent flexibility, which facilitates the incorporation of diverse teaching methodologies and learning activities tailored to meet learners' varied needs (Sun & Xu, 2024). The curriculum further emphasizes integrating knowledge and skills across multiple disciplines, promoting a holistic educational approach (Hongyan Liu, 2019).

3. Evaluation and Continuous Improvement

OBE advocates for multi-dimensional evaluation mechanisms designed to assess learners performance about predefined learning outcomes (Sun & Xu, 2024). A fundamental principle of OBE is continuous improvement, which involves establishing regular feedback loops to refine pedagogical techniques and curricular content based on evaluative insights (Hongyan Liu, 2019).

4. Learners-Centered Teaching Methods

Teaching methodologies within the OBE framework are inherently learners-centred, prioritizing active learning and developing practical skills (B. R., 2023; Sun & Xu, 2024). Innovative instructional models, such as project-based learning and school-enterprise partnerships, enhance learners engagement and facilitate the real-world application of knowledge (Hongyan Liu, 2019).

While OBE offers a structured educational paradigm, it is imperative to acknowledge the potential challenges associated with its implementation. These challenges encompass substantial shifts in pedagogical practices, the creation of comprehensive evaluation systems, and the alignment of educational objectives with industry benchmarks. Addressing these challenges necessitates collaborative efforts among educators, institutions, and industry stakeholders to ensure the successful integration of OBE frameworks (Wang, 2024).

2.6.3 Implementation of OBE in HEI

Outcome-Based Education (OBE) in higher education institutions (HEIs) presents a framework that aligns educational objectives with explicit, measurable outcomes. This pedagogical approach has numerous advantages, including enhancing educational quality and aligning with industry demands. Concurrently, OBE poses several challenges, such as resource constraints and the necessity for faculty adaptation. By concentrating on the attainment of specific learning outcomes, OBE has the potential to augment learners competencies, thus improving employability significantly. Nonetheless, the effective implementation of OBE necessitates carefully analyzing various contextual factors.

1. Advantages of OBE in Higher Education Institutions
    a) Enhanced Learning Outcomes: OBE places a premium on achieving defined competencies, producing graduates better equipped to meet the workforce standards (Kumar, 2023; Song, 2023).
    b) Curriculum Alignment: The OBE framework ensures that educational curricula are systematically aligned with desired learning outcomes, fostering

a more coherent and goal-oriented educational experience (Guimba et al., 2024).

c) Comprehensive Assessment: OBE incorporates assessment mechanisms that provide insights into learners' skill levels and generate constructive feedback. This approach can be particularly effective in e-learning settings, where tools such as e-rubrics can be used (Yuniarti et al., 2024).

d) Accreditation and Quality Assurance: Implementing OBE practices has the potential to enhance institutional accreditation status, as such practices often surpass standard requirements, consequently bolstering the institution's reputation (Hapinat, 2023).

2. Limitations of OBE in Higher Education Institutions

a) Resource Constraints: Limitations in facilities, resources, and funding may impede the execution of OBE initiatives. This often adversely impacts research initiatives and community engagement (Guimba et al., 2024; Hapinat, 2023).

b) Faculty Challenges: Faculty members frequently encounter difficulties adapting to the OBE paradigm, necessitating substantial training and support to effectively revise curricula and teaching methodologies (Guimba et al., 2024).

c) Complex Assessment Needs: The OBE approach demands sophisticated assessment tools to evaluate multifaceted learning outcomes, posing challenges in developing and implementing such instruments (Yuniarti et al., 2024).

3. Addressing Limitations

a) Resource Allocation: Institutions must strategically allocate funding and resources to support OBE initiatives, particularly in areas such as research and community involvement (Hapinat, 2023).

b) Faculty Development: Implementing robust training and support programs for faculty can facilitate a more seamless transition to OBE, ensuring educators are well-equipped to design and deliver curricula focused on achieving specified outcomes (Guimba et al., 2024).

c) Innovative Assessment Tools: The development and utilization of advanced assessment instruments, such as e-rubrics and fuzzy logic methodologies, can effectively address the challenges of evaluating diverse learning outcomes (Yuniarti et al., 2024).

OBE successful implementation requires a concerted effort to address challenges about resource limitations, faculty adaptation, and assessment intricacies. By focusing on these critical areas, HEIs can harness OBE's full potential to elevate the quality and relevance of higher education.

2.7 Technology Acceptance Model (TAM)

The perception of technology characteristics is inherently subjective, varying significantly among individuals. These perceptions are deeply rooted in cognitive processes and individual beliefs regarding technology. The Technology Acceptance Model (TAM), proposed by Davis (1989) etalong with the Theory of Reasoned Action (TRA), introduced by (Fishbein & Ajzen, 1975), has largely influenced the discourse in information systems literature. Both models posit that individual beliefs about the benefits of technology significantly impact the various constructs within the TAM and TRA frameworks (Heller et al., 2013).

User acceptance of information technology systems can be defined as the collective willingness among users to adopt and implement a new information technology system in their professional practices. Greater acceptance of the new system correlates with an increased willingness among users to modify existing practices, thereby reallocating time and effort toward integrating the new technology (Succi and Walter, 1999, as cited in Pikkarainen et al., 2003). Conversely, if users resist embracing the new information technology system, the anticipated changes may not yield significant benefits for the organization (Davis, 1989; Venkatesh & Davis, 1996).

Davis identifies five critical characteristics influencing technology acceptance, namely:

1) Relative Advantage: the extent to which the technology offers enhancements over existing solutions.
2) Suitability: the degree to which technology aligns with prevailing social practices and norms among users.
3) Complexity: the perceived ease of use or learning associated with the technology.
4) Trialability: opportunities to experiment with the technology before full implementation.
5) Observability: the clarity with which users can perceive the benefits of the technology.

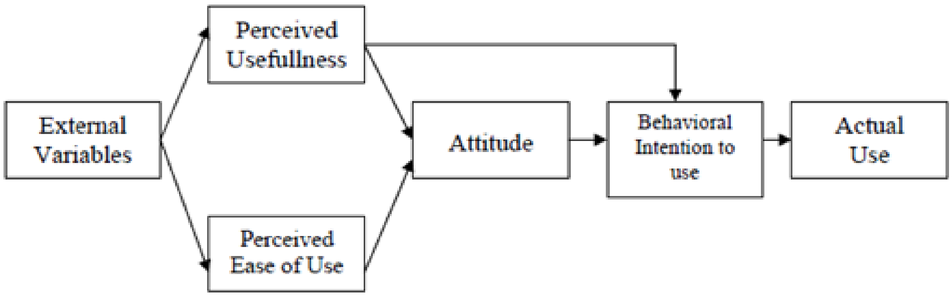
The evolution of information technology has fundamentally transformed workplace dynamics and the nature of tasks performed. Implementing such technologies necessitates varying individual perceptions, reflecting the interaction between technology acceptance and user attitudes in professional environments. Long-term predictions regarding user acceptance can be effectively derived by measuring affective responses to new technology. The foundational work of Davis (1989) which established the TAM, serves to elucidate individual behaviours pertaining to the acceptance of information technology.

The Technology Acceptance Model (TAM) is a seminal framework that elucidates two fundamental dimensions influencing technology adoption: Perceived Usefulness (PU) and Perceived Ease of Use (PEOU). Perceived Usefulness refers to an individual's belief that utilizing a specific technology will enhance job performance, whereas Perceived Ease of Use pertains to the degree to which a user perceives the technology as user-friendly (Davis, 1993; Malatji et al., 2020).

These dimensions play a pivotal role in shaping users' attitudes towards technology, which, in turn, significantly impacts their behavioural intentions to embrace its use (Marangunić & Granić, 2015; Or, 2024). Empirical studies suggest that Perceived Usefulness typically exerts a greater influence than Perceived Ease of Click or tap here to enter text.Use on actual usage behaviour, thereby underscoring the importance of functional capabilities within the design of technological solutions (Davis, 1993).

Despite the enduring relevance of the TAM, there are ongoing calls for its refinement, as critiques advocate for integrating additional factors to bolster its predictive validity across diverse contexts (Malatji et al., 2020; Marangunić & Granić, 2015). A visual representation of the TAM framework is shows Figure 2.6.

Figure 2.6: Relationship between Components in TAM



Davis, (1993) posited that user acceptance of information technology is influenced by six constructs: external variables, perceived ease of use, perceived usefulness, attitude toward usage, behavioural intention to use, and actual system usage. Central to this model, known as the Technology Acceptance Model (TAM).

1. Perceived Usefulness

Perceived usefulness (PU) is a critical determinant of technology adoption across diverse sectors such as education, finance, and e-commerce. It encompasses users' beliefs regarding how a specific technology can enhance their performance or overall satisfaction. Key Indicators of perceived usefulness:

a) System Quality and Usability: System quality and usability are paramount in enhancing perceived usefulness, particularly within educational contexts (Rubiyanti et al., 2023). High-quality and user-friendly systems contribute significantly to users' belief in technology's beneficial outcomes.

b) Impact on Financial Technology: In financial technology (fintech), perceived usefulness plays a direct role in adopting technologies among small and medium enterprises (SMEs). Research indicates that users are more inclined to engage with systems they perceive as advantageous (Sukandar & Hermawan, 2022).

c) User Experience with Recommendation Systems: The perceived usefulness of recommendation systems in e-commerce is significant for user consent regarding data collection. This underscores the necessity of recognizing user value in data-driven environments (Mican et al., 2020).

d) Cultural and Gender Influences: Meta-analyses have shown that cultural background and gender can moderate the relationship between perceived usefulness and the adoption of fitness wearable technology. This suggests that these demographic factors uniquely shape user perceptions.

While perceived usefulness is a robust predictor of technology adoption, it is crucial to acknowledge that other elements, including perceived ease of use and external influences such as cultural context, also significantly affect user intentions and behaviours.

2. Perceived Ease of Use (Perception of User Ease)

Perceived ease of use (PEOU) emerges as a pivotal factor influencing the adoption and utilization of technological systems. PEOU is the extent to which an individual believes that utilizing a specific technology will be free of physical or mental effort. This construct forms a fundamental component of the Technology Acceptance Model (TAM), which posits that PEOU and perceived usefulness significantly shape users' behavioural intentions regarding technology adoption. The subsequent sections delineate key perceived ease-of-use indicators derived from the relevant literature. Key Indicators of Perceived Ease of Use.

a) User Interface Simplicity: An intuitive and user-friendly interface is a principal indicator of PEOU. Users demonstrate a higher propensity to adopt technologies that are easy to navigate and comprehend. This phenomenon was notably observed in the context of QRIS digital payments among

Generation Z in Bandung, where simplicity and efficiency emerged as critical determinants (Ramdhani et al., 2024).

b) Effort Reduction: Technologies that minimize the effort required to execute tasks are perceived as inherently easier to use. Evidence from research on mobile payment systems indicates a direct correlation between the ease of transaction processes and heightened adoption rates (Susanti & Alamsyah, 2022).

c) Learning Curve: An abbreviated learning curve significantly enhances perceptions of ease of use. Technologies that demand minimal time and effort for learning are more likely to be embraced by users. A study focusing on the BRI mobile application illustrated this and underscored the substantial influence of ease of use on user intentions (Hamdan, 2022).

d) Integration with Existing Systems: Compatibility with pre-existing systems and processes can augment PEOU by alleviating users' need to adapt to new workflows. This aspect was demonstrated in the study on e-commerce pay-later services, wherein ease of integration played a vital role in shaping user intentions (Sebayang et al., 2023).

e) Feedback and Support: Adequate user support and feedback mechanisms can enhance PEOU by enabling users to surmount challenges rapidly, improving their overall experience (Soomro & Habeeb, 2024).

While perceived ease of use constitutes a significant determinant of technology adoption, it does not operate in isolation. Other critical factors, such as perceived usefulness, perceived risk, and individual user motivations, also substantially influence user behaviour. For example, in mobile commerce, hedonic and utilitarian values may moderate the relationship between PEOU and impulsive buying behaviour, suggesting that user motivations can substantially alter the impact of ease of use on technology adoption (Soomro & Habeeb, 2024).

3. Attitude Toward Behaviour

The psychological factors underpinning an individual's attitudes toward behaviour are multifaceted, encompassing various cognitive and social influences. The properties of attitudes are central to understanding these dynamics, including accessibility, extremity, and ambivalence. These elements collectively contribute to the robustness of an attitude and its consequential influence on behaviour (Kokkinaki, 2020). Moreover, the Theory of Reasoned Action underscores the significance of specific attitudes toward particular behaviours, positing that intentions, subjective norms, and perceived behavioural control serve as critical determinants of action (Fishbein & Ajzen, 2011).

Furthermore, social dynamics exert a consequential influence on attitude formation. The attitudes adopted by individuals are often shaped by the beliefs and behaviours of their peers, reflecting the intricate interconnectedness between personal evaluations and broader social contexts in establishing behavioural intentions (Friedkin, 2010; Friedkin, 2016). Additionally, the relationship between attitudes and behaviour is mediated by cognitive processes, notably in the methodology employed to measure attitudes and the distinction between explicit and implicit attitudes (Maio et al., 2012). Taken together, these factors exemplify the complex interplay between individual cognition and social context in shaping attitudes and, consequently, subsequent behaviours.

4. Behavioural Intention

Behavioural intention is a critical construct that encapsulates an individual's preparedness to engage in a specific behaviour, shaped significantly by various psychological and social determinants. This construct is essential for comprehending consumer behaviour within diverse contexts, including sustainable food consumption, technology adoption, and service utilization. The subsequent sections delve into the principal determinants of behavioural intention as elucidated by contemporary research. Determinants of Behavioural Intention:

a) Attitudes and Knowledge: In the realm of sustainable food consumption, evidence suggests that Generation Z's affirmative attitudes, coupled with their sustainability knowledge, serve as robust predictors of their intention to purchase sustainable products (Jakubowska et al., 2024).
b) Social Influence: The Unified Theory of Acceptance and Use of Technology (UTAUT) model emphasizes the significance of social influence in shaping individuals' intentions to adopt cryptocurrency investment platforms (Handoko et al., 2024). Moreover, social norms have impacted women's intentions to use e-learning systems (Abbas, 2024).
c) Habit and Hedonic Motivation: Research on mobile banking and app usage reveals that both habit and hedonic motivation are salient predictors of behavioural intention, while other factors, such as performance expectancy, exhibit mixed outcomes (Safitri et al., 2024; Karyoto et al., 2024).

While these studies illuminate the role of various factors in determining behavioural intention, it is imperative to acknowledge that external influences, such as market dynamics and technological advancements, may also considerably modify these intentions.

5. Actual Usage

Perceived usefulness and perceived ease of use are pivotal constructs that significantly influence the actual usage of technology, particularly through their impact on behavioural intentions and user attitudes. Extensive research has demonstrated that both perceived usefulness and perceived ease of use exert a positive influence on behavioural intention, which subsequently affects the actual usage of various digital platforms, such as e-wallets and online applications (Efendi et al., 2024). For example, users who perceive a system as useful and easy to navigate are more likely to cultivate favourable attitudes towards its utilization, ultimately leading to increased actual usage (Gusni et al., 2020). Furthermore, while perceived usefulness directly impacts actual usage, perceived ease of use often plays a more consequential role in shaping user attitudes, thereby enhancing actual usage (Gusni et al., 2020). Consequently, a comprehensive understanding of user engagement with technology necessitates an examination of both constructs.

User perceptions of technology's benefits are shaped by a multifaceted interplay of individual and contextual factors. An in-depth understanding of these factors is essential for improving user acceptance and satisfaction with technological innovations. The subsequent sections delineate the primary influences on user perceptions. Key Influencing Factors:

a) Recognized Benefits: Users are driven by the tangible advantages they associate with technology, including enhanced efficiency and convenience (Saleh et al., 2020).
b) Performance Expectancy: The expectation that technology will positively impact job performance is a significant determinant of user acceptance (Hameed & Counsell, 2014; T. Li & Wang, 2005).
c) Social Influence: The perceptions and behaviours of peers and prevailing societal norms play a pivotal role in shaping user attitudes toward technology (Hameed & Counsell, 2014; Saleh et al., 2020)

d) Facilitating Conditions: Adequate resources and support systems can enhance user perceptions, facilitating a smoother interaction with technology (Hameed & Counsell, 2014; T. Li & Wang, 2005).
e) Aesthetics and Reliability: Technology's visual appeal and dependability are critical factors influencing user perceptions, as individuals tend to favour products that are not only aesthetically pleasing but also exhibit consistent performance (John, 2003).

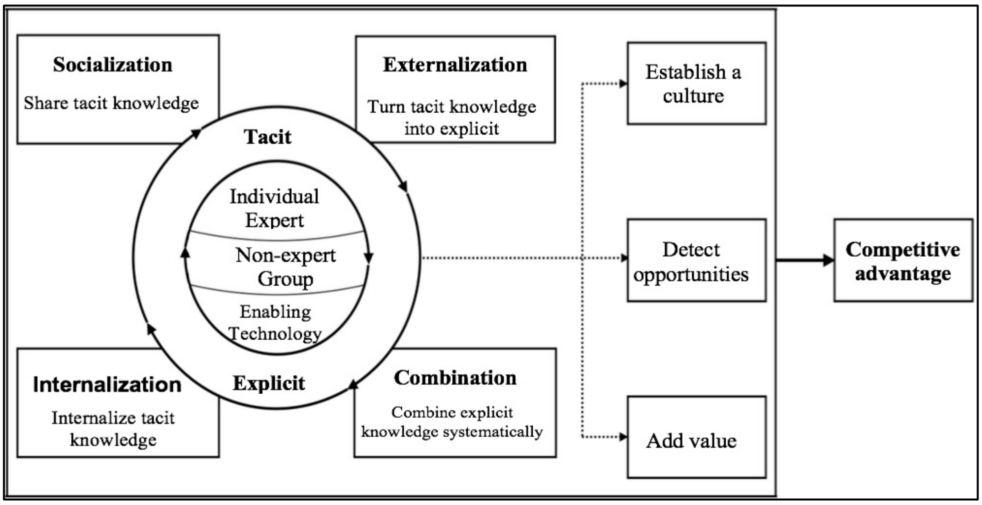
While the aforementioned factors underscore the advantages associated with technology, it is imperative to acknowledge that negative perceptions can emerge from concerns related to privacy and an increasing dependency on technological solutions, which may mitigate the perceived benefits (Gardner & Amoroso, 2004).

2.8 Related Works

Several models from previous research are used as references in developing KMS. These models generally utilize AI technology. Knowledge in KMS is developed from various sources, including big data on social media and analysis systems.

Córdova & Gutiérrez (2018) developed a KM module with the RAS Module implemented in the insurance company's ERP system. The design of the Knowledge Management System is intended for an organization that fulfils the role of liquidating claims for damage or loss in the Chilean insurance market, the company "Network of Damage Adjusters (RAS). RAS knowledge aims to create, disseminate, and express tacit knowledge, generating explicit knowledge available to all areas and jobs. Through BA Exerciser training and internalisation of tacit knowledge (combination), RAS knowledge users can practice knowledge and experiences that allow workers to acquire higher levels of expertise. The knowledge creation model (SECI model) is used as a framework for developing the KMS RAS module. However, what is different in the internalisation process is evaluating performance or measuring the level of employee expertise. This evaluation is related to evaluating the level of expertise of the job position they choose. Figure 2.7 shows the KMS RAS model.

Figure 2.7: Model KMS RAS



Source: (Córdova & Gutiérrez, 2018)

The KMS RAS model was developed to gain a competitive advantage by including cultural factors, opportunity detection, and added value influencing KMS's success. The ability to learn from experience greatly supports individual or organizational learners continuously. RAS is focused on generating user interest through access to available technology; it is hoped that spaces will be built to develop expertise.

The advantage of the KMS RAS model is that the knowledge developed comes from within the company and has utilized AI technology. To expand the capacity of knowledge creation, the developed KM model has been supported by several e-learning tools such as video streaming, online forums, and curricular and learning management systems (LMS). The results of learning can produce a knowledge profile.

The profile is formalized into five levels of expertise: Resident Novice, Advanced Beginner, Competent, Proficient and Expert. Each level of expertise will determine the knowledge action and activities in the model. This level will be related to the job position in the company.

The KMS RAS model comprehensively describes the organization's knowledge development concept. The use of several information technology tools in supporting KM is quite extensive. However, the RAS model does not explain how knowledge extraction in online discussion forums or big data is utilized. The results of the Socialisation process should present knowledge that can be externalized. The combination of knowledge should come from various internal and external sources. The knowledge combination process is expected to present complete, broad and valid knowledge. This model also does not explain how the analysis determines the level of expertise—and knowledge development needs, as well as what instruments are used. The method used to determine the level of expertise is also not explained. Learning outcomes should produce a profile determining learning needs and skill levels.

Avdeenko et al. (2016) proposed an approach to the knowledge creation process in KMS; this model facilitates knowledge transition from implicit to explicit forms and vice versa. This approach transforms knowledge from case-based and rule-based knowledge representation models. The Transformation of knowledge in the proposed model is called the Transformation of knowledge in a hybrid model. The model adopts the Case-Based Reasoning (CBR) knowledge representation model in the SECI model knowledge creation. Figure 2.8 explains the knowledge transformation model in the Hybrid model.

Figure 2.8: Knowledge Transformation in Hybrid Model

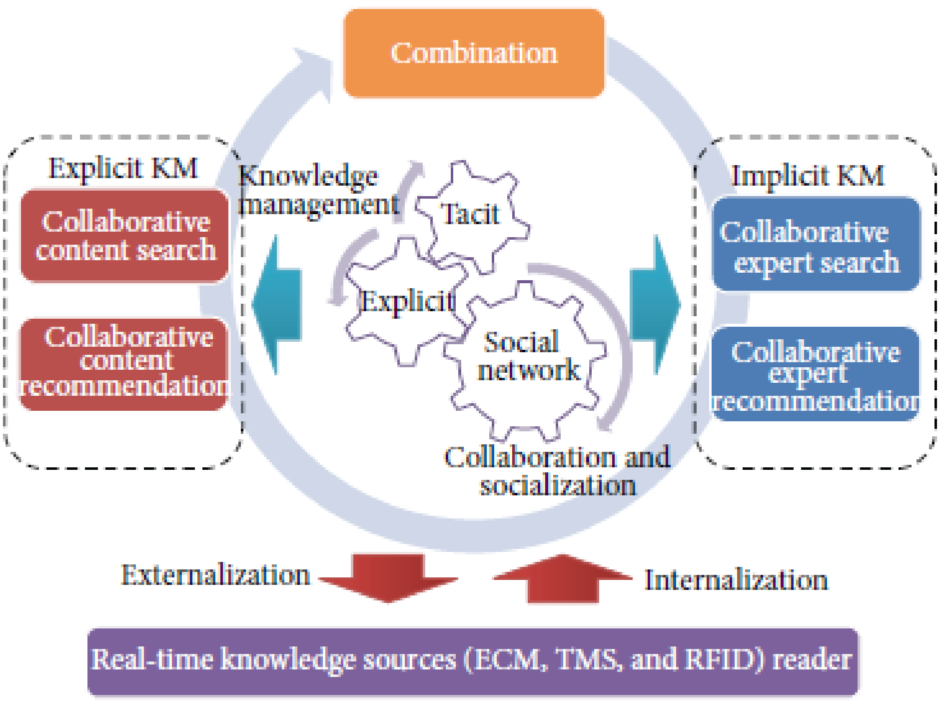
I. Accumulation of cases sample – creation of case base	II. Extracting rules from case base Cases → Rules
IV. Obtaining new cases from rules application (retain in CBR-cycle) Rules → Cases	III. The increasing complexity of rules structure based on expert analysis of the application domain

The advantage of the hybrid model is that it uses two approaches to knowledge representation: case-based and rule-based approaches. The hybrid model is a knowledge creation cycle in the SECI model. When employees/learners do not have sufficient knowledge about an object, they can use case-based knowledge representation, where knowledge is a relevant case in decision-making applied in a particular organizational area. Data mining is used in extraction, adapting past cases to solve current problems, and the results become new knowledge. The combination process in the Hybrid Model adds explicit knowledge, increasing the complexity of the rule structure based on expert analysis in the application domain. This knowledge can be cleaned, refined and interpreted by experts. New cases are obtained using the rule base, and getting new cases based on the CBR cycle means using formal (explicit) knowledge and converting it into an implicit (tacit) form.

The case-matching process in the hybrid model is quite complicated and requires a relatively complex computational process. Knowledge adaptation and case library development are difficult to implement in some circumstances, and it is difficult to build a rule base. When cases are not yet available or not well documented, experts can be asked to create cases from their experiences. However, it is as difficult as implementing the knowledge in a rule-based system. The model presents knowledge transformation, but no measurement mechanism exists to determine how many employees/learners can receive the knowledge. Knowledge needs analysis is not available, even though knowledge needs analysis is one of the keys to knowledge transformation.

Khoa & Huynh (2023) studied the impact of the Knowledge Management System (KMS) on motivation and job satisfaction among academic staff in higher education institutions in Vietnam. Data were collected from 676 university professors through self-administered questionnaires. The focus was on how KMS affects knowledge acquisition, dissemination, and utilization. The implementation of a strong KMS can significantly improve faculty satisfaction and motivation, leading to a more productive academic environment (Khoa & Huynh, 2023).

Figure 2.9: CKMS Framework



Research on the development of the Collaborative Knowledge Management System (CKMS) Framework was conducted by Cha et al., 2015). CKMS was developed to manage tacit and explicit knowledge using collaboration technology. CKMS internalizes real-time knowledge from various internal sources (e.g., ECM, TMS, and RFID readers) and external sources (web, news, and blogs). Through CKMS, members externalize their knowledge by creating documents based on available tacit and explicit knowledge. Knowledge obtained from knowledge sources is socialized through the organization's social network. To support explicit knowledge management, CKMS supports an easy content search mechanism in response to individual information needs. RFID in SCKM is used as a real-time process monitoring tool and for production and logistics activities. The RFID-enabled KMS can provide real-time information on production and logistics progress status to help knowledge seekers (e.g., from the marketing or finance sectors) apply this operational knowledge in making faster and more informed business decisions to achieve their goals.

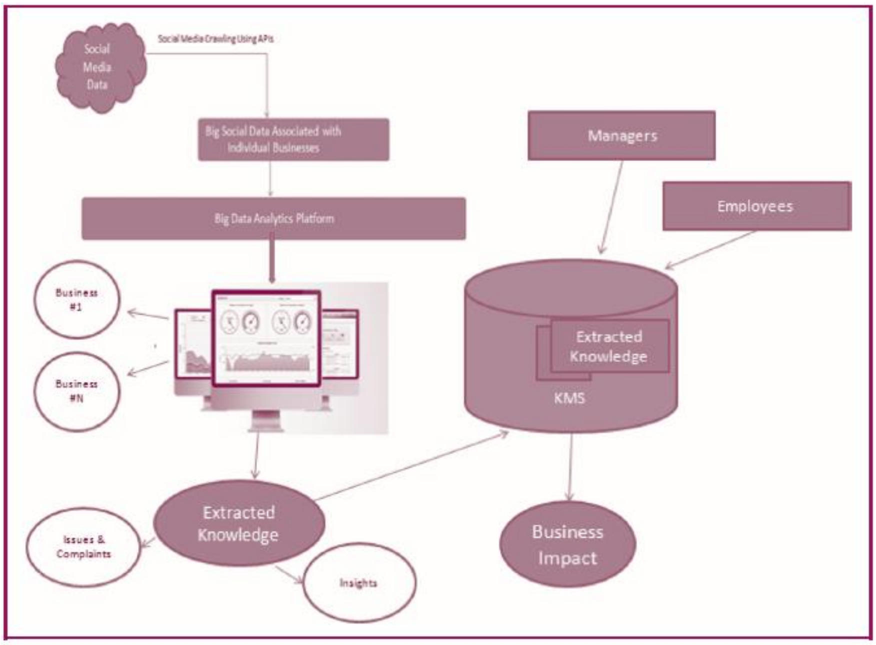
Socialisation links users seeking tacit knowledge and experts who possess that knowledge through a social network-based expert recommendation system. Combination, combining, categorizing, reclassifying, and synthesizing existing explicit knowledge through collaborative filtering recommendation systems (CFRS) and custom content search (CCS). Through CFRS and CCS, internalisation involves tremendous exposure to many knowledge sources, including online organizational information from RFID, ECM, TMS, blogs, search logs, and external sources horizontally and vertically. As information exposure increases, the internalisation mode of knowledge creation, where individuals make observations and interpretations of information that generate new tacit knowledge, can be enhanced. Externalisation is knowledge creation, which can be promoted by encouraging experts to create new documents based on knowledge collaboration and system Socialisation activities and upload them to improve the overall expert expertise and reputation ranking within the company.

The advantages of the CKMS model are that it can support easy content search mechanisms in responding to individual information needs, provide content ranking information based on collaboration factors, support collaborative content recommendations, and exploit the collaborative contributions of organizational members. The model has been equipped with a data acquisition engine that can combine and integrate knowledge from various sources, both internal and external to the organization. The model uses an input data analysis engine, a search engine, and a data indexer. The model has a mechanism for categorizing knowledge documents and a data analysis network. There is a recommender system for analyzing expert profiles and text data from the recommendation database. The model has used collaborative custom search, collaborative recommendations, collaborative expert search, collaborative expert recommendations, and a network of collaborators.

One of the shortcomings of the CKMS model is the Socialisation process. Socialisation in the CKMS model is the process of searching for tacit knowledge documents and searching for experts in the field of knowledge. Socialisation in the CKMS model is not a brainstorming process or sharing knowledge about the best experiences in solving cases among members of the organization or with experts. The combination in the CKMS model is the process of combining, categorizing or classifying knowledge. There is no room for experts or external parties to contribute to validating or adding to existing knowledge. KMS is essentially a cognitive process; internalisation in the CKSM model is the process of observing and interpreting information to produce new tacit knowledge; there is no evaluation process or measurement of the results of the observations or interpretations.

He et al. (2017) developed a knowledge management framework (VOZIQ Framework) to integrate social media data, big data technology and KMS to compare each company's social media data with competitors and find business intelligence. The extracted knowledge is presented visually in various ways to find business intelligence. The results of this study are a framework for analyzing big data processing in social media. The study compared consumer sentiment analysis from the retail industry (Costco, Walmart, Kmart, Kohl's and The Home Depot) on social media Twitter, with the number of messages processed almost 1 million messages. This study provides a practical guide to using Big Data technology to extract valuable knowledge in social media and find business intelligence contextually comparing social media knowledge among competitors.

Figure 2.10: KM VAZIQ Model



Source: (He et al., 2017)

The advantage of the VAZIQ framework is that it can be used as a solution to analyze big data social media related to organizations and their competitors. Able to visualize and compare comparisons between competitors across events, products, issues, and other areas that can affect business performance. Existing Big Data platforms can be integrated to store, manage, analyse, and compare data across social media sources. KMS has a repository system for extracted knowledge, which can be shared with managers and employees. The extracted knowledge is stored in the knowledge repository daily and shared with the organization's managers and employees. The disadvantage of the VAZIQ framework is that the knowledge is generated from social media analysis. The knowledge object is limited to text data extracted from consumer sentiment analysis on social media, such as Tweeter. There is no explanation of how the extracted knowledge is developed or enriched to produce complex and structured knowledge. A summary of KMS research is described in Table 2.4.

Table 2.4: Summary of Research Previous in the Field of KMS

Topics	Title and Author	Findings
Knowledge Management System	Innovative Trends in Knowledge Management: A Cloud Computing Perspective (Rafiq et al., 2014)	The transformation of KMS using cloud technology has resulted in various benefits, namely cost savings, better business processes, customer satisfaction, and better representation and knowledge management. Various application areas are also discussed, including KMS Collaboration, Knowledge as a Service (KaaS), Customer Knowledge Management Information System (CKMIS) and Enterprise Knowledge Management (EKM).
	Knowledge Sharing between Enterprises of the Same Group (Carvalho & Gomes, 2017)	A test of 369 skilled employees in Pakistan showed that skilled worker productivity significantly mediates between knowledge management and innovation processes. However, it differs from the relationship between knowledge sharing and innovation because knowledge sharing does not significantly affect skilled worker productivity. The research results imply that the human and cultural approach to

Topics	Title and Author	Findings
		KM still has a comprehensive role over the two emerging approaches (big data and IT approaches and System-based approaches)
	Success model for knowledge management systems used by doctoral researchers (Un Jan & Contreras, 2016)	The results show that collaborations on product or process innovation and service innovation affect knowledge sharing between companies in the same group, contributing to learning organizations. This model shows that doctoral learners find KMS useful if the knowledge stored is of good quality and useful. The developed success model found that perceived KMS user satisfaction depends directly on the external variable of organizational trust. User satisfaction also depends indirectly on extrinsic rewards. User satisfaction does not depend on intrinsic rewards or subjective norms. User satisfaction depends directly on the moderating variables: perceived KMS output quality and perceived KMS usefulness. User satisfaction also depends indirectly on perceived search

Topics	Title and Author	Findings
	Methodology for the Implementation of Knowledge Management Systems 2.0 A Case Study in an Oil and Gas Company (Orenga-Roglá & Chalmeta, 2017)	The methodology was developed under W2KM (Web 2.0 Knowledge Management) and tested on a real case study. The results obtained show its effectiveness because it helps this company carry out the implementation quickly and effectively, allowing the company to get the maximum benefit from the existing knowledge.
	Knowledge Management System in Service Companies (Cordova et al., 2018)	RAS Knowledge Management Module aims to create, disseminate, and express tacit knowledge, producing explicit knowledge available to all fields and jobs. RAS Knowledge users can practice a range of knowledge and experiences, allowing them to gain a higher level of expertise. RAS Knowledge Module allows companies to adapt and be flexible to insurance market conditions and company needs, providing continuous training, networking and collaborative learning. The management decision-making process will also experience significant

Topics	Title and Author	Findings
		improvements, as they have first-hand information to set guidelines and promote strategic management in performance evaluation applications
AI in KMS	Knowledge Management Technologies for Collaborative Intelligence: A Study of Case Company in Korea (Cha et al., 2015)	This study aims to develop a Collaborative Knowledge Management (CKM) Framework. CKM aims to manage tacit and explicit knowledge using collaboration technology. CKMS internalizes real-time knowledge from various internal sources (e.g., ECM, TMS, and RFID readers) and external sources (web, news, and blogs). Members externalize their knowledge by creating documents based on tacit and explicit knowledge. Knowledge gained from knowledge sources is socialized through social networks within an organization. To support explicit knowledge management, CKM supports easy content search mechanisms in response to individual information needs.

Topics	Title and Author	Findings
	Artificial Intelligence Support of Knowledge Transformation in Knowledge Management Systems (Avdeenko et al., 2016)	This study proposes a knowledge transformation in a hybrid model. This model combines the CBR knowledge representation model in the SECI model.
	Knowledge Management System for Failure Analysis in Hard Disk Using Case-based Reasoning (Wichawong & Chongstitvatana, 2017)	Design and implement a knowledge management system for hard disk failure analysis with case-based reasoning (CBR). Existing cases are stored, and new cases can be compared with existing ones to retrieve relevant knowledge and help with the analysis. Once a new case is solved, it can be stored to help future cases. The data/case objects used are text-based. The developed case-based reasoning (CBR) KM is quite successful. The assessment results show that the system has a high user satisfaction score, and the effectiveness of the search is acceptable.

Topics	Title and Author	Findings
	A Multi-Faceted Analysis of knowledge Management Systems (Ben et al., 2018)	This study proposes a conceptual model of the characteristics of 4 important aspects of KMS, namely, technology aspects, human resource aspects, process aspects, and context aspects - which determine the drivers of their effectiveness. The four aspects of a knowledge management system depend on the knowledge management strategy, knowledge management activities, and the environment
	Social media for knowledge-sharing: A systematic literature review (Yunis et al., 2019)	The analysis examined social media (SM) platforms among Nigerian librarians as a knowledge management (KM) tool. It found that librarians have good background knowledge of SM, but attendance at continuing professional development (CPD) is only average, and librarians seem to have a more personal interest in learning about KM.

Topics	Title and Author	Findings
	Managing extracted knowledge from big social media data for business decision making (He et al., 2017)	By combining Big Data, social media, and KM technologies, organizations can extract valuable insights from social media data to identify potential problems, opportunities, and best practices. We help organizations interested in leveraging Big Data solutions contextually compare their social media data with competitors and discover business intelligence.
Factors affecting the success of KMS	Information Technology and Individual Factors on Knowledge Sharing Activities (Indrajit & Hafiza, 2017)	The results of the path analysis showed that individual factors such as personality and self-efficacy have a more significant influence on knowledge-sharing activities, and from Information Technology, social media has a more significant influence among others.
	Knowledge Management Systems Usage From The User's Perspective: The Influence Of Organizational	This study aims to empirically evaluate the influence of organizational factors on the use of KMS among decision-makers in Jordanian banks. In this regard, a survey (self-administered questionnaire) was distributed to decision-makers who use

Topics	Title and Author	Findings
	Factors In Jordanian Banking Sector (Okour et al., 2018)	KMS within Jordanian banks, which resulted in 341 valid responses. Structural equation modelling (SEM).
	Knowledge Sharing Self-Efficacy, Motivation and Sense of Community as Predictors of Knowledge Receiving and Giving Behaviors (Ergün et al., 2018)	This study examines the extent to which knowledge-sharing self-efficacy, motivation and sense of community variables predict undergraduate learners' knowledge-sharing behaviour (knowledge receiving and knowledge giving) in an online learning environment. The participants included undergraduate learners (N = 284) from two different universities in Turkey, testing using multiple regression analysis

Lin et al. (2002) are recognized as seminal figures in multi-document summarisation research, particularly through their development of the Next Generation Automated Text Summarisation (NeATS) system. This system employs an array of content filtering and selection techniques to systematically extract salient information from a compilation of documents in a coherent and logical sequence (Lin & Hovy, 2001). The performance evaluations of NeATS indicated robust efficacy, as evidenced by its comprehensive assessment metrics (Lin & Hovy, 2001).

Subsequently, Zhang et al. (2018) explored the adaptation of models initially trained on single-document summarisation (SDS) to the more complex tasks of multi-document summarisation (MDS). Their innovative approach involved fine-tuning these models with a limited corpus of multi-document data. Empirical results from their experimentation on two benchmark DUC datasets demonstrated that their methodology surpassed several baseline neural models, achieving ROUGE-1, ROUGE-2, and ROUGE-SU4 scores of 34.0, 6.96, and 11.4, respectively (Zhang et al., 2018a).

In a related study, Shen et al. (2023) introduced a hierarchical encoder-decoder architecture, HED, to augment multi-document summarisation. This framework leverages a pre-trained model and integrates cross-document information utilizing selective intra-document attention, positional rearrangement, and the incorporation of global tokens for enhanced document representation. The findings revealed that HED attained ROUGE-1 and ROUGE-L scores of 50.0 and 25.8, respectively (Shen et al., 2023).

Jin et al. (2020) presented further contributions to this field. They proposed a joint learning framework to enhance abstractive multi-document summarisation through the leveraging of single-document summarisation datasets. Their neural network architecture featured a shared document encoder and a summary decoder, supplemented by a decoding controller that synergistically integrates outputs from the summary decoder across multiple input documents. This approach resulted in ROUGE-1, ROUGE-2, and ROUGE-SU4 evaluation metrics of 46.26, 17.02, and 20.46, respectively (Jin & Wan, 2020).

Li et al. (2021) also investigated a novel approach to multi-document summarisation based on the Semantic Link Network (SLN). This innovative methodology conceptualizes document understanding by transforming documents into SLNs that encapsulate key concepts and events, followed by summarisation of these networks to yield coherent document summaries. Their results yielded ROUGE-1, ROUGE-2, and ROUGE-SU4 scores of 0.45, 0.14, and 0.18, respectively (W. Li & Zhuge, 2021).

Liu (2019) further advanced the field by introducing BERTSum, a variant of BERT specifically designed for extractive summarisation. The system demonstrated its effectiveness through evaluation metrics that included ROUGE-1, ROUGE-2, and ROUGE-L scores of 43.25, 20.24, and 39.63, respectively (Liu, 2019). Complementarily, Savelieva et al. (2020) applied BERTSum to the domain of abstractive summarisation for narrated instructional videos, achieving fluency levels comparable to human-generated content while outperforming the performance of WikiHow articles. Their evaluation metrics recorded ROUGE-1 and ROUGE-L values of 35.91 and 34.82, respectively (Savelieva et al., 2020).

Lastly, Lamsiyah et al. (2023) conducted research employing an unsupervised methodology that utilized a pre-trained BERT model for extractive multi-document summarisation. This study integrated multi-task learning with document encoding to enhance the representation of sentences. The results indicated substantial performance improvements, achieving ROUGE-1, ROUGE-2, ROUGE-4, and ROUGE-L scores of 39.08, 9.68, 1.58, and 34.2, respectively (Lamsiyah et al., 2023).

Koto et al. (2020) undertook a comprehensive investigation into summarisation in the Indonesian language by developing the IndoBERT model, a transformer-based architecture rooted in BERT. The evaluation outcomes of the summarisation task revealed ROUGE-1, ROUGE-2, and ROUGE-L scores of 69.93, 62.86, and 69.21, respectively (Koto et al., 2020). Furthermore, the study by Lucky et al. (2022) explored the implementation of BERTSum utilizing IndoBERT for abstractive summarisation in Indonesian (Lucky & Suhartono, 2021). The findings indicated that the proposed abstractive model underperformed relative to the extractive model, a discrepancy attributed to the dataset's predominance of extractive labels (Lucky & Suhartono, 2021).

Koto et al. (2020) also developed extractive and abstractive models employing BERT as an encoder. The evaluation using Liputan6 data yielded ROUGE-1, ROUGE-2, and ROUGE-L results of 40.94, 23.01, and 37.89 for the abstractive model and 38.03, 20.72, and 35.07 for the extractive model, in comparison to canonical data (Koto et al., 2020). Moreover, Zhang et al. (2017) conducted a multi-document summarisation study employing a Convolutional Neural Network (CNN) framework. They introduced a model termed Multi-View CNN (MV-CNN), which integrates Multi-View learning to enhance the functional capabilities of the original CNN architecture (Zhang et al., 2018b). The MV-CNN model utilizes word embeddings for sentence representation, with evaluation outcomes indicating a ROUGE-1 score of 38.26, a ROUGE-2 score of 8.78, and a ROUGE-SU4 score of 14.38 (Zhang et al., 2018b).

Multi-document abstractive summarisation has been investigated without using Transformers (Severina & Khodra, 2019). The majority of extant research has predominantly focused on single-document abstractive summarisation within the Indonesian language. Several prior multi-document studies have yielded extractive summaries rather than abstract ones (Gunawan & Khodra, 2020; Widjanarko et al., 2018). Furthermore, earlier investigations have employed IndoBERT for single-document abstractive summarisation in the Indonesian context (Koto et al., 2020; Lucky & Suhartono, 2021a). In contrast, the present study proposes the development of a multi-document abstractive summarisation tool utilizing IndoBERT. This model will undergo rigorous development and evaluation using the Liputan6 dataset. The subsequent table presents a summary of prior research about text summarisation, detailed in Table 2.5.

Table 2.5: Summary of Research Previous in the Field of Text/Documents Summarisation

No	Author and Title	Type of Summa-risation	Type of Document	Methode	Language
1	Lin & Hovy, (2001) "From Single to Multi-document Summarisation: A Prototype System and its Evaluation,"	Extractive	Multy Documents	NeATS	English
2	Zhang et al. (2018). "Adapting Neural Single-Document Summarisation Model for Abstractive Multi-Document Summarisation: A Pilot Study,"	Abstractive	Multy Documents	SinABS HED	English
3	Shen et al. (2023) A Hierarchical Encoding-Decoding Scheme for Abstractive Multi-document Summarisation,"	Abstractive	Multy Documents	HED	English
4	Jin & Wan, (2020). "Abstractive Multi-Document Summarisation via Joint Learning with Single-Document Summarisation,"	Abstractive	Multy Documents	SinABS Joint Learning	English

No	Author and Title	Type of Summa-risation	Type of Document	Methode	Language
5	W. Li & Zhuge, (2021). “Abstractive multi-document summarisation based on semantic link network,”	Abstractive	Multy Documents	SLN	English
6	Liu (2019). “Fine-tune BERT for Extractive Summarisation,”	Extractive	Single Document	BERT	English
7	Savelieva et al. (2020).“Abstractive Summarisation of Spoken and Written Instructions with BERT,”	Abstractive	Single Document	BERT	English
8	Lamsiyah et al. (2023). “Unsupervised extractive multi-document summarisation method based on transfer learning from BERT multi-task fine-tuning,”	Extractive	Multy Document	BERT	English
9	Koto et al. (2020) “IndoLEM and IndoBERT: A Benchmark Dataset and Pre-trained Language Model for Indonesian NLP,”	Extractive	Single Document	BERT	Bahasa
10	(Koto et al., 2020; Lucky & Suhartono, 2021). “Investigation Of Pre-Trained Bidirectional Encoder Representations From	Abstractive	Single Document	BERT	Bahasa

No	Author and Title	Type of Summa-risation	Type of Document	Methode	Language
	Transformers Checkpoints For Indonesian Abstractive Text Summarisation,"				
11	(Koto et al., 2020; Y. Zhang et al., 2017). . "Liputan6: A Large-scale Indonesian Dataset for Text Summarisation,"	Abstractive and Extractive	Single Document	BERT	Bahasa
12	(Severina & Khodra, 2019). "Multiview Convolutional Neural Networks for Multidocument Extractive Summarisation,"	Extractive	Multy Document	CNN	English

Widayanti et al. (2023) used a hybrid approach that combines two methods, namely Collaborative Filtering (CF) and Content-Based Filtering (CBF). This study shows a high level of relevance accuracy and performance of the hybrid approach, namely 90% and 95%, compared to using each method such as CF, which has a relevance and performance accuracy of 80% and 85% and CBF, which has a relevance and performance accuracy of 75% and 80% (Widayanti, 2023). Kiran et al. (2020) performed very well using a Recommendation System with a hybrid approach. By using Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE) and Coefficient of Determination (R-squared) as Evaluation Metrics, they got good performance such as 1.2%, 6.27%, 0.7% and 2.5% on ML100K dataset, 2% 1%, 0.5% and 7.8% on FilmTrust dataset. 4.8%, 2.4%, 2.2% and 4.7% on the Book-Crossing dataset and 1.65%, 0.83%, 0.47% and 1.24% on the MLIM dataset (Kiran et al., 2020).

Shambour et al. (2022) showed very good performance of the Recommender System with a hybrid approach in reducing the Data Sparsity problem. The experiment used six datasets with the lowest Data Sparsity level of 97% to the highest level of 99.5% (i.e., 97%, 97.5%, 98.0%, 98.5%, 99.0%, and 99.5%). The experimental results showed that the percentage improvement of the Hybrid Content-Based Collaborative Filtering (HCBCF) approach in terms of MAE was 48.2%, 52.3%, and 55.6%, respectively (Shambour et al., 2022). Walek and Fojtik (2020) used a hybrid approach that combined the CF method with the SVD algorithm, Content-Based Filtering, and Fuzzy Expert System. This study showed good results in recommending movies. Using Standard Metrics (Precision, Recall, F1-Measure), the Recommendation System with a hybrid approach can achieve high results, namely 81%, 83%, and 82% (Walek & Fojtik, 2020).

Cai et al. (2020) conducted a study by combining three different basic recommendation technologies. This study produced a consistent average rating of around 3.6849, with very little variation between the best results of 3.6866 and the worst of 3.6837. The level of item diversity is quite high, with an average value of 0.9162 and a small variation between the best (0.9187) and worst (0.9139) results. The level of novelty of items in the proposed system is around 42.76%, with the best results of 42.83% and the worst of 42.68%. Then, the coverage of the recommendation system is very high, with an average value of 80.76%. The best coverage value reaches 80.95%, and the worst is 80.64%. The system proposed in this study successfully recommends diverse items and covers most of the catalogue, thus providing users with many choices. In addition, almost half of the recommended items are new content for users, enhancing the experience by offering something fresh. This system is also stable in providing good ratings on recommended items (Cai et al., 2020). Kumar and Roy (2020) developed a Recommendation System using a content-based approach (Content-Based Filtering). However, due to certain limitations, they combined this method with the Collaborative Filtering and Sentiment Analysis methods to reduce the impact and dependence on the need for previous user history. Based on the experimental results, the average precision in Top-5 and Top-10 were 0.54 and 1.04, 1.86 and 3.31, and 2.54 and 4.97, (Kumar et al., 2020).

Wang et al. (2021) combined the methods of Trust-based Collaborative Filtering (TbCF), Item-Based Collaborative Filtering (IBCF) and User-Based Collaborative Filtering (UBCF), which they called User-Item-Trust Records (UITHybrid). The proposed model can solve more Cold Start problems without damaging the prediction accuracy (Wang et al., 2022). Jomsri et al. (2024) conducted a development that combines the Collaborative Filtering (CF) and Content-Based Filtering (CBF) methods. This study compares the results of hybrid scores using Evaluation Metrics, namely Normalized Discounted Cumulative Gain (NDCG), with scenarios 50:50, 20:80, and 80:20. The study results show that the 80:20 scenario produces the highest average NDCG score of 0.47 (Jomsri et al., 2024). Arabi et al. (2020) proposed a method that integrates user characteristics such as personality traits, demographic details, and location, namely Collaborative Filtering (CF), which includes geographic filtering, personality and demographic filtering and Content-Based Filtering (CBF) which searches for books that have been rated and reviewed. The results showed that there was an increase in recommendation accuracy with error rates of 0.050 and 0.150 for Root Mean Square Error of Approximation (RMSEA) and Standardized Root Mean Square Residual (SRMR), respectively (Arabi et al., 2020).

Patro et al. (2023) proposed a method called Sparsity and Cold Start Aware Hybrid Recommendation System (SCSHRS) to cover the problems of Data Sparsity and Cold Start. This method runs in 4 stages, namely reducing data sparsity, grouping users using K-Means based on Arithmetic, data parsing using the HigherOrder Singular Value Decomposition (HOSVD) method and using the Adaptive Neuro-Fuzzy Inference System (ANFIS) using the IF-Then rule. The data used are MovieLens-20M and Last. FM. The results of the study show that the proposed system provides a Mean Absolute Percentage Error (MAPE) of 40%, a Precision of 0.16, a Recall of 0.08, an F-Measure of 0.1, and a Normalized Discounted Cumulative Gain (NDCG) of 0.65 (Patro et al., 2023). Alqallaf & Medhati (2022) proposed a hybrid recommendation framework to recommend highly accurate and efficient educational course books. The proposed framework combines three different recommendation algorithms to build a Recommendation System with a hybrid approach. Based on the experiment, the proposed system produces high results. Using Evaluation Metrics, namely Precision, Recall, and F-measure, the scores produced are 86%, 80%, and 83%, respectively (Alqallaf & Medhati, 2022).

Wayesa F et al. (2023) used Content-Based Filtering and Collaborative Filtering (CF) with semantic relationships to develop their hybrid approach Recommendation System. This system is proposed to overcome the problem of unfair recommendation results due to biased data. Based on the experimental results, 0.638, 0.404, and 0.521 scores were obtained for Precision, Recall, and F1-Score (Wayissa et al., 2022). Aljunid and Huchaiah (2021) developed a Recommendation System using a method that combines User-Based Collaborative Filtering (UBCF), Item-Based Collaborative Filtering (IBCF) and Linear Regression (LR). The proposed method has shown significant performance with minimum error. Using 100k MovieLens and 1M MovieLens data and Root Mean Squared Error (RSME) and Mean Absolute Error (MAE) as Evaluation Metrics, the proposed model can produce score values of 0.922 and 0.7219 for 100k MovieLens and 0.8506 and 0.6627 (Aljunid & Huchaiah, 2021).

Biswa P and Liu S (2022) developed a Recommendation System by combining the Collaborative Filtering method based on Alternating Least Squares (ALS) and Deep Neural Network (DNN). The results of the study show that the proposed system can outperform several other systems (Item Content, Factorization, Ranking Factorization, CF + CBF and Explicit) with a Precision score of 0.7952, Recall of 0.4589, Area Under the Curve (AUC) of 0.9307, Accuracy of 0.7449 and training time of 1679.88 seconds (Biswas & Liu, 2022). Chalkiadakis et al. (2023) combined two semantic similarity measures in Collaborative Filtering (CF): Hierarchy-Based and Non-Hierarchy-Based with Bayesian. The method proposed in this study produces an average Precision score that always exceeds 0.8 (Chalkiadakis et al., 2023). Arunruviwat and Muangsin (2022) combined two methods, namely Content-Based

Filtering (CBF) and Collaborative Filtering (CF), by giving weight to the combination of two similarity scores. The evaluation results showed an RSME score of 1.206094 for 5-fold validation and 1.2247 for Train and test Split (Arunruviwat & Muangsin, 2022).

Walek and Fajmon (2023) used Expert Fuzzy System (EFS), Collaborative Filtering (CF) and Content-Based Filtering (CBF) as methods in developing their hybrid Recommendation System. The proposed model produced an accuracy value of 98% (Walek & Fajmon, 2023). Selvaraj and Gangadharan (2021) developed a Deep Learning-based hybrid Recommendation System because using a hybrid method that combines Collaborative Filtering (CF) and Content-Based Filtering (CBF) is considered to hamper user privacy and reveal sensitive information. Experimental results show that the proposed solution provides high user privacy with reasonable accuracy (Selvaraj & Gangadharan, 2021). Yang et al. (2020) proposed the development of a Recommendation System that combines Collaborative Filtering (CF) and Content-Based Filtering (CBF) with Markov Chains. Based on this, the proposed system produces an average of 0.046 for Normalized Discounted Cumulative Gain (NDCG) and a Recall of 0.071 (Yang et al., 2020). Oyebode and Orji (2020) developed an algorithm that implicitly infers user preferences based on their transaction data to address the problem of customers not explicitly assessing products. They proposed developing a hybrid Recommendation System by combining Item-Based Collaborative Filtering and a demographics-based approach. The proposed system yielded an average RMSE score of 1.62 and an average MAE score of 1.5496 (Oyebode & Orji, 2020).

Table 2.6: Summary of Research Previous in the Field of Recommendation System

No	Title and Author	Findings
1	Widayanti, R., Chakim, M. H. R., Lukita, C., Rahardja, U., & Lutfiani, N. (2023). Improving Recommender Systems using Hybrid Techniques of Collaborative Filtering and Content-Based Filtering.	Collaborative Filtering and Content-Based Filtering can improve the accuracy, robustness, and coverage of the recommendation process, with the hope of increasing user satisfaction and engagement on the online platform.
2	Kiran, R., Kumar, P., & Bhasker, B. (2020). DNNRec: A novel deep learning based hybrid recommender system. *Expert Systems with Applications*	Deep Learning-Based Hybrid Recommender (Collaborative Filtering and Deep Neural Networks) alleviates the Cold Start problem, maintains the benefits of traditional matrix factorization techniques, enables the achievement of the highest prediction accuracy using cyclical learning rates and weight decay across multiple periods, and shows that the solution can be run both from optimization criteria (RMSE, R-squared, MSE, and MAE) and satisfaction criteria (mean and standard deviation of running time across seven processes).

No	Title and Author	Findings
3	Shambour, Q. Y., Hussein, A. H., Kharma, Q. M., & Abualhaj, M. M. (2022). Effective Hybrid Content-Based Collaborative Filtering Approach for Requirements Engineering	Hybrid Content-Based Collaborative Filtering (Collaborative Filtering and Content-Based Filtering) can support project stakeholders in mitigating the risk of missing requirements during requirements elicitation, reducing the impact of information overload problems found, improving recommendation performance, and reducing the impact of Data Sparsity and Cold Start.
4	Walek, B., & Fojtik, V. (2020). A hybrid recommender system for recommending relevant movies using an expert system	Hybrid Recommender System Predictor (Collaborative Filtering, Content-Based Filtering and Fuzzy Expert System) Able to provide appropriate movie recommendations.
5	Cai et al. (2020). A hybrid recommendation system with many-objective evolutionary algorithm	User-based collaborative Filtering (UBCF), Item-Based Collaborative Filtering (IBCD), Hybrid Content-Based Filtering and Collaborative Filtering (Con-CF Hybrid), and Many-Objective Evolutionary Algorithm

No	Title and Author	Findings
		(MaOEA) improve accuracy and overcome Diversity, Novelty, and Coverage in Recommendation Systems
6	Kumar et al. (2020). Movie recommendation system using sentiment analysis from microblogging data	Content-Based Filtering and Collaborative Filtering used in Sentiment Analysis can help minimize reliance on previous user history and habits for recommendation tasks.
7	Kumar et al. (2020). Movie recommendation system using sentiment analysis from microblogging data	User-Item-Trust Records (UITHybrid) is used to overcome the inherent weaknesses of the CF approach, which requires Neighbor data to be extracted, and the Cold Start problem
8	Wang, F., Zhu, H., Srivastava, G., Li, S., Khosravi, M. R., & Qi, L. (2021). Robust collaborative filtering recommendation with user-item-trust records	Collaborative Filtering and Content-Based Filtering are used to develop a digital library model that serves users in the Bangkok area and makes it easier for them to access the library.

No	Title and Author	Findings
9	Jomsri et al. (2024). Hybrid recommender system model for digital library from multiple online publishers	Context-Aware Personalized Hybrid Recommender System (CAPHyBR) Used to recommend books.
10	Patro, S. G. K., Mishra, B. K., Panda, S. K., Kumar et al. (2023). Cold start aware hybrid recommender system approach for E-commerce users	The Sparsity and Cold Start Aware Hybrid Recommendation System (SCSHRS) can overcome Cold Start and Data Sparsity problems.
11	Alqallaf et al. (2022). A hybrid recommender framework for selecting a course reference books	Collaborative Filtering, Content-Based Filtering, and Association Role Recommender Used to develop a hybrid Recommendation System that has high accuracy and efficiency in providing recommendations for educational course books.
12	Wayesa et al. (2023). Pattern-based hybrid book recommendation system using semantic relationships	Collaborative Filtering and Content-Based Filtering with Semantic RelationshipsCan produce fair and unbiased recommendations and capture the relationship between items and consumers.

No	Title and Author	Findings
13	Aljunid & Huchaiah (2021). An efficient hybrid recommendation model based on collaborative filtering recommender systems	User-based collaborative filtering (UBCF), Item-Based Collaborative Filtering (IBCF), and linear regression are used to overcome the limitations of UBCF and IBCF, such as Sparsity and Scalability.
14	Biswas & Liu (2022). A hybrid recommender system for recommending smartphones to prospective customers	Alternating Least Squares (ALS) Collaborative Filtering and Deep Neural Networks (DNN) can improve the overall quality of smartphone recommendations.
15	Chalkiadakis et al. (2023). A novel hybrid recommender system for the tourism domain.	Content-based methods using semantic similarity and Bayesian are utilized to avoid Cold Start in recommendation systems.
16	Arunruviwat & Muangsin (2022). A Hybrid Book Recommendation System for University Library	Content-Based Filtering and Collaborative Filtering can improve accuracy and overcome Cold Start.
17	Walek & Fajmon (2023). A hybrid recommender system for an online store using a fuzzy expert system	Content-Based Filtering, Collaborative Filtering and Fuzzy Expert Systems Used to recommend appropriate content to users.

No	Title and Author	Findings
18	Selvaraj & Gangadharan (2021). Privacy preserving hybrid recommender system based on deep learning	Deep Learning-Based Hybrid Recommender System (Global Differential Privacy (GDP) and Local Differential Privacy (LDP)) is used to protect individual privacy and provide relevant recommendations.
19	Yang et al. (2020). A hybrid recommender system for sequential recommendation: combining similarity models with markov chains	Similarity Models (Content-Based Filtering and Collaborative Filtering) with Markov Chains can provide product recommendations by considering sequential information.
20	Oyebode, & Orji (2020). A hybrid recommender system for product sales in a banking environment.	Item-based Collaborative Filtering and Demographic-Based Approach Can overcome the Cold Start problem.

2.9 Chapter Summary

The transformation process within a learning organization is inherently linked to its capacity to adapt to technological advancements. Successfully implementing Knowledge Management (KM) practices within organizations is a critical determinant of their efficacy in facilitating knowledge sharing and collaborative learning. Various Knowledge Management System (KMS) models have increasingly integrated artificial intelligence (AI) and big data technologies to enhance their functionalities. Additionally, discussion forums and social media platforms serve as vital tools for disseminating and sharing Knowledge. The organization generates Knowledge internally while leveraging external sources, such as online media or big data. This necessitates the processes of Knowledge combining, categorizing, and reclassifying. Modern KMSs often incorporate features such as recommendation systems and search engines to streamline access to Knowledge. The knowledge combination process frequently involves experts, who serve as key knowledge sources. In prior models, these experts primarily assumed the role of assessors regarding employee skill development. Further development is required in the knowledge creation process to enhance the effectiveness of cognitive processes. Integrating group discussions or brainstorming activities during the Socialisation phase is essential for creating comprehensive knowledge documents that can be utilized by organizational members. Moreover, synthesizing and summarising the outcomes of such discussions can lead to the formation of structured Knowledge. The combination process extends beyond mere aggregation and presentation of Knowledge; it is imperative to establish mechanisms that engage experts from industry or academia to validate, categorize, and enrich validate, categorize, and enrich Knowledge. Additionally, the internalisation of Knowledge should not be limited to conducting activities and analysing learning needs. Instead, it is crucial to develop robust mechanisms for measuring learning outcomes, enabling the effective mapping of learning requirements and enhancing employee or learners knowledge.

CHAPTER 3

METHODOLOGY

3.0 Introduction

This chapter discusses the research methodology for developing a KMS for personalized learning to support OBE in HEIs. The discussion will begin with creating a general research design, a framework for explaining the research design in detail, an overview of the overall concept, and a detailed description of the KMS being developed. In detail, the research discussion is divided into three main parts: (1) Development of knowledge content by learning needs, (2) Development of analytical learning, and (3) evaluation and validation of KMS using the Technology Acceptance Model (TAM) approach.

3.1 Research Design

One of the literature reviews in Chapter 2 discusses previous research that correlates with the research topic. The main discussion examines the results of previous research on KMS development. The results of the study explain the advantages or disadvantages and results of previous research. One of the results of this study discusses explicitly the development of KMS that has utilized AI technology (Avdeenko et al., 2016; Cha et al., 2015; Córdova & Gutiérrez, 2018; He et al., 2017; Sadewa et al., 2019; Tsai & Lee, 2006). Another aspect studied from previous research regarding KMS is supporting the implementation of OBE in HEIs (Galeon & Palaoag, 2019). Galeon and Paloang (2019) developed a KMS architectural framework for OBE sustainability in HEIs. This framework does not address the role of industry experts in maintaining the sustainability of OBE. The role of AI in the KM and learning processes within this framework is also not discussed. Previous research aimed to address the challenges of

Education 4.0 and the use of AI technology in the KMS to support the implementation of OBE in HEIs. Therefore, this study will explore how AI can develop relevant knowledge sets in informatics by involving industry experts, multi-document knowledge summarisation using the BERT2BERT model, and develop learning analytics techniques for KMS to support OBE implementation in HEIs using hybrid model.

Figure 3.1: Research Design

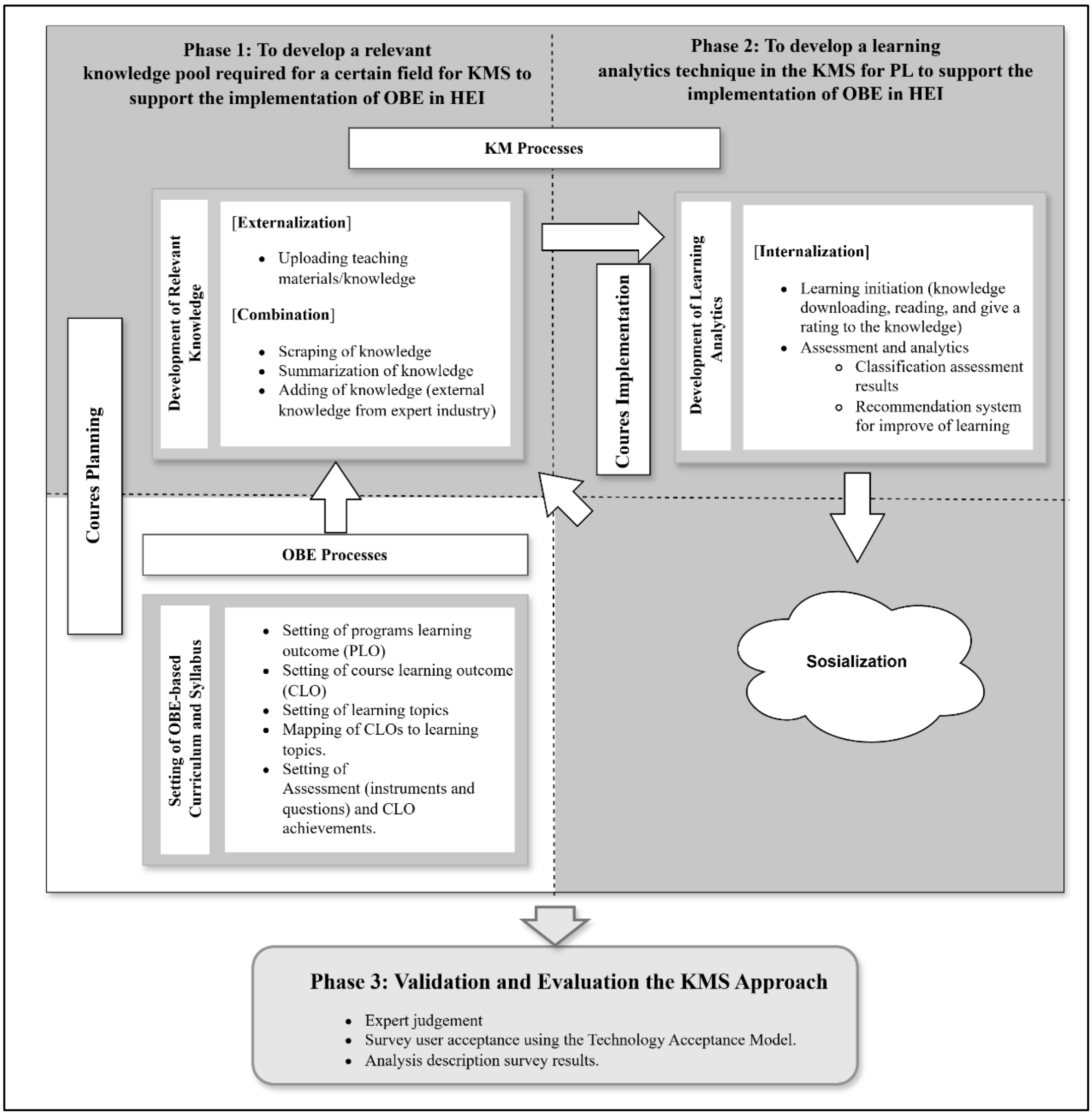


Figure 3.1 shows the summary of the research stages. There are three research objectives to be achieved to answer the research questions in Chapter 1. The objectives are, first, to develop a relevant knowledge pool in the area of informatics for the KMS in order to support the OBE implementation of in HEI. The essence of the first research objective is how lecturers prepare a course. Preparation involves the process of determining the OBE curriculum and syllabus, starting from determining the program learning outcome (PLO), course learning outcome (CLO), learning topics, mapping CLO to learning topics, and assessment. The second preparation is how knowledge is prepared in accordance with the OBE curriculum and syllabus that has been set. Knowledge preparation is contained in the KM process. These processes are the first externalisation of knowledge represented in the process of uploading learning materials/knowledge. The process of combining represented knowledge is first done by scraping knowledge from a web URL. They were second, summarising knowledge. This KMS summarizes multi-knowledge documents. The goal is to extract knowledge from various sources to make it easier to read. The three combinations of knowledge are represented through the process of adding knowledge from industry or experts. The second research objective is to develop a learning analytics technique in the KMS for personalized learning to support the implementation of OBE in HEI.

The second objective is the process of implementing a course or learning, which consists of course initiation and assessment. The learning implementation process is a representation of the internalisation of knowledge in KM (Tsai & Lee, 2016). The initiation process is represented through the activity of downloading and reading knowledge by Learners. After reading, Learners can give a rating to assess the quality of the reading or knowledge. As part of the learning process, assessment is essential to measure learning outcomes. The results of the assessment are then Figure 3.1 shows the summary of the research stages. There are three research objectives to be achieved to answer the research questions in Chapter 1. The objectives are, first, to develop a relevant knowledge pool in the area of informatics for the KMS in order to support the OBE implementation of in HEI. The essence of the first research objective is how lecturers prepare a course. Preparation involves the process of determining the OBE curriculum and syllabus, starting from determining the program learning outcome (PLO), course learning outcome (CLO), learning topics, mapping CLO to learning topics, and assessment. The second preparation is how knowledge is prepared in accordance with the OBE curriculum and syllabus that has been set. Knowledge preparation is contained in the KM process. These processes are the first externalisation of knowledge represented in the process of uploading learning materials/knowledge. The process of combining represented knowledge is first done by scraping knowledge from a web URL. They were second, summarising knowledge. This KMS summarizes multi-knowledge documents. The goal is to extract knowledge from various sources to make it easier to read. The three combinations of knowledge are represented through the process of adding knowledge from industry or experts. The second research objective is to develop a learning analytics technique in the KMS for personalized learning to support the implementation of OBE in HEI.

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Socialisation was not specifically discussed in the research design. Socialisation is the sharing and transformation of new knowledge (tacit to tacit knowledge) through shared experiences in everyday social interactions. Socialisation is a form of knowledge creation that allows us to transform tacit knowledge through interactions between individuals (Alavi & Leidner, 2001; Nonaka & Takeuchi, 1995; Nonaka & Toyama, 2003) through shared experiences in everyday social interactions. Socialisation is a form of knowledge creation that allows us to transform tacit knowledge through interactions between individuals (Alavi & Leidner, 2001; Nonaka & Takeuchi, 1995a; Nonaka & Toyama, 2003).

3.2 Research Framework

Table 3.1 shows each stage of the research in detail. The proposed methodology in the development of KMS for personalized learning to support OBE in HEI is divided into two main parts. The first part is the development environment or KMS production process. The KMS development environment is divided into two parts; the first is to develop a relevant knowledge pool required for a particular field or learning planning.

The main activity is to prepare the curriculum and knowledge or teaching materials. The output of the preparation of the curriculum and knowledge is the availability of knowledge following the needs of the course program. The second part of the KMS production process is to develop a learning analytics technique in the KMS for personalized learning to support the implementation of OBE in HEI or learning implementation. The main activity is course implementation. Course implementation is divided into two activities: course initiation, course assessment, and analytics. The second part of the development of KMS for personalized learning to support OBE in HEI is the evaluation and validation of the developed KMS by users. The technology acceptance model (TAM) is used as a framework in the evaluation and validation of KMS (Daria & Kostiantyn, 2018; Mamorobela & Buckley, 2017; Okour et al., 2018; Suroso & Fernando, 2017). The output of both is the level of user acceptance of the KMS that has been developed.

Table 3.1: Research Framework

Research Objective	Research Process	Activities	Sub Activities	Output
To develop a relevant knowledge pool in the area of informatics for the KMS in order to support the OBE implementation of in HEI.	Course Planning	Setting of OBE-Based Curriculum and Syllabus	• Setting of PLO • Setting of CLO • Mapping CLOs to PLO • Setting learning topics • Mapping of CLOs to learning topics. • Setting of assessment (instruments and questions) and learning achievements.	Availability of knowledge following the needs of the course program
		Development of Relevant Knowledge	• Knowledge uploading • Knowledge scraping using parsing HTML in the library BeautifulSoup and Scrapy Python	

Research Objective	Research Process	Activities	Sub Activities	Output
			• Summarising multi-documents of knowledge using the BERT2BERT model and comparing it with the BERT2BERT+Extrem model Adding knowledge (external knowledge from industrial expert)	
To develop a learning analytics technique for KMS in order to support the implementation of OBE in HEI.	Course Implementation	Course initiation	• Knowledge downloading, reading, and giving a rating to the knowledge.	Learner profile: Learning achievement and Improved of learning
		Assessment and analytics for Course Evaluation	• Classification assessment results • Automatic recommendation using the hybrid model combines Rule-based and Content-based filtering algorithms.	

Research Objective	Research Process	Activities	Sub Activities	Output
To validate KMS developed for KMS in order to support the implementation of OBE in HEI and evaluate its acceptance among the users	Validation and Evaluation of KMS	Expert Judgement and Survey User Acceptance for KMS	Expert assessment and survey of learners acceptance using the TAM model	The level of expert judgement results and user acceptance of the KMS

3.3 AI Based KMS Conceptual Model for OBE Implementation in HEI

Based on the research framework described in Table 3.1, a AI Based KMS conceptual model was compiled. The conceptual model describes the entire system being developed, whether input, process, or output. This conceptual model is a reference in developing KMS for personalised learning to support OBE in HEI.

Figure 3.2: Conceptual Overview of KMS

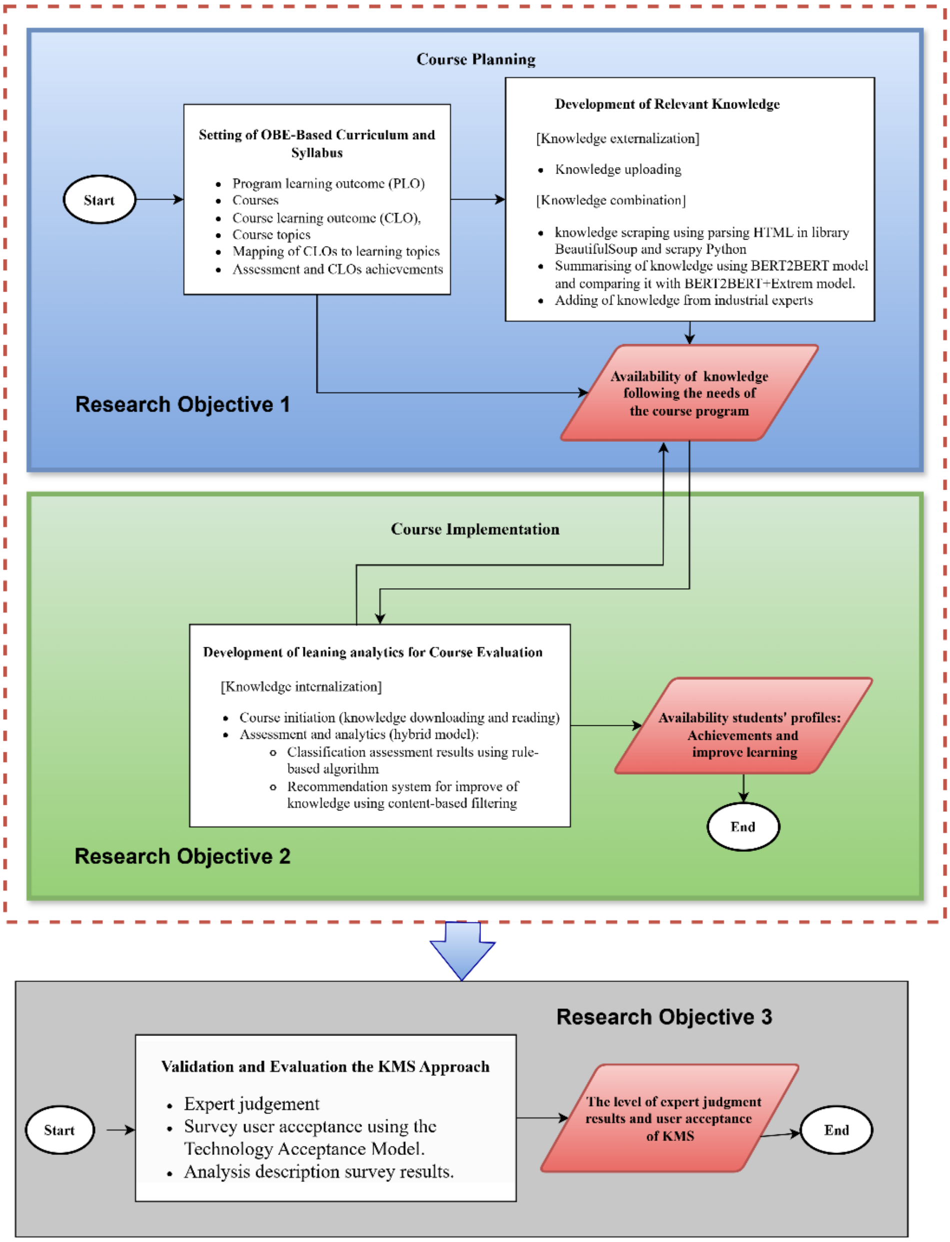
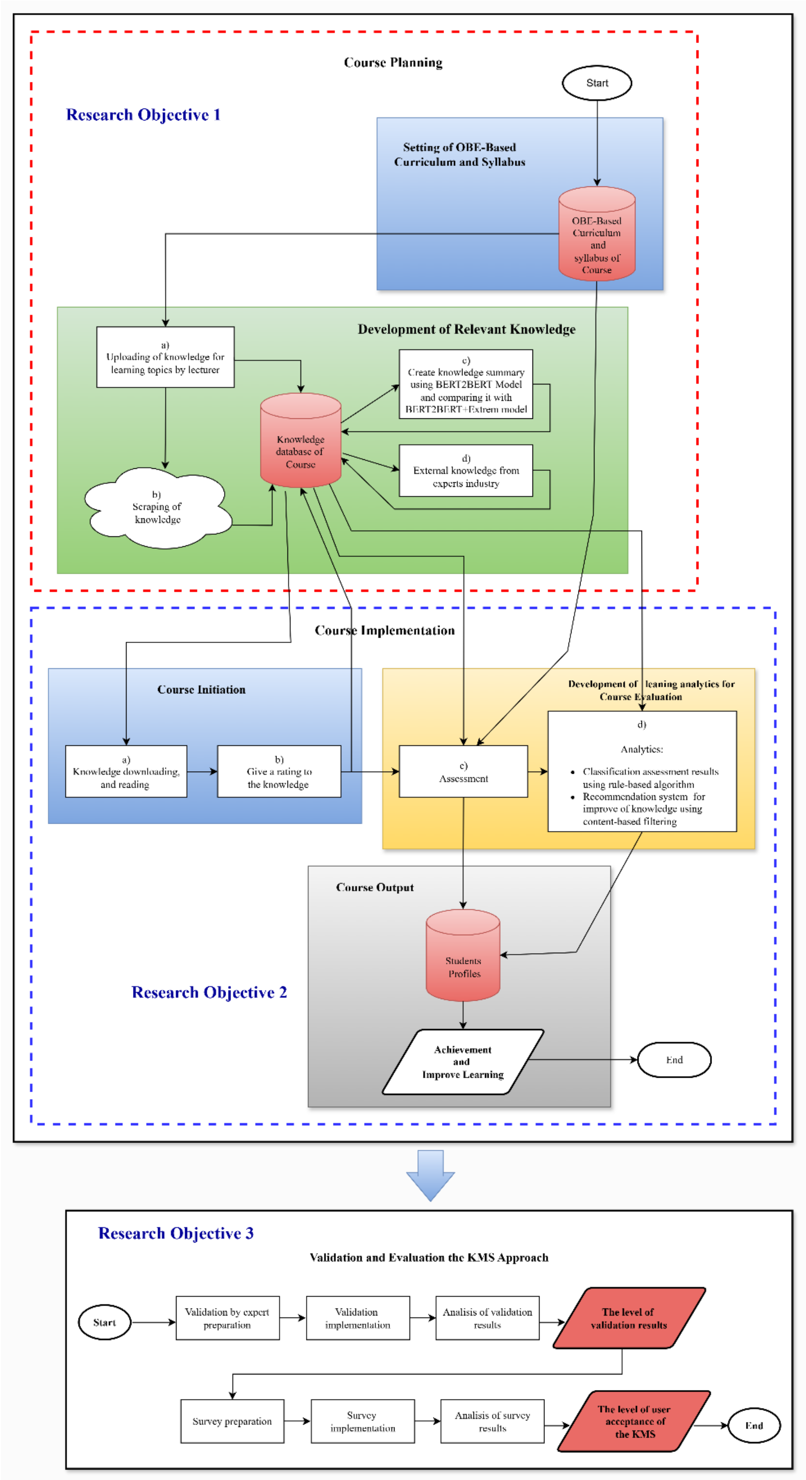


Figure 3.2, shows the overview of the knowledge management system (KMS). The first research objective is course planning, which involves creating the course by establishing a curriculum and syllabus based on Outcomes-Based Education (OBE) principles, and developing knowledge to meet learning needs from internal and external sources. This objective represents the externalisation and combination of knowledge. The second research objective, course implementation, focuses on the learners learning process, representing the internalisation of knowledge. This phase involves developing AI based learning analytics for course evaluation, including assessing learning outcomes and creating an automatic recommendation system for learners learning results. The third research objective, evaluation and validation, involves user assessment of the effectiveness of the developed KMS.

For the course planning research objective, the focus is on how the course is prepared, including establishing an OBE-based curriculum and syllabus and developing knowledge to meet learning needs from internal and external sources. The course implementation research objective explains the learners learning process, including developing learning analytics for course evaluation and creating an automatic recommendation system for learners learning results. Lastly, the evaluation and validation research objective involves user assessment of the effectiveness of the developed KMS.

Figure 3.3 shows the process of developing an OBE-based curriculum and syllabus involves establishing the program learning outcome (PLO), defining course learning outcomes (CLO), identifying course topics, aligning CLO with learning topics, conducting assessments, and setting standard CLO achievement scores. The assessment phase includes selecting the assessment tools, crafting questions for learning analysis, and evaluating the results. Once the curriculum and syllabus have been determined, the next step in the course planning process is to develop relevant knowledge. The goal is to provide knowledge that aligns with the learning topics outlined in the curriculum. This stage involves lecturers uploading or extracting knowledge from online sources. The extraction method involves using HTML parsing, which can be done using the Beautifulsoup and Scrapy Python libraries. To make the reading process more accessible for Learners, lecturers can automatically create summarized knowledge from multiple documents. The document summarisation technique utilises the BERT2BERT Model. Moreover, to determine the best summarisation results, the BERT2BERT model is compared with BERT2BERT+Extrem model. Lecturers or industry practitioners can then include the knowledge documents obtained from extraction or summarisation. The outcome of the course planning process is the availability of knowledge that meets the requirements of the course.

Figure 3.3: Flow Process of AI Base KMS



After course planning, the next step is course implementation. This process explains the learning process, which is divided into two parts: course initiation and developing learning analytics for course evaluation. The course initiation process consists of a knowledge download process. After reading or studying, Learners can provide a rating or qualitative value regarding the quality of the downloaded knowledge document. Meanwhile, the process of developing learning analytics for course evaluation consists of assessment and analytics processes.

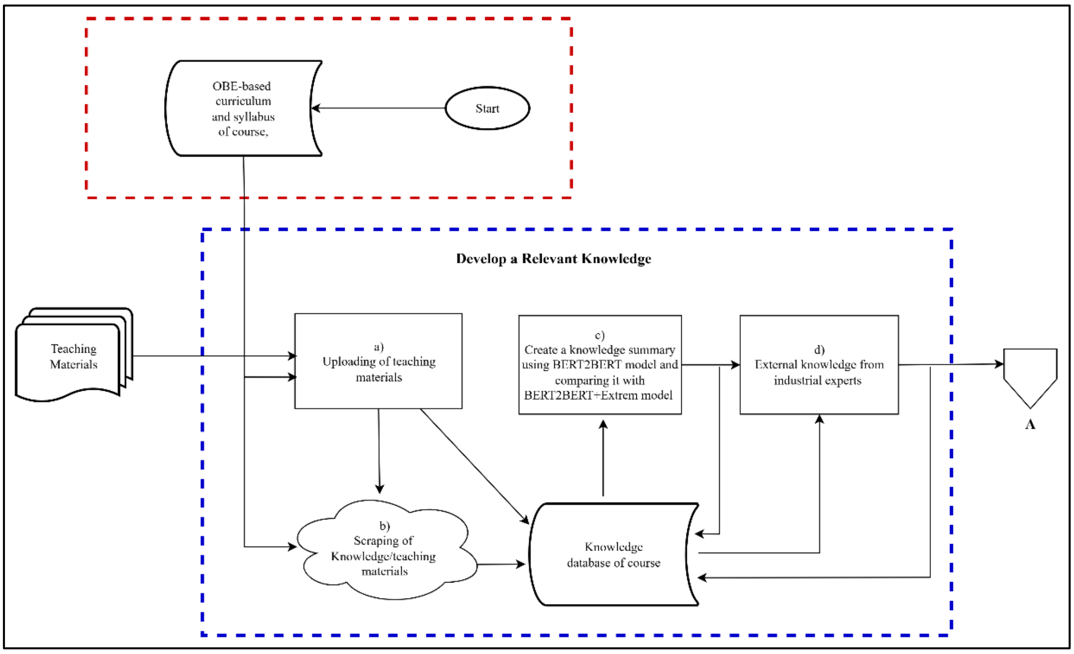
Assessments are carried out to measure learners learning achievements. The assessment results are classified using a rule-based filtering algorithm, to provide recommendations regarding the advantages and disadvantages of learning assessment results. The Content-based filtering algorithm provides recommendations for the order of knowledge that can be read or studied based on ratings. Cosine similarity is used to calculate the similarity of profile items from learning assessment results and knowledge profile items. The output from course implementation is a learners profile, which contains the achievements and progress of increasing learners knowledge.

The final part of the KMS development process for personalized learning to support OBE in HEI is Learners' evaluation and validation of the KMS. Evaluation and validation of the KMS development results are carried out in the form of a survey. The technology acceptance model (TAM) framework is used as an evaluation and validation approach, with the main instrument using a questionnaire. The output of the KMS validation and evaluation process is the level of user acceptance of the KMS that has been developed.

3.4 To Develop a Relevant Knowledge Pool in the Area of Informatics for the KMS in Order to Support the OBE Implementation of in HEI

Development of relevant knowledge pool required for a particular field for KMS in HEI, which is represented in course planning activities. Figure 3.4 shows the general steps of course planning.

Figure 3.4: Development of a Relevant Knowledge Process

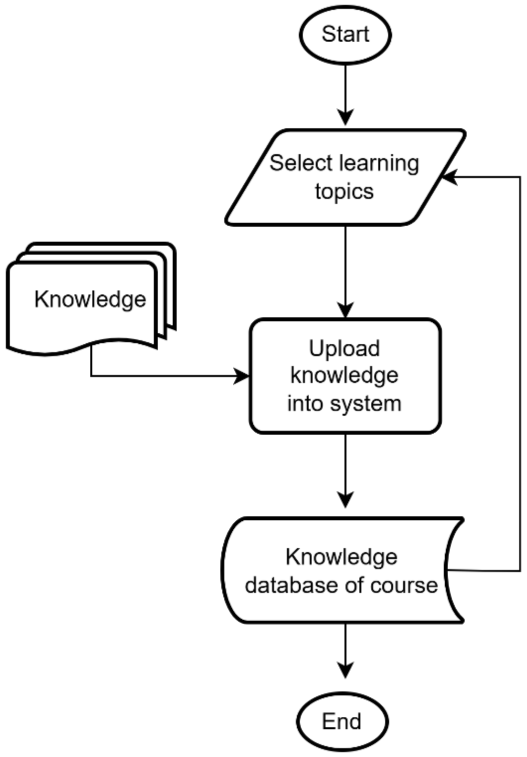


After the OBE-based curriculum and syllabus have been determined, the following process is developing knowledge that suits the course needs. Figures 3.5, 3.6, 3.7 and 3.8 show the development of a relevant knowledge process. Uploading knowledge/teaching materials by a lecturer into KMS begins the process of developing knowledge in accordance with course requirements. Knowledge can be obtained one way from online media, through document scraping (explained in full in Figure 3.9). In the following process, lecturers can carry out knowledge summarisation automatically. The main aim is to gain the essence of knowledge and save reading time. The summarising technique uses the BERT2BERT model on multiple Indonesian language knowledge documents. Moreover, to determine the best summarisation results, the BERT2BERT model is compared with BERT2BERT+Extrem model. The process of developing knowledge in accordance with course requirements involves an expert from the industry to add knowledge to the KMS.

3.4.1 Teaching Materials/Knowledge Uploading

Teaching materials uploading is shown in Figure 3.5.

Figure 3.5: Teaching Materials Uploading

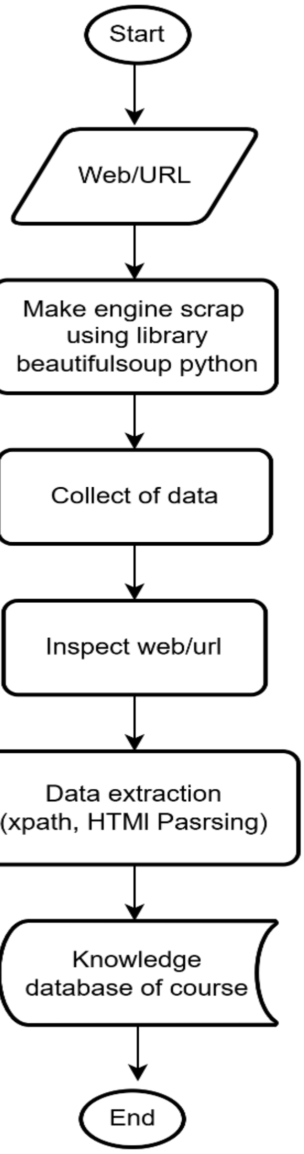


The first phase in developing relevant knowledge is uploading teaching materials. Lecturers upload knowledge/teaching materials according to course topics. Knowledge can be in the form of a PDF document, PowerPoint presentation, journal, or e-book.

3.4.2 Teaching Materials Scraping

Figure 3.6 shows the process of teaching materials scraping.

Figure 3.6: Teaching Materials Scraping

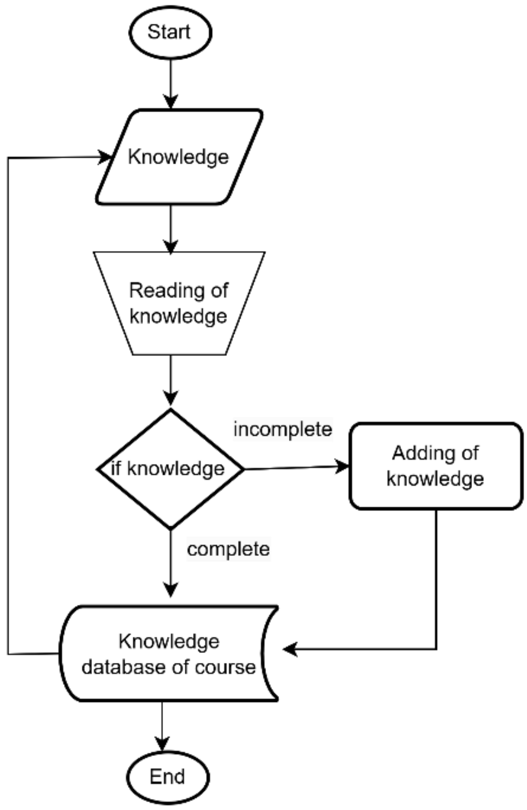


The first step in the process of web scraping is to identify the sources of knowledge or web URLs. Next, the scraping engine using is created the HTML parsing method, utilizing the BeautifulSoup and Scrapy libraries in Python. BeautifulSoup is used to process the HTML and retrieve data from websites, while Scrapy is used to collect data. The collected data is then examined for HTML structure, and the HTML tags of the website are analysed. Finally, data extraction is performed using Python to retrieve and save data in the required format.

3.4.3 Adding Knowledge from Industrial Experts

Figure 3.7 shows the process of adding knowledge in KMS.

Figure 3.7: Adding of Knowledge

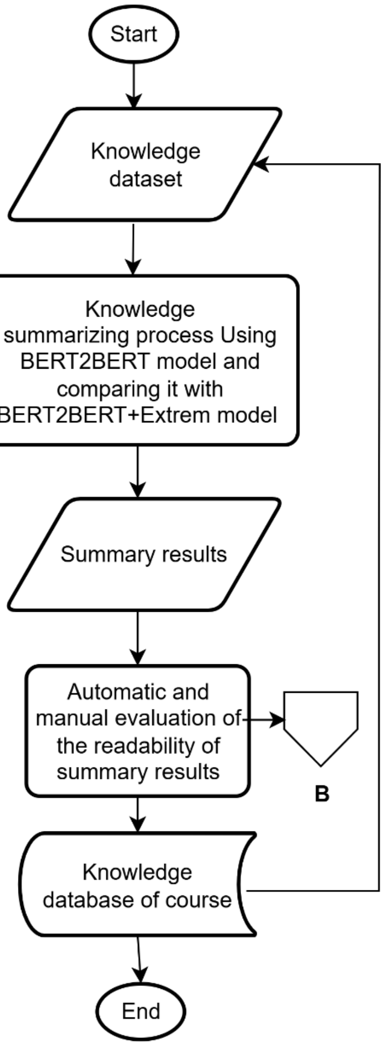


An industrial experts can contribute to developing Knowledge to suit learning needs. This contribution is in the form of adding knowledge that already exists in the database; the aim is to reduce the gap with industries.

3.4.4 Summarisation of Knowledge Documents

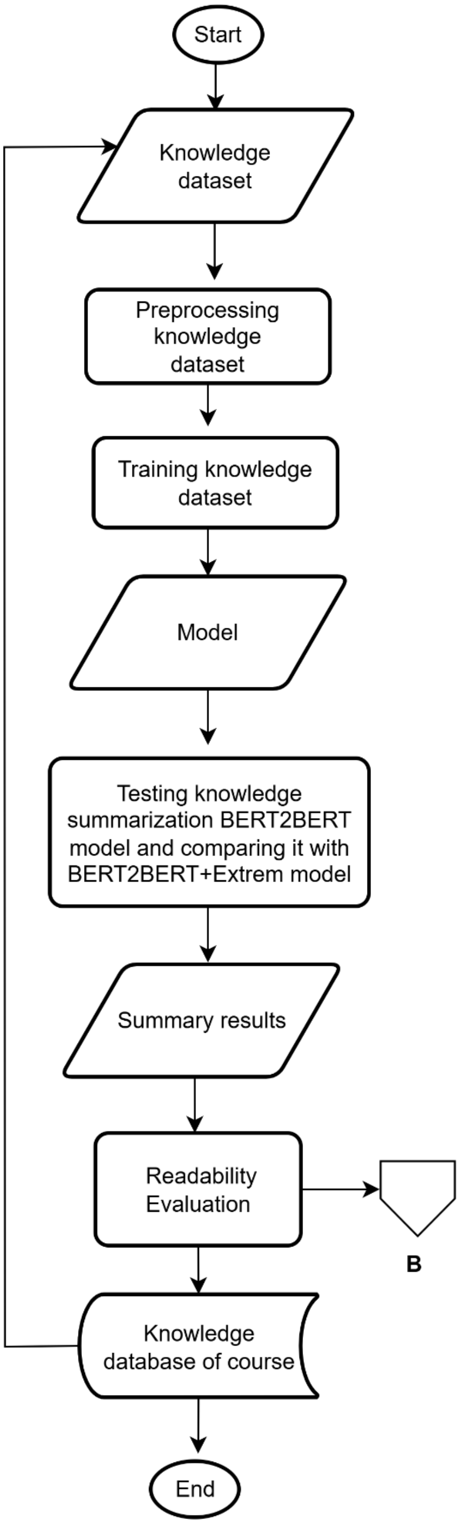
Automatic knowledge summarisation aims to make reading, including multi-document knowledge, easier. Figure 3.8 shows the outline of summarising knowledge documents in KMS.

Figure 3.8: Knowledge Summarisation Process



The knowledge summarisation process is divided into three main stages. The first stage is providing a knowledge dataset, followed by the knowledge dataset summarisation process and evaluating the knowledge summarisation results. Figure 3.9 shows the sequence of steps in summarising knowledge documents in detail.

Figure 3.9: Stages in Summarisation of Knowledge



This process starts with providing a knowledge dataset already available in the database. The summarisation of the knowledge process generally consists of a preprocessing process, model training using BERT2BERT and comparing it with

BERT2BERT+Extrem, and model testing. The final part of the knowledge summarisation process is evaluation. In order to obtain an optimal level of readability, the summarisation results were then tested using the FKGL, GFI, and Pranowo (2011) methods, as well as a manual evaluation by an Indonesian language expert.

1) Preprocessing knowledge dataset

The collected dataset is case-folding or makes all letters lowercase, and then unique characters such as punctuation and mathematical symbols are removed. Next, the data is tokenized using BERT Tokenizer. The tokenization results are divided into two parts: single and multi-document data. Single document data is used for model training. Multi-document data is used to test the model's capabilities for multi-document purposes. This data is then subjected to cosine similarity to filter sentences with similar information.

2) Training knowledge dataset

Training and knowledge evaluation datasets are prepared with a data-loader to be used efficiently when training. For each epoch, data is taken based on the batch in the data-loader, and then the model will carry out a forward pass using train data; from this process, the loss value is calculated, and propagation is carried out to update the model parameters. When the batch of data runs out, the model will perform a forward pass using evaluation data, then calculate the loss and store the checkpoint model.

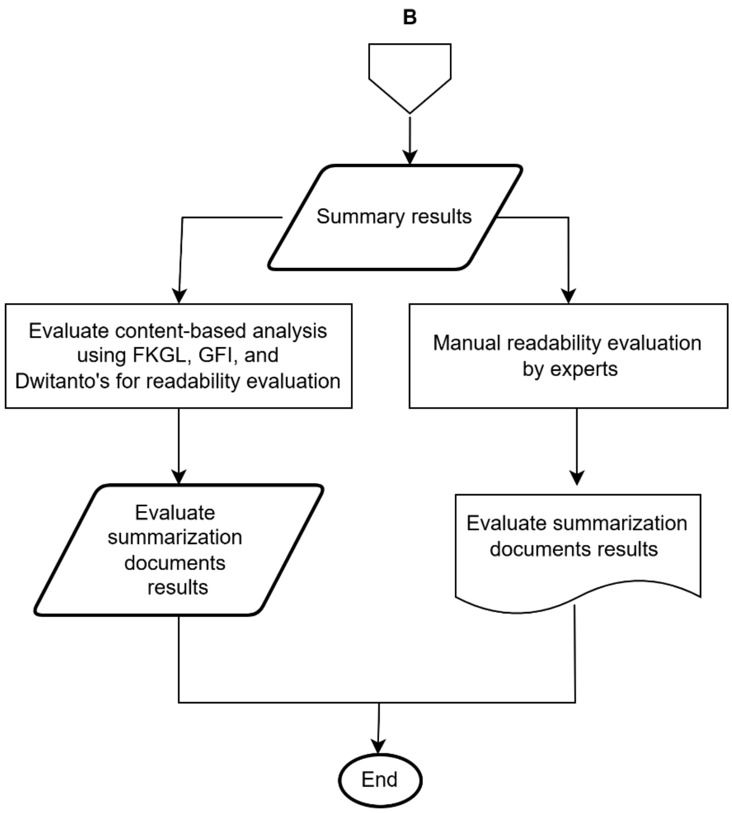
3) Testing knowledge summarisation BERT2BERT model and comparing it with BERT2BERT+Extrem model

The testing dataset is prepared with a dataloader for each batch, and a forward pass is carried out. To determine the best text summarisation results, the BERT2BERT model, using the canonical dataset, was compared with the BERT2BERT+Extrem model, which used the extreme dataset. Next, calculations are carried out for each evaluation metric. Data in vector form will be input into the model training process.

4) Evaluation of readability knowledge document

Figure 3.10 shows the process of evaluation readability document.

Figure 3.10: Stages in Summarisation of Knowledge



The readability evaluation process is divided into two parts. The first uses content assessment-based evaluation using the FKGL, GFI, and Pranowo (2011) methods to measure the readability of the summary results. Second, evaluate the manual readability by an Indonesian language expert, with the condition of considering

a. the summary should be understandable, non-redundant, and focused on the main topic;

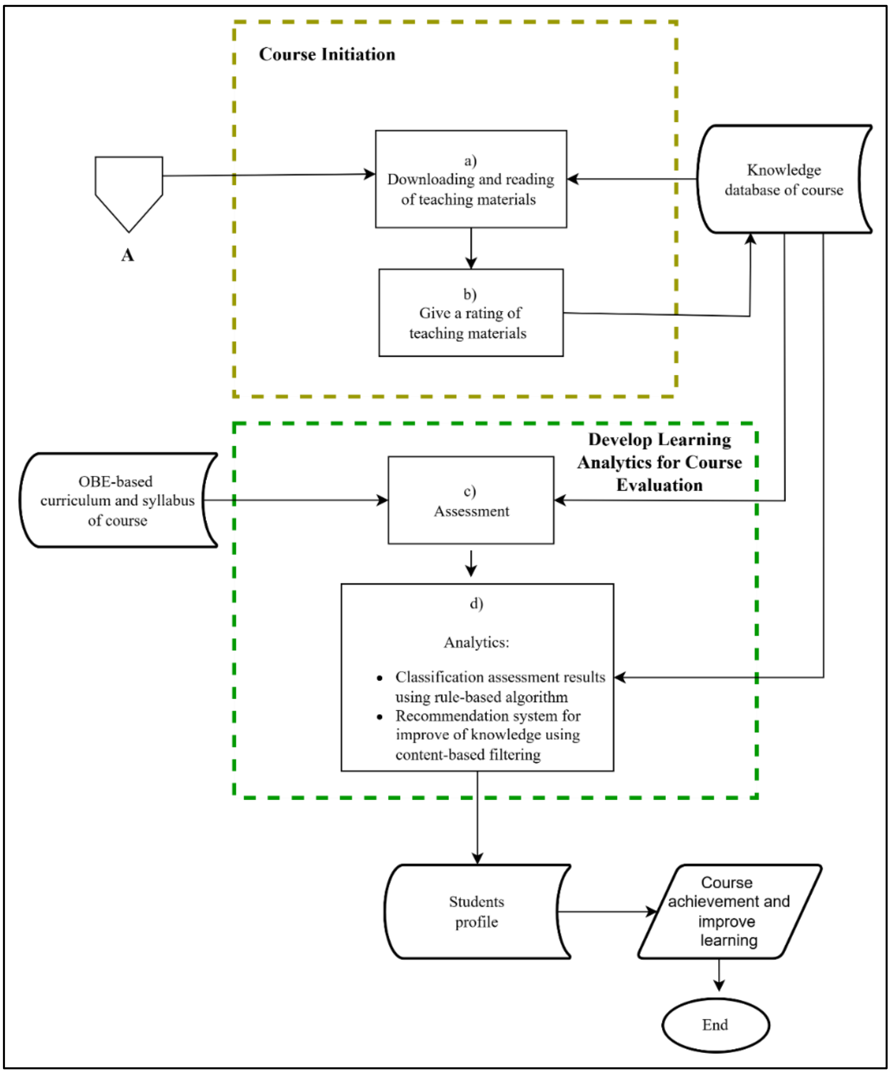
b. sentences of the summary should be complete and related to each other, and

c. the summary should be simple sentences.

3.5 Development a Learning Analytics Technique for KMS in Order to Support the Implementation of OBE in HEI

Figure 3.11 shows the process of develop a learning analytics technique for KMS in order to support the implementation of OBE in HEI.

Figure 3.11: Development of Learning Analytics Technique



Internalisation in KM is a cognitive process that consists of planning, implementing, and evaluating. Research Objective 1 represents the learning planning process, while Research Objective 2 represents the implementation of learning.

Learning implementation is divided into two main activities: course initiation and the development of a learning analytics technique for course evaluation. Figures 3.12, 3.13, 3.14, 3.15, and 3.16 explain the processes of course implementation.

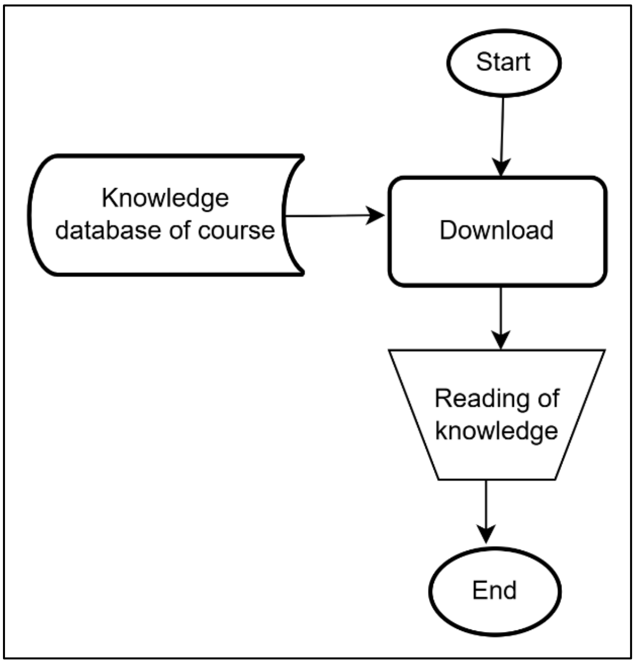
3.5.1 Course Initiation

Course initiation is the initial process of learning. Learners start the first lesson by downloading and reading teaching materials/knowledge and rating them.

a) Downloading and reading of teaching materials/knowledge

Figure 3.12 shows the process of downloading and reading of teaching materials by Learners.

Figure 3.12: Downloading and Reading of Teaching Materials

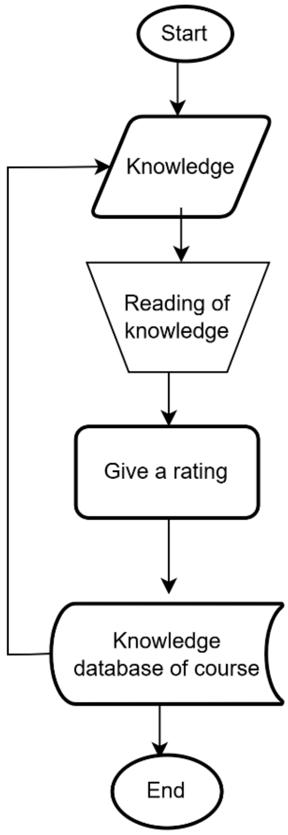


Teaching materials available in the database can be used by Learners in the learning process. Learners can download teaching materials according to their learning needs. One of the processes of internalising knowledge by Learners is obtained from reading knowledge.

b) Give a rating to the knowledge

One way the course initiation process is described is by giving a rating of learning materials. Figure 3.13 shows the process of rating learning materials.

Figure 3.13: Give a Rating of Learning Materials



Assessment of the quality of reading/knowledge by Learners is carried out by providing a qualitative assessment (rating) using a Likert scale. The assessment is represented in the star symbol. Table 3.2 shows the process assessment scale (rating) of teaching materials.

Table 3.2: Assessment of the Quality of Teaching Materials

No	Number of stars	Symbol meaning	Value scale
1	★★★★★	Very good	5
2	★★★★	Good	4
3	★★★	Quite good	3
4	★★	Not good	2
5	★	Not very good	1

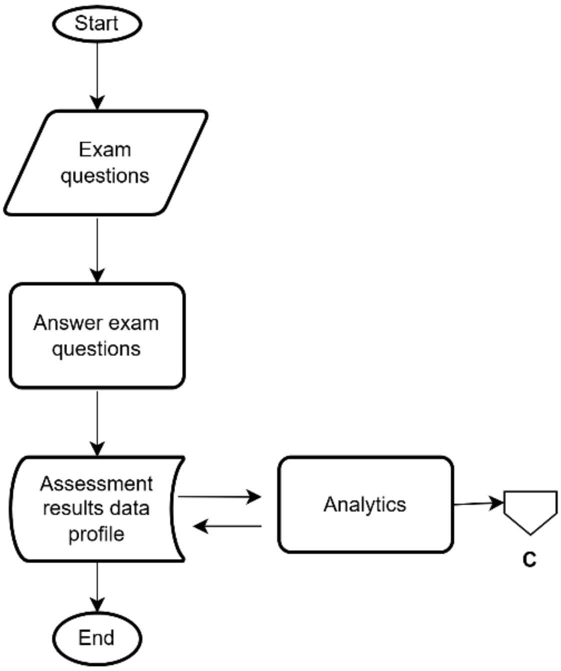
3.5.2 Development of Learning Analytics for Course Evaluation

Development learning analytics course evaluation consisting of learning assessment and analytics stages. Assessment of learning outcomes is carried out through a multiple-choice question test mechanism. The assessment results are then classified and analysed. The results of the analysis are in the form of learning outcomes and recommendations for improving learning outcomes. The system will recommend knowledge that Learners can use to increase their knowledge. The results of the course evaluation will then become the learners learning profile.

1) Assessment of learning outcome

There are two main course evaluation activities: assessment and analysis. Figure 3.14 shows the assessment process.

Figure 3.14: Assessment Process

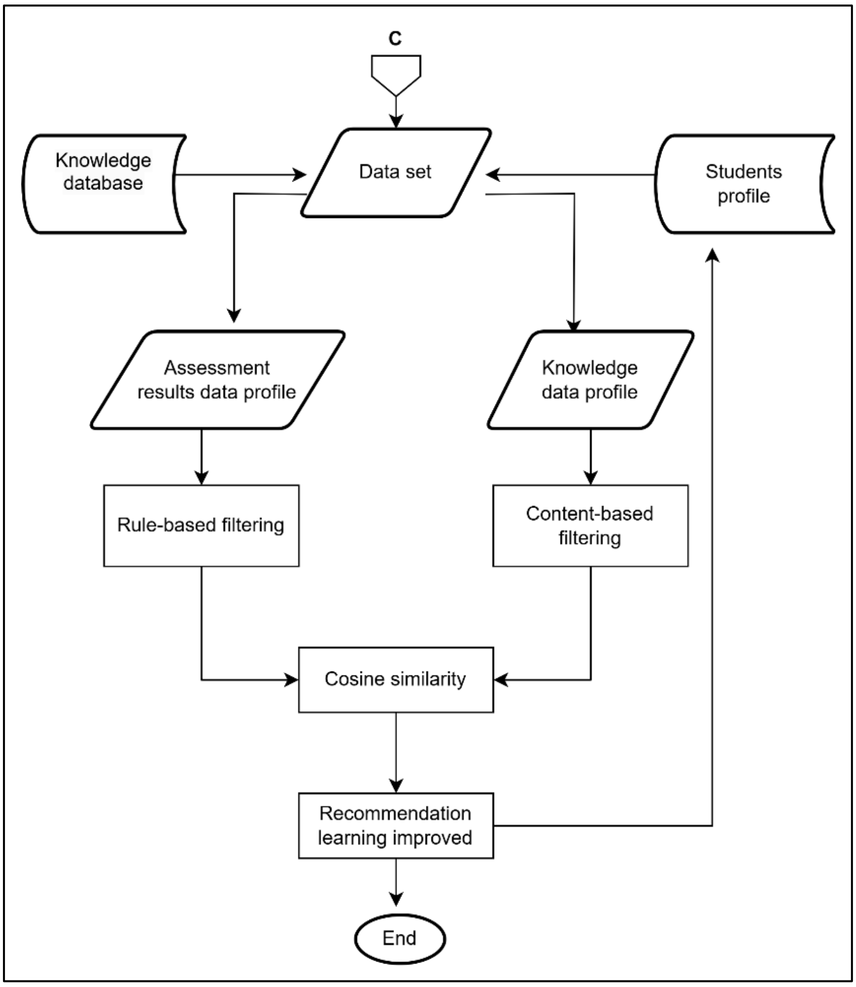


The assessment process involves established OBE curriculum standards and a knowledge database of courses. Learners carry out assessments to measure the achievement of learning outcomes. The assessment instrument used is an online multiple-choice exam. The assessment results are then stored and analysed.

2) Analytics

Figure 3.15 shows the learning analytics process in KMS. The recommendation system is the most critical learning analytics component for measuring learning outcomes and providing recommendations for increasing knowledge.

Figure 3.15: Learning Analytics

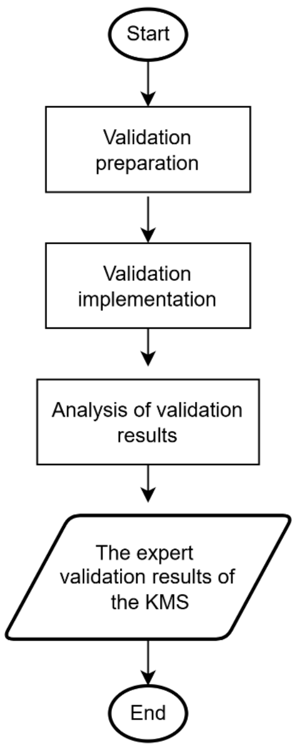


The initial stage of learning analytics is providing a data set of assessment results and knowledge. The data that has been collected is then formed as a profile item resulting from the assessment course and a knowledge profile item. Rule-based filtering provides recommendations about the strengths and weaknesses of the assessment course results. Meanwhile, Content-based filtering provides recommendations for the order of knowledge that can be read or studied based on ratings. Cosine similarity is used to calculate the similarity of profile items from assessment results and knowledge profile items. The results of similarity calculations become recommendations for improving learning outcomes for Learners. The recommendation results will be saved as a learners profile. Evaluation of the recommendation system was carried out using k-fold cross-validation by dividing the dataset of knowledge assessment and recommendation results into training and testing data sets.

3.6 Validation and Evaluation of KMS in Supporting the Implementation OBE in HEI Among the Users

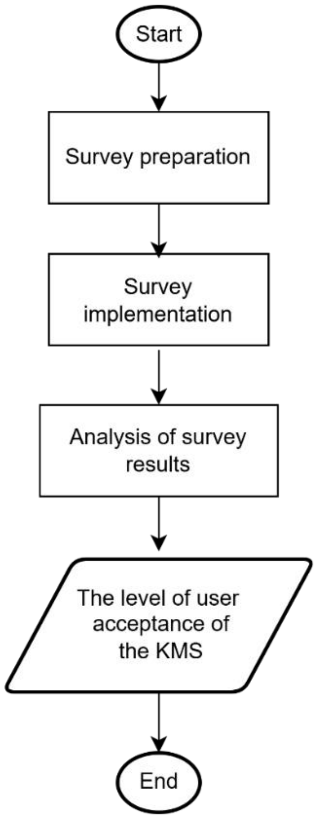
Validation and evaluation represent critical processes in assessing the efficacy of a system. The concluding phase of this research focuses on validating and evaluating the newly developed Knowledge Management System (KMS). Experts conduct the validation process to ascertain the feasibility of the KMS. Specifically, two specialists are involved: one with expertise in learning content and information and communication technology (ICT) and another with a background in learning media. The validation process these experts undertake is illustrated in Figure 3.16, shows the steps involved in the KMS validation procedure.

Figure 3.16: The KMS Validation Process by Experts



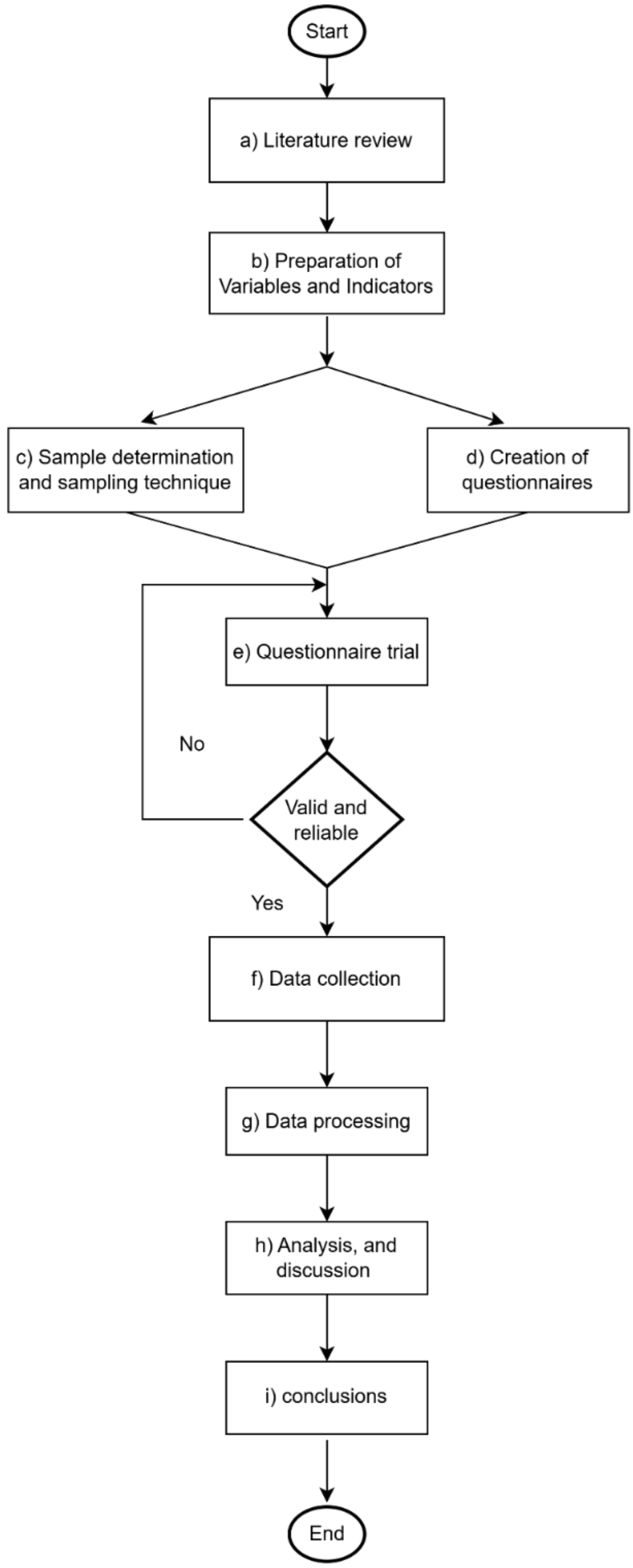
Evaluation is carried out to determine the factors that influence the success of KMS implementation. One of the commonly used evaluation techniques is survey research. The Technology Acceptance Model (TAM) is used as a survey approach to measure the level of user acceptance of KMS. The survey instrument used is a questionnaire with learners respondents. Figure 3.17 shows the stages of survey research.

Figure 3.17: The Main Stages in the KMS Acceptance Survey



The first stage of survey preparation consists of a literature review of relevant theories, model development, preparation of variables and indicators, instrument creation, testing of the instrument's validity and reliability, and determining the survey sample. Survey implementation consists of distributing, filling out, collecting, and processing questionnaire data. Meanwhile, the evaluation includes data analysis, description, and concluding research results. Figure 3.18 shows the survey methodology for measuring the level of user acceptance of KMS.

Figure 3.18: Survey Flow of KMS User Acceptance



The stages in the user acceptance survey of KMS are divided into eight stages. These stages start with literature study, developing TAM models and hypotheses, preparing variables, determining samples, making instruments, testing instruments, data collection, data processing, analysis, and conclusions.

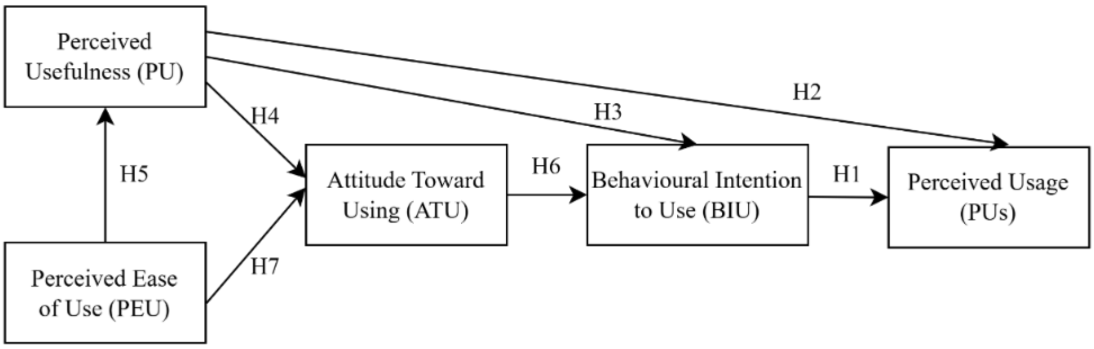
a) Literature Study

Aims to find out theories related to user acceptance of information technology products. The focus of the literature study is research results on TAM and SEM, which are a reference for knowing the level of learners acceptance of KMS.

b) Development of the TAM Model and research hypotheses

The TAM model was developed based on the results of the literature study. The stages of developing the model consist of identifying TAM variables, forming a research model, preparing research hypotheses, and developing the TAM model to obtain a TAM model. Figure 3.19 shows the adopted TAM model.

Figure 3.19: Model of TAM



Source: (Davis, 1987; Gardner dan Amoroso, 2004; Kim et al, 2009; Lee et al, 2011)

Research hypotesis:

H_1 : There is influence of Behavioural Intention to Use (BIU) and Perceived Usage (PUs) in the implementation of KMS for personalized learning to support OBE implementation in HEI.

H_2 : There is influence of Perceived Usefulness (PU) and Perceived Usage (PUs) in the implementation of KMS for personalized learning to support OBE implementation in HEI.

H_3 : There is influence of Perceived Usefulness (PU) and Behavioural Intention to Use (BIU) in implementing KMS for personalized learning to support OBE implementation in HEI.

H_4 : There is influence of Perceived Usefulness (PU) and Attitude Toward Using (ATU) in implementing KMS for personalized learning to support OBE implementation in HEI.

H_5 : There is influence of Perceived Ease to Use (PEU) and Perceived Usefulness (PU) on the implementation of KMS for personalized learning to support OBE implementation in HEI.

H_6 : There is influence of Attitude Toward Using (ATU) and Behavioural Intention to Use (BIU) on the implementation of KMS for personalized learning to support OBE implementation in HEI.

H_7 : There is influence of Perceived Easy to Use (PEU) on Attitude Toward Using (ATU) on the implementation of KMS for personalized learning to support OBE implementation in HEI.

c) Preparation of survey variables

With the model developed, variables are arranged based on the specified constructs, namely:

1. Perceived Usefulness/ perceived usefulness of KMS.
2. Perceived Ease of Use/ perceived ease of KMS.
3. Behavioural Intention to Use/ intention to use KMS.
4. Actual system use/perception of KMS use.

d) Making research instruments

Data collection used in this research used a questionnaire instrument. This questionnaire was prepared and developed in the following steps:

1. Refers to predetermined variables

2. The questionnaire distributed to Learners is divided into three parts, namely:

   a. Charging instructions
   b. Demographic data contains the respondents' demographic composition, including name and gender. This data is supporting data in the research.
   c. TAM Basic Data is the primary data in the research that will be analysed to obtain conclusions.

3. Research instrument grid

Before use, the instrument must be tested to determine validity and reliability. Before a research instrument is created, the concept needs to be arranged in grid form. Table 3.3 shows the research instrument grid.

Table 3.3: The Instrument Grid

Construct	Indicator	Code	No	Statements	Scale
Perceived Usefulness (Sun, 2003)	Learning is easier	PU1	1	Using KMS in learning makes my learning easier	Likert Scale 4
	Beneficial	PU2	2	Having KMS helps me in studying	
	Increase productivity	PU3	3	Using KMS can improve my learning outcomes	
	Increase effectiveness	PU4	4	By utilizing KMS, you can increase effectiveness in gaining knowledge	
	Improve the performance	PU5	5	Having KMS can improve performance	
Perceived Ease of Use (Davis, 1989)	Easy to learn	PEU1	6	KMS has apparent features, navigation, and information, easy to learn and understand	Likert Scale 4
	Easy to control	PEU2	7	KMS provides information if an error occurs	
	Easy to master	PEU3	8	KMS has apparent features, navigation, and information, is easy to learn and easy to master	

	Easy to use	PEU4	9	KMS has apparent features, navigation, and information and is easy to use	
Behavioural Intention to Use (Taylor & Todd, 1995)	Helps learning	BIU1	10	I always try to use KMS for studying because it has features to help me in learning	Likert Scale 4
	Handling cases	BIU2	11	I always try to use KMS in some learning	
	Usage planning	BIU3	12	I plan to use KMS in the future	
	Intention to use in the future	BIU4	13	I intend to continue using KMS in the future	
	Future use	BIU5	14	I hope to continue using KMS in the future	
Attitude Toward Using (Davis, 2003)	Interaction	ATU1	15	I enjoy interacting using KMS	Likert Scale 4
	Enjoyment	ATU2	16	Using KMS gives me satisfaction	
	Like	ATU3	17	I enjoy using KMS	
	Bored	ATU4	18	Using KMS makes me bored	
Perceived Usage	Speed	PUs1	19	Using KMS will make learning faster	Likert

(Davis, 2003)	Problem-solving skill	PUs2	20	Using KMS will be able to improve problem-solving abilities in learning	Scale 4
	Makes it easier	PUs3	21	Using KMS will make the learning process easier	
	Increase learning productivity	PUs4	22	Using KMS in learning will be able to improve learning outcomes	
	increase learning effectiveness	PUs5	23	Using KMS can increase effectiveness in the learning process	
	Helps learning	PUs6	24	Using KMS is very helpful in learning	

4. Preparation of alternatives and answer measurement scales

Alternative answers to the questionnaire consist of 4 answers: 1) Strongly disagree, 2) Disagree, 3) Agree, 4) Strongly agree. The measurement scale for each alternative answer uses 4 Likert scale. "The 4 Likert scale is commonly used to measure attitudes, opinions, and perceptions of a person or group of people about social phenomena. The answers to each questionnaire item are arranged from very positive to negative gradations. Table 3.4 shows quantitative alternatives, so the answers are given a score as follows:

Table 3.4: Alternatives and Answer Scores

No	Alternative Answers	Positive statement score
1	Strongly agree	4
2	Agree	3
3	Disagree	2
4	Strongly disagree	1

e) Determination of Sample

The population of this research instrument is Learners in the eighth semester of Department of informatics the Sunan Gunung Djati State Islamic University, Bandung, Indonesia. The total learners population is 126 learners.

f) Data collection

After the questionnaire trial was complete, data was collected by distributing the questionnaire online via the Google Form facility to Learners as respondents.

Determining the number of samples used in the research used the small sample technique from Krejcie and Morgan (1970), with the formula:

$$s = X^2NP(1-P) \div d^2(N-1) + X^2P(1-P) \qquad (3.1)$$

Information:

s = required sample size.

X^2 = the table value of chi-square for 1 degree of freedom at the desired confidence level (3.841)

N = the population size.

P = the population proportion (assumed to be .50 since this would provide the maximum sample size).

d = the degree of accuracy expressed as a proportion (.05)

Based on the formula (Krejcie and Morgan (1970), this research will use sample data with an accuracy level of 5% (0.05), namely:

$$s = X^2NP(1-P) \div d^2(N-1) + X^2P(1-P)$$

$$s = 3.841.126.\,0.5(1-0{,}5) \div 0.05^2(126-1) + 3.841.0.5(1-0.5)$$

$$s = 120.99 \div 1.27$$

$$s = 95.06$$

Based on the calculation results, the number of respondents obtained was 95,06, rounded up to 95 learners. This number is the same as the sample size table for determining a specific population (Krejcie & Morgan, 1970).

g) Data processing

Data processing in this study utilizes the Python programming language, renowned for its extensive suite of libraries that significantly enhance data manipulation and analysis capabilities. Pandas is a pivotal library in this context, which provides robust functionalities for creating and modifying tabular data structures and facilitating tasks such as data examination and cleaning. The Data-Frame, a core component of Pandas, is an essential data structure that efficiently processes files in various formats, including .txt, .csv, and .tsv.

Complementing Pandas, the NumPy library is invaluable for data cleaning, transformation, and aggregation operations. The *Sklearn-library* is specifically tailored to prepare and train datasets in machine learning and data science applications, thereby facilitating the development of predictive models. The Seaborn library, offering advanced features for statistical graphics, is employed to visualize the outcomes of data processing. Furthermore, the Matplotlib library generates diverse plots and visual representations. Lastly, the *Statsmodels* module in Python provides a comprehensive framework for estimating various statistical models, conducting hypothesis tests, and performing thorough statistical data analyses. This combination of libraries and modules underscores the study's emphasis on rigorous and effective data processing methodologies. The methodology for utilizing libraries in Python for data processing is delineated as follows.

```
#import libraries
import pandas as pd
import numpy as np
from sklearn.decomposition import FactorAnalysis
from sklearn.preprocessing import MinMaxScaler
```

```
import seaborn as sns
import matplotlib.pyplot as plt
import statsmodels.api as sm
```

To conduct factor analysis on the Technology Acceptance Model (TAM) and derive factor scores, the following syntax is employed:

```
# Function to perform factor analysis and return the factor scores
def perform_factor_analysis(items):
fa = FactorAnalysis(n_components=1)
factor_scores = fa.fit_transform(df[items])
return factor_scores
```

The function designed to adjust and summarize the regression model for each hypothesis is structured in the manner outlined below:

```
# Function to fit and summarize a regression model for each hypothesis
def fit_and_summarize(dependent_var, independent_vars):
    X = sm.add_constant(df[independent_vars])
    y = df[dependent_var]
    model = sm.OLS(y, X).fit()
    print(f"Regression results for {independent_vars[0]} on {dependent_var}:\n")
    print(model.summary())
    p_value = model.pvalues[1]  # p-value for the first independent variable
    significance_level = 0.05  # Common significance level (5%)
    print()

    # Determine whether to reject the null hypothesis
    if p_value < significance_level:
```

```
            conclusion = f"Null hypothesis (H0) Ditolak. Ada hubungan signifikan antara
            {independent_vars[0]} Terhadap {dependent_var}."
        else:
            conclusion = f"Null hypothesis (H0) Diterima. Tidak ada hubungan signifikan
            antara {independent_vars[0]} Terhadap {dependent_var}."


        print("Kesimpulan: ",conclusion)
        print("\n")


        plt.figure(figsize=(10, 6))
        sns.scatterplot(x=df[independent_vars[0]], y=y, label='Data')
        sns.regplot(x=df[independent_vars[0]], y=y, scatter=False,
        label='Regression Line')
        plt.xlabel(independent_vars[0])
        plt.ylabel(dependent_var)
        plt.title(f'Scatter Plot {dependent_var} Terhadap {independent_vars[0]}')
        plt.legend()
        plt.show()
```

For the examination of each hypothesis about the constructs or variables within the TAM framework (for example, hypotheses H1 through H7), the ensuing syntax may be utilized:

```
# Hypotheses H1 to H7
hypotheses =[
    ('Perceived_Usage', ['Behavioral_Intention_to_Use']), #H1
    ('Perceived_Usage', ['Perceived_Usefulness']), #H2
    ('Behavioral_Intention_to_Use', ['Perceived_Usefulness']), #H3
    ('Attitude_Toward_Using', ["Perceived_Usefulness"]), #H4
```

```
    ('Perceived_Usefulness', ['Perceived_Ease_of_Use']), #H5
    ('Behavioral_Intention_to_Use', ['Attitude_Toward_Using']), #H6
    ('Attitude_Toward_Using', ['Perceived_Ease_of_Use']), #H7
]
# Fit and summarize models
for dependent_var, independent_vars in hypotheses:
    fit_and_summarize(dependent_var, independent_vars)
```

3.7 Chapter Summary

This chapter presents the methodological framework of how the research objectives are achieved. This research has three main activities, namely stage I, to develop a relevant knowledge pool required for a certain field for KMS in HEI. This stage is divided into two processes. First, the curriculum and syllabus in KMS are set in the OBE framework. This first part consists of the setting of PLO, CLO and topics. Mapping of CLO to PLO, mapping of course topics to CLO. Finally, the assessment (instruments and questions) and CLO achievements will be determined. Second, the knowledge acquisition process consists of uploading teaching materials, scraping knowledge, knowledge summarisation, and external knowledge from experts or industry. The output of stage I is the availability of knowledge following the needs of the course program. Stage II is to develop a learning analytics technique in the KMS for personalized learning to support the implementation of OBE in HEI. This stage is divided into two processes: course implementation and course evaluation. First, course implementation consists of downloading, reading, and giving ratings for the quality of teaching materials. Second, course evaluation consists of conducting assessments for each CLO and analysing CLO assessment results. The output of this stage is the availability of learner profiles, consisting of CLO achievement and improved learners learning. Stage III is to validate and evaluate KMS developed for personalized learning to support OBE in HEI. Validation of the developed KMS is carried out using expert judgment. Experts involved in the validation consist of learning media experts, learning content experts, and ICT experts. The evaluation in this section adopts the TAM framework. The evaluation uses a survey method, with the main instrument being a questionnaire and learners as respondents. The output of this stage is a description of the level of expert assessment and user acceptance of the KMS by users.

CHAPTER 4

RESULTS

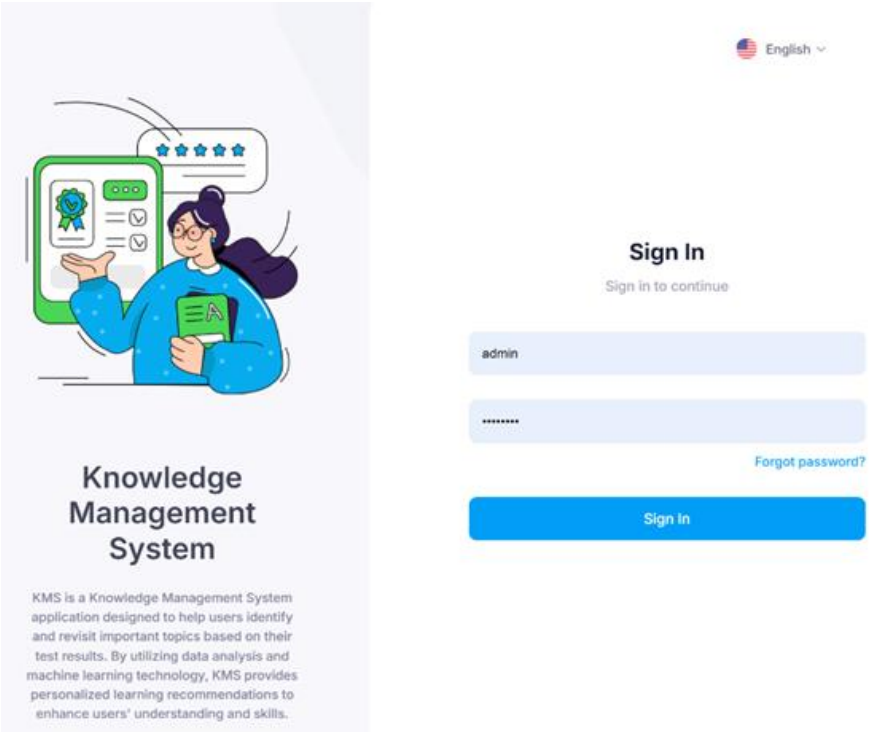
4.0 Introduction

In general, KMS is divided into two parts of system functions: the backend system and the frontend system. The backend system provides system configuration or system master data management, while the frontend system provides the transactional function of the learning process. Lecturers are the managers or users of the backend system, while learners and experts from the industry are the users of the frontend system. The first part of the backend system is for the development of a relevant knowledge pool required for a particular field for KMS in the HEI or learning preparation phase. The phase is divided into two main activities: OBE curriculum and syllabus setting and knowledge acquisition. OBE curriculum and syllabus setting consists of setting program learning outcome (PLO), course learning outcome (CLO), course topics, mapping CLO to course topics and assessment configuration. Knowledge acquisition represents the process of knowledge creation in KM, externalisation, and combination of knowledge. The knowledge upload function is a representation of knowledge externalisation. The scraping function represents knowledge combination, knowledge addition by an expert, and summarisation of knowledge documents. The summarisation function in KMS is an automatic summarisation system for multi-document knowledge in Indonesian. The summarisation is a type of multi-document abstractive summarisation. The summarisation model produced is the best model that has gone through the process of model testing and evaluating the readability of summarisation results both systemically and manually by an Indonesian language expert. The second part of the frontend system is for the Development of learning analytics in the KMS for PL to support the implementation of OBE in HEI or the learning implementation phase. This phase represents the internalisation of knowledge in KM. The implementation of learning is divided into two main parts, namely, the learning process and the evaluation of learning outcomes. The learners learning process is represented by downloading and rating knowledge, while the evaluation of learning outcomes consists of setting assessments and analytics of learners learning outcomes. The developed learning analytics combines two algorithms, namely Rule-based and content-based filtering. The data used in learning analytics is data from learners CLO assessment results. The final part of this chapter discusses the evaluation and validation of the developed KMS. KMS evaluation is done through a survey using the TAM model approach. The survey was conducted to measure users' level of acceptance of KMS. User respondents are learners with the main instrument using a questionnaire.

4.1 Develop a Relevant Knowledge Pool in the Area of Informatics for the KMS in Order to Support the OBE Implementation of in HEI

Figure 4.1 shows the initial display of the KMS.

Figure 4.1: Initial Display of the KMS



The initial display of the KMS contains a brief description of the KMS and user login. They are providing system security functions through user authentication. Users must log in with the appropriate username and password. Login is divided into two levels: admin for lecturers and regular users for learners. In general, KMS has two main functions. First, the backend system consists of functions for managing the curriculum and OBE syllabus, as well as knowledge acquisition to meet learners' learning needs. Second, the frontend system includes functions for managing the implementation of learning and evaluating learning outcomes.

The knowledge management is represented by two main functions of the system, namely:

a) Management of master data for the curriculum and syllabus based on OBE in the KMS

b) Management of knowledge that aligns with learning needs in the KMS

Figure 4.2: Frontend Menu Structure of the KMS

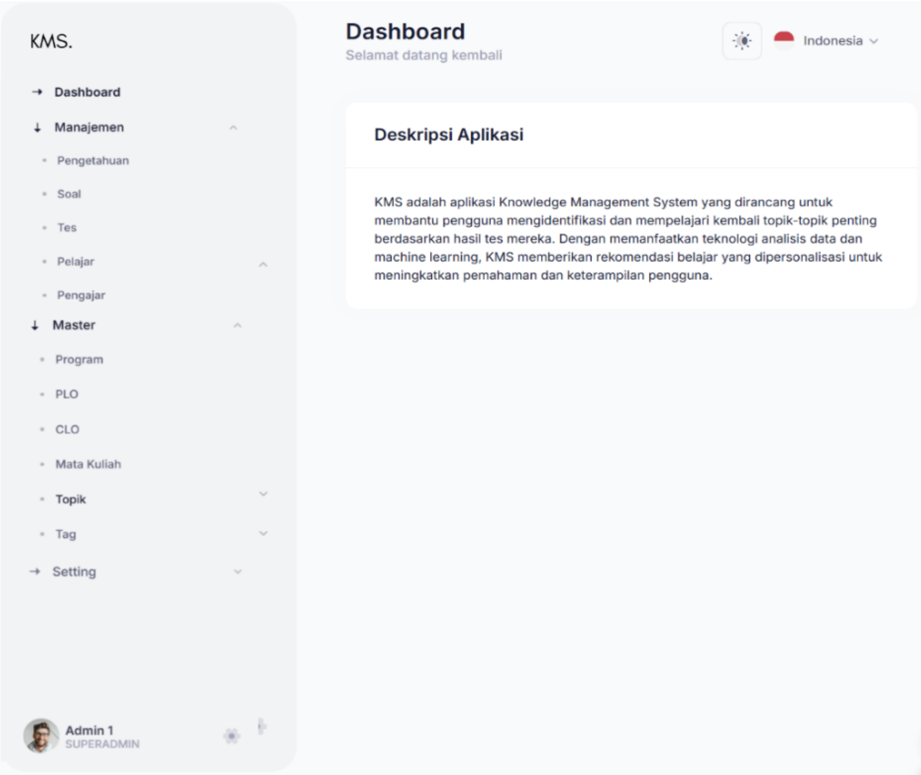


Figure 4.2 shows the frontend menu structure of the KMS system. In addition to knowledge management and OBE curriculum settings, there are menus for master data on assessment questions, test management, learners, and instructors. Meanwhile, the settings menu contains access rights configurations for the KMS.

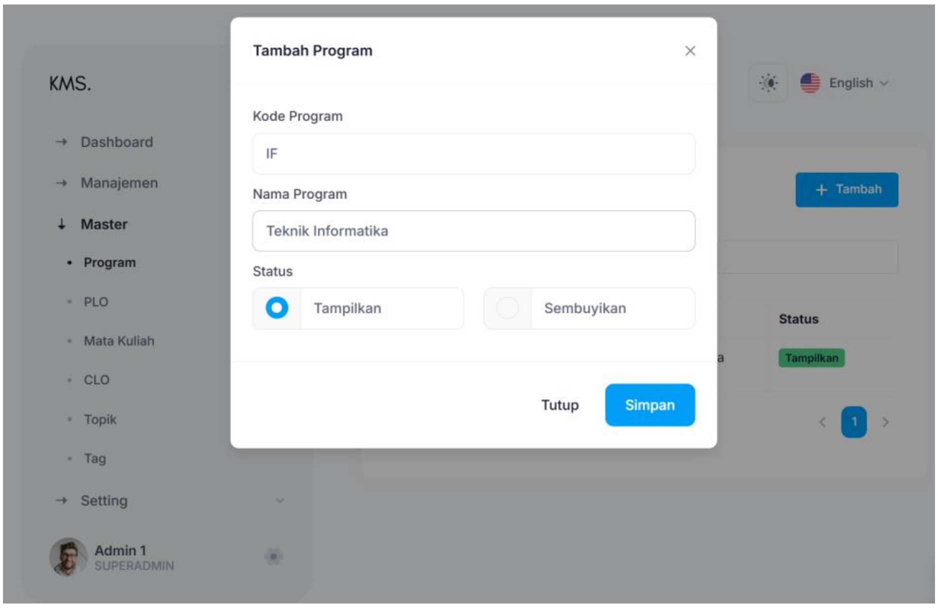
4.1.1 Setting of OBE-Based Curriculum and Syllabus

The OBE curriculum and syllabus framework is part of the backend system in the KMS. The developed curriculum and syllabus are then entered as master data into the KMS. The resulting curriculum becomes a framework for organising knowledge and implementing learning. The OBE curriculum used as a reference is the Bachelor of Informatics program at Sunan Islamic University (UIN) Gunung Djati Bandung. The stages of organising the OBE-based curriculum and syllabus master data include:

a) Organization of master program data in the KMS

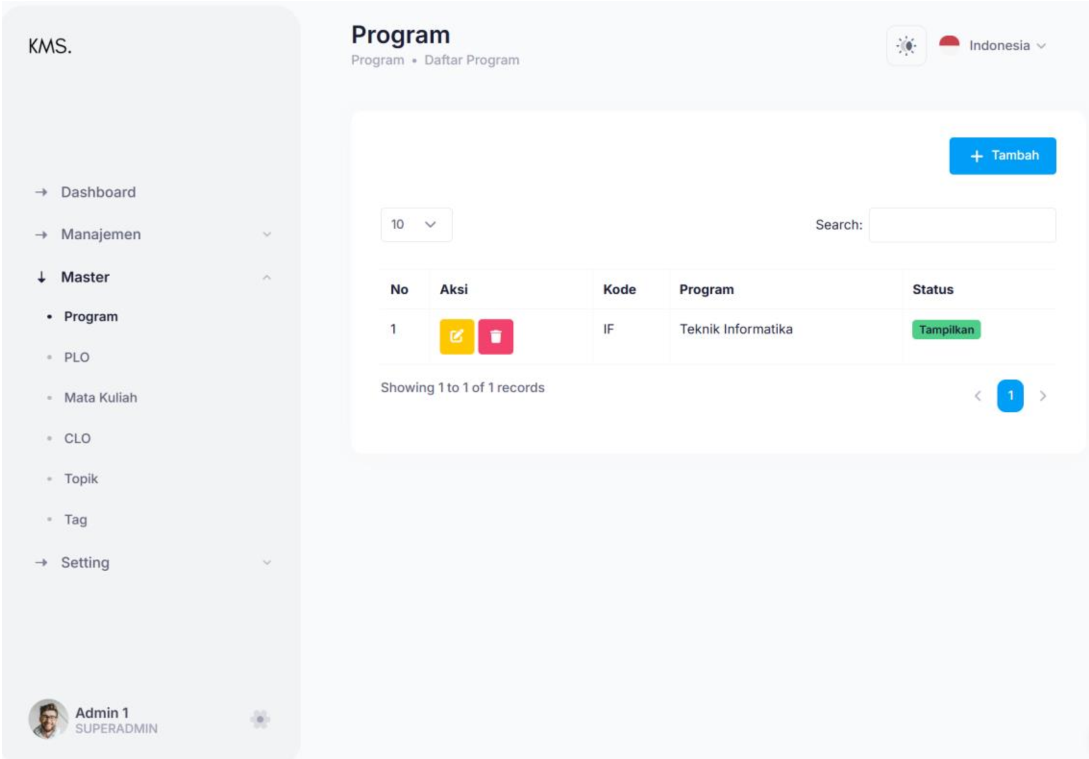
Figure 4.3 shows the arrangement of master program data in the OBE curriculum and syllabus.

Figure 4.3: Organization of Master Program Data



The curriculum arrangement begins with organizing the master program data. The lecturer can enter the program code and program name in the add program interface. If the configuration results want to be displayed on the system's front end, they can select the Display settings. Figure 4.4 shows the master program data.

Figure 4.4: List of Master Program Data

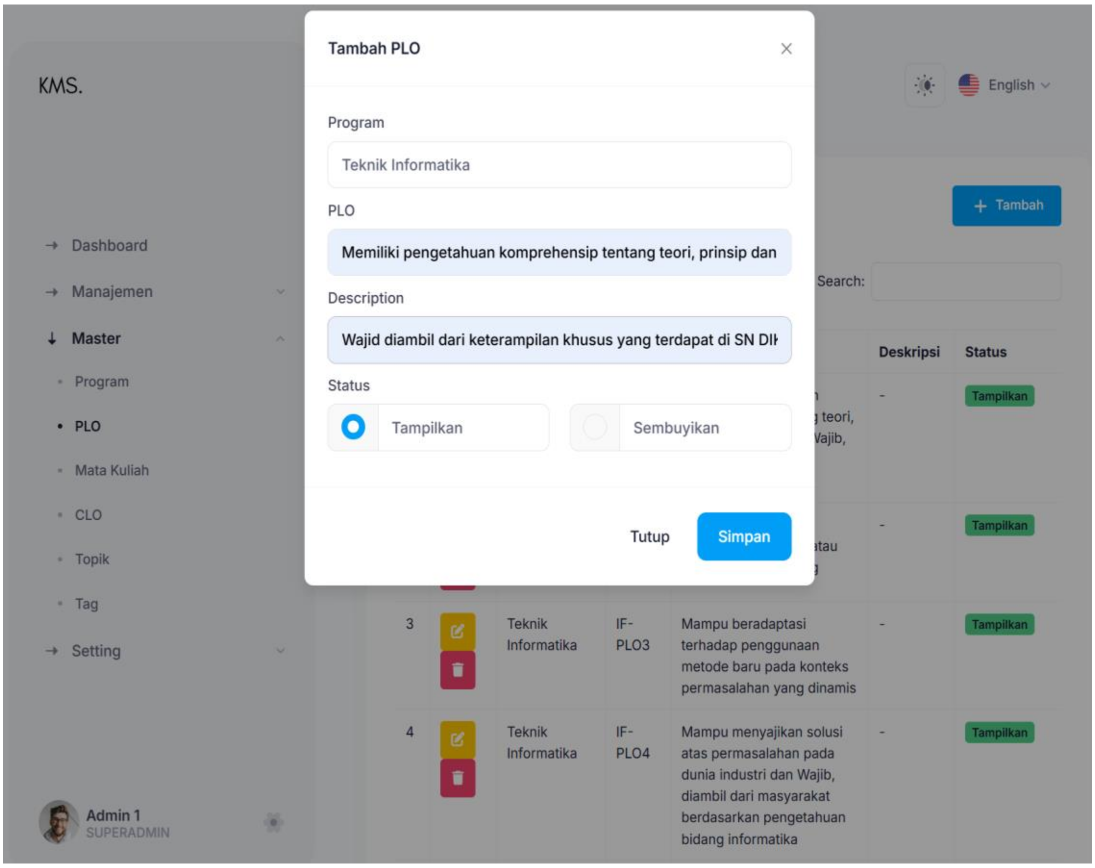


The data master program in the KMS consists of program codes, program names, and status settings. It is equipped with an edit and delete settings menu.

b) Configuration of master data for the program learning outcomes (PLO) in the KMS.

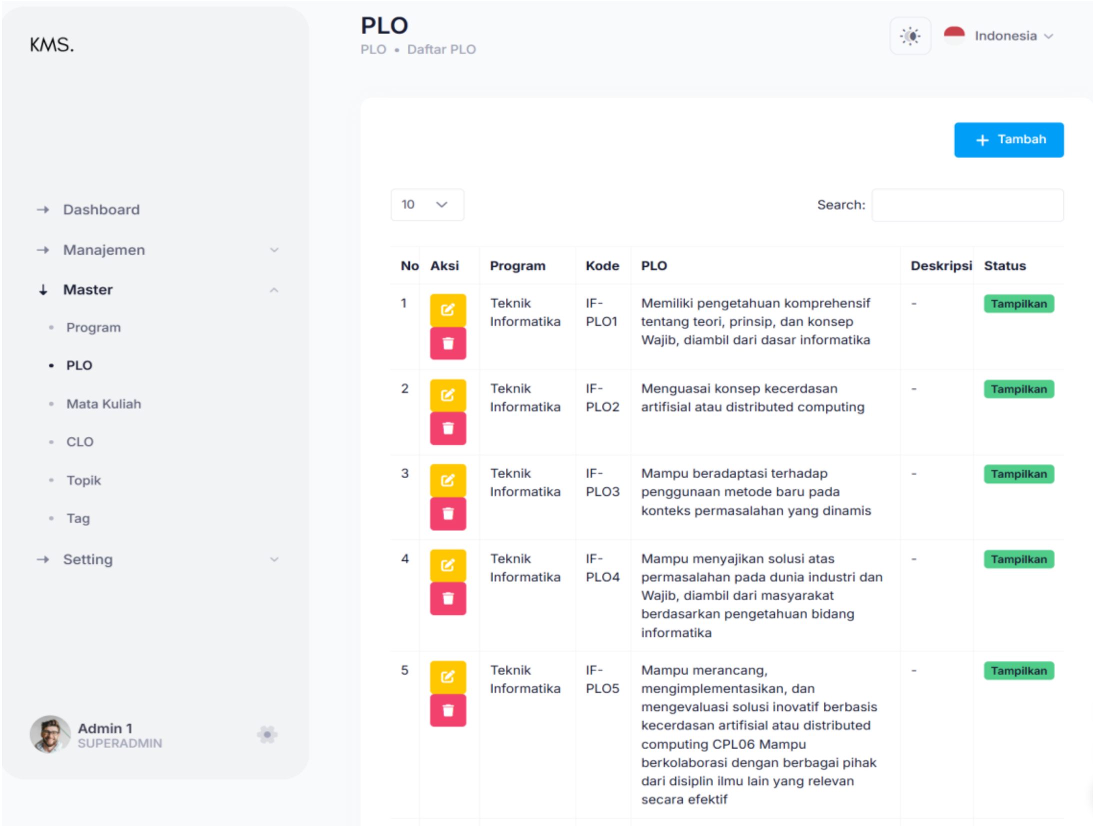
Figure 4.5 shows the configuration for the master data of the program learning outcomes (PLO) in the OBE curriculum and syllabus.

Figure 4.5: Master Data Settings for the Learning Outcome



After selecting the Add menu, the lecturer can fill in the master data for the PLO, which consists of the program name and the PLO statement, along with a description. There is a display settings menu if the PLO wants to be shown and a hidden menu if the master data for the PLO is not displayed in the front of the system. Figure 4.6 shows the results of the master data arrangement for PLO on KMS.

Figure 4.6: List of PLO Master Data

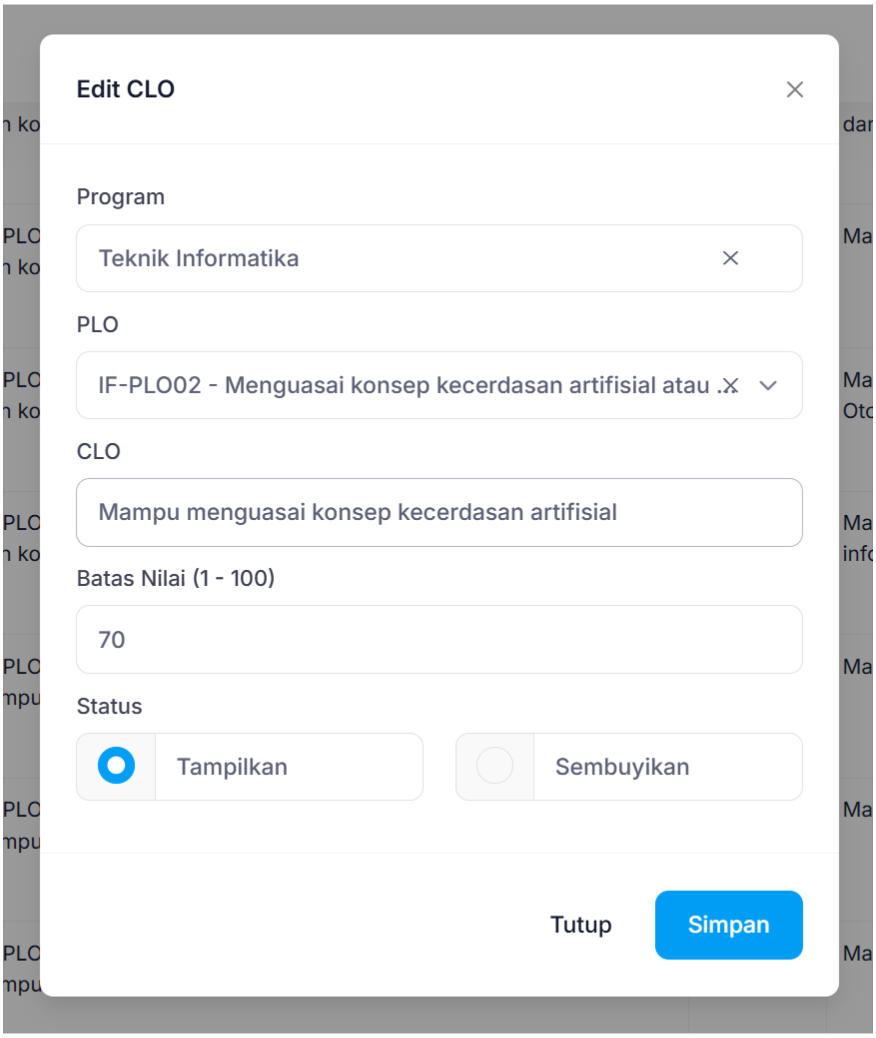


The master PLO data list in the KMS consists of the program name, PLO code, PLO statement, and status. The system generates the PLO code automatically. The master PLO data list is equipped with an edit and delete settings menu.

c) Arrangement of master data for course learning outcomes (CLO) and its mapping to PLO in the KMS.

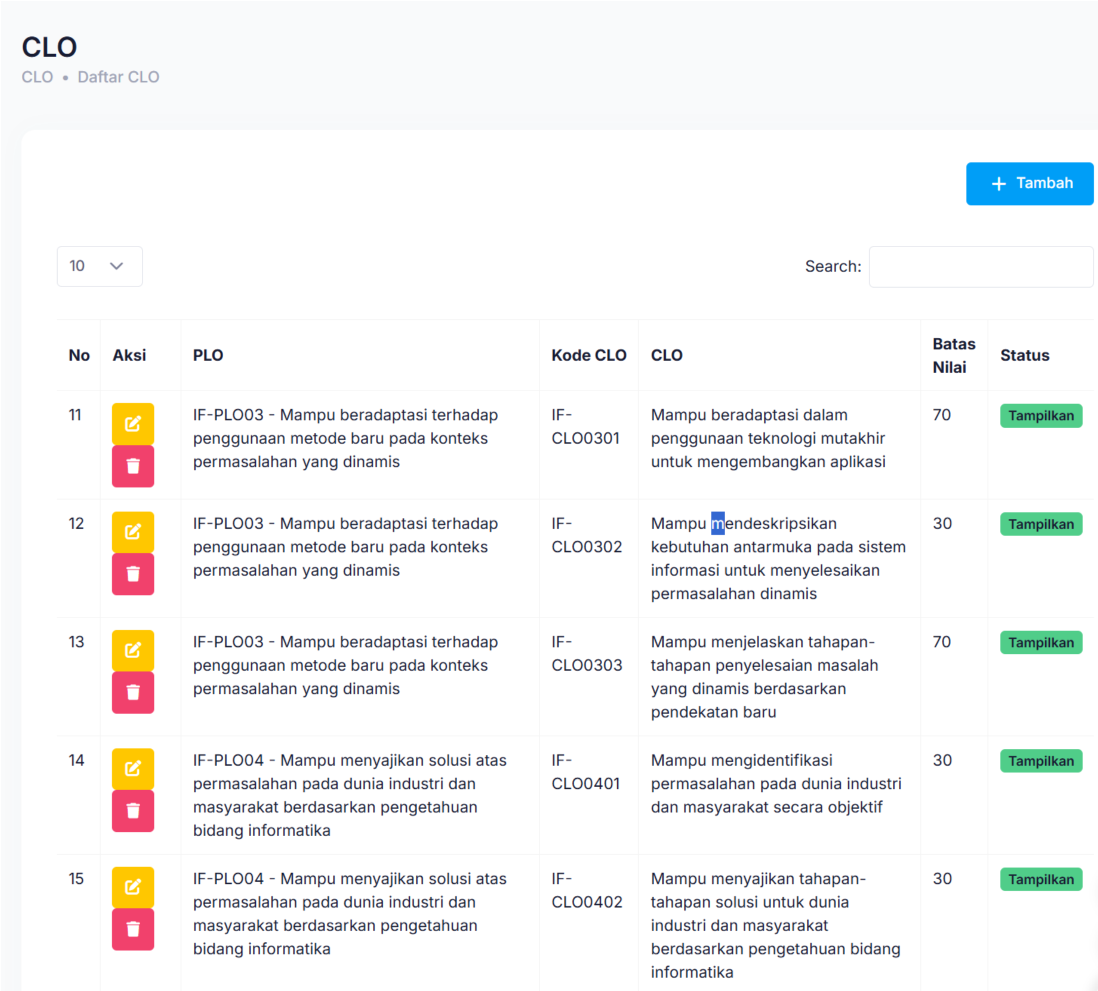
Figure 4.7 shows the arrangement for master data of course learning outcomes (CLO) and its mapping to PLO for the OBE curriculum and syllabus.

Figure 4.7: Arrangement of Master data for Course Learning Outcomes (CLO) and Their Mapping to Program



After selecting the add menu, the lecturer can begin filling in the master CLO data. The CLO data setup can start by selecting the program, choosing the course, filling in the CLO statement and the minimum passing score (benchmarking), and finally selecting the PLO related to the CLO. Figure 4.8 shows the results of the master CLO data setup in the KMS.

Figure 4.8: List of CLO Master Data



CLO

CLO • Daftar CLO

+ Tambah

10

Search:

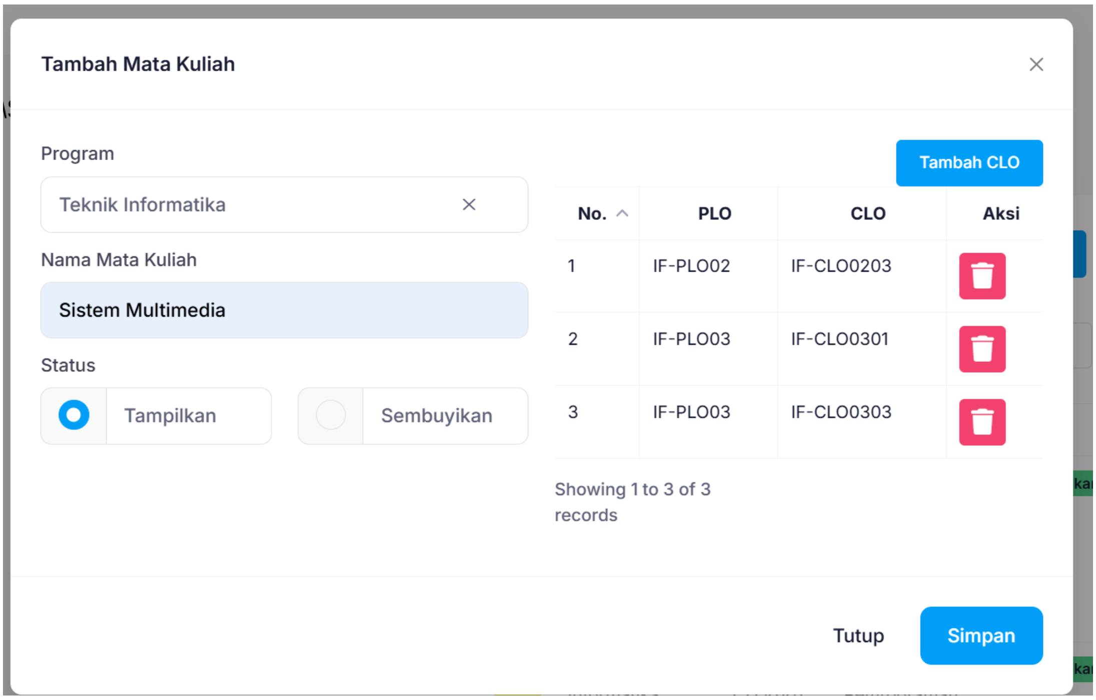
No	Aksi	PLO	Kode CLO	CLO	Batas Nilai	Status
11		IF-PLO03 - Mampu beradaptasi terhadap penggunaan metode baru pada konteks permasalahan yang dinamis	IF-CLO0301	Mampu beradaptasi dalam penggunaan teknologi mutakhir untuk mengembangkan aplikasi	70	Tampilkan
12		IF-PLO03 - Mampu beradaptasi terhadap penggunaan metode baru pada konteks permasalahan yang dinamis	IF-CLO0302	Mampu mendeskripsikan kebutuhan antarmuka pada sistem informasi untuk menyelesaikan permasalahan dinamis	30	Tampilkan
13		IF-PLO03 - Mampu beradaptasi terhadap penggunaan metode baru pada konteks permasalahan yang dinamis	IF-CLO0303	Mampu menjelaskan tahapan-tahapan penyelesaian masalah yang dinamis berdasarkan pendekatan baru	70	Tampilkan
14		IF-PLO04 - Mampu menyajikan solusi atas permasalahan pada dunia industri dan masyarakat berdasarkan pengetahuan bidang informatika	IF-CLO0401	Mampu mengidentifikasi permasalahan pada dunia industri dan masyarakat secara objektif	30	Tampilkan
15		IF-PLO04 - Mampu menyajikan solusi atas permasalahan pada dunia industri dan masyarakat berdasarkan pengetahuan bidang informatika	IF-CLO0402	Mampu menyajikan tahapan-tahapan solusi untuk dunia industri dan masyarakat berdasarkan pengetahuan bidang informatika	30	Tampilkan

The master CLO data on the KMS is displayed along with the PLO, CLO code, CLO statement, minimum passing grade, and status. The system generates the CLO code automatically. The master CLO data list is equipped with an edit and delete settings menu.

d) Arrangement of master course data on KMS.

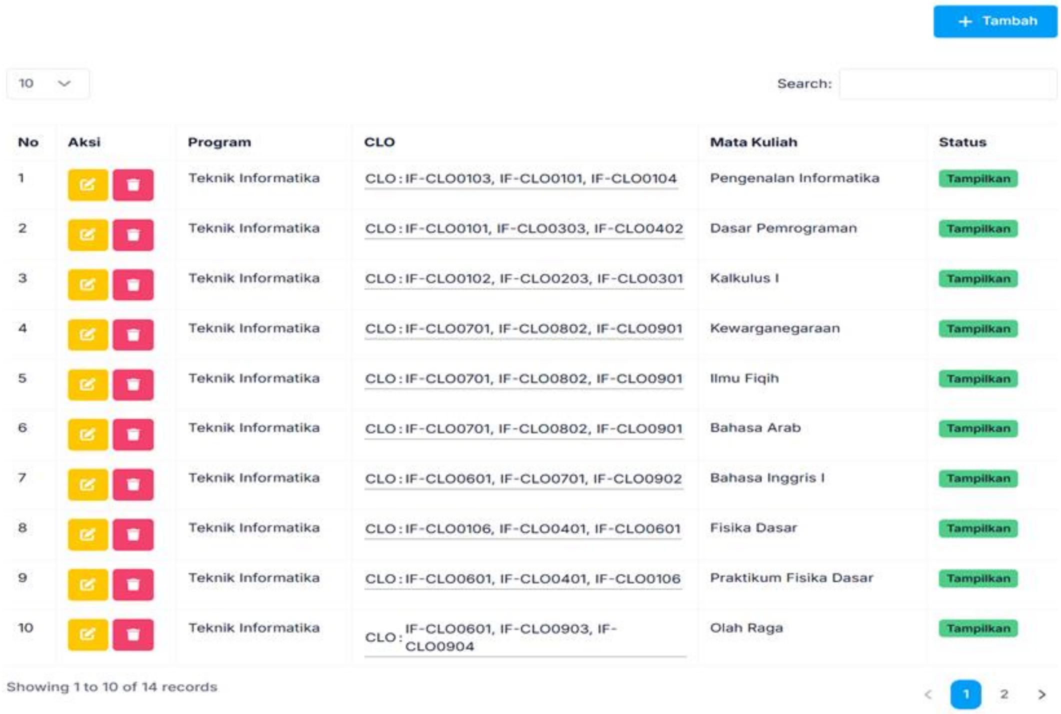
Figure 4.9 shows the arrangement for master course data in the OBE curriculum and syllabus.

Figure 4.9: Master Course Data Arrangement and CLO Mapping



After selecting the Add menu, the lecturer can fill in the master course data, which consists of the program name and course name. The course must be equipped with CLO that automatically synchronizes with PLO. There is a display settings menu if the course wants to be shown and a hidden menu if the master course data will not be displayed on the front end of the system. Figure 4.10 shows the results of the master course data arrangement on the KMS.

Figure 4.10: Master Course Data List



+ Tambah

10

Search:

No	Aksi	Program	CLO	Mata Kuliah	Status
1		Teknik Informatika	CLO : IF-CLO0103, IF-CLO0101, IF-CLO0104	Pengenalan Informatika	Tampilkan
2		Teknik Informatika	CLO : IF-CLO0101, IF-CLO0303, IF-CLO0402	Dasar Pemrograman	Tampilkan
3		Teknik Informatika	CLO : IF-CLO0102, IF-CLO0203, IF-CLO0301	Kalkulus I	Tampilkan
4		Teknik Informatika	CLO : IF-CLO0701, IF-CLO0802, IF-CLO0901	Kewarganegaraan	Tampilkan
5		Teknik Informatika	CLO : IF-CLO0701, IF-CLO0802, IF-CLO0901	Ilmu Fiqih	Tampilkan
6		Teknik Informatika	CLO : IF-CLO0701, IF-CLO0802, IF-CLO0901	Bahasa Arab	Tampilkan
7		Teknik Informatika	CLO : IF-CLO0601, IF-CLO0701, IF-CLO0902	Bahasa Inggris I	Tampilkan
8		Teknik Informatika	CLO : IF-CLO0106, IF-CLO0401, IF-CLO0601	Fisika Dasar	Tampilkan
9		Teknik Informatika	CLO : IF-CLO0601, IF-CLO0401, IF-CLO0106	Praktikum Fisika Dasar	Tampilkan
10		Teknik Informatika	CLO : IF-CLO0601, IF-CLO0903, IF-CLO0904	Olah Raga	Tampilkan

Showing 1 to 10 of 14 records

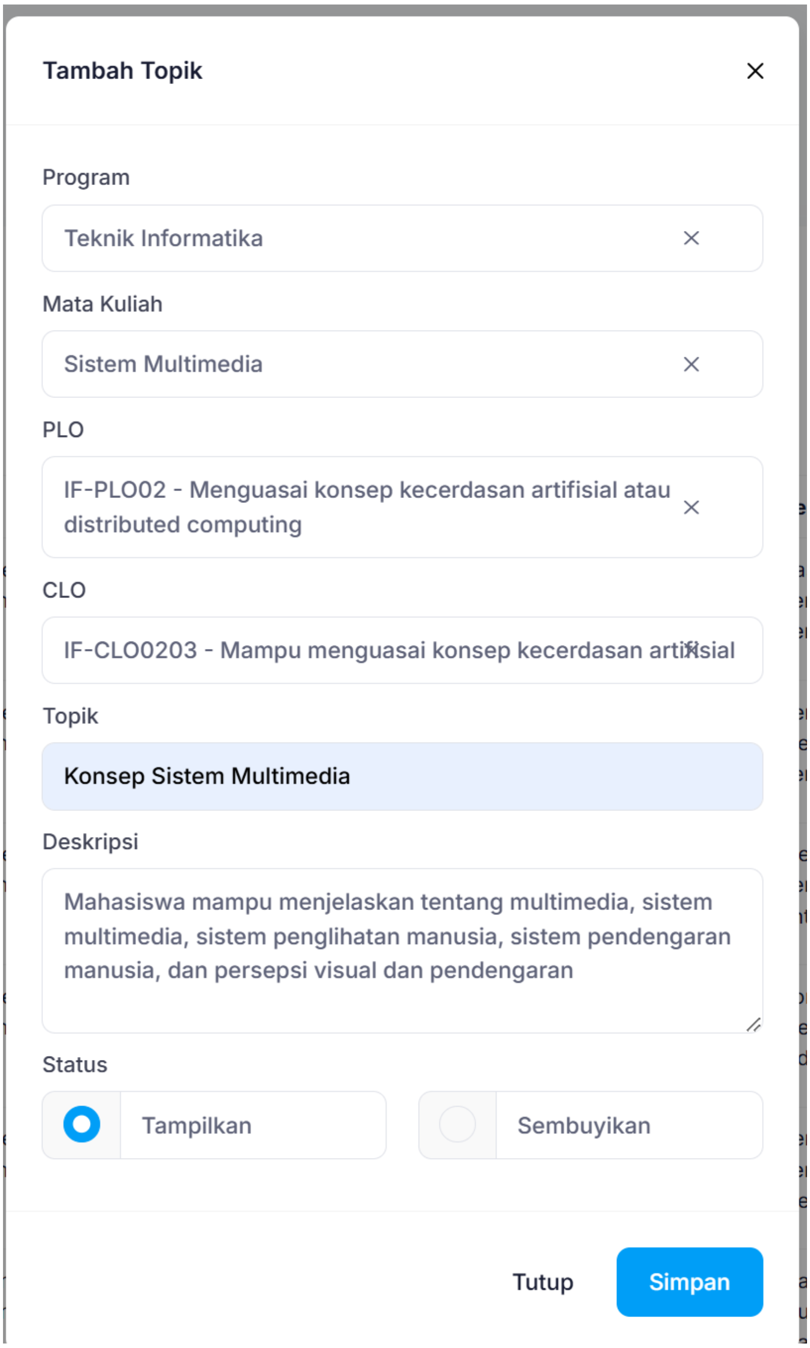
< 1 2 >

The KMS's list of master course data includes the program name, CLO, course name, and status. It also has edit and delete settings menus.

e) Course topic settings and their mapping to CLO in the KMS.

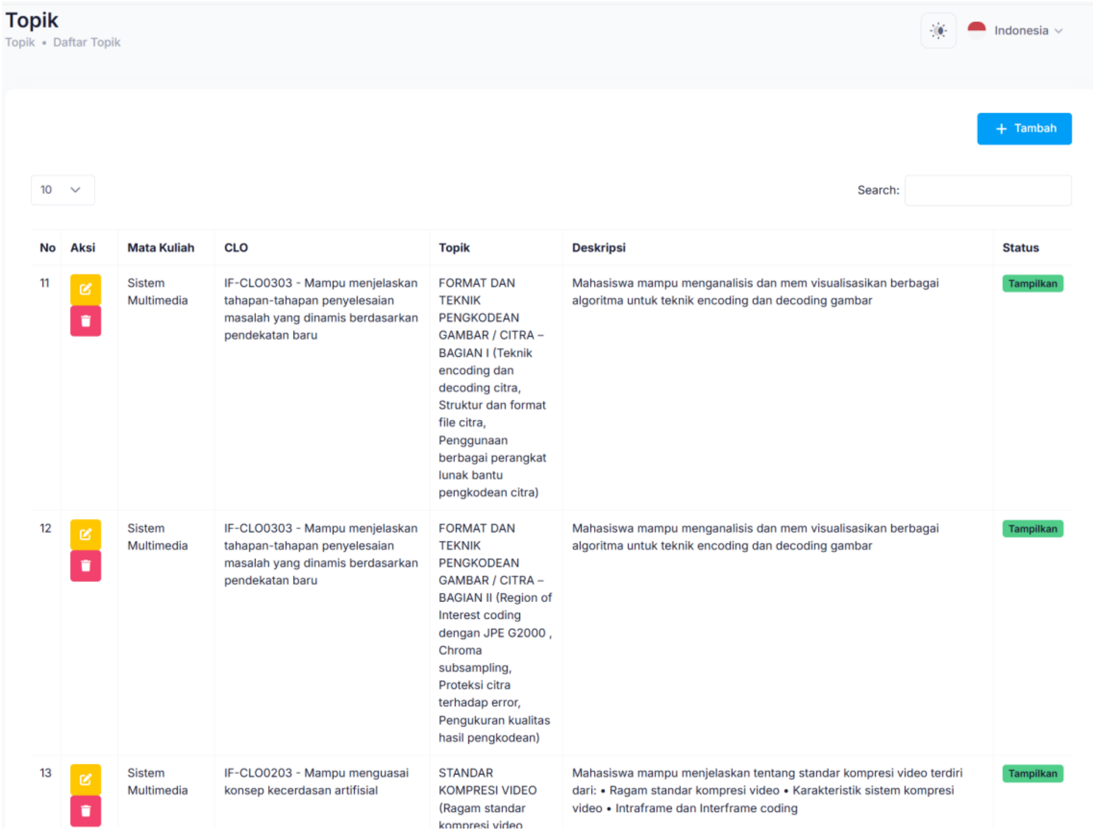
Figure 4.11 shows the settings for master course topic data and their mapping to CLO and PLO.

Figure 4.11: Master Data Configuration for Course Topics



After selecting the add menu, the lecturer can begin filling in the master data for course topics and their mapping to CLO and PLO. The setup of master topic data starts with selecting the program, choosing the course, and selecting CLO and PLO. The lecturer is required to fill in a description for each course topic. There is a display settings menu if topics want to be shown and a hidden menu if the master data of topics will not be displayed in the front end of the system. Figure 4.12 shows the results of the master topics data arrangement in the KMS.

Figure 4.12: List of CLOs for Each Course



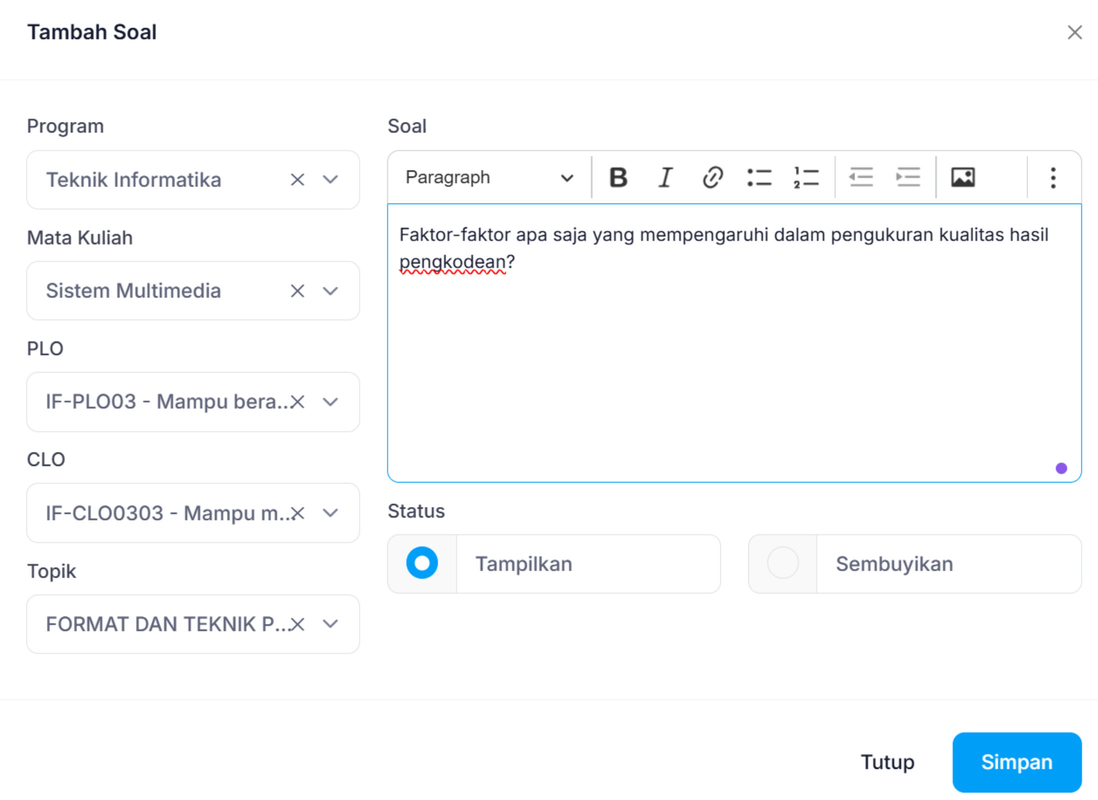
No	Aksi	Mata Kuliah	CLO	Topik	Deskripsi	Status
11		Sistem Multimedia	IF-CLO0303 - Mampu menjelaskan tahapan-tahapan penyelesaian masalah yang dinamis berdasarkan pendekatan baru	FORMAT DAN TEKNIK PENGKODEAN GAMBAR / CITRA – BAGIAN I (Teknik encoding dan decoding citra, Struktur dan format file citra, Penggunaan berbagai perangkat lunak bantu pengkodean citra)	Mahasiswa mampu menganalisis dan mem visualisasikan berbagai algoritma untuk teknik encoding dan decoding gambar	Tampilkan
12		Sistem Multimedia	IF-CLO0303 - Mampu menjelaskan tahapan-tahapan penyelesaian masalah yang dinamis berdasarkan pendekatan baru	FORMAT DAN TEKNIK PENGKODEAN GAMBAR / CITRA – BAGIAN II (Region of Interest coding dengan JPE G2000 , Chroma subsampling, Proteksi citra terhadap error, Pengukuran kualitas hasil pengkodean)	Mahasiswa mampu menganalisis dan mem visualisasikan berbagai algoritma untuk teknik encoding dan decoding gambar	Tampilkan
13		Sistem Multimedia	IF-CLO0203 - Mampu menguasai konsep kecerdasan artifisial	STANDAR KOMPRESI VIDEO (Ragam standar kompresi video	Mahasiswa mampu menjelaskan tentang standar kompresi video terdiri dari: • Ragam standar kompresi video • Karakteristik sistem kompresi video • Intraframe dan Interframe coding	Tampilkan

The KMS displays a list of master topics along with the course name, CLO, and topic names. The list of master topics has an edit and delete settings menu.

f) Configuration of master assessment data on KMS.

The configuration of master assessment data is divided into three parts: question settings, schedule, and assessment question details. Figure 4.13 shows the arrangement of questions for the assessment of a CLO.

Figure 4.13: Assessment Question Arrangement



The assessment questions prepared are a representation of the topics, CLO, and PLO. The number of questions is arranged according to the topics and the assessment needs of the CLO.

Figure 4.14: Detailed Answer to the Assessment Question

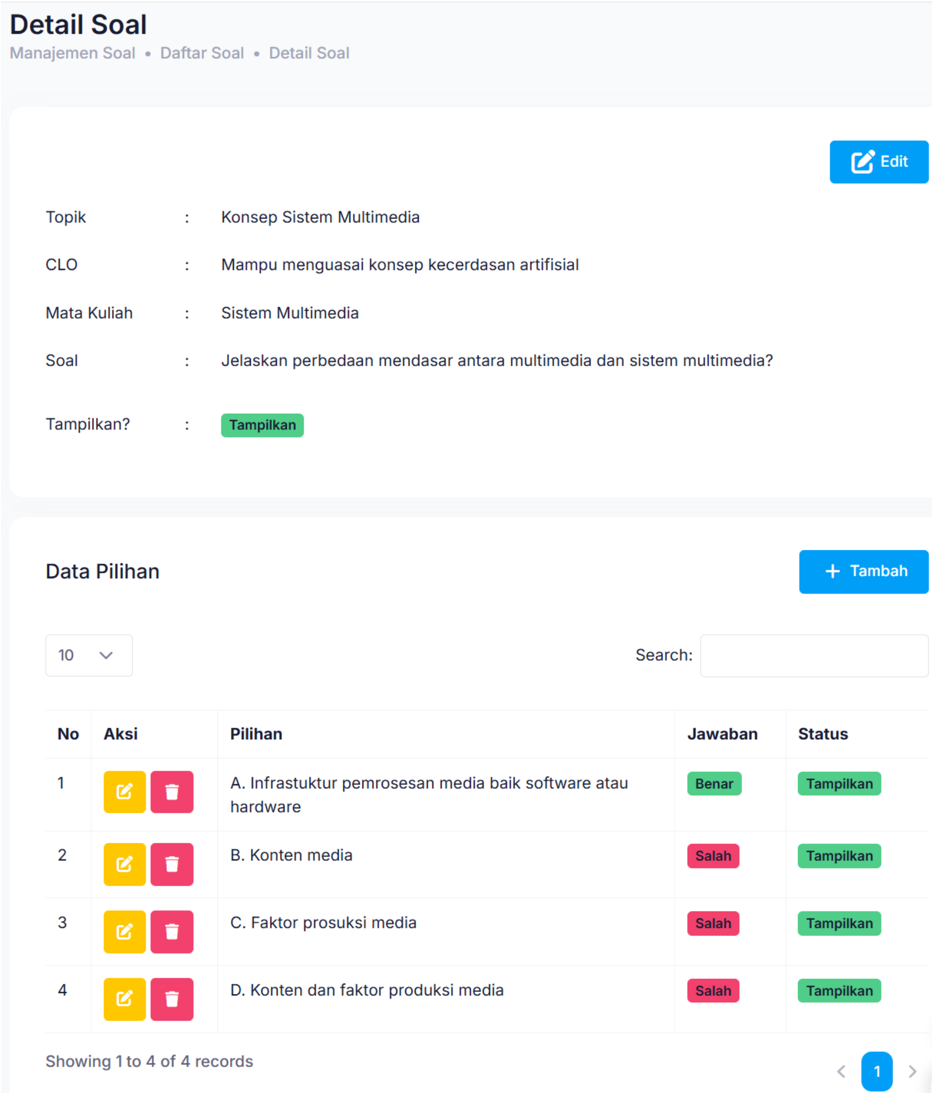
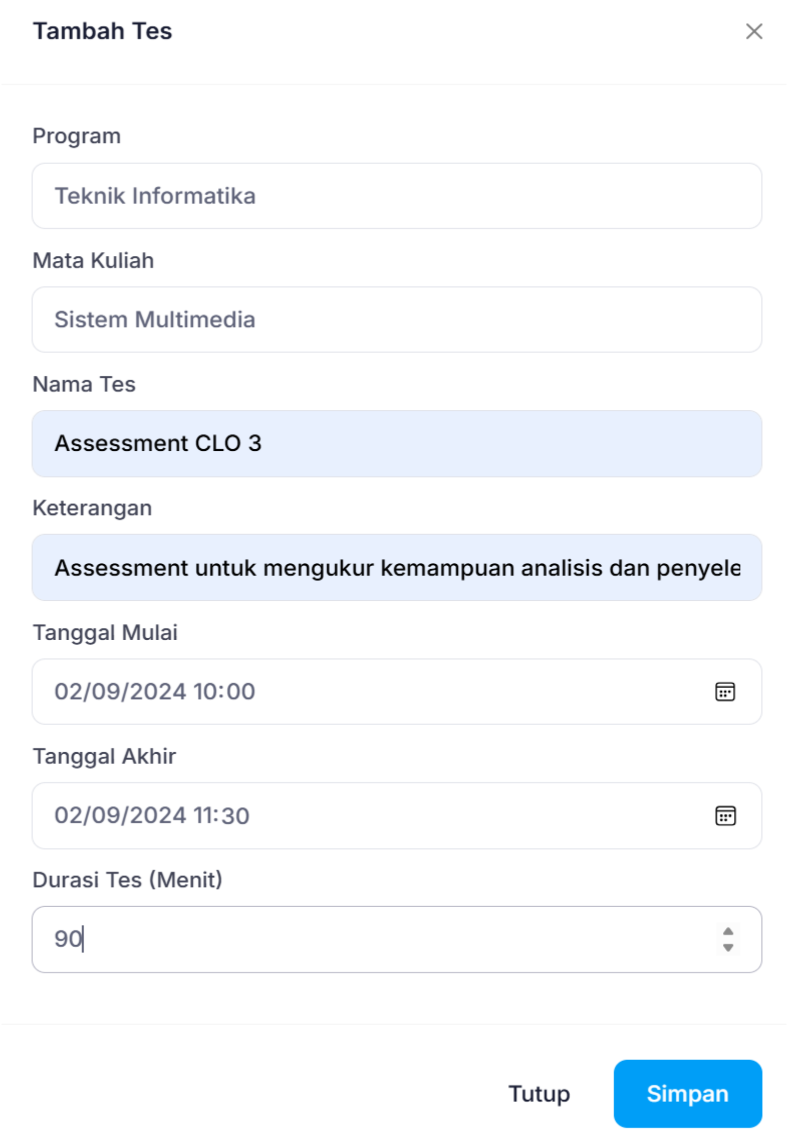


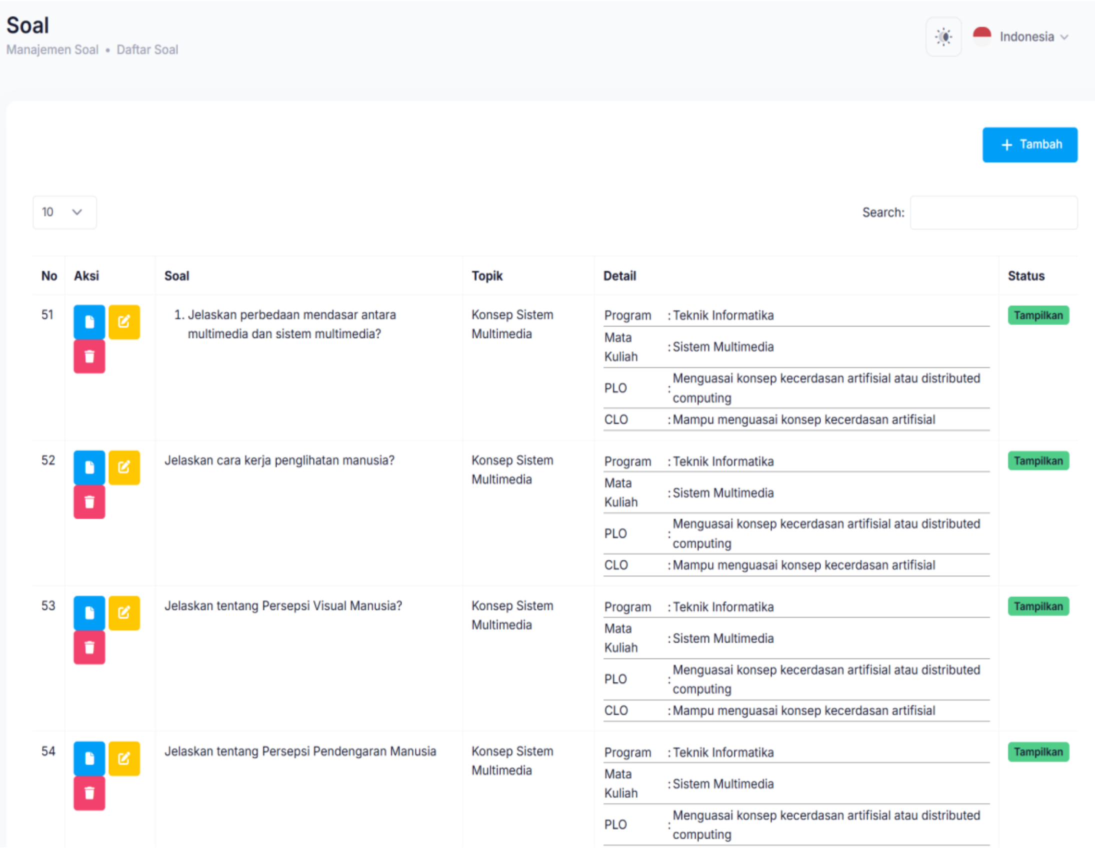
Figure 4.14 shows the detailed arrangement of the assessment questions. The answers can be formatted as multiple choice. The answers are created with answer options and the correct answer key for the questions.

Figure 4.15: Schedule Arrangement for Assessment



The settings include the assessment name, description, execution time, and duration. The purpose of the assessment is to measure the achievement of a Course Learning Outcome (CLO) for a course, and the assessment is conducted in a formative format. Figure 4.16 shows the master data list of assessment questions in the KMS.

Figure 4.16: List of Master Data for Assessment Questions



The assessment questions has been connected to topics such as CLO, PLO, and the program's course. The interface is equipped with an edit, update, and delete settings menu.

Table 4.1 provides a summary of the master data arrangement for the OBE curriculum and syllabus.

Table 4.1: Summary of the Master Data Arrangement for the OBE Curriculum and Syllabus

No	Variable data setting	Name of data	Status	
			Success	Failure
1	Program	IF. Informatics	✓	
2	Program Learning	IF-PLO01. Possess comprehensive knowledge of mandatory theories,	✓	

No	Variable data setting	Name of data	Status	
			Success	Failure
	Outcome (PLO)	principles, and concepts derived from the fundamentals of informatics.		
		IF-PLO02. Master the concepts of artificial intelligence or distributed computing.	✓	
		IF-PLO03. Able to adapt to the use of new methods in the context of dynamic problems.	✓	
		IF-PLO04. Capable of presenting solutions to problems in the industrial world and mandatory, derived from a society based on knowledge in the field of informatics.	✓	
		IF-PLO05. Able to design, implement, and evaluate innovative solutions based on artificial intelligence or distributed computing.	✓	
		CPL06. Able to collaborate effectively with various parties from other relevant disciplines.	✓	
		IF-PLO07. Having a commitment to Islamic principles and values as a foundation derived from elements of	✓	

No	Variable data setting	Name of data	Status	
			Success	Failure
		life in the context of both individuals and organizations.		
		IF-PLO08. Having a lifelong learning spirit that is creative and innovative.	✓	
3	Course Learning Outcome (CLO)	IF-CLO05. Able to explain the basic components of various forms of digital media formats.	✓	
		IF-CLO06. Able to analyze and visualize various algorithms to represent multimedia objects.	✓	
		IF-CLO7. Able to demonstrate and implement various algorithms and multimedia processing technologies.	✓	
4	Topics	Concept of multimedia systems	✓	
		Audio representation	✓	
		udio compression standards	✓	
		Audio encoding techniques and formats	✓	
		Image compression standards	✓	
		Image encoding techniques and formats	✓	
		Video encoding techniques and formats	✓	

No	Variable data setting	Name of data	Status	
			Success	Failure
		Multimedia streaming	✓	
		Radio broadcasting systems	✓	
		Digital rights management	✓	
5	Assessment data quetions (example)	Formatif Assessment IF-CLO023	✓	
		Formatif Assessment IF-CLO0301	✓	
		Formatif Assessment IF-CLO0303	✓	

Based on the results of the master data setup for the OBE curriculum and syllabus, which consists of program data variables, PLO (8 master data), CLO (3 master data), and topics (11 master data), as well as test arrangements (4 sample data), everything has been successfully stored in the database and can be displayed on the KMS web page.

The OBE-Based curriculum and syllabus setting on KMS refer to the OBE curriculum applicable at the Department of Informatics, Sunan Gunung Djati State Islamic University, Bandung. (Sunan Gunung Djati Islamic University Bandung., 2022). The curriculum book is derived from the Indonesian government's policy, specifically the Ministry of National Education, regarding education standards and guidelines for curriculum development (Directorate General of Learning and Learners Affairs Ministry of Research, 2015; Ministry of National Education of Indonesia. Directorate General of Higher Education. Ministry of Education and Culture, 2020).

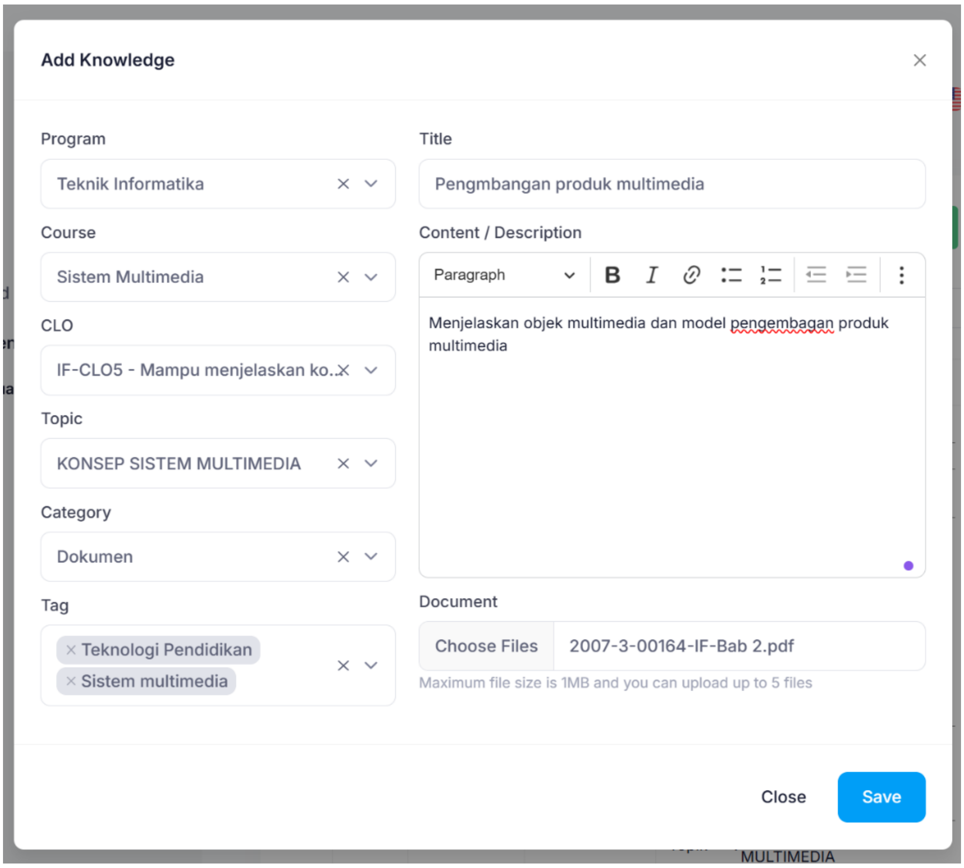
4.1.2 Knowledge Acquisition

After the arrangement of the OBE-based curriculum and syllabus is complete, the next step is knowledge acquisition. The acquisition of knowledge aims to provide knowledge that is suitable for learning needs. Knowledge is obtained from various sources, both internal and external to the organization. This acquisition process consists of uploading, scraping, summarisation, and knowledge contribution from industrial experts. This knowledge acquisition also represents the process of knowledge creation in Knowledge Management (KM), starting from the processes of socialisation, externalisation, combination, and internalisation.

a) Knowledge Externalisation

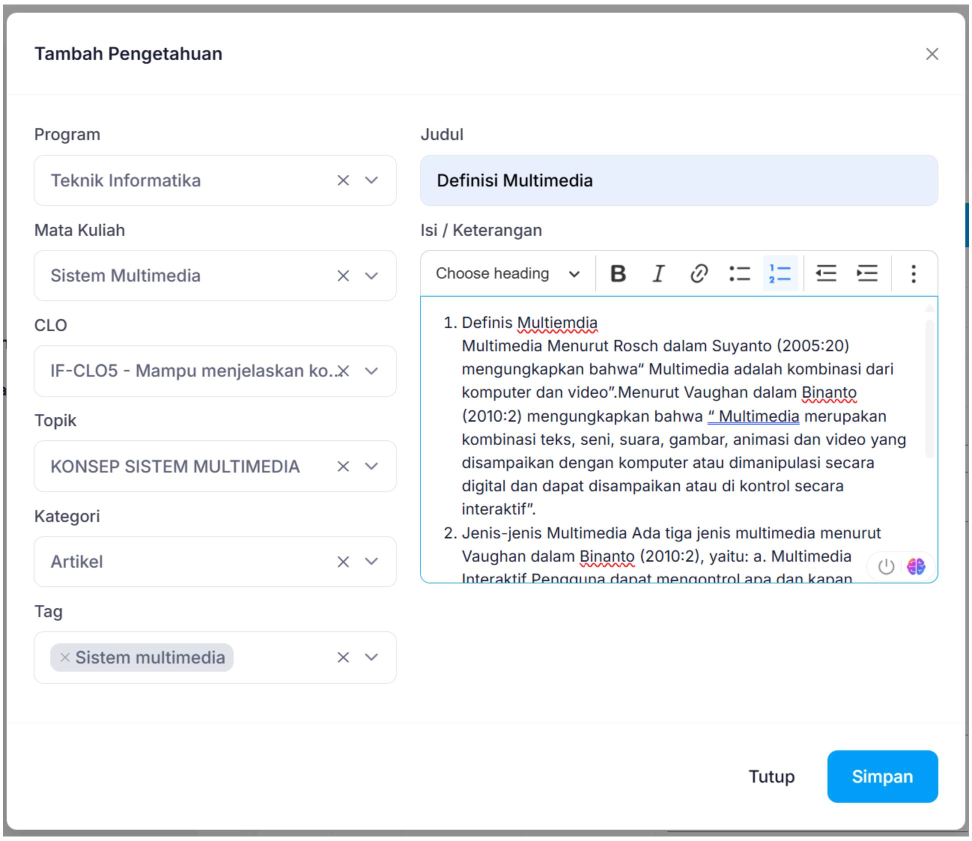
Knowledge acquisition in knowledge externalisation is represented through knowledge uploading. Knowledge structured as documents or articles is uploaded into the knowledge database. Figure 4.17 shows an example of knowledge acquisition for the uploading document.

Figure 4.17: Knowledge Uploading Category Document



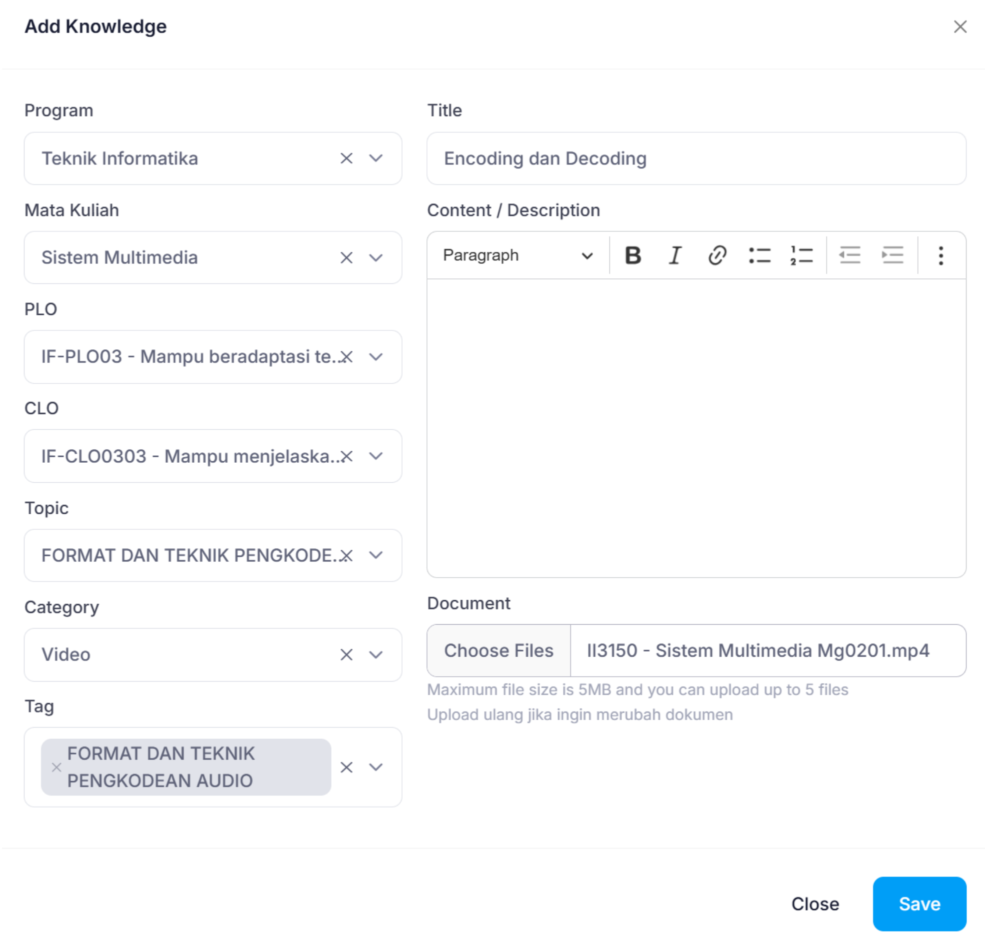
After the program, course, CLO, topics, and categories are selected, a lecturer can upload knowledge. The types of knowledge that can be uploaded can be in the form of documents, URLs, videos, and articles. A text area is provided for a lecturer and an expert to create an article and save the article in the knowledge database. Figure 4.18 shows an example of knowledge uploading for the article category.

Figure 4.18: Knowledge Uploading Category Article



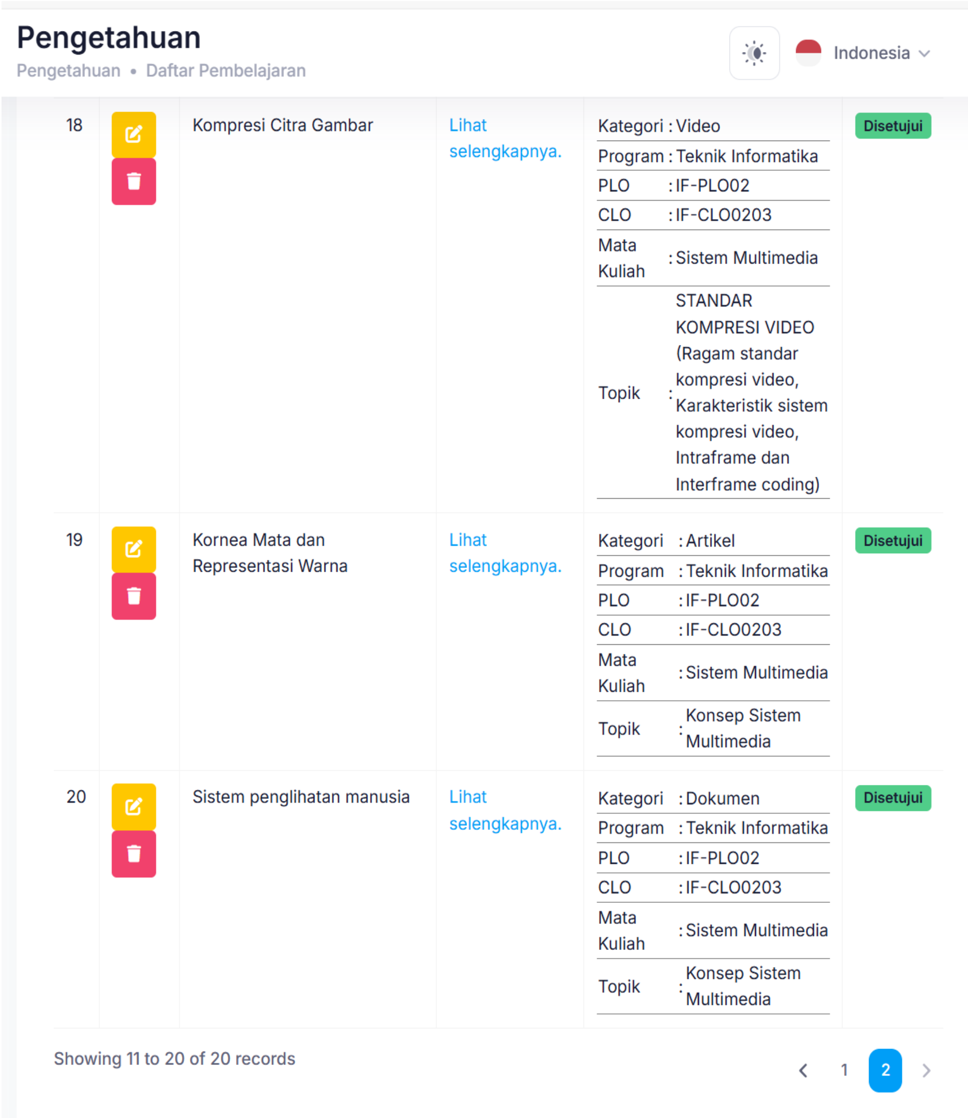
In addition to documents and articles, knowledge that can be uploaded into the KMS includes video categories. Figure 4.19 shows the acquisition of knowledge in video categories. After the program, course, CLO, topics, and categories are selected, a lecturer can upload knowledge. The category of knowledge that can be uploaded can be tutorial videos. Lecturers are required to provide a title and description in the designated text area.

Figure 4.19: Knowledge Uploading Video Category



The knowledge list page displayed all categories of knowledge uploaded into the KMS. Each piece of knowledge stored in the KMS database is accompanied by detailed information. The information includes categories of knowledge, programs, PLO, CLO, courses, and topics. Figure 4.20 shows the list of knowledge uploaded.

Figure 4.20: List of Knowledge Categories Examples that Have Been Uploaded



A lecturer uploading knowledge is an articulation of explicit knowledge (Alavi & Leidner, 2001; Nonaka, 1994). That knowledge is the result of pedagogical experience, and it is shared in the form of digital documents so that it can be read, understood, and become new knowledge for learners (Canonico et al., 2020; Mendoza et al., 2022; Nonaka & Takeuchi, 1995).

b) Knowledge Combination

The combination of knowledge in the knowledge acquisition process is represented through activities such as scraping, contributions from industry experts, and knowledge summarisation.

1. Knowledge scraping

The KMS scraping technique automatically extracts data from web pages using BeautifulSoup, a Python library for parsing HTML and XML. Table 4.2 presents an example of knowledge scraping from a web page using BeautifulSoup (Complete example in Appendix B).

Table 4.2: Example of Knowledge Scraping Results (Appendix)

Source of Knowledge (URL):
https://medium.com/@eman-lotfy-elrefai/how-to-build-arabic-audio-classifier-using-tensorflow-1986e3480a21
Scraping Results:
 Eman Elrefai Share In this tutorial, you'll learn how to deal with audio, train the model, test it, and develop using tensorflowjs. Are you eager to start? Let's start! This is the dataset used in building the project. When you check their website, you have two versions of the dataset: one is a sample with only 20 recordings and another is the complete dataset with about 9992 audio files.

For each audio, you'll find only one recorded word by 50 native speakers who repeated each word 10 times for 20 words in total. So the naming for the audio file can tell you about this information. For example this audio name: S01.02.05.wav. The first part is the speaker number from 1 to 50: S01, the second part is the repetition number from 1 to 10: 02 and the last part is the word number from 1 to 20: 05 . You can check the README file as well for more details.
Source of Knowledge (URL):
https://medium.com/syncedreview/googles-generative-video-compression-technique-outperforms-traditional-neural-video-compression-9e1ce361f715
Scraping Results:
Share While the increasing use of video streaming and conferencing has enabled new entertainment and remote work opportunities, efficiently lessening data transmission loads has proven challenging for most existing video compression techniques. Video compression is the process of reducing the total number of bits needed to store a video while preserving visual content quality by leveraging temporal and spatial redundancies. Recent research has demonstrated the promising potential of neural networks for this task, as they can outperform the more broadly used non-neural standard High Efficiency Video Coding (HEVC). In a new paper, a Google Research team takes a step forward in this field, proposing a neural video compression method based on generative adversarial networks (GANs) that outperforms previous neural video compression methods. The team summarizes their contributions as: The team's approach uses three strategies to obtain high-fidelity reconstructions: 1) Synthesize plausible details in the I-frame; 2) Propagate those details wherever

possible and as sharp as possible; 3) For new content appearing in P-frames, synthesize plausible details.

The proposed I-frame branch used to synthesize plausible details is based on a lightweight version of the architecture used in HiFiC, in which the encoder CNN maps the initial input image to a quantized latent. At a high level, the P-frame branch used to propagate those details comprises auto-encoders for both the flow and the residual. The team employs a powerful optical flow predictor network, UFlow, on the encoder side. The resulting flow outputs the quantized and entropy-coded flow-latent, while the generator predicts both a reconstructed flow and a confidence mask. Intuitively, this mask predicts the accuracy for each pixel in the flow, which is used to determine how much to blur the "scale-space blur" component described next.

The approach first warps the previous reconstruction with compressed flow using bicubic warping, then uses scale-space blurring — a light variation of the "scale-space flow" approach — to enable a more efficient implementation. Together, bicubic warping and blurring help to propagate sharper details and facilitate smoother blurring.

To synthesize plausible details in new content appearing in P-frames, the proposed approach employs the light version of the HiFiC architecture for residual auto-encoders, and introduces an additional source of information for the residual generator to enable it to synthesize high-frequency details from the residual latent.

The researchers also propose a technique to mitigate temporal error-accumulation problems, which is crucial for obtaining high visual quality. To this end, and motivated by a spectral analysis, they adopt a new training schema by randomizing the shifting of residual inputs followed by an un-shifting of the outputs.

The team evaluated their proposed model on 30 diverse videos from MCL-JCV, which include a wide variety of motion from natural videos, computer animation and classical animation. They compared their approach with baseline “MSE-only,” “Scale-Space Flow” (SSF), and the non-learned HEVC. They reported results based on non-overlapping 256×256 patches and the unsupervised perceptual quality Perceptual Information Metric (PIM), introduced by Bhardwaj et al. in 2020.

Overall, the study shows that the proposed method is competitive to HEVC and outperforms previous neural video compression codecs, validating the promising potential of GANs for improving video compression performance.

The paper Towards Generative Video Compression is on arXiv.

Author: Hecate He | Editor: Michael Sarazen, Chain Zhang

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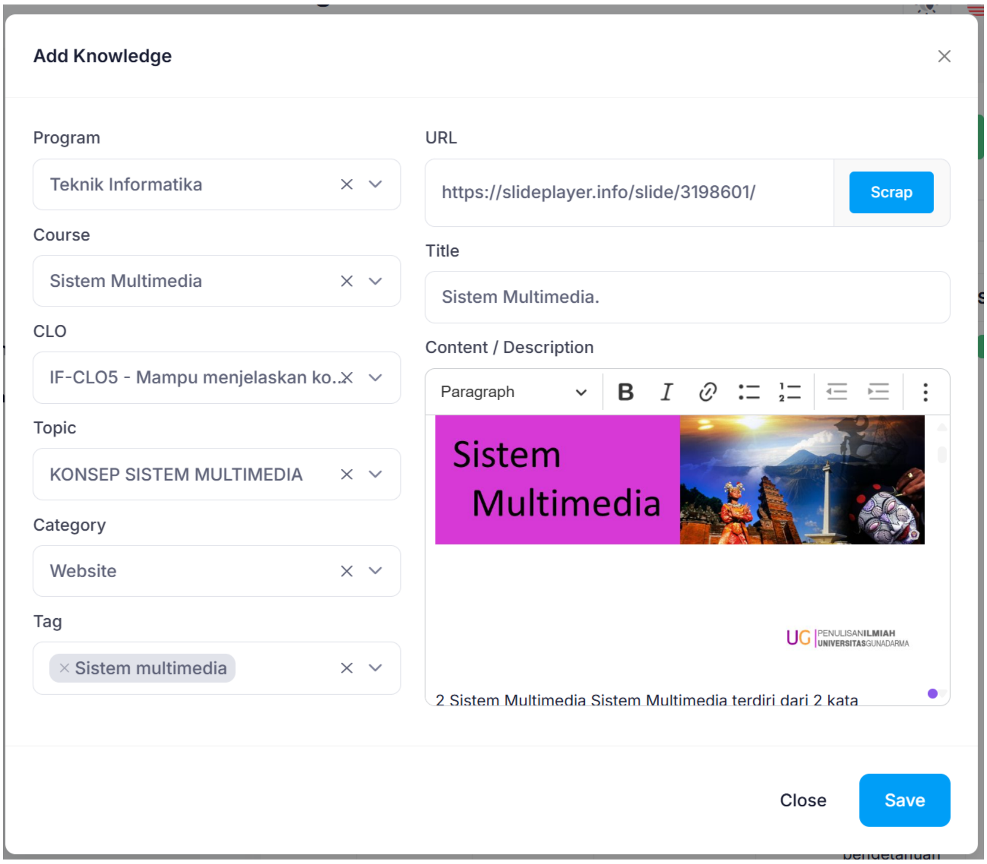
After selecting the program, course, CLO, topics, category, and tags, the essential part of knowledge scraping is the selection of the category. The website category can be chosen to start knowledge scraping. The user fills in the URL (uniform resource locator) or website address in the provided column by adding a title. The knowledge document resulting from scraping will be displayed in a text area and can then be saved in the knowledge database. Figure 4.21 Shows knowledge scraping in KMS.

Figure 4.21: Knowledge Scraping

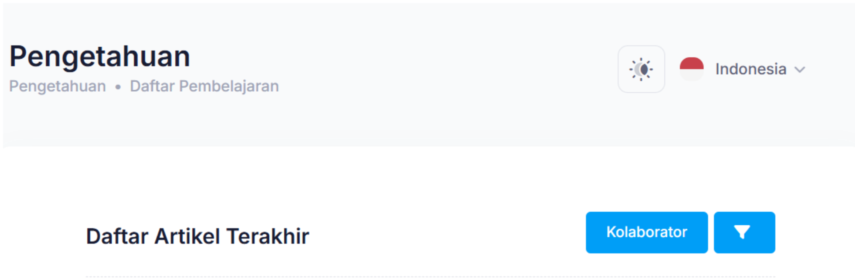


The amount of knowledge available in online media is vast. Containing structured knowledge from research and best practices, knowledge in online media needs to be optimized as one of the knowledge sources within organizations (Avdeenko et al., 2016; Córdova & Gutiérrez, 2018; Supic, 2018). KMS leverages big data to provide significant advantages. Knowledge is obtained from various sources, processed more flexibly, and easily integrated and combined. (Sumbal et al., 2021).

2. Knowledge Collaboration

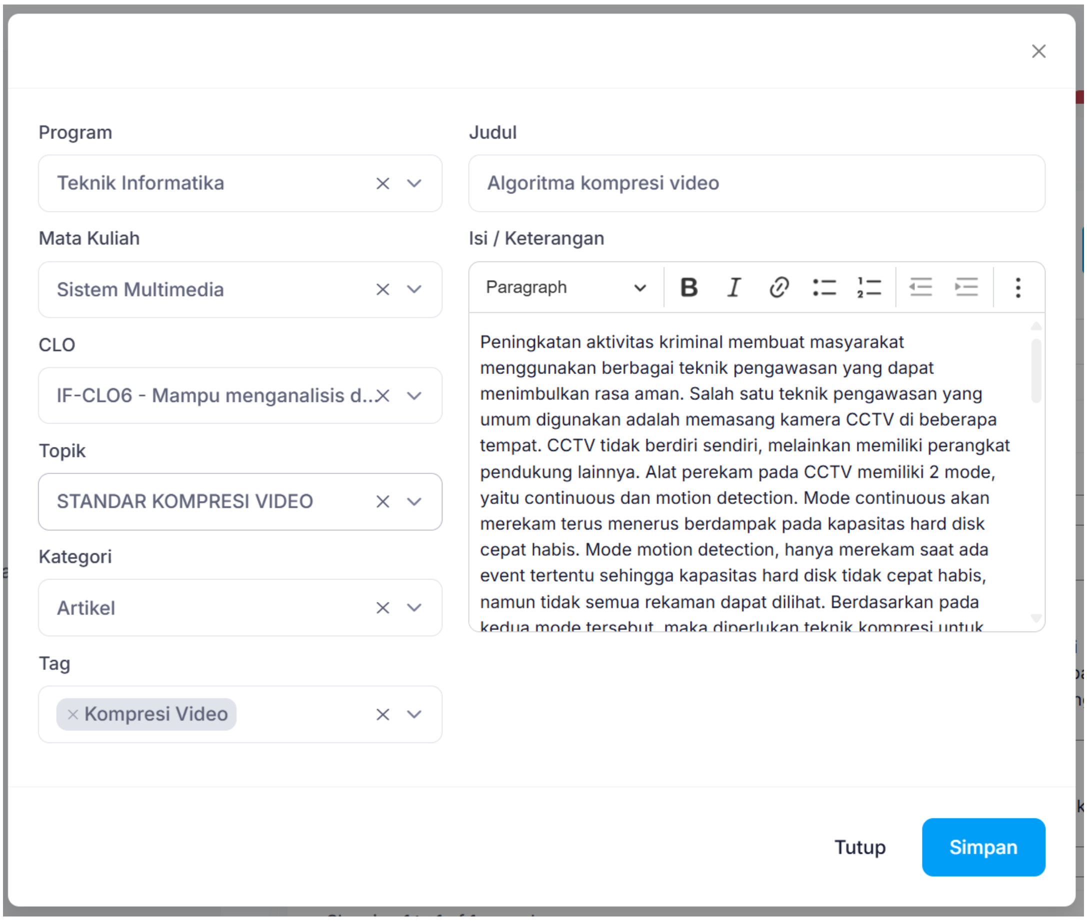
Knowledge of KMS is derived from external organisations. Acquisition of knowledge from an expert or industrial expert is a form of collaboration and implementation of HEI cooperation with industry. HEI internally determines expert criteria. The frontend system section provides knowledge collaboration with industry experts. Figure 4.22 shows the frontend system display of the knowledge collaboration.

Figure 4.22: Initial Display of Knowledge Collaboration



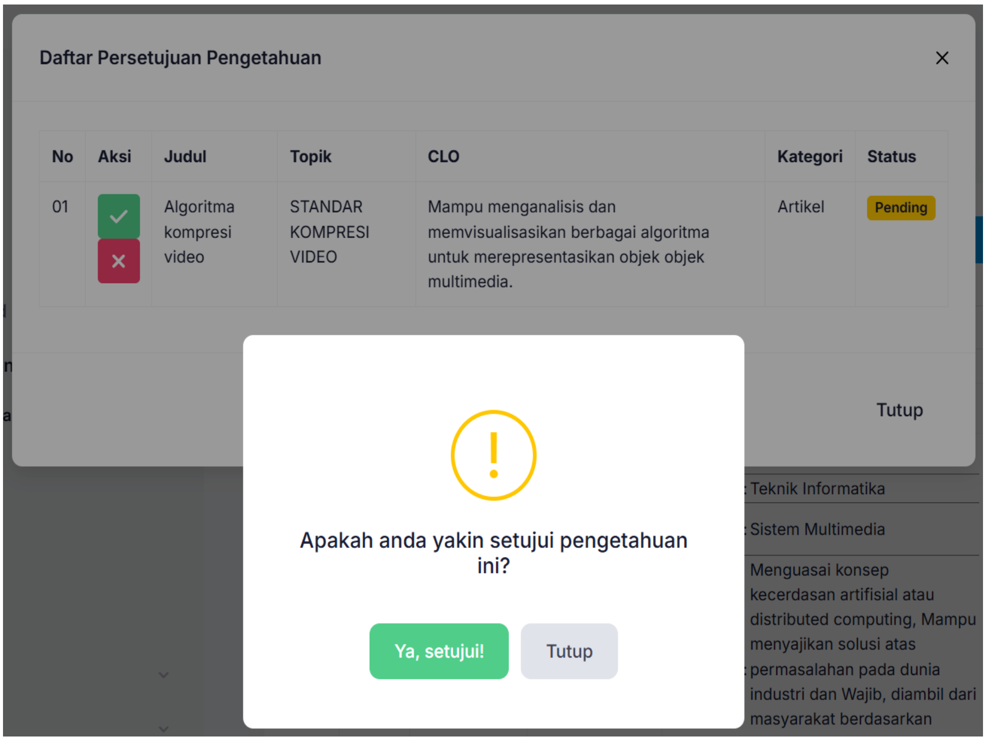
Industrial experts can contribute their knowledge to the KMS by clicking on the collaborator menu. Figure 4.23 shows the details of knowledge collaboration.

Figure 4.23: Details of Knowledge Collaboration



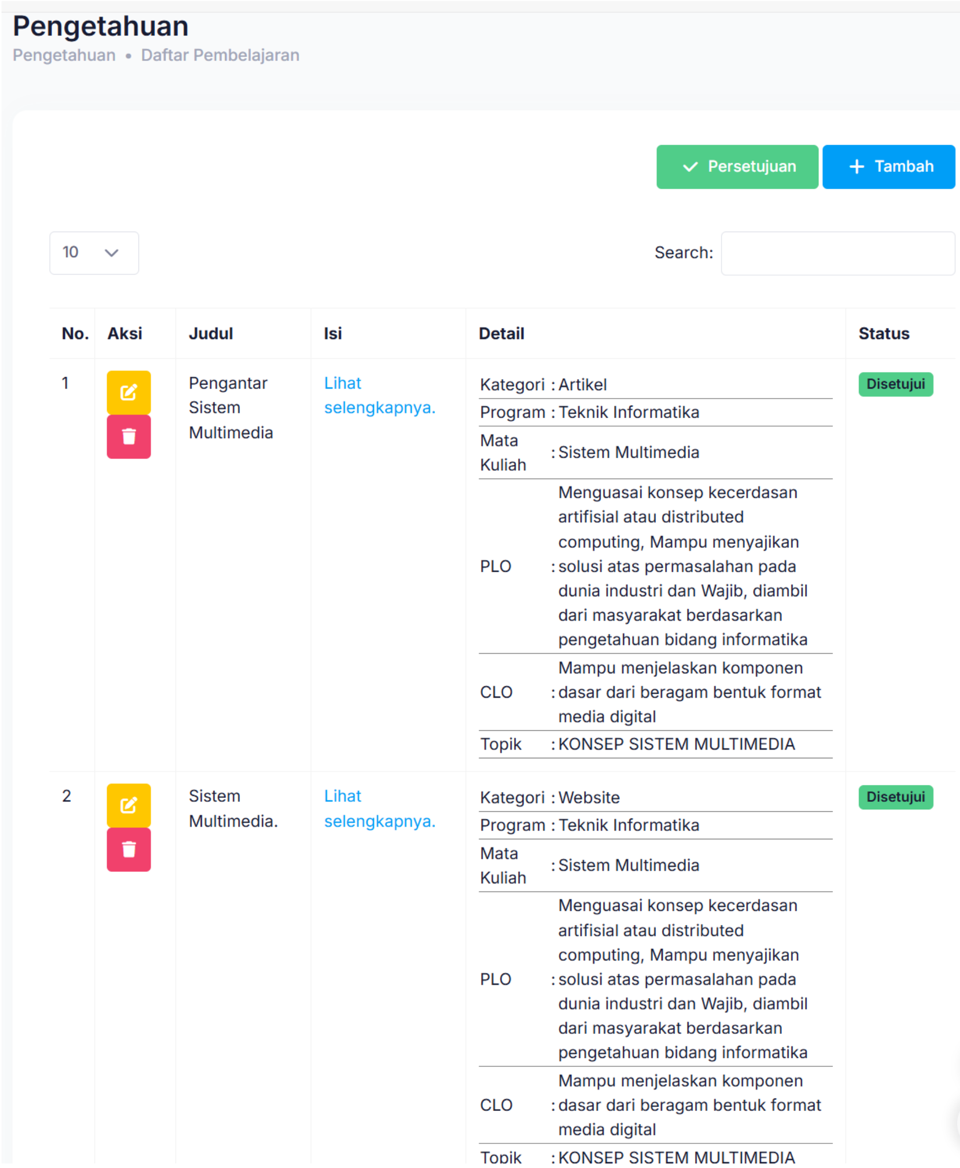
Admin approval is required to display and store knowledge resulting from a contribution by an expert so that it can be saved in the KMS. The status of the knowledge contributed by an expert will be "Pending" if the admin has not yet approved it. Figure 4.24 shows the approval of the knowledge document resulting from the collaboration.

Figure 4.24: Approval of the Knowledge Document Resulting from the Collaboration



All the acquired knowledge will be displayed in both the system's backend and front end. Figure 4.25 shows the knowledge already available in the KMS database.

Figure 4.25: List of Knowledge (example)



The knowledge creation cycle in KMS involves experts from the industry (Córdova & Gutiérrez, 2018). The addition of knowledge by industry experts to KMS plays a vital role in reducing the knowledge gap between HEIs and the industry. Collaboration between higher education institutions and industry is the key to successfully building a learning environment within organisations. (Galeon & Palaoag, 2019).

Table 4.3 explains the summary of the knowledge acquisition results that align with the learning needs of learners in the KMS.

Table 4.3: Summary of Knowledge Acquisition Results (Example)

No	KM Processes	Knowledge Acquisition Processes	File Name	Status	
				Success	Failed
1	Knowledge Externalisation	Knowledge uploading	Multimedia definition	✓	
			Multimedia product development	✓	
			Introduction to multimedia systems	✓	
			Encoding and Decoding	✓	
			Sampling and quantaization	✓	
			Images compression	✓	
2	Knowledge Combination	Knowledge scraping	Multimedia systems	✓	
			Images compression	✓	
			Video compression	✓	
			Audio compression	✓	
			Audio representation	✓	

No	KM Processes	Knowledge Acquisition Processes	File Name	Status	
				Success	Failed
			Image compression techniques	✓	
			Huffman coding algorithm	✓	
			Aritmetic coding algorithm	✓	
			LZW algorithm	✓	
			Shanon Fano algorithm	✓	
		Knowledge adding (Collaboration with industrial expert)	Steganografi	✓	
			Multiemdia streaning	✓	
			Digital right management	✓	
			Audio compression algorithm	✓	

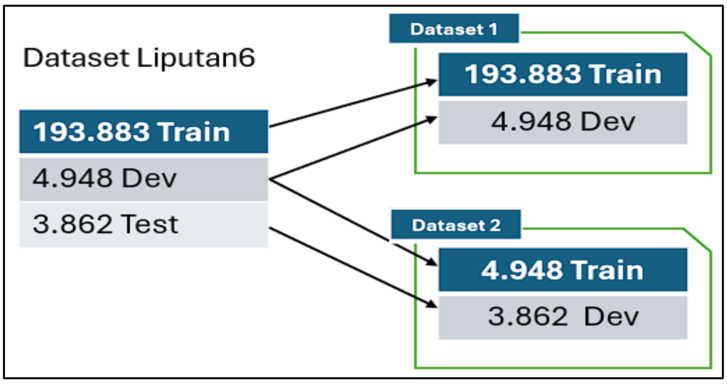
2. Summarisation of knowledge

The combination of knowledge is also represented in the KMS by the automatic summarisation function of knowledge sources. The automatic ranking function is developed through several stages, including data set preparation, preprocessing, and evaluation.

a. Data set preparation

The Liputan6 dataset is an Indonesian-language dataset used in the training and evaluation of the BERT2BERT model. This dataset consists of 193,883 data points, which are divided into two datasets, dataset1 and dataset2. Each document in this dataset includes article text, extractive summaries, and abstractive summaries. Figure 4.26 shows the division of the liputan6 dataset.

Figure 4.26: Data Division



In the Liputan6 training dataset, the number of words in article documents ranges from 31 to 6,570, with an average of 195.74 words, a mode of 121 words, and a median of 163 words. Meanwhile, the reference documents for abstractive summaries range from 11 to 80 words, with an average of 27.08 words, a mode of 27 words, and a median of 27 words.

b. Tokenizing data

Tokenisation is part of data preparation. The training dataset is used to train the model, with the article text as features and the abstract summary text as labels. Table 4.4 shows examples of the results from the data tokenisation process (Complete example in Appendix C).

Table 4.4: Example of Tokenised Data Results (Appendix)

Type	Article	Tokenized data bert2bert		Tokenized Data Bert2bert Xtreme	
2-doc	[Doc 1] Web developer memiliki peran yang semakin krusial dalam dunia digital yang terus berkembang. Dengan munculnya teknologi baru seperti Web3, AI, dan AR/VR, masa depan profesi ini menuntut kemampuan untuk beradaptasi dan mempelajari keterampilan baru.	[[3, 4362, 26445, 1842, 3631, 1497, 2718, 19015, 1558, 1950, 6559, 1497, 2402, 3522, 18, 1545, 7748, 3279, 1836, 1730, 4362, 964, 16, 11559, 16, 1501, 1680, 19, 64, 934,	[[1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,	[[3, 4362, 26445, 1842, 3631, 1497, 2718, 19015, 1558, 1950, 6559, 1497, 2402, 3522, 18, 1545, 7748, 3279, 1836, 1730, 4362, 964, 16, 11559, 16, 1501, 1680, 19, 64, 934,	[[1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,

	Developer tidak hanya dituntut untuk membangun website yang responsif, tetapi juga menciptakan pengalaman interaktif yang lebih imersif. Seiring dengan meningkatnya permintaan untuk solusi digital yang inovatif, profesi web developer diprediksi akan tetap relevan, namun membutuhkan kesiapan untuk terus berkembang bersama teknologi. [Doc 2] Profesi web developer akan mengalami revolusi besar seiring dengan berkembangnya tren teknologi seperti Progressive Web Apps (PWA), machine learning, dan blockchain. Dalam	16, 2106, 2616, 4256, 1540, 4581, 3378, 1559, 17371, 1501, 5897, 9463, 1836, 18, 26445, 1580, 1821, 9643, 1559, 3500, 8479, 1497, 27698, 955, 16, 1925, 1614, 4262, 4167, 11313, 1497, 1716, 18513, 31735, 4517, 18, 6165, 1545, 9834, 4816, 1559, 6920, 6559, 1497, 17867, 16, 4256, 4362, 26445, 14831, 1634, 2261, 10936, 16, 1853, 4712,	1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,	16, 2106, 2616, 4256, 1540, 4581, 3378, 1559, 17371, 1501, 5897, 9463, 1836, 18, 26445, 1580, 1821, 9643, 1559, 3500, 8479, 1497, 27698, 955, 16, 1925, 1614, 4262, 4167, 11313, 1497, 1716, 18513, 31735, 4517, 18, 6165, 1545, 9834, 4816, 1559, 6920, 6559, 1497, 17867, 16, 4256, 4362, 26445, 14831, 1634, 2261, 10936, 16, 1853, 4712,	1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,

	beberapa tahun ke depan, pengembang web tidak hanya perlu menguasai bahasa pemrograman tradisional, tetapi juga memahami konsep-konsep seperti keamanan data, interkoneksi aplikasi, dan pengoptimalan AI. Dengan kemajuan ini, web developer memiliki peluang besar untuk menciptakan inovasi yang tidak hanya mendukung bisnis, tetapi juga mempercepat transformasi digital di berbagai sektor.	13680, 1559, 2402, 3522, 2113, 3279, 18, 4256, 4362, 26445, 1634, 2803, 4499, 1819, 6165, 1545, 14546, 13110, 3279, 1730, 29755, 10084, 4362, 8408, 944, 12, 20009, 936, 13, 16, 25581, 11961, 16, 1501, 17511, 11507, 1488, 18, 1558, 1841, 1620, 1500, 2616, 16, 11987, 4362, 1580, 1821, 2506, 5180, 2097, 15967, 4263, 16, 1925, 1614, 4720,	1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1]]	13680, 1559, 2402, 3522, 2113, 3279, 18, 4256, 4362, 26445, 1634, 2803, 4499, 1819, 6165, 1545, 14546, 13110, 3279, 1730, 29755, 10084, 4362, 8408, 944, 12, 20009, 936, 13, 16, 25581, 11961, 16, 1501, 17511, 11507, 1488, 18, 1558, 1841, 1620, 1500, 2616, 16, 11987, 4362, 1580, 1821, 2506, 5180, 2097, 15967, 4263, 16, 1925, 1614, 4720,	1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1]]

		3618, 17, 3618, 1730, 3492, 3145, 16, 2065, 15537, 2637, 5952, 16, 1501, 1602, 17107, 1696, 11559, 18, 1545, 5942, 1540, 16, 4362, 26445, 1842, 4617, 1819, 1559, 4262, 9602, 1497, 1580, 1821, 3669, 3567, 16, 1925, 1614, 10436, 13036, 6559, 1485, 2190, 4044, 18, 4]]		3618, 17, 3618, 1730, 3492, 3145, 16, 2065, 15537, 2637, 5952, 16, 1501, 1602, 17107, 1696, 11559, 18, 1545, 5942, 1540, 16, 4362, 26445, 1842, 4617, 1819, 1559, 4262, 9602, 1497, 1580, 1821, 3669, 3567, 16, 1925, 1614, 10436, 13036, 6559, 1485, 2190, 4044, 18, 4]]	

c. Results of abstractive multi-document knowledge summarisation for the Indonesian language

Table 4.5 presents the results of automatic multi-document knowledge summarisation in the Indonesian language using the Bert2Bert and Bert2Bert+Xtreme models (Complete example in Appendix D). Each model produces fairly good document summarisation results, whether for two or three knowledge documents.

Table 4.5: Example of Abstractive Multi-Document Knowledge Summarisation Results for the Indonesian language

Type	Articles	Bert2Bert	Bert2Bert+Xtreme
2-Doc	[Doc 1] Kecerdasan buatan (AI) telah menjadi bagian integral dari kehidupan sehari-hari kita, mulai dari asisten virtual seperti Siri dan Google Assistant hingga sistem rekomendasi di platform seperti Netflix dan Amazon. AI memungkinkan mesin untuk belajar dari data, mengenali pola, dan membuat keputusan dengan sedikit intervensi manusia. Dalam aplikasi sehari-hari, AI digunakan untuk meningkatkan efisiensi dan kenyamanan pengguna. Misalnya, algoritma pencarian Google menggunakan AI untuk memberikan hasil yang paling relevan dengan pertanyaan pengguna. Di media sosial, AI	kecerdasan buatan (ai) telah menjadi bagian integral dari kehidupan sehari - hari kita, mulai dari asisten virtual seperti siri dan google assistant hingga sistem rekomendasi di platform seperti netflix dan	kecerdasan buatan (ai) telah menjadi bagian integral dari kehidupan sehari - hari. ai memungkinkan mesin belajar dari data, mengenali pola, dan membuat keputusan

Type	Articles	Bert2Bert	Bert2Bert+Xtreme
	digunakan untuk mempersonalisasi umpan berita berdasarkan preferensi pengguna dan interaksi sebelumnya. [Doc 2] Dalam industri transportasi, mobil otonom menggunakan AI untuk memproses data dari sensor dan kamera untuk menavigasi jalan secara aman. Ini melibatkan teknik pembelajaran mendalam (deep learning) dan jaringan saraf tiruan (neural networks) untuk mengenali objek di sekitar kendaraan dan membuat keputusan mengemudi yang tepat. AI juga digunakan dalam aplikasi navigasi seperti Google Maps untuk memberikan rute tercepat berdasarkan kondisi lalu lintas terkini.	amazon. ai memungkinkan mesin untuk belajar dari data, mengenali pola, dan membuat keputusan dengan sedikit intervensi manusia.	dengan sedikit intervensi manusia.
3-Doc	[Doc 1] Keamanan siber telah menjadi isu kritis di era digital ini, mengingat meningkatnya jumlah serangan siber yang menargetkan individu, perusahaan, dan bahkan pemerintah. Ancaman siber dapat datang dalam berbagai bentuk, termasuk malware, phishing, ransomware, dan serangan	ancaman siber dapat datang dalam berbagai bentuk, termasuk malware, phishing, ransomware, dan	ancaman siber kini menjadi isu serius di era digital ini. hal ini disebabkan oleh

Type	Articles	Bert2Bert	Bert2Bert+Xtreme
	DDoS (Distributed Denial of Service). Malware adalah perangkat lunak berbahaya yang dirancang untuk merusak, mengganggu, atau mendapatkan akses tidak sah ke sistem komputer. Phishing adalah teknik penipuan yang digunakan untuk memperoleh informasi sensitif, seperti kata sandi atau nomor kartu kredit, dengan menyamar sebagai entitas tepercaya dalam komunikasi elektronik. [Doc 2] Ransomware adalah jenis malware yang mengenkripsi data korban dan meminta tebusan untuk memulihkan akses. Serangan DDoS melibatkan membanjiri server dengan lalu lintas internet yang berlebihan, sehingga menyebabkan gangguan atau penghentian layanan. Serangan-serangan ini dapat mengakibatkan kerugian finansial yang signifikan, hilangnya data berharga, dan kerusakan reputasi. Oleh karena itu, penting untuk	serangan ddos (distributed denial of service).	meningkatnya jumlah serangan siber yang menargetkan individu, perusahaan, dan negara.

Type	Articles	Bert2Bert	Bert2Bert+Xtreme
	mengembangkan strategi keamanan siber yang efektif untuk melindungi sistem dan data dari ancaman ini. [Doc 3] Salah satu solusi utama untuk meningkatkan keamanan siber adalah dengan menerapkan langkah-langkah keamanan yang kuat, seperti enkripsi data, firewall, dan sistem deteksi intrusi. Enkripsi data memastikan bahwa informasi sensitif diubah menjadi bentuk yang tidak dapat dibaca oleh pihak yang tidak berwenang. Firewall bertindak sebagai penghalang antara jaringan internal dan jaringan eksternal, memfilter lalu lintas yang mencurigakan. Sistem deteksi intrusi (IDS) digunakan untuk memantau jaringan dan mendeteksi aktivitas mencurigakan atau tidak sah.		

d. Readability Evaluation Results

The readability evaluation of the knowledge document summarisation results was conducted using two approaches: automatic and manual. Figures 4.27 shows automatic evaluation using the Flesch-Kincaid Grade Level (FKGL) method (Onwuegbuzie et al., 2013; Salihah et al., 2020) and the Gunning Fog Index (GFI) (Djaber et al., 2023; Yaffe, 2022). Table 4.6 explains the evaluation using Dwiyanto Djoko Pranowo metrics (Pranowo, 2011). Meanwhile, the manual evaluation by a single Indonesian language expert is discussed at the end of the evaluation section.

1. FKGL and GFI Test

The visualisation of the readability evaluation results is shows in Figure 4.27.

Figure 4.27: FKGL and GFI Evaluation Result

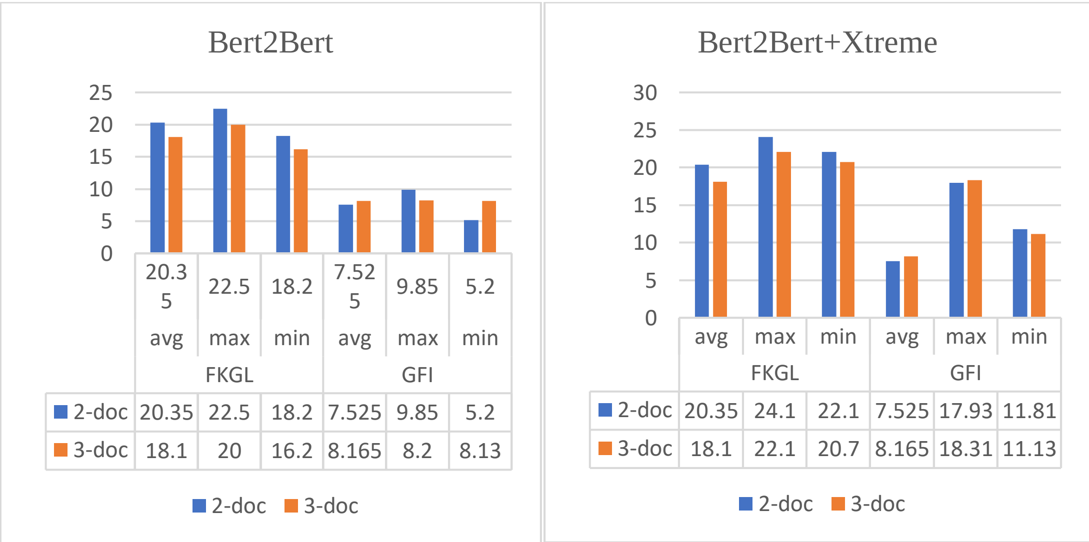


Figure 4.27 shows the evaluation results of FKGL and GFI for the Bert2Bert models in summarising the knowledge of 2 and 3 documents. Based on the FKGL evaluation results, each document received an

average score of 20.35 and 18.1. This average score indicates that the summaries of the knowledge documents are challenging to read, requiring or being suitable for individuals with an advanced education level (Jacobs et al., 2024; Kianian et al., 2024; Maylawati et al., 2019b; Molher et al., 2021). In contrast to the FKGL scores, the average GFI scores for the summaries of each document were 7.52 and 8.165. Based on these average scores, the summaries of the knowledge documents are easy to understand and suitable for the general reader (Aljawi & Hantzakos, 2024; Maylawati et al., 2019b; Świeczkowski & Kułacz, 2021).

In general, the results of the FKGL and GFI evaluations can be understood by the adult age group. This is because the knowledge source for the model testing is educational documents at the university level, and the readers are adults (Aljawi & Hantzakos, 2024; Jacobs et al., 2024; Maylawati et al., 2019; Salihah et al., 2020). Adult readers can mostly accept the FKGL and GFI assessment results.

2. Dwiyanto's Evaluation of Bert2Bert

In addition to FKGL and GFI, the Dwiyanto Djoko Pranowo metric is used. The Dwiyanto Djoko Pranowo metric is used to measure the readability of knowledge documents in Indonesian. The evaluation results indicate that the summaries from Bert2Bert fall within a moderate readability range, precisely 20.33 and 32.2.

Table 4.6: Dwiyanto's Evaluation Results of Bert2Bert Model

Indicators	Bert2Bert	
	2 docs	3 Docs
	Average of Dwiyanto's Score	
1. Paragraph	1.00	1.00
2. Sentence Count	1.5	1.5
3. Sentence Length	23.5	19.25
4. Extension	0.71	0.72
5. Compound	0.76	0.73
6. Polysemy	0.75	0.75
7. Passive Sentence	0.58	0.61
8. Unfamiliar Word	0.01	0.01
9. Abstract Word	0.71	0.71
10. Terms	0.77	0.75
11. Conjunctions	0.68	0.69
12. Loan	0.70	0.70
13. Phrase	0.54	0.57
Dwiyanto's Total Score	32.2	27.99

The results indicate that the multi-document summary of Indonesian knowledge using Bert2Bert and Bert2Bert+Xtreme is well-read and still comprehensible. In line with the FKGL and GFI results, the summary is still understandable, as the documents used are knowledge documents at the higher education level, which adults consume.

3. Human readability evaluation result

This research involved an expert in the Indonesian language to evaluate the readability of the summary results. All evaluators have agreed to participate voluntarily and without any conflicts of interest. Their declaration statement is included in Appendix A. Evaluators are required to read and complete the evaluation instruments that have been prepared. The evaluation form includes objectives, instructions, a summary of the results from Bert2Bert and Bert2Bert+Xtreme, and questions aimed at assessing the readability of Indonesian text. The results of the human readability evaluation are categorized based on questions. There are five questions related to the readability of Indonesian texts, collected from various references, as listed below.

1) Question 1 (Q1): Which summary is easier to read? (Which summary is easier to read?). This question aims to gather opinions on which summary content is easier to read. The response evaluator will influence their answers to the next question. There are three options available for this question: Bert2Bert, Bert2Bert+Xtreme, or both.
2) Question 2 (Q2): What is the readability level of the summary you chose in question 1? This question aims to gauge the evaluator's opinion on the readability of the summary selected in Question 1. This question offers three options: Readable, Partially readable, or Unreadable (Verma & Om, 2019). "Readable" indicates that the summary conveys a precise meaning, allowing the reader to understand the main ideas or events related to the topic. "Partially

readable" means that only part of the summary can be understood, enabling the reader to grasp the main idea. "Unreadable" means that the reader struggles to understand the main idea of the summary.

3) Question 3 (Q3): Does the summary result you choose in Question 1 focus on the main topic? This question aims to determine whether the evaluator believes the content of the summary aligns with the news topic. The news topic categories are taken from the Liputan6 dataset. In this study, the evaluator will answer "Yes" if they feel the summary is related to the topic and "No" if they feel it is not related (Verma & Om, 2019).
4) Question 4 (Q4): Are all the sentences in the summary you selected related to each other? (This question aims to evaluate the coherence between sentences in the summary, which is an indicator of the text's readability. The answer choices are "Yes" and "No." "Yes" indicates that the summary has good coherence between sentences, while "No" indicates a lack of connection between sentences.) (Verma & Om, 2019). 5. Question 5 (Q5): Does the summary result you chose in Question 1 contain incomplete sentences (lacking Subject, Predicate, and Object)?). This question aims to determine whether the generated summary includes complete sentence attributes, ensuring that the text is structurally sound and easy to understand. The evaluator will respond "Yes" if the summary contains complete sentence attributes and "No" if it does not.

Figures 4.28 and 4.29 show the summary of readability test documents resulting from summarisation by only one Indonesian language expert. Figure 4.28 shows the evaluation results of the readability of multiple documents (two documents) based on the knowledge obtained from the summarisation. Based on the summarisation experiments conducted 20 times, Indonesian language experts provided feedback indicating that 75% of the summaries produced using the Bert2Bert model were more accessible to read, 90% of the summarisations were readable, 85% of the summaries were relevant to the topic, 80% of the summaries had good coherence between sentences, and 80% of the summaries contained complete sentence attributes.

Figure 4.28: Readability Evaluation Results of 2 Knowledge Documents

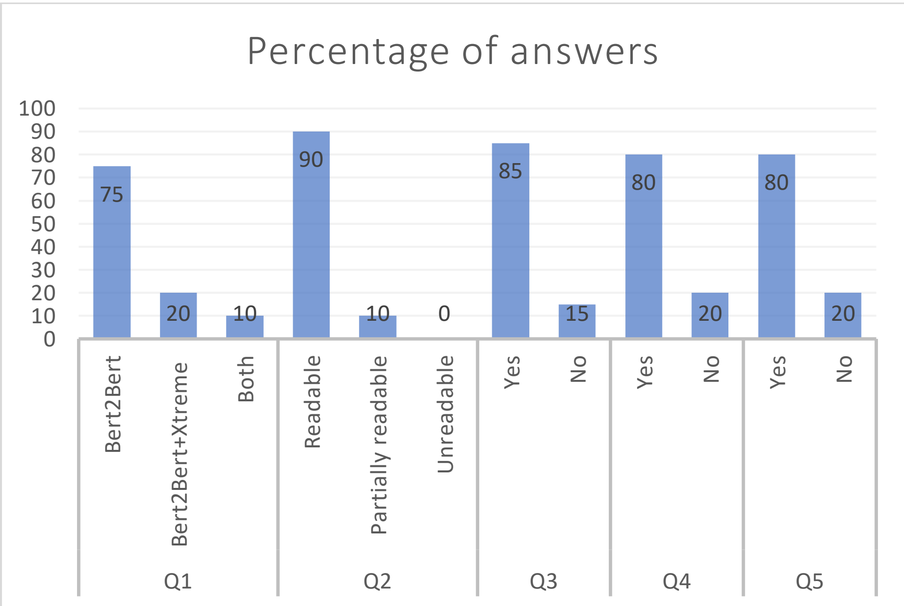
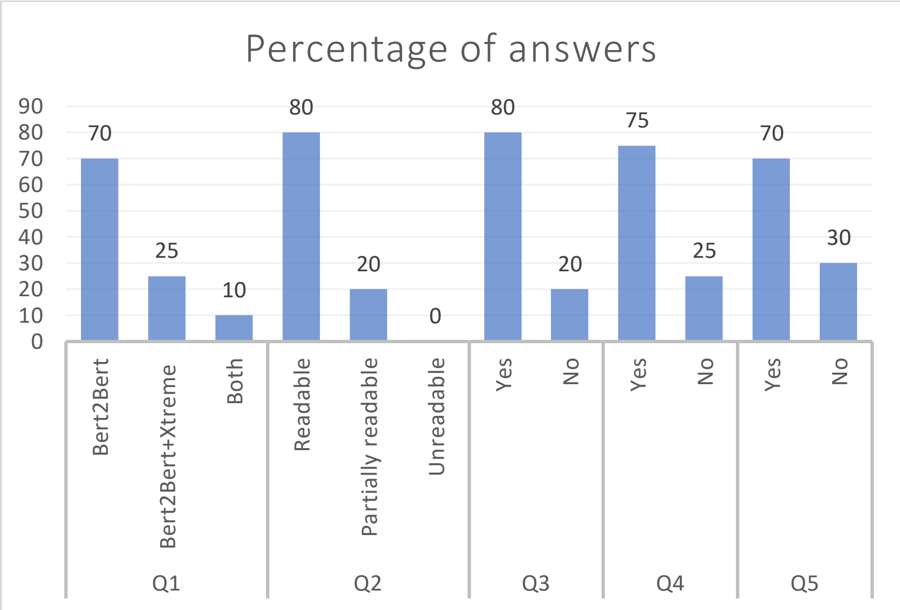


Figure 4.29 shows the results of the readability evaluation of multi-documents (three documents) regarding the knowledge obtained from summarisation.

Figure 4.29: Readability Evaluation Results of 3 Knowledge Documents



Based on the 20-time summarisation experiments, Indonesian language experts provided feedback indicating that 70% of the summaries using the Bert2Bert model were easier to read, 80% were readable, 80% were relevant to the topic, 75% had good coherence between sentences, and 70% contained complete sentence attributes.

4. Results of knowledge document summarisation in KMS

Summarisation of knowledge documents in KMS using the BERT2BERT Model. Knowledge summarisation in KMS supports the learning process for students, making it easier to obtain multiple knowledge documents from various sources. Lecturers or students can select knowledge available in the database and process it to generate summaries. Figure 4.30 shows the knowledge summarisation function in KMS.

Figure 4.30: Multi-document Knowledge Summarisation

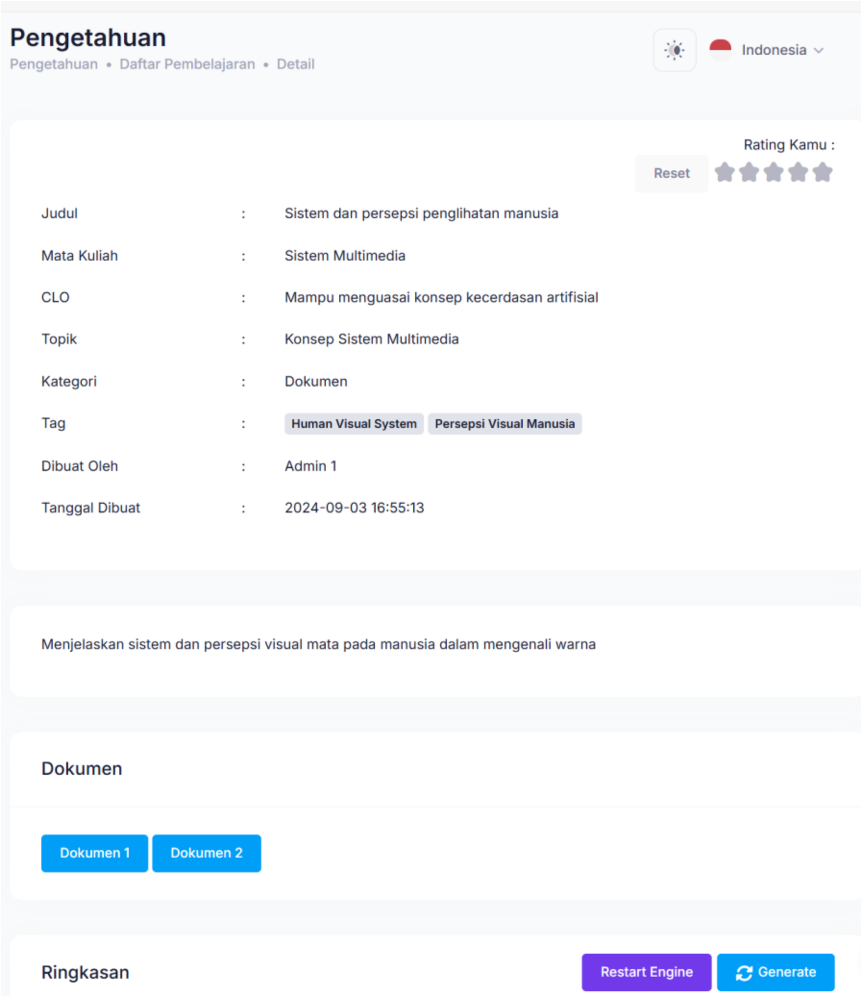
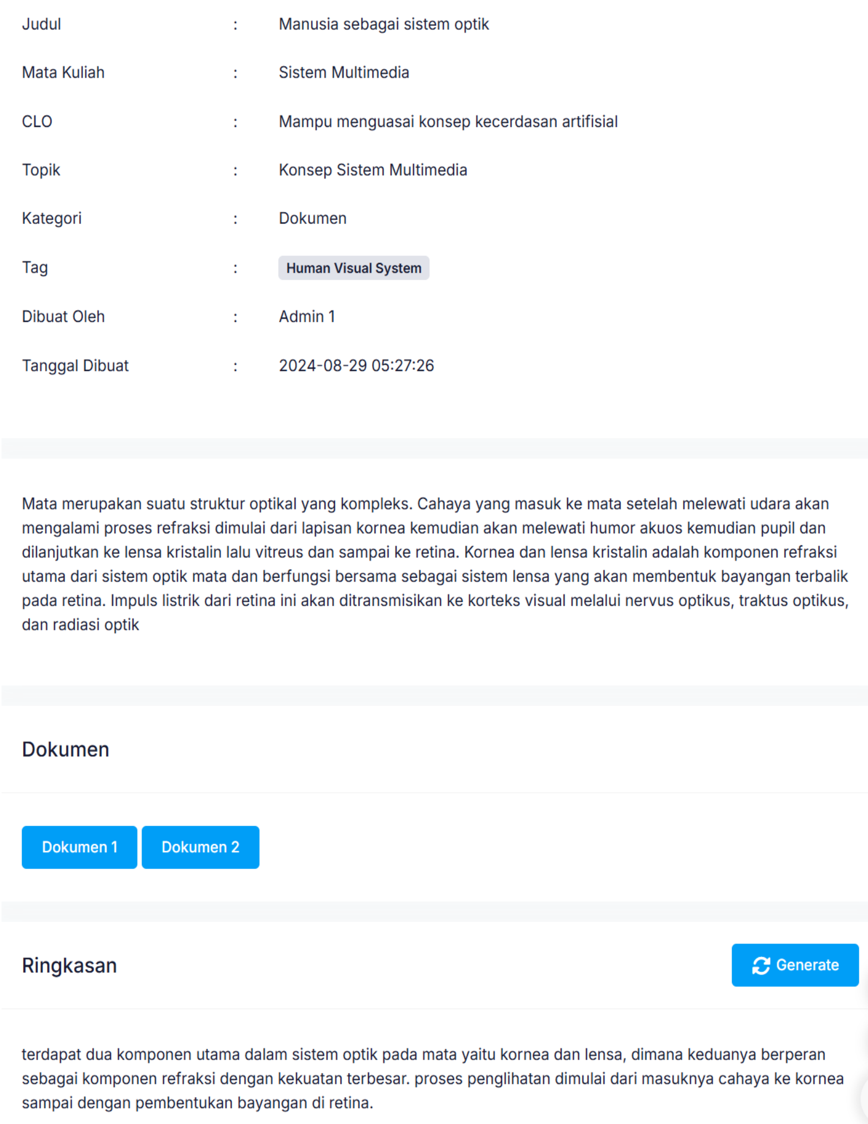


Figure 4.31: Shows an Example of Multi-document Knowledge Summarisation in the KMS



The summary details displays knowledge information, consisting of the title, course, CLO, topics, and knowledge categories. The function of multi-document automatic summarisation is to generate knowledge summaries that are easy to read and understand as shows in Figure 4.31.

Knowledge summarisation in KMS aims to facilitate the reading of knowledge from a single document or multiple documents. Users can choose the knowledge documents that will be summarized. The summarisation results will be displayed in the text area of the 'Summary' menu. The results prove that the use of AI technology in the automatic summarisation of knowledge documents in KMS has a significant impact on the knowledge combination process (Shen et al., 2023). In addition to being used in automatic document summarisation, the BERT model is also utilized to assess teacher performance. The combination of educational psychology, artificial intelligence, and language processing, the results of BERT's analysis present an example of how tacit knowledge can be articulated and transformed into explicit knowledge (W. Li et al., 2024).

The primary goal of KMS development is to create a relevant knowledge base in a specific field to support the implementation of OBE in HEIs. This phase serves as the preparation for learning or the backend system and is divided into two parts: the arrangement of the OBE curriculum and knowledge acquisition. The stages of organizing the OBE curriculum, from setting the PLO to arranging assessments, have been represented in the KMS. Knowledge acquisition in the KMS represents the relevant knowledge needed to support the learning process within the OBE curriculum framework. The automatic multi-document summarisation of knowledge in Indonesian within the KMS produces content that is easy for learners to read and understand. Knowledge acquisition in the KMS reflects the processes of externalisation and combination of knowledge in KM.

Knowledge and assessments based on the OBE curriculum in the learning preparation phase are utilized during the implementation phase of learners learning. The implementation of learning is part of the KMS frontend system, which represents the process of internalizing knowledge in KM. The second part of the results and discussion of the research explains the implementation of learning, consisting of the initiation process and evaluation of learning outcomes.

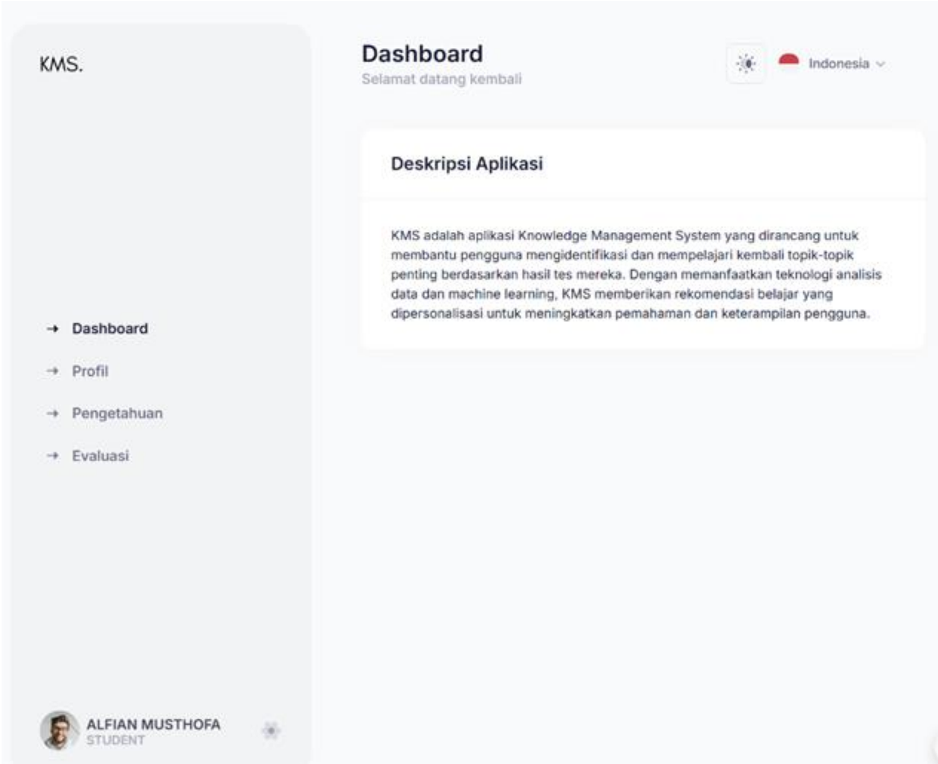
4.2 Learning Analytics Developed for KMS in Order to Support the Implementation of OBE in HEI

This section discusses how the implementation of learning takes place. The implementation of learning is the frontend system of KMS, with the main users being learners. The implementation of learning is divided into two main parts: course initiation and evaluation. The evaluation activities of learning are divided into two main activities: assessment and analytics. The implementation of learning is a representation of the internalisation of knowledge in KM.

4.2.1 Knowledge Internalisation Process

Explicit knowledge that is available in the system is transformed into implicit knowledge through the implementation of learning. The implementation of learning in KMS is represented in course initiation and evaluation, which consists of learning assessment and analytics. Figure 4.32 shows the initial page for the implementation of learning.

Figure 4.32: Main View of the Learning Implementation Page on KMS

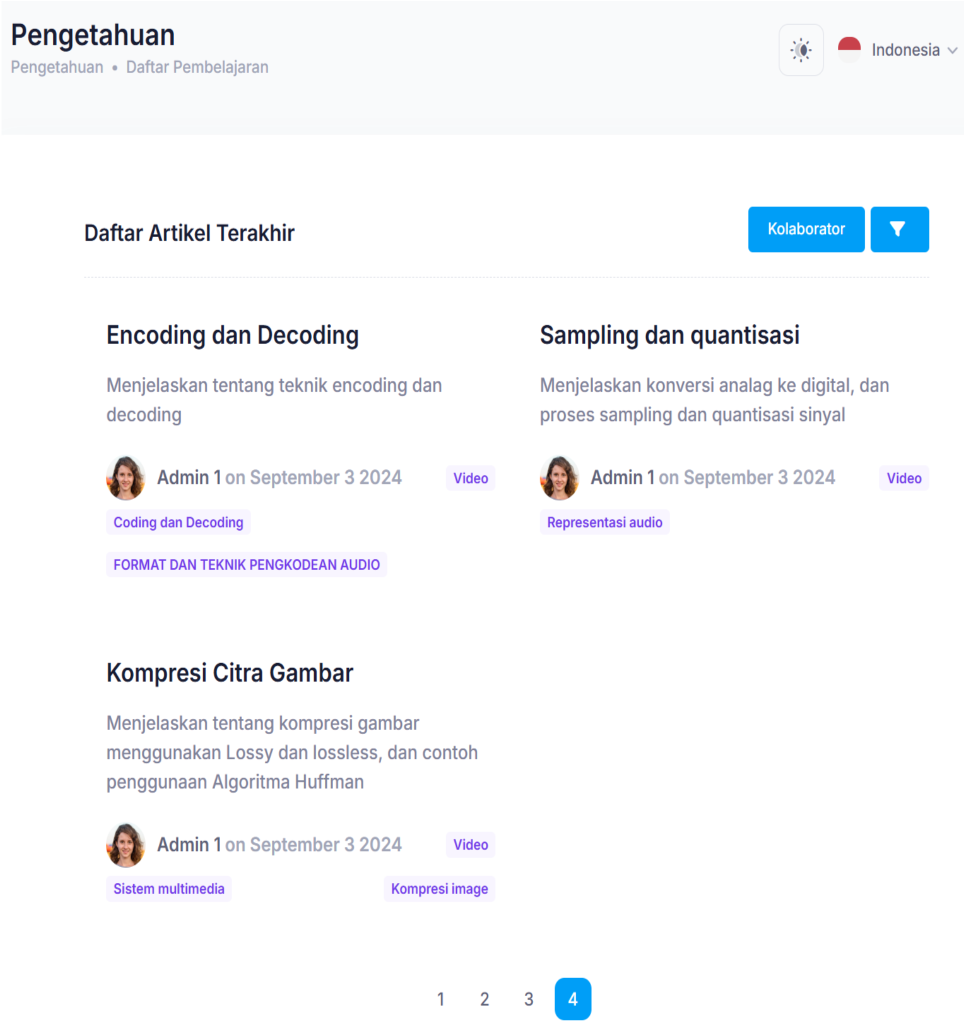


The main menu on the initial page of the learning implementation consists of knowledge that provides a collection of knowledge relevant to the course. The evaluation menu includes assessments and analysis of learning outcomes and learners achievement profiles.

a) Course initiation

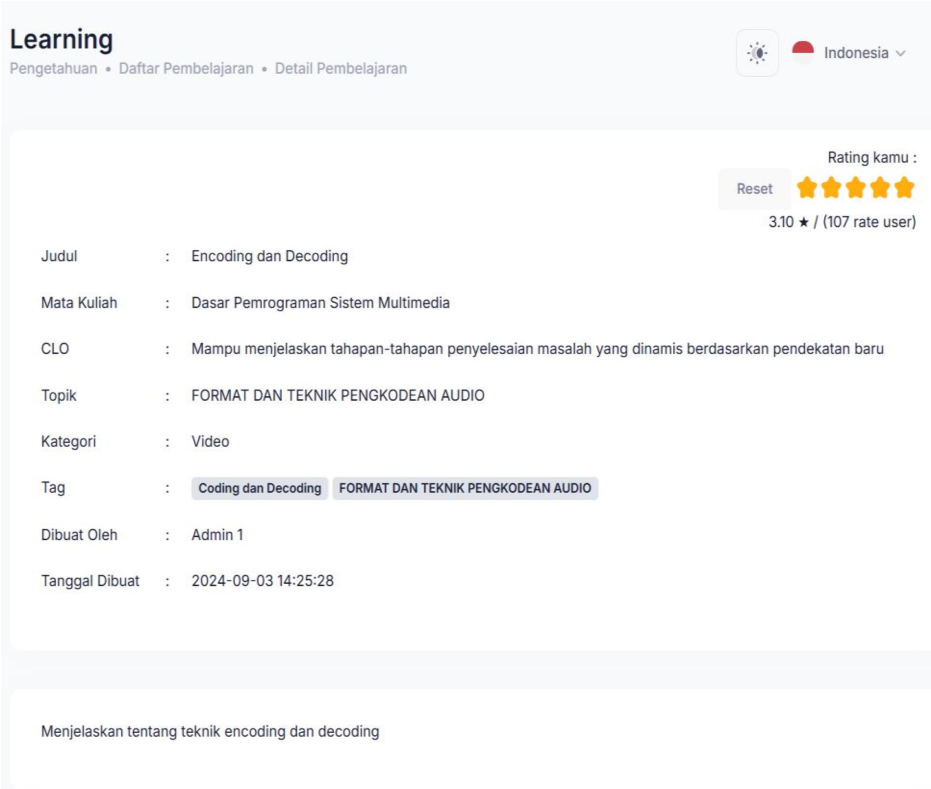
The initiation of the course consists of activities such as downloading knowledge, reading, and assessing knowledge. Figures 4.33 and 4.34 shows the course initiation in KMS.

Figure 4.33: Knowledge List



Knowledge in KMS is obtained from various sources, which can be read and downloaded in file formats, articles, and videos.

Figure 4.34: Give a Rating for Knowledge

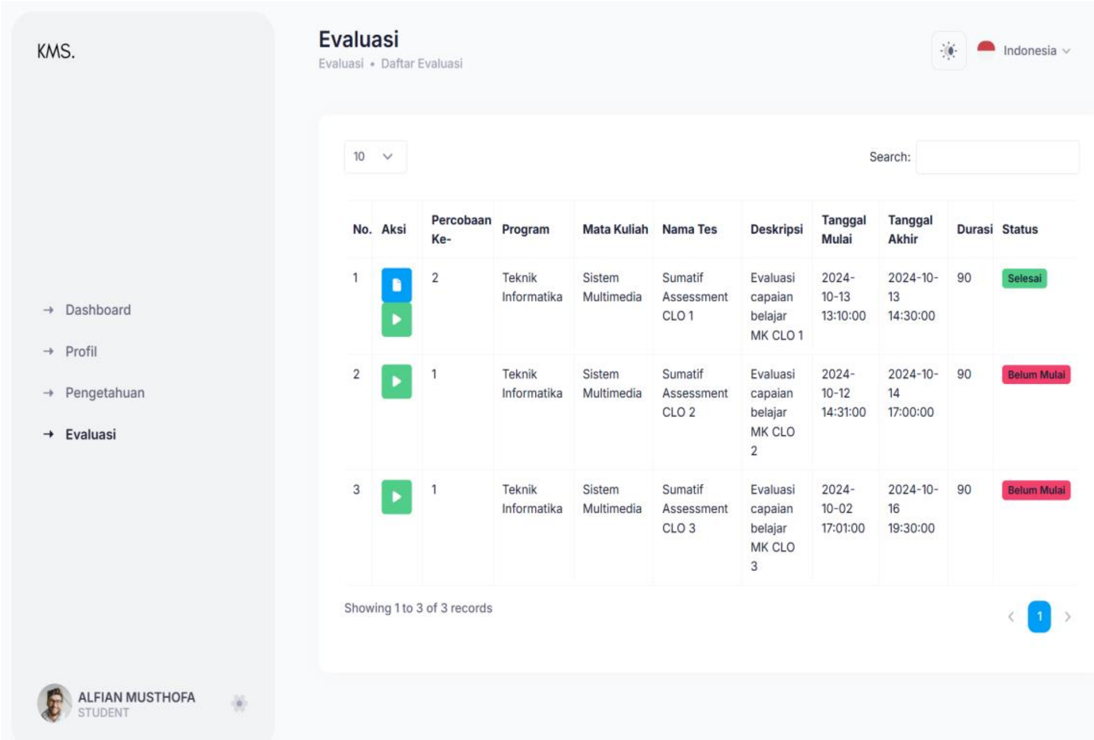


After reading, learners can evaluate the knowledge in the form of a qualitative rating. The rating results are used as recommendations for other learners.

b) Course assessment

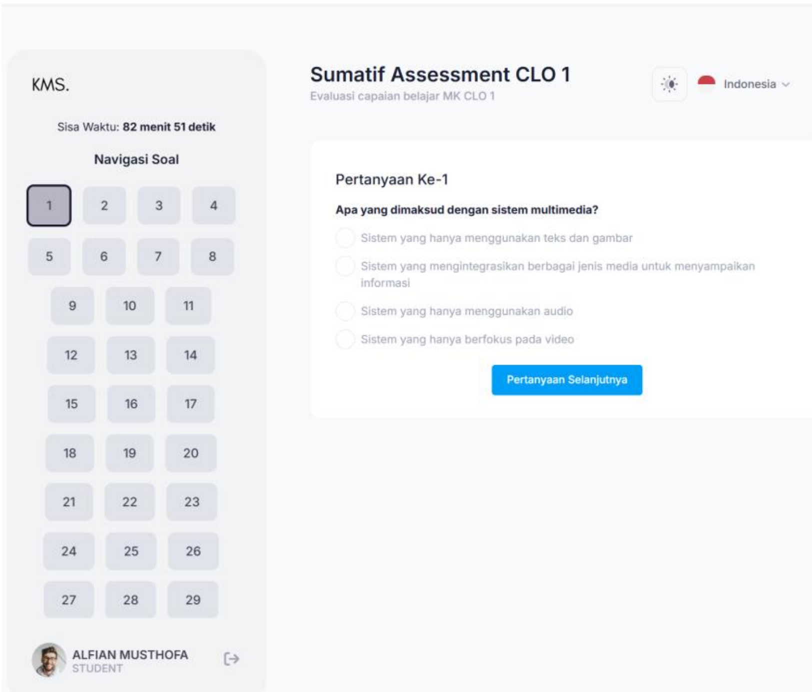
Course evaluation is divided into two main activities, assessment and analytics. After the schedule and assessment questions are set, learners can evaluate their learning outcomes. Figure 4.35 shows the list of CLO assessments for learners.

Figure 4.35: List of CLO Assessment



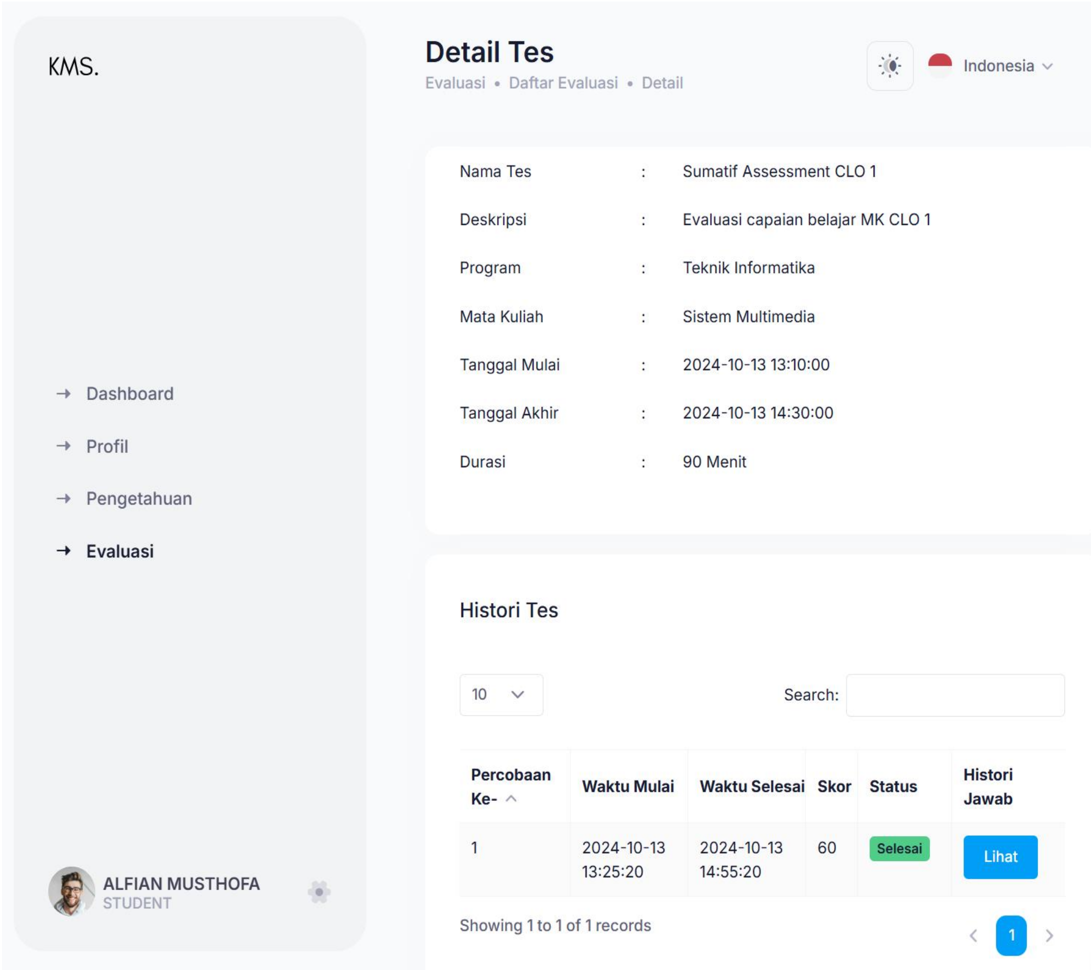
Through the evaluation function, learners know the assessments that need to be carried out. Learners start the assessment by pressing the start button. Figure 4.36 shows the assessment questions that learners must fill out.

Figure 4.36: CLO Assessment Question



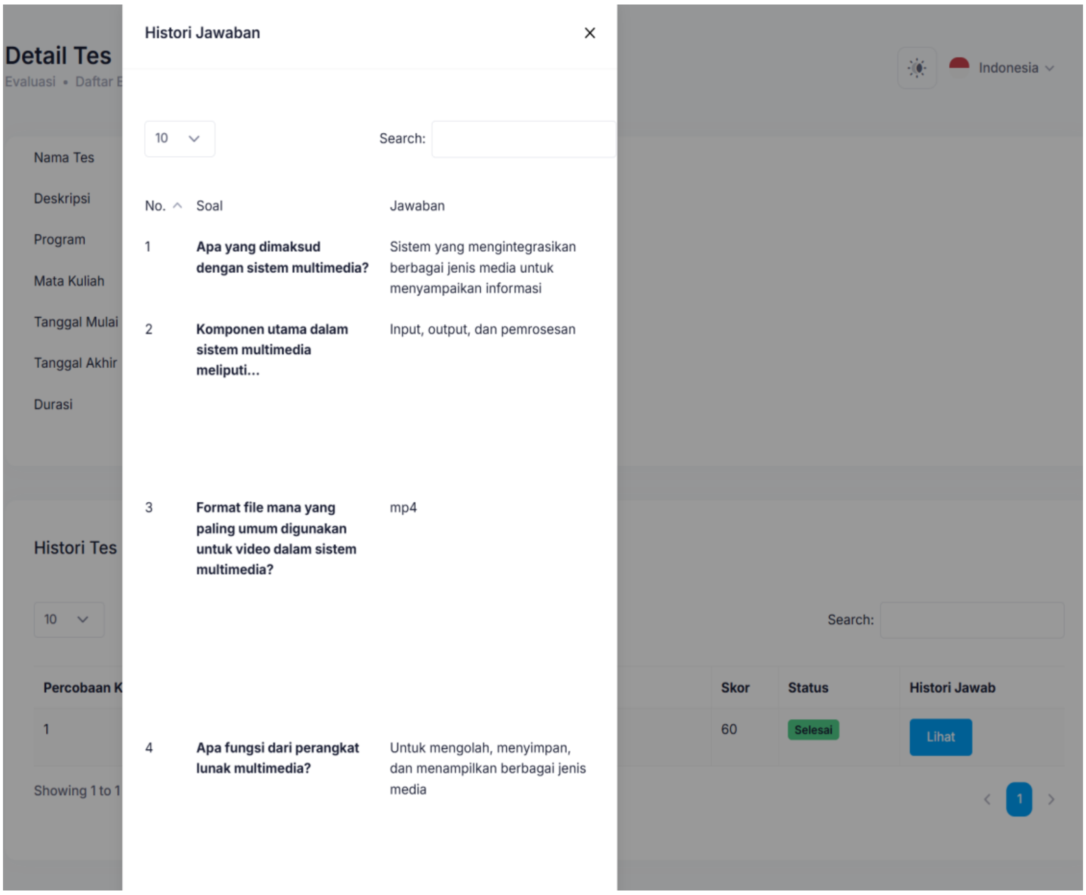
Assessment is conducted in the form of formative evaluation. The assessment questions are presented in multiple-choice format, with the number corresponding to each CLO. Figure 4.37 shows the details of the assessment results.

Figure 4.37: Test details and Results



The frontend evaluation function in the KMS provides a history of learners assessment answers. Start time, end time of the assessment, assessment score, and status. Figure 4.38 shows an example of the answer history for the assessment question.

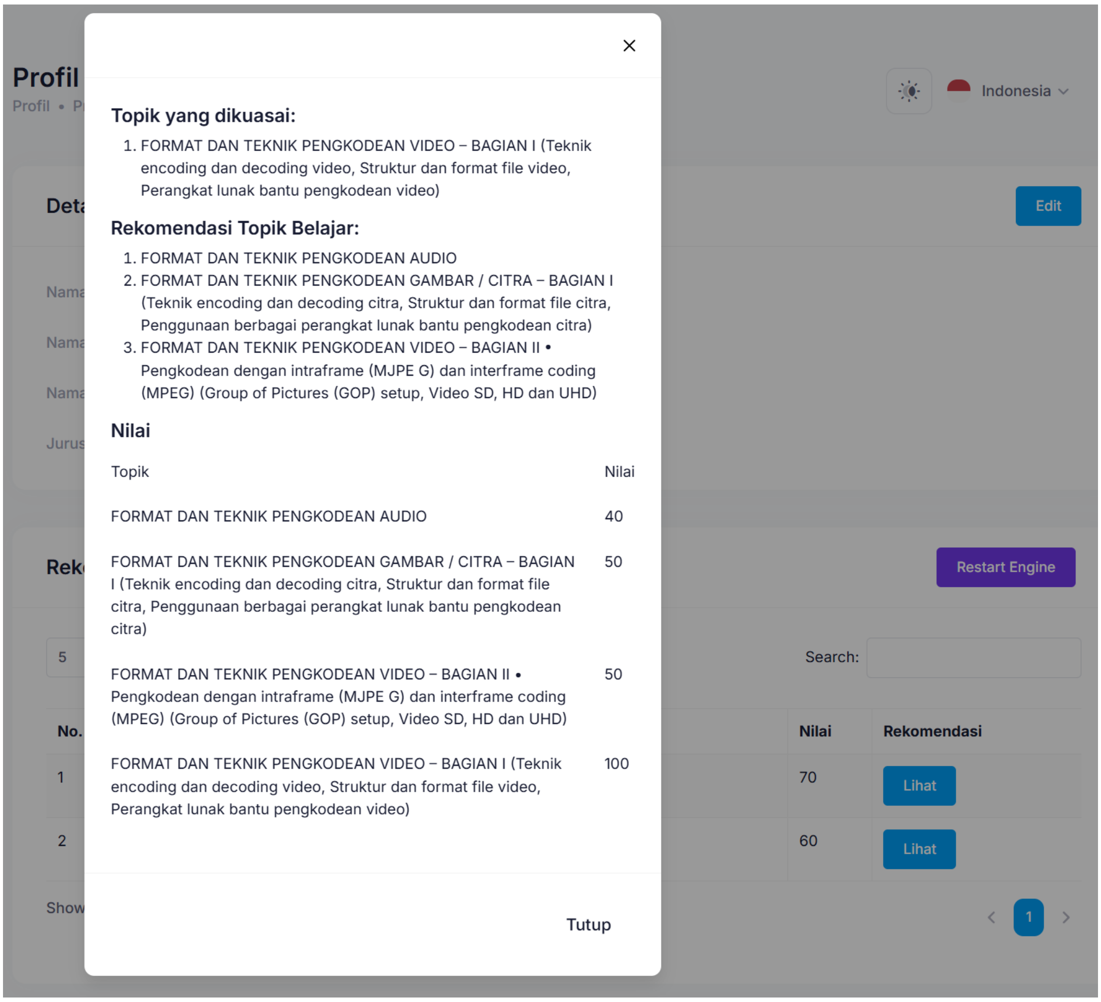
Figure 4.38: Assessment Answer History



c) Course analytics

Through course assessment, learners know the value or achievement of a CLO. In addition to course assessment, KMS provides a course analytics function for the assessment results of each CLO. Figure 4.39 shows the course analytics of the CLO assessment results. Course analytics on KMS explain the assessment value of each CLO and make recommendations for assessment results to improve learners learning. The learning analytics mechanism, which starts with the classification of assessment results and provides recommendations for learning topics to learners, is implemented automatically through the system. The learning analytics mechanism utilises a hybrid recommendation system that combines Rule-based and Content-based filtering algorithms.

Figure 4.39: Recommendations from the CLO Assessment Results



Rule-based filtering in learning analytics uses the rule that learners pass if the assessment scores for each CLO meet the threshold already determined in the curriculum (≥ 70). The input consists of learners' CLO assessment scores, which are then compared with the graduation threshold. The output generated is a recommendation of which topics the participants are considered to have mastered and which they have not.

Content-based filtering in KMS can provide recommendations for learning topics learners must learn. Providing recommendations involves searching for knowledge similar to the topics that have been rated, and the output is a recommendation for similar material to be studied next. Learning analytics explains the CLO achievement results, what has been achieved, and what has not been achieved. The representation of CLO achievement is based on the results of the learning topics assessment. The output of the analytics results is a recommendation for knowledge that learners must achieve or improve.

d) Evaluation of Recommendation System Results.

The recommendation system on KMS is evaluated using two methods: confusion matrix and mean absolute error (MAE). Evaluation is done automatically using the Python programming language and the Sklearn.Metrics library.

1) Confusion matrix

a. Precision explains the number of positive category data correctly classified and divided by the total data to calculate Precision. Precision formula:

$$\text{Precision} = TP / (TP + FP) \tag{4.1}$$

TP = True positives

FP = False positives

b. Recall and explain how many per cent of positive category data is correctly classified by the system. Here is the formula for calculating Recall. Recall formula:

$$\text{Recall} = TP/(FN+TP) \tag{4.2}$$

TP = True positives

FP = False positives

FN = False Negatives

c. F1-Score. It is a comparison of the average Recall and Precision that are crowned. Here is the equation for calculating F1-Score. F1-Score Formula:

F1-Score = (2 x Precision x Recall)/Precision + Recall (4.3)

2) Mean Absolute Error (MAE)

After the test results are classified, MAE is then used to calculate the difference between the predicted rating value and the actual user rating value. The MAE formula is as follows:

$$\text{MAE} = \frac{\sum(pi - qi)}{N} \quad (4.4)$$

$pi =$ predicted rating

$qi =$ actual rating

N = number of pairs of predicted actual ratings.

The test was conducted on 31 learners who had followed the testing, with an average of 7 knowledge topics, and 5 rating categories. Table 4.7 describes the classification results from MAE. The MAE classification description is adapted from Hunt and Bunker (2004). Table 4.8 explains the example of the results of evaluating the recommendation system.

Table 4.7: Descriptive Classification of Mean Absolute Error (MAE) Values

Mean Absolute Error (MAE)	**Goodness of Fit Description Accuracy**
(0-1)	Very Good
(1-2)	Good
(2-3)	Quite good
(3-4)	Not good
(4-5)	Not very good

Source: Hunt & Bunker (2004)

Table 4.8: Sample of the Results on Recommendation System

No	Students Id	Students Name	Recommendation Results				
			Topics Recommended by The System	Recall	Precision	F1-Score	MAE
1	1217050001	ABDULLAH AMALI AL GHASYIYAH ARRIDHUANI	1. STANDAR KOMPRESI GAMBAR / CITRA 2. SISTEM PENYIARAN DIGITAL (Standar televisi digital, Teknologi berbagai sistem televisi digital, Model bisnis televisi digital, TV 3D dan Free Viewpoint) 3. Representasi Audio 4. MULTIMEDIA STREAMING (Jaringan multimedia, Multimedia streaming, Playout buffer, Distribusi konten multimedia) 5. STANDAR KOMPRESI AUDIO	0.5	1	0.67	1.22

No	Students Id	Students Name	Recommendation Results				
			Topics Recommended by The System	Recall	Precision	F1-Score	MAE
2	1217050003	AGUNG ISKANDAR YUDA	1. STANDAR KOMPRESI GAMBAR / CITRA 2. SOCIAL MEDIA SHARING (Representative Social Media Services, User-Generated Media Content Sharing, Media Propagation in Online Social Networks) 3. SISTEM PENYIARAN DIGITAL (Standar televisi digital, Teknologi berbagai sistem televisi digital, Model bisnis televisi digital, TV 3D dan Free Viewpoint) 4. Konsep Sistem Multimedia 5. Representasi Audio	0.67	1	0.8	1.24

No	Students Id	Students Name	Recommendation Results				
			Topics Recommended by The System	Recall	Precision	F1-Score	MAE
			6. STANDAR KOMPRESI VIDEO (Ragam standar kompresi video, Karakteristik sistem kompresi video, Intraframe dan Interframe coding) 7. STANDAR KOMPRESI AUDIO				
3	1217050004	ALDRIAN RIZKI KUSUMA	1. STANDAR KOMPRESI GAMBAR / CITRA 2. SOCIAL MEDIA SHARING (Representative Social Media Services, User-Generated Media Content Sharing, Media Propagation in Online Social Networks)	0.67	1	0.8	1.18

No	Students Id	Students Name	Recommendation Results				
			Topics Recommended by The System	**Recall**	**Precision**	**F1-Score**	**MAE**
			3. STANDAR KOMPRESI VIDEO (Ragam standar kompresi video, Karakteristik sistem kompresi video, Intraframe dan Interframe coding) 4. MULTIMEDIA STREAMING (Jaringan multimedia, Multimedia streaming, Playout buffer, Distribusi konten multimedia) 5. Representasi Audio 6. STANDAR KOMPRESI AUDIO				
Average Scores				**0.61**	**1**	**0.76**	**1.21**

Evaluation of recommendation results is automatically performed in Python. Confusion matrix (F1 Score, Recall, Precision) is available in the scikit-learn library using the confusion_matrix() function, and sklearn. Metrics and numpy use the mean_absolute_error() function. A confusion matrix was used to measure performance in both binary classification problems and multiclass classification problems. MAE was used in the evaluation of recommendation systems to measure the quality or accuracy of prediction results.

The average values of the evaluation metrics for the three students, as presented in Table 4.8, are as follows:

1) Recall (0.61 or 61%): This metric indicates that the model successfully identified 61% of all relevant samples, suggesting that some pertinent instances were not captured.
2) Precision (1 or 100%): The model achieved a perfect precision score, meaning that all instances it classified as positive were indeed correct, thereby resulting in the absence of false positives.
3) F1-Score (0.76 or 76%): The F1-score, representing the harmonic mean of precision and recall, indicates a moderate balance between these critical metrics. However, the recall figure falling below 1 suggests that the F1-score does not reach maximum results. The resulting F1-score reflects a reasonably good equilibrium between precision and recall; however, the model's overall efficacy could be significantly enhanced by focusing on increasing recall without compromising precision.
4) Mean Absolute Error (MAE). The results of testing 3 data students with 5 categories target range of topic assessments obtained an average MAE value

of 1.21. This value explains that the rating prediction with the user rating value is Accurate.

4.3 Validation and Evaluation of KMS Developed for Personalizd Learning to Support OBE in HEI

Validation of the developed KMS aims to ensure the feasibility of the process, technology, and content to meet learners' learning needs. Experts in learning media, content, and ICT technology carry out validation. Evaluation is carried out to determine learners' acceptance of the developed KMS. The evaluation framework uses TAM with a survey method.

4.3.1 Validation of KMS Developed for Personalized Learning to Support OBE in HEI by Expert (Expert Judgement)

The expert validation test aims to obtain assessments and input from experts on the KMS that have been developed. The validation includes aspects of technology and KMS as a learning medium. The expert test consists of validation tests from information technology experts and from learning media experts. A learning media expert and an information technology expert carry out KMS validation. The calculation of the percentage of validation results uses the following formula:

$$Percentage = \frac{\sum(answer\ x\ weight\ of\ each\ choice)}{n\ \ x\ highest\ weight}\ x\ 100 \tag{4.5}$$

The conversion of assessment results is explained in Table 4.9.

Table 4.9: Conversion of Achievement Level with Scale 5

Qualification	Achievement Level	Description
90% ≤ p ≤ 100%	Very Good	There is no need to revise
75% ≤ p < 90%	Good	No need to revise
65% ≤ p < 75%	Quite	Revised
55% ≤ p < 65%	Less	Revised
0% ≤ p < 55%	Very Less	Revised

Conversion of assessment results using a scale 1 to 5. The lowest percentage of assessment results is if the percentage of achievement level is 0% ≤ p < 55% with very poor qualifications; these results require revision. Including achievement levels of 55% ≤ p < 65% and 65% ≤ p < 75% also require revision. While achievement levels of 75% ≤ p < 90% and 90% ≤ p ≤ 100% with good and very good qualifications do not need to be revised. Expert assessment question items adopted from the Gerhana YA (Indonesian education university, 2016) dissertation research report.

1) Validation Test of Learning Content and ICT Expert

Dian Sa'adillah Maylawati, Ph.D., Head of the Informatics Department of Sunan Gunung Djati Islamic University, Bandung, conducted the validation test of learning content and IT. The assessment aspects in the KMS validation test include learning content and information technology; these aspects consist of (a) suitability of learning objectives and materials; (b) depth and breadth of learning materials; (c) suitability of learning materials with course CLOs; (d) distribution of learning materials with each CLO; (e) Ease of access to learning materials; (f) Form and completeness of assessments; (g) Suitability of learning analytics; (h) suitability of technology selected in KMS; (i) speed of processing time; (j) quality of data management in the KMS system and; (k) Clarity of language and use of menus in KMS. The material validation test assessment results show a good level of achievement. Table 4.9 explains the assessment results from the material and ICT expert test. Table 4.10 explains the conversion of the assessment results.

Table 4.10: Results of the Teaching Material and ICT Expert

No.	Assessment Aspects	Score
1	Suitability of learning objectives and materials	3
2	Depth and breadth of learning materials	3
3	Suitability of learning materials with course CLOs	4
4	Distribution of learning materials with each CLO	4
5	Ease of access to learning materials	4
6	Form and completeness of assessments	2
7	Suitability of learning analytics	3
8	Suitability of technology selected in KMS	3
9	Speed of processing time	3
10	Quality of data management in the KMS system and	3
11	Clarity of language and use of menus in KMS	3
Number		**35**

$$Percentage = \frac{\sum(answer\ x\ weight\ of\ each\ choice)}{n\ \ x\ highest\ weight}\ x\ 100 \tag{4.6}$$

$$Percentage = \frac{35}{11\ x\ 4}\ x\ 100 = 79{,}54\%$$

The assessment results from learning content and ICT experts as described in Table 4.8 show a percentage of assessment results of 79.54%, or with a level of achievement in the ***Good*** and suitable category for use.

2) Validation Test of Learning Media Expert

The second validation test was conducted by learning media expert Dr. Ayu Puji Rahayu, M.Pd, a lecturer of the Department of Educational Technology of Indonesian Education Institute (IPI). The aspects assessed were the appearance and functionality of the learning media, where the assessment consisted of (a) quality of technology selection, (b) quality of appearance or design, (c) quality of menu layout, (d) quality of colour used on display; (e) quality of features used; (f) quality of text and language used; (g) ease of use; (h) availability of media operating assistance; (i) availability of learning support.

Table 4.11: Results of Assessment of Learning Media Expert

No	Assessment Aspects	Score
1	Quality of technology selection for learning media	4
2	Quality of display or design	3
3	Quality of menu layout	3
4	Quality of colour use on display	3
5	Quality of features used	3
6	Quality of text and language used	4
7	Ease of use	4
8	Availability of media operation assistance	4
9	Availability of learning support	3
Number		**31**

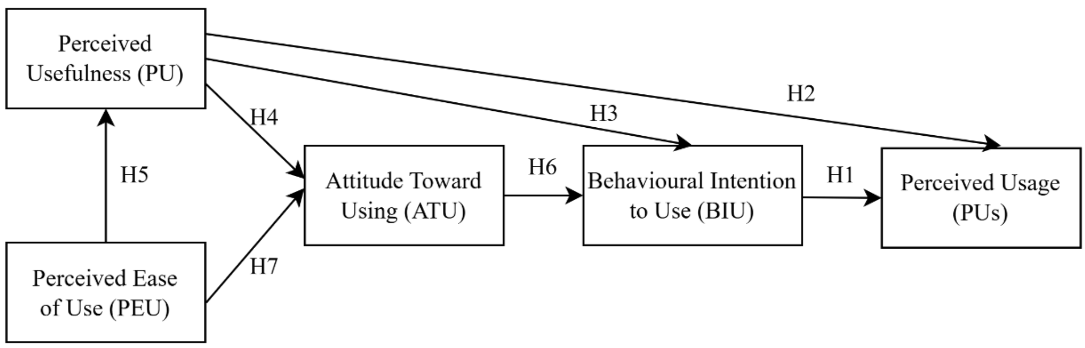
The assessment results by media experts, as described in Table 4.9, show a percentage of assessment results of 86.1%, or with a level of achievement in the ***Good*** and suitable category for use.

4.3.2 Evaluation of KMS Developed for Personalized Learning to Support OBE in HEI by User

Evaluation and validation are carried out to determine the extent to which the effectiveness of the KMS that has been developed meets the objectives. The level of user acceptance is one of the references to the effectiveness of KMS. The framework used to evaluate and validate KMS is the technology acceptance model (TAM). The instrument used is a questionnaire with respondents from informatics engineering learners at UIN Sunan Gunung Djati Bandung who have taken multimedia system lectures. Data was collected at the end of the lecture in August 2024, with 95 learners as respondents. Figure 4.40 shows the TAM model used to evaluate and validate KMS.

Model of TAM (Davis, 1987; Gardner dan Amoroso, 2004; Kim et al, 2009; Lee et al, 2011).

Figure 4.40: Model of TAM



Source: Davis (1987); Gardner and Amoroso (2004); Kim et al (2009); Lee et al. (2011)

The TAM model's questionnaire data for each construct was processed using the Python programming language. With a comprehensive library for statistical data processing, Python also visualizes analysis results. Some data visualisations used in Python include correlation heatmaps, ordinary least squares (OLS) regression, and scatter plots.

The following are the research hypotheses for each TAM model construction used:

H_1 : There is a significant influence of Behavioural Intention to Use (BIU) and Perceived Usage (PUs) in the implementation of KMS for personalized learning to support OBE implementation in HEI.

H_2 : There is a significant influence of Perceived Usefulness (PU) and Perceived Usage (PUs) in the implementation of KMS for personalized learning to support OBE implementation in HEI.

H_3 : There is a significant influence of Perceived Usefulness (PU) and Behavioural Intention to Use (BIU) in implementing KMS for personalized learning to support OBE implementation in HEI.

H_4 : There is a significant influence of Perceived Usefulness (PU) and Attitude Toward Using (ATU) in implementing KMS for personalized learning to support OBE implementation in HEI.

H_5 : There is a significant influence of Perceived Ease to Use (PEU) and Perceived Usefulness (PU) on the implementation of KMS for personalized learning to support OBE implementation in HEI.

H_6 : There is a significant influence of Attitude Toward Using (ATU) and Behavioural Intention to Use (BIU) on the implementation of KMS for personalized learning to support OBE implementation in HEI.

H_7 : There is a significant influence of Perceived Easy to Use (PEU) on Attitude Toward Using (ATU) on the implementation of KMS for personalized learning to support OBE implementation in HEI.

Using statistical techniques to accept or reject the null hypothesis (H0) will contain the risk of error or decision-making error. Therefore, in social research, research will never get a level of certainty or 100% confidence in the decision to support the hypothesis. This means the decision to reject or accept the hypothesis contains the probability (chance) of error. The smaller the possibility of error, the greater our confidence in the decision. Social research generally sets a significance level of 5% or 1% before statistical testing. The selection of a significance level of 5% or 1% is merely an agreement that has become a habit among social scientists (McCall, 1970).

4.3.3 Data Analysis Results

The TAM questionnaire questions for each construct were adopted from the published research results of Gardner & Amoroso (2004) and Suroso & Fernando (2017). The questions in the questionnaire have gone through data validation and reliability tests. There are seven hypotheses tested to measure user acceptance of the developed KMS. Table 4.8 summarises the measurement results of factors influencing learners acceptance of KMS. The measurement items of the TAM constructs were adopted from the research of Gardner and Amoroso (2004, pp. 1-10). Measuring the relationship between each variable in the TAM uses a simple linear regression test, with data analysis using Ordinary Least Squares (OLS). A summary of the results of the TAM variable tests is presented in Table 4.12 as follows:

Table 4.12: Summary of TAM Variable Test Results

Relationship of Each Variable	**Coef (x)**	**y**	**R^2**	**F-statistic**	**P-value**
H1: BIU against PUs	0.6762	-5.464e-17	0.457	5.38e-14	0.000
H2: PU against PUs	0.6738	-5.464e-17	0.529	6.77e-17	0.000
H3: PU against BIU	0.7355	-5.378e-17	0.630	8.29e-22	0.000
H4: PU against ATU	0.7579	-3.816e-17	0.590	1.01e-19	0.000
H5: PEU against PU	0.8523	-2.168e-17	0.588	1.35e-19	0.000
H6: ATU against BIU	0.7435	-5.378e-17	0.627	1.29e-21	0.000
H7: PEU against ATU	0.8350	-3.816e-17	0.580	3.33e-19	0.000

Referring to Table 4.12, regarding the summary of the test results of each TAM variable, the test results of each variable can be explained as follows:

1) The effect of BIU on PUs

The magnitude of the influence of the independent variable (BIU) on the dependent variable (PUs) is 0.457, so there is an influence of other independent variables besides those studied on the dependent variable of (1-0.457), which is 0.543. The independent variables studied have a significant influence, indicated by the Prob value (F-statistic) = = 5.38 x 10^{-14}, smaller than the alpha used, namely α = 0.05. The resulting linear regression equation is: $\hat{y} = -5.464 \text{ x } 10^{-17} + 0.6762X$, meaning that for every additional independent variable, the dependent variable will increase by

0.6762. The linear regression equation is significant, as indicated by $P = 0.000 < \alpha = 0.05$. Based on the analysis above, it can be concluded that a significant influence exists between behavioural intention to use (BIU) and perceived usage (PUs) in implementing KMS for personalized learning to support OBE implementation in HEI.

2) The influence of PU on PUs

The magnitude of the influence of the independent variable (PU) on the dependent variable (PUs) is 0.529, so there is an influence of other independent variables besides those studied on the dependent variable of (1-0.529), which is 0.471. The independent variables studied have a significant influence, indicated by the Prob value (F-statistic) = 6.77×10^{-17}, smaller than the alpha used, namely $\alpha = 0.05$. The resulting linear regression equation is: $\hat{y} = -5.464 \times 10^{-17} + 0.6738X$, which means that for every additional independent variable, the dependent variable will increase by 0.6738. The linear regression equation is significant, as indicated by $P = 0.000 < \alpha = 0.05$. Based on the analysis above, it can be concluded that there is a significant influence between perceived usefulness (PU) and perceived usage (PUs) in implementing KMS for personalized learning to support OBE implementation in HEI.

3) Influence of PU on BIU

The magnitude of the influence of the independent variable (PU) on the dependent variable (BIU) is 0.630, so there is an influence of other independent variables besides those studied on the dependent variable of (1-0.630), which is 0.370. The independent variables studied have a significant influence, indicated by the Prob value (F-statistic) = 8.29×10^{-22}, smaller than the alpha used, namely $\alpha = 0.05$. The resulting linear regression equation is $\hat{y} = -5.378 \times 10^{-17} + 0.7355X$, which means that for every additional independent variable, the dependent variable will increase by 0.7355. The linear regression equation is significant, as indicated by $P = 0.000 < \alpha = 0.05$. Based on the results of the analysis above, it can be concluded that there is a significant influence between perceived usefulness (PU) on behavioural intention to use (BIU) in the implementation of KMS for personalized learning to support OBE implementation in HEI.

4) The influence of PU on ATU

The magnitude of the influence of the independent variable (PU) on the dependent variable (ATU) is 0.590, so there is an influence of other independent variables besides those studied on the dependent variable of (1-0.590), which is 0.410. The independent variables studied have a significant influence, indicated by the Prob value (F-statistic) = 1.01×10^{-19}, smaller than the alpha used, namely $\alpha = 0.05$. The resulting linear regression equation is: $\hat{y} = -3.816 \times 10^{-17} + 0.7579X$, which means that for every additional independent variable, the dependent variable will increase by 0.7579. The linear regression equation is significant, as indicated by $P = 0.000 < \alpha = 0.05$. Based on the analysis above, it can be concluded that there is a significant influence between perceived usefulness (PU) and attitude toward using (ATU) in implementing KMS for personalized learning to support OBE implementation in HEI.

5) Influence of PEU on PU

The magnitude of the influence of the independent variable (PEU) on the dependent variable (PU) is 0.588, so there is an influence of other independent variables besides those studied on the dependent variable of (1-0.588), which is 0.412. The independent variables studied have a significant influence, indicated by the Prob value (F-statistic) = 1.35 x 10^{-19}, smaller than the alpha used, namely $\alpha = 0.05$. The resulting linear regression equation is: : $\hat{y} = -2.168 \text{ x } 10^{-17} + 0.8523X$, which means that for every additional independent variable, the dependent variable will increase by 0.8523. The linear regression equation is significant, as indicated by P = $0.000 < \alpha = 0.05$. Based on the analysis above, it can be concluded that there is a significant influence between perceived ease of use (PEU) and perceived usefulness (PU) in implementing KMS for personalized learning to support OBE implementation in HEI.

6) The Influence of ATU on BIU

The magnitude of the influence of the independent variable (ATU) on the dependent variable (BIU) is 0.627, so there is an influence of other independent variables besides those studied on the dependent variable (1-0.627), which is 0.373. The independent variables studied have a significant influence, indicated by the Prob value (F-statistic) = 1.29 x 10^{-21}, smaller than the alpha used, namely $\alpha = 0.05$. The resulting linear regression equation is: $\hat{y} = -5.378.10^{-17} + 0.7435X$, which means that for every additional independent variable, the dependent variable will increase by 0.7435. The linear regression equation is significant, as indicated by P = $0.000 < \alpha = 0.05$. Based on the results of the analysis above, it can be concluded that there is a significant influence between attitude toward using (ATU) and behavioural intention to use (BIU) in the implementation of KMS for personalized learning to support OBE implementation in HEI.

7) The Influence of PEU on ATU

The magnitude of the influence of the independent variable (PEU) on the dependent variable (ATU) is 0.580, so there is an influence of other independent variables besides those studied on the dependent variable (1-0.580), which is 0.420. The independent variables studied have a significant influence, indicated by the Prob value (F-statistic) = 3.33×10^{-19}, smaller than the alpha used, namely $\alpha = 0.05$. The resulting linear regression equation is: $\hat{y} = -3.816.10^{-17} + 0.8350X$, which means that for every additional independent variable, the dependent variable will increase by 0.8350. The linear regression equation is significant, as indicated by $P = 0.000 < \alpha = 0.05$. Based on the analysis above, it can be concluded that there is a significant influence between perceived ease of use (PEU) and attitude toward using (ATU) in implementing KMS for personalized learning to support OBE implementation in HEI.

Using the TAM model in the evaluation is quite effective in determining the extent to which learners accept the KMS developed for personalized learning in supporting the implementation of OBE at HEI. Based on the overall analysis results, each construct in the TAM model has a significant influence. Learners' positive responses to the KMS developed are important capital in supporting the implementation of OBE at HEI and increasing learners' ability to adapt to technological advances. Learners' belief in the value of the benefits of using KMS is inseparable from the ease of using KMS.

4.4 Chapter Summary

The developed KMS has implemented the OBE curriculum framework. The OBE components (PLOs, CLOs, and topics) and the mapping of each component have referred to the OBE curriculum book of the Informatics Department of UIN Sunan Gunung Djati Bandung, with an example of a multimedia system course. The OBE curriculum framework in KMS has become a reference for providing knowledge in the learning process. Knowledge acquisition in KMS is obtained from various sources.

Knowledge acquisition has represented the process of externalisation and combination in knowledge management (KM). The function of uploading knowledge marks the externalisation of knowledge in KMS. At the same time, the combination of knowledge in KMS is represented by the function of adding knowledge by an expert. The next combination of knowledge is a multi-document summarisation of knowledge. Multi-document summarisation in KMS has implemented the BERT model. The model has gone through testing phases, including automatically or manually testing summarised documents' readability. The readability test results (FKGL, GFI and Dwiyanto Djoko Pranowo metric) of the summarized results show that the documents are easy for adults or learners in college to understand. Likewise, with manual testing by Indonesian language experts, the summary results show that the summary document is easy to understand. The learning process in KMS represents the internalisation of knowledge. Assessment of learning outcomes is part of the learning process, which measures the achievement of the learners learning process. KMS has been equipped with a recommendation system for improving learners' knowledge. The evaluation results use a confusion matrix and MAE. The classification of the resulting recommendation data is good, and the predictions are very accurate. In addition to system functional testing, the KMS developed has undergone a validation and evaluation process using a questionnaire instrument. Validation was carried out by experts in learning media, learning content and ICT, and the results were good. The evaluation used a quantitative approach to learners using the TAM framework. The analysis results using simple regression for each construct in TAM have a very significant influence. These results indicate that the KMS developed has a high level of learner acceptance.

CHAPTER 5

DISCUSSION AND CONCLUSION

5.0 Introduction

This chapter summarizes the research findings reported in the previous chapters of this thesis. It also discusses the research's conclusion, limitations, implications, and contribution. The final section discusses recommendations for future research.

5.1 Conclusion of Research

Some of the conclusions of the research results are explained as follows:

A. The first objective of the research is to develop a relevant knowledge pool required for a certain field for KMS to support the implementation of OBE in HEI. This objective represents the process of knowledge creation in KMS. This knowledge has met the learning needs of a course and is based on the OBE framework. Explicitly, the first objective of the research was included in the KMS back-end system.

   1) The OBE curriculum framework consists of PLO settings, courses, CLOs, course topics and assessments successfully implemented in KMS. The OBE framework in KMS has referred to the curriculum book in the informatics department of Sunan Gunung Djati Islamic University Bandung Indonesia, with the multimedia system course as an example. The OBE curriculum framework has become a reference in providing knowledge according to learning needs and assessments for students.

   2) Knowledge creation in KMS represents the process of externalisation and the combination of knowledge. The knowledge possessed by a

lecturer has been successfully externalized into structured knowledge by storing it in KMS. Knowledge in KMS has been successfully combined with other knowledge through the web scraping process from online media. Externalized knowledge has been successfully combined with knowledge from an expert. Creating a summary of knowledge sourced from several Indonesian language documents automatically is another way to combine knowledge in KMS.

3) Summarisation of knowledge in KMS has successfully implemented the Bidirectional Encoder Representations Transformers (BERT) model. This model can automatically summarize multi-document knowledge in Indonesia. This model has undergone a series of readability evaluation processes, either through a system or manually by an Indonesian language expert. The evaluation results using the Flesch-Kincaid Grade Level (FKGL) method obtained an average value of 20.35 and 18.1, the Gunning Fog Index (GFI) method 7.52 and 8.165, and the Dwiyanto Djoko Pranowo method 20.33 and 32.2. The evaluation results explain that the summary document is readable well by adult readers at university or student education levels. The results of manual evaluation by Indonesian language experts on 20 summary knowledge documents can still be read well.

B. The study's second objective is to develop a learning analytics technique in the KMS for PL to support the implementation of OBE in HEI. This second objective describes the learning process, which represents the internalisation process of knowledge. Explicitly, the second research objective has been implemented in the KMS's back-end system.

1) The OBE framework was implemented in the first research objective and has become the framework for the learning process in KMS. CLO and topics have become the reference for evaluating the achievement of learning outcomes.

2) The knowledge available in the KMS supports learning. The KMS has implemented a mechanism for providing ratings for students' knowledge.

3) Evaluation of learning outcomes is part of the learning process. The KMS has implemented formative assessment with multiple-choice assessment questions to facilitate analysis.

4) The automatic recommendation system in the KMS can analyse student learning outcomes. The assessment results and the provision of knowledge ratings in the KMS have become the reference for providing recommendations for improving student knowledge. Based on the evaluation results using the confusion matrix, the Recall value was 59.1%, Precision was 100%, F1-Score was 74%, and the Mean Absolute Error (MAE) of 0.97 (testing 31 data with 5 categories and a target range of 0-4), indicating that the recommendation system in the KMS has good classification capabilities and high accuracy in prediction.

C. The third objective of the study is to validate the KMS developed for OBE implementation in HEI and evaluate its acceptance among the users. The validation and evaluation process involves determining, compiling, distributing, and analysing.

1) The validation instrument used is a questionnaire, referring to Gerhana's dissertation research (2016). KMS validation has been carried out by learning media experts, learning content experts, and ICT experts. The percentages of assessment results are 79.54% and 86.1%, respectively. These results indicate that the developed KMS achieved a suitable level for the use category and does not need revision.
2) Students have evaluated KMS. The evaluation framework adopts the Technology Acceptance Model (TAM) with a questionnaire instrument. The evaluation was carried out to measure students' acceptance of the developed KMS. The results of a survey of 95 students and data analysis show that each construct in the TAM has a significant effect. These results explain that student acceptance of KMS is very good.

5.2 Limitation of Research

This study has several limitations.

1) KMS still focuses on a one-course theme: information technology (IT). It needs to be developed to accommodate other course themes.
2) Lecturer involvement in entering knowledge into KMS is still low. Knowledge in KMS is mostly sourced from online media through the scraping process. Efforts are needed to increase lecturer productivity to contribute maximally to knowledge in KMS.
3) Knowledge in KMS has not been maximally combined with knowledge from experts or industry.

5.3 Implications of Research

This research provides broad opportunities for developing KMS to support OBE implementation at HEI. The backend system in KMS can represent OBE processes and the KM knowledge creation process. Knowledge acquisition in KMS is an implementation of the externalisation and combination of knowledge processes. KMS can optimize knowledge management. Provides complete knowledge to meet student learning needs obtained from internal and external organizations. Much knowledge can be obtained from online media through web scraping. KMS facilitates an expert's contribution to knowledge, thus providing an opportunity to reduce the gap in knowledge mastery between HEI and industry. Automatic text summarisation using the BERT model provides a multi-document knowledge summarisation facility in Indonesian. Knowledge summarisation in KMS has undergone a series of readability tests automatically (by machine) and manually by Indonesian language experts. Based on the readability test results, the summary results are quite good for adults or those with university education levels.

The adaptive learning process in KMS is a front-end system that interprets the internalisation process of KM knowledge. KMS learning supports personalized learning. Learning analytics in KMS support implementing learning that suits students' interests and talents. KMS is equipped with an automatic recommendation system that can guide knowledge development. The recommendation test results produced have good classification capabilities and high accuracy in prediction.

The developed KMS has gone through an expert validation process and user evaluation. According to experts in learning content, ICT technology, and learning media, KMS is suitable for use as a learning media. Meanwhile, the results of the evaluation of the use of KMS using the TAM model show that the student acceptance of KMS is quite good. Each construct in the TAM model has a significant relationship, so users have a good perception of KMS.

5.4 Contributions of Research

Some of the contributions resulting from the research are explained as follows:

A. Theoretical contribution

1) This section outlines theoretical contributions to the framework for developing Knowledge Management Systems (KMS), focusing on the integration of Personalized Learning (PL) and Outcome Education (OBE) to improve the quality of education in Higher Education Institutions (HEIs). The results explain the implementation of OBE and PL in KMS, showing how this combination enhances the educational experience. The discussion covers the role of Artificial Intelligence (AI) in knowledge creation and assessing learning outcomes, highlighting its potential to create adaptive and personalized learning environments. Overall, it emphasizes the importance of KMS, PL and OBE in fostering adaptive learning.

2) Several approaches can be used to measure the success of KMS implementation. This study successfully used qualitative and quantitative approaches to measure the success factors of KMS implementation in higher education institutions, obtaining a fairly comprehensive picture of validations and of user evaluations of the KMS developed.

B. Practical Contribution

1) The implementation of KMS at HEI is a valuable asset in improving the quality of education. Knowledge is available to support implementing

adaptive learning and OBE at HEI. How the BERT model is used for summarising multi-knowledge documents so that it produces knowledge documents with good readability.

2) Implementing KMS at HEI provides experience in measuring the effectiveness of the KMS model developed. This study provides a practical framework for measuring the success of KMS in HEI, both in terms of functionality and non-functionality.

C. Contribution to Methodology

1) Most KMS development focuses on the knowledge creation process. The focus of this development is quite good in managing knowledge assets. This study has guided me in integrating the knowledge creation processes with the OBE framework so that the knowledge available in KMS can meet the learning needs of students at HEI.

2) AI technology has been used in the development of KMS. Some research on KMS produces a conceptual model of how AI technology is utilized. This study has provided an explanation of the steps in integrating AI technology into KMS and how to evaluate the performance of AI implementation in KMS through both qualitative and quantitative approaches.

5.5 Recommendation for Future Research

In addition to limitations, implications and contributions, the opportunities for future research are identified as follows:

1) A more complete assessment component must support the OBE framework in KMS. Variations and models of assessment questions can be essays,

independent, or structured assignments. The assessment must calculate the achievement of PLO, CLO, and sub-CLO.

2) In addition to the BERT model, other transformer models, such as T5, can be used for multi-document summarisation of Indonesian text. They can also be used in summarisation assessment in the form of essays. In addition to automatic text summarisation, KMS can be equipped with a chatbot.

3) Evaluation of text summarisation results can use other methods, such as N-gram Graphs, to compare the extracted summary with the model summary. To evaluate the summary based on readability and informativeness, using a network to assess linguistic quality and semantic similarity can try using the linguistic quality and semantic similarity model (LQSSM).

4) In addition to collaborative filtering, content-based filtering, or hybrid models, the recommendation system can use a deep learning model, such as the Convolutional Neural Networks (CNNs) approach.

5) In addition to accuracy metrics such as precision, recall, and MAE, for evaluating the performance of the recommendation system, nDCG (Normalized Discounted Cumulative Gain) can be used To evaluate the quality of the ranking of recommended items, which emphasizes the importance of the position of relevant items in the list. 6. Validation of the developed KMS can involve many experts, such as curriculum experts, knowledge management experts, and AI technology experts. Meanwhile, the evaluation of KMS users, in addition to the TAM model, can also use the Why Because Analysis (WBA) model, which provides a comprehensive and complete analysis framework for system failures and system successes.

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APPENDICES

Appendix A

EXPERTS AS EVALUATOR

DECLARATION OF EXPERTS AS EVALUATOR

I am willing to be one of the readability evaluators of the summary results for a thesis entitled "Knowledge Management System for Personalized Learning to Support OBE Implementation in Higher Education Institutions". According to my field expertise, the evaluation process is done objectively and without coercion.

Signature :

Name : DR. YETI HERYATI, M.PD.

Job/Profession : LECTURER OF LANGUAGE

Expertise : INDONESIAN LANGUAGE

Date : MARCH 2024

Note:

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PENDIDIKAN

- 2009 - UPI Bandung, Program Pendidikan Bahasa Indonesia (Dr)
- 2003 – UPI Bandung, Program Pendidikan Bahasa Indonesia (M.Pd.)
- 1994 - IAIN Sunan Gunung Djati Bandung, Pendidikan Agama Islam (S.Ag)

Pengalaman Mengajar

- Dosen UIN Sunan Gunung Djati Bandung tahun 1997 s.d. sekarang

Pengalaman lain

- (2022 - seakarang) Ketua Prodi Tadris Bahasa Indonesia Fak. Tarbiyah UIN Bandung
- (2018 - sekarang): Fasilitator Nasional pembelajaran pada Tanoto Foundation
- 2018 s.d sekarang): Instruktur nasional program Madrasah Reform Kementerian Agama RI.
- (2015 - 2017): TTI Development Specialist Jawa Barat pada Education Development Center (EDC) untuk program Prioritas USAID.
- (2012-2015): Teacher Training Officer Jawa Barat Education Development Center (EDC) untuk program Prioritas USAID.
- (2007-2011): District Coordinator Save the Children (SC) pada program DBE 3 USAID.
- (2005-2007) Fasilitator Nasional for Citizenship Education Subject pada project Asia Foundation.
- (2005-2007) Fasilitator Daerah/District Facilitator Jawa Barat dan Banten pada project Asia Foundation.
- Trainer Hypnotherapy (telah melatih di beberapa instansi seperti BJB Cabang Soreang Banten, Guru-guru di lingkungan Dinas Pendidikan Kota Bekasi, Guru-guru di lingkungan Kemenag Kota Bandung, Hypnotherapy di di

Lingkungan Mahasiswa UIN Bandung, Guru-guru SMP di Kabupaten Kuningan, Guru-Guru dan orang tua Yayasan Tunas Unggul Bandung).

-

Karya ilmiah yang ditulis:

- Penerapam Model Pembelajaran Siswa Aktif dalam Meningkatkan Keterampilan Berbicara Siswa SD, **Metalingua Jurnal Penelitian Bahasa 674/AU2/P2MI-LIPI** 2015;
- Model Pelaksanaan Perkuliahan Bahasa Indonesia di Fakultas Saintek UIN Bandung, **Jurnal Istek Volume IX No.1, 2015;**
- Model Pembelajaran Tematik Integratif untuk Mengembangkan Kemampuan Berpikir Kreatif Siswa; 2018**;**
- Model Penguatan Pendidikan Karakter Berwawasan Kebangsaan di Pesantren; 2019**;**
- Implementasi Model Pembelajaran Tematik Integratif untuk Meningkatkan Skill Siswa Era Revolusi Industri 4.0**;**
- The Implementation of Character Education on Bahasa Indonesia through Active Learning in Elementary Schools; Developing ELT in the 21st Century: Proceedings of Bandung English Language Teaching International Conference - BELTIC 2018;
- Model Pembelajaran STEAM dalam meningkatkan Keterampilan Abad 21: 2020;
- Implementation of The Thematic-Integrative Learning to Enhance;Students Skill in The 4.0 Era. Jurnal Pendidikan Islam Vo.7 No.2 (2021)
- Cultivating Students Communication Skill Through the STEAM Learning Model with Indonesian Prosedur Text Materials, Proceedings of Bandung English Language Teaching International Conference - BELTIC 2022.

Validation Test of Learning Content and ICT Expert

A. Instructions

Based on your opinion, please give an assessment:

a. VG (very good); G (good); S (sufficient); L (less); VL (very less).

b. Score: VG: 5; G: 4; S: 3; L: 2; VL:1.

B. Fill in the following columns (√):

No	Assessment Aspects	Qualification				
		VG	G	S	L	VL
1	Suitability of learning objectives and materials			✓		
2	Depth and breadth of learning materials			✓		
3	Suitability of learning materials with course CLOs		✓			
4	Distribution of learning materials with each CLO		✓			
5	Ease of access to learning materials		✓			
6	Form and completeness of assessments				✓	
7	Suitability of learning analytics			✓		
8	Suitability of technology selected in KMS			✓		
9	Speed of processing time			✓		
10	Quality of data management in the KMS system			✓		
11	Clarity of language and use of menus in KMS			✓		

C. Notes

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D. Recommendations

General assessment (mark √):

✓ a. Suitable for use without revision

b. Suitable for use with revisions according to suggestions

c. Not suitable for use.

Bandung, 5 /03/ 2024

Validator

Dian Sa'adillah Maylawati, Ph.D

DAFTAR RIWAYAT HIDUP

IDENTITAS DIRI

Nama	:	Dian Sa'adillah Maylawati, MT., Ph.D
NIP/NIK	:	198905262019032023
Perguruan Tinggi	:	Universitas Islam Negeri Sunan Gunung Djati Bandung
Jabatan	:	Ketua Program Studi Informatika
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Alamat Rumah	:	Komp. Cipadung Permai. Jl. Terusan Permai V No. 46, Cibiru, Bandung. 40614
Nomor Telepon	:	0857-2028-8584
Alamat *e-mail*	:	diansm@uinsgd.ac.id

RIWAYAT PENDIDIKAN PERGURUAN TINGGI			
Tahun Lulus	Program Pendidikan (diploma, sarjana, magister, spesialis, dan doctor)	Perguruan Tinggi	Jurusan/Program Studi
2023	Ph.D/Doktor	Universiti Teknikal Malaysia Melaka	Center for Advanced Computing Technology, FTMK
2015	Magister	Institut Teknologi Bandung	Informatika
2011	Sarjana	Universitas Pendidikan Indonesia	Ilmu Komputer

PELATIHAN PROFESIONAL/KEILMUAN/KEAHLIAN				
Tahun	Jenis Pelatihan (Dalam/Luar Negeri)	Penyelenggara/ Penerbit Sertifikat	Sertifikat	Jangka Waktu
2023	Certified in Data Science	American Academy of Project Management	#2024930520230260	
2022	Training for Certified International Specialist Data Visualization (CISDV)	Data Academy	08092022.CDA.CISDV.8201	24 JP
2022	Pelatihan Kompetensi	Kementerian Agama	02/2023/Academy/2	200 JP

	Dosen Pemula Kementerian Agama RI		449/LPDP	
2022	Program Non Gelar Beasiswa Indonesia Bangkit: Moralitas IPTEK	Kementerian Agama	02/2023/Academy/2449/LPDP	7 Hari
2022	Program Non Gelar Beasiswa Indonesia Bangkit: Student Character in Digital Era	Kementerian Agama	02/2023/Academy/2449/LPDP	7 Hari
2022	Program Non Gelar Beasiswa Indonesia Bangkit: Digital Mindset	Kementerian Agama	02/2023/Academy/2449/LPDP	7 Hari
2022	Program Non Gelar Beasiswa Indonesia Bangkit: Pendidikan Menuju Era Digital Society 5.0	Kementerian Agama	02/2023/Academy/2449/LPDP	7 Hari
2022	Program Non Gelar Beasiswa Indonesia Bangkit: Moderasi Beragama	Kementerian Agama	02/2023/Academy/2449/LPDP	7 Hari
2022	Program Non Gelar Beasiswa Indonesia Bangkit: Pelatihan Dasar dan Konsep TPACK	Kementerian Agama	02/2023/Academy/2449/LPDP	7 Hari
2022	Program Non Gelar Beasiswa Indonesia Bangkit: Moralitas IPTEK	Kementerian Agama	02/2023/Academy/2449/LPDP	7 Hari
2021	Pelatihan Data Scientist Artificial Intelligence untuk Dosen dan Instruktur Kominfo	Kominfo	05124873120-6/TA.DTS/ BLSDM.KOMINFO/2021	32 JP
2021	Workshop Inovasi Pembelajaran di era Revolusi Industri 4.0	Fakultas Sains dan Teknologi	B-1238/Un.05/III.7/PP.00.9/ 08/2021	3 Hari

PENGALAMAN PENELITIAN				
Tahun	Judul Penelitian	Ketua/Anggota Tim	Sumber Dana	Luaran
2021	National Survey on Religion, Pandemic, and Disaster in Indonesia, collaboration with Pusat Pengkajian Islam dan Masyarakat (PPIM) UIN Syarif Hidayatullah Jakarta, as an invited researcher for Social Media Analytics	Anggota	PPIM	Buku, Artikel Ilmiah
2020	Digital Culture in Higher Education	Anggota	Kementerian Agama	Buku ISBN, Artikel Jurnal, HKI
2022	Learning Loss Pendidikan Agama Islam	Ketua	Kementerian Agama	Buku ISBN, Artikel Jurnal, HKI, Program Komputer
2023	Sains Data untuk Rekomendasi Kebijakan Kesiapan Madrasah dalam Implementasi Kurikulum Merdeka	Ketua	Kementerian Agama	Buku ISBN, Artikel Jurnal, HKI
2017	Sistem Pakar Hukum Kewarisan Islam di Indonesia menggunakan Metode Rule Based Learning	Anggota	BOPTN	Buku ISBN, Artikel Jurnal, HKI
2018	Executive Information System Persiapan Akreditasi Perguruan Tinggi	Anggota	BOPTN	Buku ISBN, Artikel Jurnal, HKI
2022	Chatbot Layanan Peradilan Agama di Indonesia	Anggota	BOPTN	Buku ISBN, Artikel Jurnal, HKI

2019	Analisis Kebutuhan Sistem Monitoring dan Evaluasi Penelitian dan Publikasi Ilmiah	Anggota	BLU	Buku ISBN, Artikel Jurnal, HKI
2021	Pengembangan Rumah Konsultasi Hukum Islam dengan Metodologi Scrum	Anggota	BLU	Buku ISBN, Artikel Jurnal, HKI

KARYA ILMIAH		
Tahun	Judul	Penerbit/Jurnal/Penyelenggara
A. Buku/ Bab Buku/ Jurnal		
2024	Sains Data: Kurikulum Merdeka di Madrsah	CV. Sentra Publikasi Indonesia
2024	Deep sequential pattern mining for readability enhancement of Indonesian summarisation	International Journal of Electrical and Computer Engineering 14(1), pp. 782-795
2024	Exploratory data analysis to reveal learning loss condition in Islamic religious education	International Journal of Evaluation and Research in Education 13(1), pp. 43-56
2023	Chatbot Layanan Peradilan Agama di Indonesia	CV. Sentra Publikasi Indonesia
2023	Combination of convolutional neural network and long short-term memory to enhance the sentiment analysis result with the Indonesian language	AIP Conference Proceedings 2646 (1)
2023	Comparison of the Fisher-Yates Shuffle and the Linear Congruent Algorithm for Randomizing Questions in Nahwu Learning Multimedia	Khazanah Journal of Religion and Technology 1 (1), 10-14
2023	Analysis of K-popers Sentiment of Indonesian Entertainment World with Convolutional Neural Network Algorithm	9th International Conference on Computing, Engineering and Design
2023	Sentiment Analysis on the Pros and Cons of Cryptocurrencies using the Multinomial Naïve Bayes Algorithm	9th International Conference on Computing, Engineering and Design
2023	Football Supporters Club Opinion Analysis using Recurrent Neural Network	9th International Conference on Computing, Engineering and Design

2023	Changes Analysis in Public Opinion Regarding Binary Option Trends using K-Means++	9th International Conference on Computing, Engineering and Design
2023	Sentiment Analysis Regarding the Name of "Nusantara" in Indonesia's New Capital City Using Convolutional Neural Network	9th International Conference on Computing, Engineering and Design
2023	Natural Feature Tracking Algorithm in Augmented Reality Recognition of Asmaul Husna	9th International Conference on Wireless and Telematics (ICWT), 1-6
2023	Sentiment Analysis on the Issue of the Palestine-Israel Conflict on Twitter Using the Convolutional Neural Network Algorithm	9th International Conference on Wireless and Telematics (ICWT), 1-6
2023	Big Five Personality Type Prediction on Twitter Users with the Long Short-Term Memory Algorithm	9th International Conference on Wireless and Telematics (ICWT), 1-6
2023	LMS-google classroom digital platform: Between learning readiness and anxiety	AIP Conference Proceedings 2734 (1)
2023	Combination of Graph-based Approach and Sequential Pattern Mining for Extractive Text Summarisation with Indonesian Language	Khazanah Informatika: Jurnal Ilmu Komputer dan Informatika 9 (2), 132-145
2023	Feature-based approach and sequential pattern mining to enhance quality of Indonesian automatic text summarisation	Indonesian Journal of Electrical Engineering and Computer Science 30(3), pp. 1795-1804
2022	Society's Perspectives on Contemporary Islamic Law in Indonesia through Social Media Analysis Technology: A Preliminary Study	International Journal of Islamic Khazanah (IJIK) 12 (1), 14-31
2022	Logical framework of information technology: Systematization of software development research	Telfor Journal 14 (1), 26-32
2022	Leather Product Recommendation System using Collaborative Filtering Algorithm	8th International Conference on Wireless and Telematics (ICWT), 1-5
2022	Indonesian Citizens' Health Behavior in a Pandemics: Twitter Conversation Analysis using Latent Dirichlet Allocation	8th International Conference on Wireless and Telematics (ICWT), 1-6
2022	Social-Politic in a Pandemics Indonesian Citizens' Twitter Conversation Analysis using Latent Dirichlet Allocation	8th International Conference on Wireless and Telematics (ICWT), 1-6

2022	Pneumonia Prediction System Using Classification and Regression Trees Algorithm	8th International Conference on Wireless and Telematics (ICWT), 1-6
2022	Implementation of K-Nearest Neighbor to Predict the Chances of COVID-19 Patients' Recovery	8th International Conference on Wireless and Telematics (ICWT), 1-6
2022	Sentiment Analysis of the Use of Telecommunication Providers on Twitter Social Media using Convolutional Neural Network	8th International Conference on Computing, Engineering and Design

KONFERENSI/SEMINAR/LOKAKARYA/SIMPOSIUM			
Tahun	Judul Kegiatan	Penyelenggara	Panitia/Peserta/Pembicara
	Cyber IT Service Management (CITSM) 2023		
2023	Pendampingan Percepatan Guru Besar IAIN Palangkaraya	IAIN Palangkaraya	Pembicara
2023	Pendampingan Akselerasi Guru Besar IAIN Kediri	IAIN Kediri	Pembicara
2022	Workshop "Penyusun LED dan LKPS LAM INFOKOM" by APTIKOM Jabar	APTIKOM	eserta
2022	Workshop "Pengembangan Rencana Pembelajaran Semester dalam Rangka Implementasi Outcome-based Education"	UIN SGD Bandung	Peserta
2022	Launching Research Result "Anak Muda dan Covid-19: Bhineka Kita teguh, Ber-Hoax Kita Runtuh"	PPIM	Pembicara

PENGHARGAAN/PIAGAM		
Tahun	Bentuk Penghargaan	Pemberi
2023	10 Peneliti Terbaik versi Sinta Tahun 2023 di Lungkungan UIN Sunan Gunung Djati Bandung	UIN Sunan Gunung Djati Bandung
2022	The most productive researcher in Science and Technology Faculty from Department of Informatics, UIN Sunan Gunung	UIN Sunan Gunung Djati Bandung

	Djati Bandung 2022	
2021	The most productive researcher in Science and Technology Faculty from Department of Informatics, UIN Sunan Gunung Djati Bandung 2021	UIN Sunan Gunung Djati Bandung
2020	500 Best Researcher (#124) SINTA, Ministry of Research and Technology /National Agency for Research and Innovation	Kemenristek Dikti
2020	Best Paper on International Conference on Computing, Engineering and Design (ICCED) 2020	Universitas Nusaputra
2019	Best Presenter on Annual Applied Science and Engineering Conference (AASEC) 2019	Universitas Pendidikan Indonesia

Bandung, 16 Februari
2024 Yang Menyatakan,

Dian Sa'adillah Maylawati, MT, Ph.D

Validation Test of Learning Media Expert

A. Instructions

a. VG (very good); G (good); S (sufficient); L (less); VL (very less).

b. Score : VG: 5; G: 4; S: 3; L: 2; VL: 1.

B. Fill in the following columns (√):

No	Assessment Aspects	Qualification				
		VG	G	S	L	VL
1	Quality of technology selection for learning media		√			
2	Quality of display or design			√		
3	Quality of menu layout			√		
4	Quality of colour use on display			√		
5	Quality of features used			√		
6	Quality of text and language used		√			
7	Ease of use		√			
8	Availability of media operation assistance		√			
9	Availability of learning support			√		

C. Notes

....

....

....

D. Rekomendasi

General assessment (mark √):

√ a. Suitable for use without revision

b. Suitable for use with revisions according to suggestions

c. Not suitable for use.

Bandung, 2/II 2024

Validator

Dr. Ayu Puji Rahayu, M.Pd

Dr. Ayu Puji Rahayu, M.Pd

Domisili: Jl Sidqia No.07 Rt.03 Rw.27 Kel. Kota Kulon Kec. Garut
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PENDIDIKAN

Fujian Normal University – Fujian, China — **Sept, 2019 – Des, 2023**
S-3, Kurikulum dan Metodologi Pengajaran

Universitas Pendidikan Indonesia – Bandung, Indonesia — **Juli, 2017 – Jan, 2018**
S-3, Pendidikan Umum dan Karakter （1 semester）

Institut Pendidikan Indonesia – Garut, Indonesia — **Jan, 2013 – Des, 2014**
S-2, Teknologi Pendidikan

Institut Keguruan Ilmu Pendidikan Siliwangi – Cimahi, Indonesia — **Agst, 2006 – Jul, 2010**
S-1, Pendidikan Bahasa dan Sastra Indonesia

PENGALAMAN KERJA

Madrasah Aliyah Arafah – Kab. Bandung, Indonesia — **2010 – 2013**
Guru Bahasa Indonesia

MTs As-Shiddiq – Kab.Bandung, Indonesia — **2013 – 2015**
Guru Bahasa Indonesia

STAI Darul Falah – Kab.Bandung Barat, Indonesia — **2014 – Juni 2024**
Dosen Tetap

IPI Garut — **2024**
Dosen Tetap

KURSUS/SERTIFIKASI

Overseas Education College, Fujian Normal University — **Sept, 2018 – Jul, 2019**
Mandarin language

SERTIFIKAT PROFESI

Jabatan Tenaga Pengajar — **Lektor**
Pangkat/Gol.Ruang/TMT — **Penata Tk.1/III.d/01-10-2021**

SK INPASSING

Nomor — **0169/KOP.II/SK/12/2021**
Jabatan,angka kredit, tmt — **Lektor, 300, 1 Oktober 2016**

Sinta ID: *6783629*
Google Scholar:
https://scholar.google.com/citations?user=Aj9b0W8AAAAJ&hl=en

Appendix B

Examples of Knowledge Scraping Results Using BeautifulSoup

Source of Knowledge (URL):
https://medium.com/@eman-lotfy-elrefai/how-to-build-arabic-audio-classifier-using-tensorflow-1986e3480a21
Scraping Results:
 Eman Elrefai Share In this tutorial, you'll learn how to deal with audio, train the model, test it, and develop using tensorflowjs. Are you eager to start? Let's start! This is the dataset used in building the project. When you check their website, you have two versions of the dataset: one is a sample with only 20 recordings and another is the complete dataset with about 9992 audio files. For each audio, you'll find only one recorded word by 50 native speakers who repeated each word 10 times for 20 words in total. So the naming for the audio file can tell you about this information. For example this audio name: S01.02.05.wav. The first part is the speaker number from 1 to 50: S01, the second part is the repetition number from 1 to 10: 02 and the last part is the word number from 1 to 20: 05 . You can check the README file as well for more details.
Source of Knowledge (URL):
https://medium.com/syncedreview/googles-generative-video-compression-technique-outperforms-traditional-neural-video-compression-9e1ce361f715
Scraping Results:
Share While the increasing use of video streaming and conferencing has enabled new entertainment and remote work opportunities, efficiently lessening data transmission loads has proven challenging for most existing video compression techniques.

Video compression is the process of reducing the total number of bits needed to store a video while preserving visual content quality by leveraging temporal and spatial redundancies. Recent research has demonstrated the promising potential of neural networks for this task, as they can outperform the more broadly used non-neural standard High Efficiency Video Coding (HEVC).

In a new paper, a Google Research team takes a step forward in this field, proposing a neural video compression method based on generative adversarial networks (GANs) that outperforms previous neural video compression methods.

The team summarizes their contributions as:

The team's approach uses three strategies to obtain high-fidelity reconstructions: 1) Synthesize plausible details in the I-frame; 2) Propagate those details wherever possible and as sharp as possible; 3) For new content appearing in P-frames, synthesize plausible details.

The proposed I-frame branch used to synthesize plausible details is based on a lightweight version of the architecture used in HiFiC, in which the encoder CNN maps the initial input image to a quantized latent. At a high level, the P-frame branch used to propagate those details comprises auto-encoders for both the flow and the residual. The team employs a powerful optical flow predictor network, UFlow, on the encoder side. The resulting flow outputs the quantized and entropy-coded flow-latent, while the generator predicts both a reconstructed flow and a confidence mask. Intuitively, this mask predicts the accuracy for each pixel in the flow, which is used to determine how much to blur the "scale-space blur" component described next.

The approach first warps the previous reconstruction with compressed flow using bicubic warping, then uses scale-space blurring — a light variation of the "scale-space flow" approach — to enable a more efficient implementation. Together, bicubic warping and blurring help to propagate sharper details and facilitate smoother blurring.

To synthesize plausible details in new content appearing in P-frames, the proposed approach employs the light version of the HiFiC architecture for residual auto-encoders, and introduces an additional source of information for the residual generator to enable it to synthesize high-frequency details from the residual latent.

The researchers also propose a technique to mitigate temporal error-accumulation problems, which is crucial for obtaining high visual quality. To this end, and motivated by a spectral analysis, they adopt a new training schema by randomizing the shifting of residual inputs followed by an un-shifting of the outputs.

The team evaluated their proposed model on 30 diverse videos from MCL-JCV, which include a wide variety of motion from natural videos, computer animation and classical animation. They compared their approach with baseline “MSE-only,” “Scale-Space Flow” (SSF), and the non-learned HEVC. They reported results based on non-overlapping 256×256 patches and the unsupervised perceptual quality Perceptual Information Metric (PIM), introduced by Bhardwaj et al. in 2020.

Overall, the study shows that the proposed method is competitive to HEVC and outperforms previous neural video compression codecs, validating the promising potential of GANs for improving video compression performance.

The paper Towards Generative Video Compression is on arXiv.

Author: Hecate He | Editor: Michael Sarazen, Chain Zhang

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Written by Synced

SyncedReview

AI Technology & Industry Review — syncedreview.com | Newsletter: http://bit.ly/2IYL6Y2 | Share My Research http://bit.ly/2TrUPMI | Twitter: @Synced_Global

Source of Knowledge (URL):

https://www.digitalguardian.com/blog/what-digital-rights-management

Scraping Results:

International

TECHNICALOVERVIEW

Read how a customer deployed a data protection program to 40,000 users in less than 120 days.

DEFINITIVE GUIDETO DLP

Digital Guardian's Blog

by Conor Roach on Thursday August 22, 2024

Learn about digital rights management and why it is important in Data Protection 101, our series on the fundamentals of information security.

Digital rights management (DRM) is a way to protect copyrights for digital media. This approach includes the use of technologies that limit the copying and use of copyrighted works and proprietary software.

In a way, digital rights management allows publishers or authors to control what paying users can do with their works. For companies, implementing digital rights management or processes can help to prevent users from accessing or using certain assets, allowing the organization to avoid legal issues that arise from unauthorized use. Today, DRM is playing a growing role in data security.

With the rise of peer-to-peer file exchange services such as torrent sites, online piracy has been the bane of copyrighted material. DRM technologies do not catch those who engage in piracy. Instead, they make it impossible to steal or share the content in the first place.

How Digital Rights Management Works

Most of the time, digital rights management includes codes that prohibit copying, or codes that limit the time or number of devices on which a certain product can be accessed.

Publishers, authors, and other content creators use an application that encrypts media, data, e-book, content, software, or any other copyrighted material. Only those with the decryption keys can access the material. They can also use tools to limit or restrict what users are able to do with their materials.

There are many ways to protect your content, software, or product. DRM allows you to:

Digital rights management also allows publishers and authors to access a log of people and times when certain media, content, or software was used. For instance, you can see when a particular e-book was downloaded or printed and who accessed it.

Digital Rights Management Use Cases

In today's digital world, digital rights management is increasingly important, not only for digital content creators but also for companies and individuals that make use of digital assets licensed or purchased from third-party creators. Here are a few common use cases for digital rights management:

1. Digital rights management allows authors, musicians, movie professionals, and other creators to prevent unauthorized use of their content. It can also protect their bottom lines and control the distribution of their products.

2. Digital rights management can help companies control access to confidential information. They can use these technologies to restrict access to sensitive data, while at the same time allowing it to be shared securely. Furthermore, having DRM technologies makes it easier for auditors to investigate and identify leaks. When used in a business setting, digital rights management may be called by a different name, such as information rights management or enterprise rights management. Healthcare organizations and financial services companies turn to DRM to meet data protection regulations such as HIPAA or GLBA.

3. Digital rights management ensures that digital work remains unaltered. Creators often want their work to be distributed in its original form to serve its intended purposes. The FDIC uses digital rights management to prevent the unauthorized redistribution of sensitive digital information, for example.

4. Many companies in the manufacturing, technology, and biotech sectors store sensitive patents, trademarks, customer information, and processes across multiple storage platforms, both on-prem and off-prem. To protect that data and IP, they would need a digital right management tool to secure those files wherever they may reside.

Challenges of Traditional Digital Rights Management Tools

Traditional digital rights management tools can present some challenges. Some are limited by the file types they support (such as only protecting Office and PDF files). "Others have an inflexible framework that requires a client at all times, making for a more challenging implementation and acting as a barrier to collaboration.

Benefits of Digital Rights Management

Digital rights management solutions provide the ability to share data/file but still retain control over who can access and what they can do. Secure file collaboration and the need to share files with sensitive information with 3rd parties is a necessity for companies of any size, in any industry. DRM’s benefit include:

1. Digital rights management educates users about copyright and intellectual property. Most people are not concerned with copyrights and are passive when it comes to DRM. As long as they can access the content they like, they have no issue with smaller details. With DRM in place, companies can communicate to users what they can and cannot do with respect to digital content.

2. DRM helps make way for better licensing agreements and technologies. Digital rights management technologies are aimed at restricting the ways in which users interact with content, such as listening to music on multiple devices or sharing content with friends with family. Users who do not want to be restrained by DRM codes are able to support vendors who offer and sell DRM-free content, thus encouraging vendors to look for other technologies that are better at licensing than DRM.

3. Digital rights management helps authors retain ownership of their works. It is very easy for a company or user to copy content from someone else’s e-book and rebrand it as their own. With DRM, it is possible to stop anybody from altering content. This also applies to scientists who rely on DRM to protect their inventions.

4. Digital rights management helps protect income streams. Video and moviemakers spend money to create their videos in the hopes that they will be able to recoup their investments once it hits screens, or when it streams or is distributed online. DRM can help ensure that only paying users are able to watch the video or movie. It also ensures that the video is only accessible to a certain audience. For instance, videos with adult-oriented content should only be accessible to adults who can verify their age.

5. Digital rights management can help secure files and keep them private. DRM effectively prevents unauthorized users from seeing or reading confidential files.

Digital assets comprise a substantial portion of the content that people consume and interact with on a daily basis. The digital world opens up the door to a whole new realm of possibilities when it comes to protecting sensitive information, including intellectual property. Far gone are the days when authors needed to be concerned only with consumers running a book through a copy machine. In today’s digital world, digital rights management is imperative for companies spanning every industry to protect their information assets.

Frequently Asked Questions

What is meant by digital rights management?

Digital rights management (DRM) refers to the approach used to protect copyrights for digital media. It uses a variety of methods and technologies to accomplish this goal including:

1) Restricting or preventing users from editing, saving, sharing, forwarding, or printing content.

2) Setting limits on the number of copies that can be made of a specific work.

3) Preventing users from taking screenshots of digital content.

4) Setting expiration dates after which users cannot access digital content.

5) Controlling access to digital media by county or region.

6) Watermarking content to verify authenticity and ownership.

Why is DRM important?

DRM is important for the following reasons.

1) DRM provides users with education regarding how they can use digital content.

2) DRM paves the way for innovative and more equitable digital media licensing agreements.

3) DRM can be used to ensure the privacy of confidential and sensitive data.

4) DRM assists creators in retaining ownership of their works.

5) DRM protects income streams spawned from digital media distribution.

What is an example of digital rights management?

Examples of digital rights management are the methods streaming video and audio services use to limit the number of devices that an account can use to access the content. DRM ensures that users cannot share accounts for services like Apple Music or Netflix with an unlimited number of friends or family members.

What is DRM and why is it used?

DRM stands for digital rights management. It is used to protect an organization's digital media from unauthorized use and to ensure a company retains control over the distribution of digital content. DRM can also be used to protect sensitive and confidential information by controlling access and limiting it to authorized users.

Who uses DRM?

DRM is used by companies in all industries to protect their digital information assets. This includes protecting sensitive customer and internal data as well as an organization's intellectual property. All entities involved in the creation, sale, or distribution of digital media should implement DRM to safeguard their valuable assets. Tags: Data Protection 101 **Recommended Resources** All the essential information you need about DLP in one eBook. Expert views on the challenges of today & tomorrow. The details on our platform architecture, how it works, and your deployment options.
Source of Knowledge (URL):
Basic JavaScript control flow. 1. Equality in java script | by Satyendra Jaiswal | Medium
Scraping Results:
in JavaScript there are actually two different equality operators, the double equals and the triple equals.when comparing two basic values, numbers or strings for example with the triple equals it checks to see if the two values are of the same type as well as whether the two values are equal to each other. if two values are not the same data type they won't be treated as equal by the triple equals operator.for example , 5 === 5 is true" and Hi"=== "Hi" is true double equals compares to values without regard to their types. This means that if we use the double equals to compare a number and that same number as a string it'll return true. And likewise if we compare a regular number and that same number as a bigint. Different Data Types → Not equal5 === "5" is false10 === 10n is false "Double equals" doesn't check for type5 == "5" is true **10 == 10n is true**

== operator performs type coercion, converting the 10 on the left side to a BigInt (10n) on the right side before making the comparison.

== 10 10n

This behavior is due to type coercion in JavaScript's loose equality comparison (==), where values of different types are converted to a common type before the comparison.

==

there are pretty big number of situations where we get some somewhat unexpected results. For example if we use the double equals to compare the number zero with the string zero we get true which we'd expect.0 == "0" is true

But zero double equals an empty string as well and its also equal to an empty array. 0 == "" is true0== [ ] is true

But, zero double equal null or undefined is not true but false.0 == null is false0 == undefined is false

There are other cases, for example the string's true and false aren't double equals equal to the boolean values true and false."true" == true is false"false"== false is false

So, we should mostly use triple equals operator for equality comparision. And in cases where its required to use a double equals; For example if for some reason you have to check if a number is equal to a number in string form what you could do instead is use the triple equals and explicitly convert the string to an actual number using what's called the "number constructor" 5 === Number ("5")

In JavaScript, comparing objects and arrays involves understanding how references and values are compared. Here are some insights into comparing objects and arrays with another object or array:

===const obj1 = { key: 'value' };const obj2 = { key: 'value' };console.log(obj1 === obj2); // false

2. Shallow Equality:

const obj1 = { key: 'value' };const obj2 = { key: 'value' };const shallowEqual = (a, b) => { return a.key === b.key;};console.log(shallowEqual(obj1, obj2)); // true

3. Deep Equality:

const deepEqual = (a, b) => { return JSON.stringify(a) === JSON.stringify(b);};console.log(deepEqual(obj1, obj2)); // true===

Arrays are also compared by reference.

const arr1 = [1, 2, 3];const arr2 = [1, 2, 3];console.log(arr1 === arr2); // false

2. Shallow Equality:

const arr1 = [1, 2, 3];const arr2 = [1, 2, 3];const shallowEqualArray = (a, b) => { return a.every((val, index) => val === b[index]);};console.log(shallowEqualArray(arr1, arr2)); // true

3. Deep Equality:

const deepEqualArray = (a, b) => { return JSON.stringify(a) === JSON.stringify(b);};console.log(deepEqualArray(arr1, arr2)); // true

Keep in mind that using JSON.stringify for deep comparison has limitations (e.g., it won't work well with functions or circular references) and might have performance implications for large objects or arrays. Depending on your use case, you may need to implement a custom deep comparison function or use a dedicated library like Lodash's isEqual for more robust comparisons.

JSON.stringify isEqual

In JavaScript, condition has to be surrounded by parentheses. In other words, we can't leave the parentheses off like we can in languages such as Java or Python.

if (someCondition) { // do something}if (someCondition) {// do something} else if (otherCondition) {// do something else} else {// do another thing}

While there are only two possible values for the boolean type, true and false, JavaScript treats all the possible values of other types as either true or false as well. For example, instead of explicitly checking of a string's length as greater than zero, we can simply check if(myString) and since empty strings are treated as falsy in JavaScript, the body of this if statement won't be executed if the string's length is zero.

let myString = "";if (myString) {// this won't be executed} else {// …but this will execute}

this used as a sort of shorthand instead of saying if myString.length equals zero.

List of falsy values in JavaScript

These are the seven values that JavaScript treats as falsy. The rest of the possible values in JavaScript are treated as truthy.1. “”2. 03. 0n4. NaN5. undefined6. null7. false

based on above, following are some comparisons :

“” == false is true0 == false is true0n == false is trueNaN == false is falsenull == false is falseundefined == false is false

Note: These are very common cause of bugs in JavaScript programs

Note: These are very common cause of bugs in JavaScript programs

Combine conditions by using the boolean operators such as and, or, and not.

let x = 100;if(x > 5 && x < 100){// do something} let x = 100;if(x > 5 || x < 100){// do something} let x = 100;if(! (× < 99)){// do something}

Loops allow us to execute us a block of code multiple times. Sometimes, this number of times is known beforehand and sometimes it isn’t. In JavaScript, for loops are primarily used only when we know ahead of time how many times we want our code to execute. For example, if we have an array of items and we want to loop through all those items one by one and work on them. JavaScript basically provides us with a few different ways of doing for loops.

1. For loop :

similar to what we might see in C++ or Java, for(; ;){}We have for and the parenthesis that contain three statements separated by semicolons. The first statement is where we define any new variables we want to use such as an index variable. The second statement is the condition that needs to be true in order to for the loop to repeat or start in the first place for that matter. for example a check to make sure that the indexing variable that we defined is less than the length of array.And the third statement is the change that should take place after every iteration of the loop.For example, incrementing our index variable.Finally, the body of the for loop is where we define the code that we want to be executed over and over again until the condition that we defined up top is no longer true.example: we have an array ar and we just want to print every element in that array to the console

for (let i = 0; i < ar.length; i = i + 1) { console. log (ar [i]) ;}

2. for-of loop :

A much cleaner way to write loops

for (let item of ar) { console.log(item) ;}this will loop through all of the elements for each iteration, item will be equal to the current element we’re looking at. Basically the for-of loop just takes care of all the indexing logic for us.

for (let person of people) { console.log(person.name) ;}

3. for-in loop :

Let's say that instead of looping through all the items in an array, we have an object e.g. a person object and we want to loop through all the properties of the person.

let person = { name: "John", age: 39, interests: ["movie", "food"],}

here, for-in loop helps us.

for (let key in person) { console.log(key ": " person[key]) ;} for each iteration of our loop, key will be one of the property names in our person object. So for instance name, age, interests, etc. So in above example it will print out each of the person's keys along with the current value of that key.

4. forEach :forEach isn't technically a for loop like the others rather it's a function that we can call on any array.

arr.forEach(function(x)){ console.log(x) ;});

when we call forEach, we would pass it a function with one argument (Note: we can pass functions as arguments to other functions in JavaScript). in above example forEach will loop through each of the elements in array arr and call whatever function we pass with each element as the argument. So here it's printing each element in array arr to the console.

Example : We have an array of people and want to print all of their names - arr.forEach(function(person)){ console.log(person.name);});

The while loop checks the condition before executing the loop body, and the do while loop checks the condition after executing the loop body. This means that the do while loop will always execute at least once, even if the condition we pass to it is false from the very beginning.

while (someCondition) {// do something} while (false) {// never executed} do {// do something} while (someCondition);do {// executed once} while (false);

Similar to java, in JavaScript we handle errors by using a try-catch block

try {// code that might fail} catch (err) {// error handling logic}

We have a try block which contains some code that might throw an error and this is followed by a catch block which will get executed if an error does occur inside the try block.

if there's code we want to be executed regardless of whether or not an error occurs such as closing a database connection or a file we're reading, JavaScript provides us with a finally block that we can add onto the end of our try-catch block and this block isn't necessary all the time and we can simply leave it off if we don't need it.

try{ // code that might fail} catch(err){ // error handling logic} finally { // clean-up logic}

Most of the time when doing error-prone things such as making network requests or reading files in JavaScript, we'll be using some library that will throw the error for us. However, there are situations when we'll want to throw our own errors (custom error). The way we do this in JavaScript is by using the throw keyword. This is usually followed by a string or object which we can use to provide information about the error that occurred, but it can also be a Boolean or a number as well.

throw "Invalid input!"; throw { message: "Error" } throw false;throw 500;

Example :

try{ //some code throw "due to some condition, throwing An Error!"} catch(err){ console.log(err);}

it prints "due to some condition, throwing An Error!"

putting throw directly in the try block isn't always necessary. We could just as easily use throw inside some function we define without a try-catch block and rely on whatever part of our program uses this function to handle it correctly.

Similar to java, Switch-case in Javascript is used when our program is faced with a range of possible values for a given variable.For example, let's say that the user had to answer a multiple choice question with possible answers A, B, C and D. Based on the response, we could give them individualized answers using an if statement with a lot of else/if blocks like below,

if (userAnswer === "a") { console.log("A… is wrong I'm afraid");} else if(userAnswer === "b") { console.log("Sorry, not quite");} else if(userAnswer === "c") { console.log("Yes!");} else if(userAnswer === "d") { console.log("You're very close…");} else if{ console.log("Invalid answer");}

but it's a little more verbose than it could beSo, in this case we can use Javascript's switch-case statement

switch (userAnswer) {case "a": console.log(…); break;case "b": //some code break;default: //some code}

at the bottom, we have a default case if the value of our variable falls outside those expected values. The default case is sort of like the else block on an if/else statement.We need to add the break keyword at the end of each of our cases; except for the default case.Without break keyword, javaScript will execute whatever the first matching case is, as well as every other case after that even if those cases don't match.

for example in below code since in case "b" break keyword is missing . so, if userAnswer is "b" then javascript will execute both case "b" and default

switch (userAnswer) {case "a": console.log(…); break;case "b": //some codedefault: //some code}

Ternary Operator is like an abbreviated version of an if statement, that we can use as part of larger statements. The basic syntax issomeCondition? valuel : value2;

We have some sort of Boolean condition, followed by a question mark, and then two different values separated by a colon. Now, if the first Boolean statement is truthy, the whole turnery statement evaluates to the first value. If it's falsy, it evaluates to the second value.

true ? value1 : value2;evaluates to value1false ? value1 : valuez;evaluates to value2

Without the Ternary Operator, we'd have to do something like this,

let greeting;if(isBeforeNoon){greeting = "Good morning";} else {greeting = "Good afternoon";}

Here, we define a new variable without assigning it any value, and then use an if statement to assign the correct value to the variable. And this works, but it's a little more verbose than it should be.

That's where the Ternary Operator comes in. Instead of using an if statement to assign one of two different values to a variable, we can write it in a much more compact way like we have here. Note: Ternary Operator is usually written on multiple lines like this to make it more readable.

let greeting = isBeforeNoon? "Good morning": "Good afternoon";

we can write nested Ternary Operators as well :

let greeting = isBeforeNoon? "Good morning" : isBeforeFiveO'Clock? "Good afternoon": "Good evening";

Global Scope:

// Global variablevar globalVar = "I am global";function exampleFunction() {   console.log(globalVar); // Accessing globalVar}exampleFunction(); // Outputs: I am global

Local Scope:
// Global variablevar globalVar = "I am global";function exampleFunction() { // Local variable var localVar = "I am local"; console.log(localVar); // Accessing localVar // Accessing globalVar within the local scope console.log(globalVar); // Outputs: I am global}exampleFunction();// console.log(localVar); // This would cause an error as localVar is not accessible outside exampleFunction
Block Scope (ES6 and later):
let const let constfunction exampleFunction() { if (true) { // Block-scoped variable let blockVar = "I am block-scoped"; console.log(blockVar); // Accessing blockVar } // console.log(blockVar); // This would cause an error as blockVar is not accessible here}exampleFunction();
var:
varvar x = 10;console.log(x); // Output: 10
let:
letlet y = 20;if (true) { let y = 30; console.log(y); // Output: 30 (scoped within the if block)}console.log(y); // Output: 20 (scoped outside the if block)
const:
const letconst z = 40;console.log(z); // Output: 40// Uncommenting the line below would result in an error// z = 50; // Error: Assignment to a constant variable
Implicit Global Variables:
var let constmyVar = "Hello, World!"; // Implicit global variable
When choosing between var, let, and const, it's recommended to use let and const over var due to the improved scoping rules. Additionally, use const for variables that should not be reassigned and let for variables that may change their value.
var let const let const var const let
Examples of using let and const:
let const// Using letlet age = 25;age = 26; // Valid// Using constconst pi = 3.14;// pi = 3.14159; // Error: Assignment to a constant variable
Choose the appropriate variable declaration method based on the scope and mutability requirements of your variables.

Source of Knowledge (URL): https://www.hostinger.co.id/tutorial/lossy-vs-lossless
Kompresi Lossy VS Lossless untuk Gambar

Scraping Results:
Hosting Web Hosting Untuk website skala kecil dan medium. Website Builder Create your website with ease. Cloud Hosting Untuk website skala besar. Hosting untuk WordPress Hosting teroptimasi untuk WordPress. VPS VPS Hosting Server virtual yang flexible dengan dedicated resource untuk website dan web aplikasi. CyberPanel VPS Hosting Control panel dengan Open/LiteSpeed Webserver. Minecraft Server Hosting Bermain bersama komunitas Minecraft. Email Google Workspace Paket layanan terbaik Google untuk kerja tim.

Email Hosting

Promosikan bisnis & jangkau banyak pelanggan.

Domain

Cari Domain

Temukan domain impian Anda.

WHOIS Lookup

Cari info WHOIS Domain.

Transfer Domain

Transfer domain murah dan mudah.

Hosting

VPS

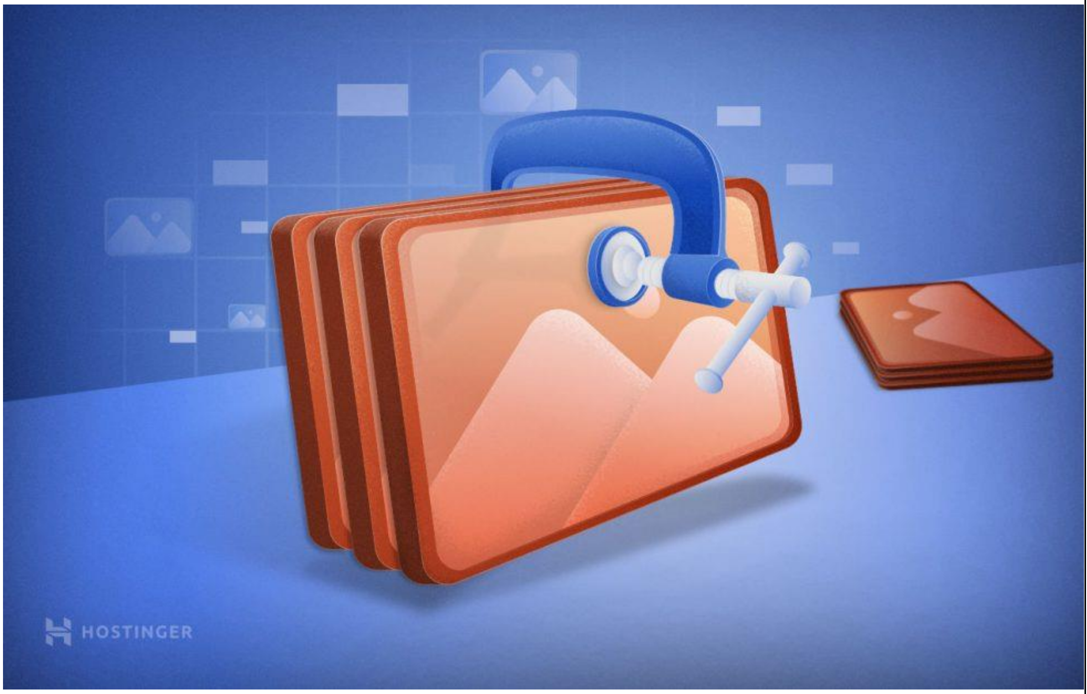
Email

Domain

Mar 29, 2023

Faradilla A.

5menit Dibaca



Kompresi Lossy dan lossless adalah dua metode populer untuk mengurangi ukuran gambar. Kami sangat merekomendasikan untuk menggunakan salah satu di antara kedua metode ini ketika mengupload file gambar ke website Anda.

Di artikel ini, kami akan menjelaskan keunggulan Lossy vs Lossless dan cara menggunakan keduanya untuk meningkatkan performa situs Anda.

Mengapa Anda Harus Mengompres Gambar?

Gambar dengan ukuran besar dapar memperlambat performa website, dan akan berisiko pada experience pengunjung dan juga peringkat SEO Anda.

Studi dari Google menyatakan bahwa 45% orang enggan mengunjungi situs yang sama saat mereka menjumpai user experience yang buruk.

Gambar berukuran besar dapat memperlambat waktu loading situs. Minimal, efek negatifnya adalah delay singkat yang menyebalkan bagi pengunjung website. Sedangkan kemungkinan terburuknya adalah membuat situs web Anda menjadi tidak responsif atau bahkan tidak bisa diakses sama sekali.

Seperti yang sudah kami katakan sebelumnya, peringkat SEO menjadi faktor lain yang bisa berada dalam ancaman. Google mengonfirmasi bahwa kecepatan loading halaman menjadi faktor utama untuk sebuah website agar dapat bertengger pada posisi terbaik di SERP. Page yang lambat dapat memengaruhi web crawler dan indexation. Bing pun sedanada dengan Google mengenai hal ini.

Performa halaman situs yang lambat juga dapat memengaruhi conversion rate. Dankie melaporkan bahwa semakin cepat halaman situs loading, semakin tinggi pula mobile revenue-nya, yaitu hingga 45%. Salah satu cara mereka untuk mempercepat performa situs adalah dengan mengoptimasi gambar pada websitenya.

Gambar yang kecil lebih menguntungkan untuk pelanggan hosting. Intinya, gambar dengan ukuran kecil dapat menghemat resource hosting itu sendiri sehingga Anda dapat menghemat uang di kemudian hari.

Hal ini terjadi karena gambar berukuran kecil dapat menghemat kapasitas penyimpanan dan mengurangi penggunaan bandwidth. Jika Anda menggunakan paket shared hosting, persoalan ini begitu serius, terlebih jika website Anda memiliki banyak gambar.

Ditambah lagi, jika Anda mengoptimasi gambar pada website, proses backup website Anda akan berjalan dengan cepat. Anda tidak perlu mengkhawatirkan kualitas gambar nantinya ketika dikompres. Lossy dan lossless merupakan metode yang canggih untuk menghapus informasi yang tidak perlu di dalam file gambar.

Nah, selanjutnya kami akan membahas kompresi gambar dengan Lossy vs Lossless.

Kompresi Gambar dengan Lossy

Kompresi gambar dengan Lossy adalah sebuah proses pengambilan data dari gambar Anda. Dengan proses ini, ukuran gambar akan berkurang. Prosesnya irreversible, yang artinya informasi yang tidak perlu akan dihapus secara permanen.

Beberapa algoritme untuk kompresi lossy adalah discrete wavelet transform, fractal compression, dan transform encryption.

Teknik ini memang dapat mengecilkan ukuran foto, tetapi kualitas gambar biasanya juga turun. Selain ukuran yang sangat kecil, gambar Anda juga menjadi gambar pixel karena penurunan kualitasnya. Itulah mengapa Anda perlu mem-backup file sebelum mengompres gambar.

Ada dua contoh format gambar yang sesuai dengan kompresi lossy, yaitu JPEG dan GIF. File JPEG cocok untuk gambar atau foto yang tidak transparan, sedangkan GIF adalah pilihan terbaik untuk gambar animasi. Format-format tersebut sangat sesuai untuk situs yang memerlukan loading cepat, karena Anda dapat menyesuaikan ukuran serta kualitas gambarnya.

Inilah contoh yang kami buat dengan menggunakan Shortpixel untuk kompresi Lossy:

Seperti yang Anda lihat, hasil dari kompresi nyaris tidak terlihat bedanya dengan foto yang asli. Anda dapat mengetahuinya ketika Anda melihat ada piksel di foto setelah memperbesar foto yang telah dikompres. Menariknya, kami telah berhasil mengurangi ukuran file hingga 85%.

Jika Anda menggunakan WordPress, ketika gambar yang Anda upload merupakan file .JPEG, maka gambar tersebut akan terkompres secara otomatis melalui media library. Itulah mengapa nantinya gambar Anda akan terlihat pixelated dalam di situs WordPress.

Pada dasarnya, image akan berkurang ukurannya sebesar 82% dari ukuran sebenarnya. Anda dapat meningkatkan persentasenya atau menonaktifkan fiturnya, dan nanti kami akan membahas caranya.

Kompresi Gambar dengan Lossless

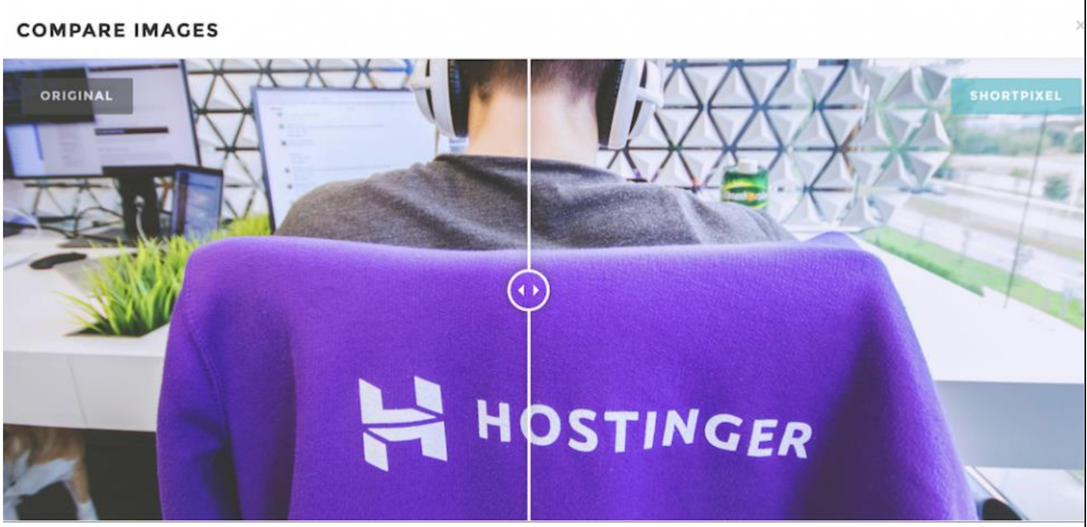
Tidak seperti opsi sebelumnya, lossless tidak akan menurunkan kualitas gambar yang dikompres. Hal ini terjadi karena lossless hanya menghapus informasi tambahan yang ada dalam gambar. Informasi tambahan tersebut berupa metadata non-esensial yang dibuat secara otomatis oleh perangkat yang digunakan ketika mengambil gambar atau editor gambarnya.

Kekurangan dari lossless adalah tidak adanya perubahan ukuran file yang signifikan, bahkan kadang tidak berbeda dengan ukuran file aslinya. Alhasil, menggunakan lossless tidak akan terlalu menghemat memori penyimpanan.

Algoritme kompresi lossless standar di antaranya adalah Huffman coding, arithmetic encoding, dan run-length encoding.

Metode kompresi lossless sangat cocok untuk gambar yang dominan akan teks dan gambar dengan background transparan – alpha layer. Format yang sesuai untuk dikompres dengan lossless adalah RAW, BMP, GIF, dan PNG.

Berikut adalah contoh hasil kompresi gambar lossless.



Sebagaimana yang dapat Anda lihat, antara gambar kiri dan kanan hampir sama kualitasnya. Faktanya, menggunakan layanan yang sama seperti sebelumnya, kami hanya berhasil mengurangi ukuran gambar sebesar 5%.

Lossy vs Lossless: Mana yang Lebih Baik?

Kami percaya bahwa jawaban yang tepat adalah ‘tergantung kebutuhan Anda’. Mayoritas user yang mengelola situs ecommerce, blog, atau website portofolio akan memilih lossy compression. Lossy compression dapat mengurangi ukuran file secara signifikan sehingga menghemat memori penyimpanan dan bandwith. Dengan begitu, situs dapat loading dengan cepat.

Di sisi lain, website bertema fotografi, fashion, modeling dan topik yang konsepnya menonjolkan gambar berkualitas tinggi akan membutuhkan lossless. Bidang tersebut membutuhkan lossless karena gambar yang teroptimasi hasilnya tidak jauh dengan gambar asli.

Kompresi Gambar Lossy di WordPress

Jika Anda memilih kompresi lossy dan menggunakan CMS WordPress, tersedia fitur yang memungkinkan Anda melakukannya secara otomatis. Jika Anda ingin mengubah persentasenya, Anda dapat menggunakan beberapa kode, dan mengubah besarannya.

Penting: Selalu buat file backup sebelum membuat perubahan apapun pada situs Anda.

Mari kita bahas terlebih dahulu beberapa modifikasi yang harus Anda ketahui. Untuk menonaktifkan kompresi gambar otomatis, tambahkan filter berikut ke file function.php tema aktif dan gunakan metode kompresi manual (seperti menggunakan software seperti Adobe Photoshop, Affinity Photo, dan editor gambar lainnya) sebagai gantinya.

add_filter('jpeg_quality', create_function('', 'return 100;'));

Jika Anda ingin meningkatkan rasio kompresi otomatis WordPressnya, Anda dapat melakukannya dengan menambahkan filter di bawah ini. Pada cuplikan contoh di bawah ini, gamabar akan dikompres sebanyak 70%.

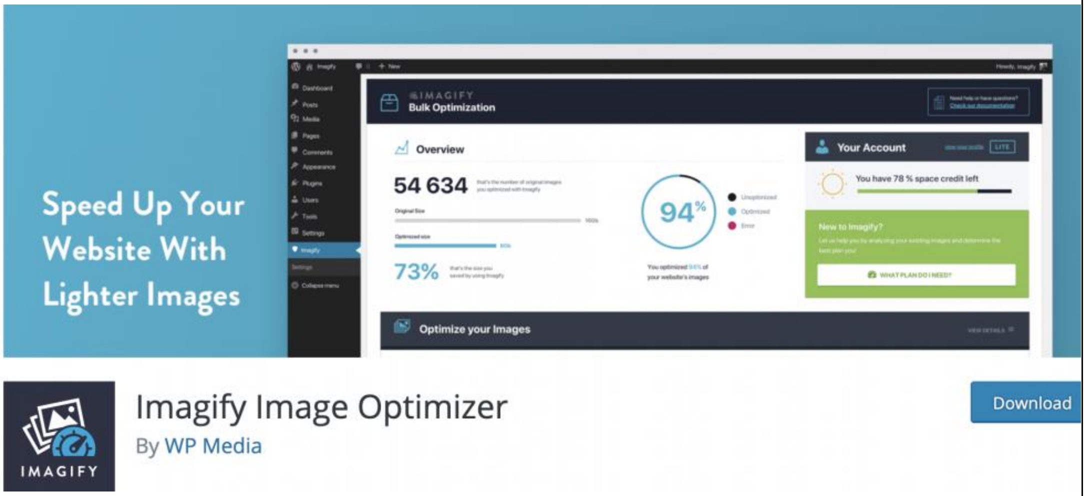
add_filter('jpeg_quality', create_function('', 'return 70;'));

Perlu Anda ingat bahwa metode ini tidak akan memengaruhi gambar yang telah diunggah di website Anda. Jika ingin memperbaruinya, Anda akan memerlukan plugin seperti Regenerate Thumbnails.

Atau, jika Anda merasa bahwa cara ini tidak praktis, kami merekomendasikan untuk menggunakan plugin. Cara ini pun lebih aman. Pada tutorial kali ini, kami akan menunjukkan cara mengompres gambar dengan plugin Imagify.

Jika Anda pengguna baru WordPress dan belum tahu cara menginstal plugin, silakan kunjungi artikel tentang cara menginstal dan mengaktifkan plugin WordPress.

Imagify



Imagify dapat mempercepat situs web Anda dengan gambar yang lebih ringan dan juga mengoptimalkan rasio gambar sesuai dengan kebutuhan Anda.

Tidak hanya akan membantu Anda mengompres, tetapi juga akan secara otomatis mengoptimalkan semua thumbnail yang Anda unggah. Plugin ini jelas membuat seluruh proses pengolahan gambar di halaman website menjadi jauh lebih efisien.

Ada tiga level optimasi yang tersedia jika Anda menggunakan plugin ini:

Imagify juga membantu mengonversi dan menyajikan gambar WebP. Ini adalah format gambar terbaru yang dikembangkan oleh Google, menawarkan gambar berkualitas lebih kaya sekaligus mengurangi ukuran file secara signifikan. Kami telah membahas WebP dalam artikel ini.

Ada juga berbagai plugin alternatif untuk mengompres gambar di WordPress, seperti WP Smush dan ShortPixel.

Kesimpulan

Sekarang Anda mengetahui dasar-dasar cara menggunakan lossy vs lossless sekaligus perbedaannya.

Kompresi lossy dapat mengurangi ukuran file secara signifikan, pada trade-off untuk kualitas.

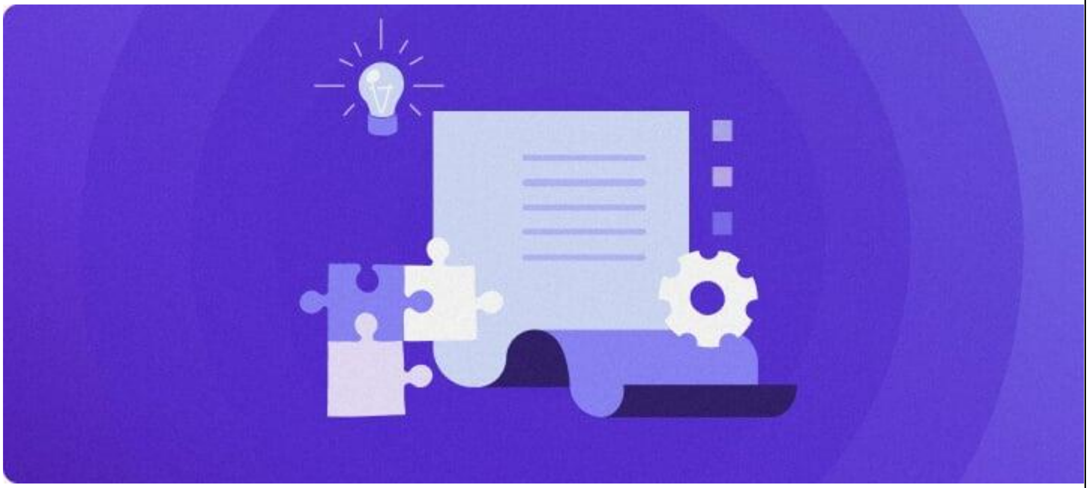
Di sisi lain, Anda dapat mempertahankan kualitas gambar menggunakan kompresi lossless yang seminimal mungkin mengompres gambar Anda. Untuk cara yang lebih mudah, Anda dapat memanfaatkan plugin untuk mengompres gambar di website WordPress Anda.

Apakah Anda siap untuk mencobanya sekarang? Semoga berhasil!

Faradilla A.

Faradilla, yang lebih akrab disapa Ninda, adalah Content Marketing Specialist di Hostinger. Ia suka mengikuti tren teknologi, digital marketing, dan belajar bahasa. Melalui tutorial Hostinger ini, Ninda ingin berbagi informasi dan membantu pembaca menyelesaikan masalah yang dialami. Kenali Ninda lebih dekat di LinkedIn.

Tutorial Terkait



30 Jan • WordPress •

Error “Updating failed. The response is not a valid JSON response” biasanya terjadi ketika editor WordPress gagal menerima respons yang...

Oleh Faradilla A.

28 Jan • WordPress •

Terkadang, saat memuat website, Anda mungkin menjumpai error “your PHP installation appears to be missing the MySQL extension which is required...

Oleh Faradilla A.

28 Jan • WordPress • Toko Online dan Bisnis •

Saat membuat toko online dengan WooCommerce, ada beberapa opsi yang perlu Anda atur sebelum mulai menerima pesanan. Apabila Anda menjual produk fisik,...

Oleh Faradilla A.

Apa Kata Pelanggan Kami

Tinggalkan Komentar Cancel reply

Dengan menggunakan formulir ini, maka Anda setuju bahwa data pribadi Anda akan diproses sesuai dengan Kebijakan Privasi Hostinger.

Δ

This site uses Akismet to reduce spam. Learn how your comment data is processed.

Appendix C

Examples of Tokenized Data Results

Type	Article	Tokenized data bert2bert		Tokenized Data Bert2bert Xtreme	
2-doc	[Doc 1] Di masa depan, blockchain akan menjadi fondasi utama dalam ekonomi digital, memungkinkan transaksi yang cepat, aman, dan tanpa perantara. Teknologi ini akan mendukung sistem pembayaran global yang lebih inklusif serta memungkinkan inovasi seperti mata uang digital bank sentral (CBDC). Dengan adopsi yang semakin luas, blockchain akan	[[3, 37, 12296, 21, 39, 1485, 2106, 2616, 16, 17511, 11507, 1488, 1634, 1649, 18868, 2408, 1558, 2498, 6559, 16, 5202, 7044, 1497, 3218, 16, 4022, 16, 1501, 2327, 15707, 18, 3279, 1540, 1634, 3669, 2289, 6983, 4684, 1497, 1716, 28790, 1999, 5202,	[[1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,	[[3, 37, 12296, 21, 39, 1485, 2106, 2616, 16, 17511, 11507, 1488, 1634, 1649, 18868, 2408, 1558, 2498, 6559, 16, 5202, 7044, 1497, 3218, 16, 4022, 16, 1501, 2327, 15707, 18, 3279, 1540, 1634, 3669, 2289, 6983, 4684, 1497, 1716, 28790,	[[1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,

	mempercepat transformasi digital di sektor keuangan dan perdagangan internasional, menciptakan ekosistem yang lebih efisien dan terdesentralisasi.[Doc 2] Blockchain masa depan akan mengadopsi pendekatan yang lebih berkelanjutan dengan efisiensi energi yang lebih baik. Teknologi konsensus baru, seperti Proof of Stake, akan menggantikan sistem lama yang boros energi. Selain itu, blockchain akan mempermudah	9602, 1730, 2704, 2755, 6559, 2747, 9616, 12, 24484, 933, 949, 13, 18, 1545, 23329, 1497, 2718, 2993, 16, 17511, 11507, 1488, 1634, 10436, 13036, 6559, 1485, 4044, 3842, 1501, 3962, 2909, 16, 4262, 12772, 1497, 1716, 10094, 1501, 1960, 22408, 3423, 5616, 1539, 18, 37, 12296, 22, 39, 17511, 11507, 1488, 2106,	1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,	1999, 5202, 9602, 1730, 2704, 2755, 6559, 2747, 9616, 12, 24484, 933, 949, 13, 18, 1545, 23329, 1497, 2718, 2993, 16, 17511, 11507, 1488, 1634, 10436, 13036, 6559, 1485, 4044, 3842, 1501, 3962, 2909, 16, 4262, 12772, 1497, 1716, 10094, 1501, 1960, 22408, 3423, 5616, 1539, 18, 37, 12296, 22, 39, 17511, 11507,	1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,

	pengelolaan data untuk pelacakan emisi karbon, mendukung inisiatif hijau global. Dengan inovasi ini, blockchain akan tidak hanya relevan secara teknologi tetapi juga selaras dengan tujuan keberlanjutan lingkungan.	2616, 1634, 11906, 5415, 1497, 1716, 10461, 1545, 11311, 4129, 1497, 1716, 1983, 18, 3279, 17902, 1836, 16, 1730, 3572, 2294, 2219, 21303, 929, 16, 1634, 4937, 2289, 2461, 1497, 25452, 4129, 18, 2175, 1570, 16, 17511, 11507, 1488, 1634, 15282, 5936, 3145, 1559, 13408, 1538, 12291, 8089, 16, 3669,	1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1]]	1488, 2106, 2616, 1634, 11906, 5415, 1497, 1716, 10461, 1545, 11311, 4129, 1497, 1716, 1983, 18, 3279, 17902, 1836, 16, 1730, 3572, 2294, 2219, 21303, 929, 16, 1634, 4937, 2289, 2461, 1497, 25452, 4129, 18, 2175, 1570, 16, 17511, 11507, 1488, 1634, 15282, 5936, 3145, 1559, 13408, 1538, 12291, 8089,	1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1]]

		10657, 5486, 4684, 18, 1545, 9602, 1540, 16, 17511, 11507, 1488, 1634, 1580, 1821, 10936, 1789, 3279, 1925, 1614, 17118, 1545, 2933, 28457, 3049, 18, 4]]		16, 3669, 10657, 5486, 4684, 18, 1545, 9602, 1540, 16, 17511, 11507, 1488, 1634, 1580, 1821, 10936, 1789, 3279, 1925, 1614, 17118, 1545, 2933, 28457, 3049, 18, 4]]	

3-Doc	[Doc 1] Kecerdasan Buatan (Artificial Intelligence/AI) telah berkembang dari sekadar konsep dalam fiksi ilmiah menjadi kekuatan transformasi yang membentuk dunia modern. Ide awal tentang AI, seperti teori Alan Turing, meletakkan dasar bagi mesin yang dapat meniru kecerdasan manusia. Selama beberapa dekade, kemajuan dalam daya komputasi, ketersediaan data, dan algoritma mendorong AI menjadi aplikasi praktis seperti	[[3, 9792, 6131, 12, 27278, 28680, 25433, 19, 11559, 13, 1703, 3522, 1542, 6563, 3618, 1558, 8792, 3082, 1649, 3112, 13036, 1497, 3598, 1950, 3880, 18, 3426, 2524, 2036, 11559, 16, 1730, 3847, 13266, 20923, 938, 16, 9043, 2776, 1896, 3742, 1497, 1708, 13286, 9792, 2112, 18, 2015, 1841, 8934, 16,	[[1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,	[[3, 9792, 6131, 12, 27278, 28680, 25433, 19, 11559, 13, 1703, 3522, 1542, 6563, 3618, 1558, 8792, 3082, 1649, 3112, 13036, 1497, 3598, 1950, 3880, 18, 3426, 2524, 2036, 11559, 16, 1730, 3847, 13266, 20923, 938, 16, 9043, 2776, 1896, 3742, 1497, 1708, 13286, 9792, 2112, 18, 2015, 1841, 8934,	[[1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,

	pemrosesan bahasa alami, pengenalan gambar, dan sistem otonom. Saat ini, AI memengaruhi berbagai industri, mulai dari kesehatan hingga keuangan, mendorong inovasi sekaligus memunculkan pertanyaan tentang etika dan dampak sosial. [Doc 2] Evolusi AI ditandai oleh tonggak-tonggak penting yang mencerminkan kecerdikan dan ketekunan manusia. Dari penciptaan jaringan saraf pertama pada tahun 1950-an hingga munculnya	5942, 1558, 3296, 21650, 16, 14173, 3145, 16, 1501, 28948, 5026, 11559, 1649, 5952, 7972, 1730, 24413, 2097, 5694, 16, 12508, 3894, 16, 1501, 2289, 13227, 18, 1759, 1540, 16, 11559, 13405, 2190, 3123, 16, 2198, 1542, 3144, 1967, 3842, 16, 5026, 9602, 3749, 11544, 4146, 2036, 8505, 1501, 5239,	1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,	16, 5942, 1558, 3296, 21650, 16, 14173, 3145, 16, 1501, 28948, 5026, 11559, 1649, 5952, 7972, 1730, 24413, 2097, 5694, 16, 12508, 3894, 16, 1501, 2289, 13227, 18, 1759, 1540, 16, 11559, 13405, 2190, 3123, 16, 2198, 1542, 3144, 1967, 3842, 16, 5026, 9602, 3749, 11544, 4146, 2036, 8505, 1501,	1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,

	pembelajaran mesin pada tahun 1980-an, setiap era membawa terobosan yang mendefinisikan ulang kemungkinan-kemungkinan baru. Abad ke-21 menyaksikan pertumbuhan eksponensial dengan hadirnya pembelajaran mendalam (deep learning) dan model AI generatif seperti GPT dan DALL-E, yang merevolusi tugas-tugas kreatif dan analitis. Seiring AI terus berkembang, potensinya untuk mengatasi tantangan global dan meningkatkan	2763, 18, 6769, 11559, 8043, 1617, 21184, 17, 21184, 2544, 1497, 10249, 9374, 1717, 1501, 24550, 2112, 18, 1542, 9599, 3595, 10226, 1889, 1560, 1620, 7160, 17, 1550, 1967, 7748, 5878, 3742, 1560, 1620, 5968, 17, 1550, 16, 2189, 4897, 2925, 14946, 1497, 14429, 4052, 3464, 17, 3464, 1836, 18, 2874, 1500,	1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,	5239, 2763, 18, 6769, 11559, 8043, 1617, 21184, 17, 21184, 2544, 1497, 10249, 9374, 1717, 1501, 24550, 2112, 18, 1542, 9599, 3595, 10226, 1889, 1560, 1620, 7160, 17, 1550, 1967, 7748, 5878, 3742, 1560, 1620, 5968, 17, 1550, 16, 2189, 4897, 2925, 14946, 1497, 14429, 4052, 3464, 17, 3464, 1836, 18,	1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,

	kemampuan manusia	17, 2983,	1, 1, 1,	2874, 1500,	1, 1, 1,
	menjadi janji	6495, 4690,	1, 1, 1,	17, 2983,	1, 1, 1,
	sekaligus tanggung	7108, 5657,	1, 1, 1,	6495, 4690,	1, 1, 1,
	jawab. [Doc 3]	8031, 1545,	1, 1, 1,	7108, 5657,	1, 1, 1,
	Perjalanan	19216, 5878,	1, 1, 1,	8031, 1545,	1, 1, 1,
	Kecerdasan Buatan	7850, 12,	1, 1, 1,	19216, 5878,	1, 1, 1,
	(AI) mencerminkan	20021, 11961,	1, 1, 1,	7850, 12,	1, 1, 1,
	perubahan luar biasa	13, 1501,	1, 1, 1,	20021, 11961,	1, 1, 1,
	dalam peran	3956, 11559,	1, 1, 1,	13, 1501,	1, 1, 1,
	teknologi di	11336, 2321,	1, 1, 1,	3956, 11559,	1, 1, 1,
	masyarakat, dari	1730, 10950,	1, 1, 1,	11336, 2321,	1, 1, 1,
	mengotomatisasi	930, 1501,	1, 1, 1,	1730, 10950,	1, 1, 1,
	tugas-tugas berulang	24683, 17, 47,	1, 1, 1,	930, 1501,	1, 1, 1,
	hingga meningkatkan	16, 1497,	1, 1, 1,	24683, 17, 47,	1, 1, 1,
	kreativitas dan	12061, 12334,	1, 1, 1,	16, 1497,	1, 1, 1,
	pemecahan masalah	7690, 939,	1, 1, 1,	12061, 12334,	1, 1, 1,
	manusia. Dimulai	3151, 17,	1, 1, 1,	7690, 939,	1, 1, 1,
	dengan sistem	3151, 6947,	1, 1, 1,	3151, 17,	1, 1, 1,
	berbasis aturan pada	1501, 8810,	1, 1, 1,	3151, 6947,	1, 1, 1,
	pertengahan abad ke-	3875, 18,	1, 1, 1,	1501, 8810,	1, 1, 1,
	20, AI telah	6165, 11559,	1, 1, 1,	3875, 18,	1, 1, 1,
	berkembang menjadi	2402, 3522,	1, 1, 1,	6165, 11559,	1, 1, 1,
	alat yang kuat yang	16, 4658,	1, 1, 1,	2402, 3522,	1, 1, 1,
	digerakkan oleh	1519, 1559,	1, 1, 1,	16, 4658,	1, 1, 1,
	pembelajaran mesin	5730, 6609,	1, 1, 1,	1519, 1559,	1, 1, 1,

	dan jaringan saraf. Inovasi seperti ChatGPT dan kendaraan otonom menunjukkan potensi AI untuk merevolusi industri dan mendefinisikan ulang pengalaman manusia. Namun, seiring dengan meningkatnya pengaruhnya, muncul pula kekhawatiran tentang privasi, bias, dan penggantian pekerjaan, sehingga pengembangan AI yang bertanggung jawab menjadi hal yang penting untuk masa depan yang berkelanjutan.	4684, 1501, 3552, 3378, 2112, 1649, 6453, 3749, 5123, 3001, 18, 3498, 9792, 6131, 12, 11559, 13, 10249, 2985, 2315, 2799, 1558, 3631, 3279, 1485, 1956, 16, 1542, 1529, 3101, 20238, 1539, 3151, 17, 3151, 7829, 1967, 3552, 11847, 1501, 14747, 2340, 2112, 18, 3647, 1545, 2289, 5546, 4760, 1560, 5036, 2874,	1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1]]	5730, 6609, 4684, 1501, 3552, 3378, 2112, 1649, 6453, 3749, 5123, 3001, 18, 3498, 9792, 6131, 12, 11559, 13, 10249, 2985, 2315, 2799, 1558, 3631, 3279, 1485, 1956, 16, 1542, 1529, 3101, 20238, 1539, 3151, 17, 3151, 7829, 1967, 3552, 11847, 1501, 14747, 2340, 2112, 18, 3647, 1545, 2289, 5546, 4760,	1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1]]

		1500, 17, 1611, 16, 11559, 1703, 3522, 1649, 3161, 1497, 3180, 1497, 17394, 1617, 5878, 3742, 1501, 3595, 10226, 18, 9602, 1730, 15611, 938, 20351, 1501, 3835, 13227, 2924, 4658, 11559, 1559, 12061, 12334, 7690, 939, 3123, 1501, 14429, 4052, 4167, 2112, 18, 1853, 16, 6165, 1545, 9834, 14180, 16, 2812, 2547,		1560, 5036, 2874, 1500, 17, 1611, 16, 11559, 1703, 3522, 1649, 3161, 1497, 3180, 1497, 17394, 1617, 5878, 3742, 1501, 3595, 10226, 18, 9602, 1730, 15611, 938, 20351, 1501, 3835, 13227, 2924, 4658, 11559, 1559, 12061, 12334, 7690, 939, 3123, 1501, 14429, 4052, 4167, 2112, 18, 1853, 16, 6165, 1545, 9834, 14180,	

		10008, 2036, 25098, 16, 14661, 16, 1501, 14523, 3543, 16, 2081, 3884, 11559, 1497, 5071, 3001, 1649, 1794, 1497, 2544, 1559, 2106, 2616, 1497, 10461, 18, 4]]		16, 2812, 2547, 10008, 2036, 25098, 16, 14661, 16, 1501, 14523, 3543, 16, 2081, 3884, 11559, 1497, 5071, 3001, 1649, 1794, 1497, 2544, 1559, 2106, 2616, 1497, 10461, 18, 4]]	

Appendix D

Examples of Result of Abstractive Multi-document Knowledge Summarisation for the Indonesian language

Type	Articles	Bert2Bert	Bert2Bert+Xtreme
2-Doc	[Doc 1] Kecerdasan buatan (AI) telah menjadi bagian integral dari kehidupan sehari-hari kita, mulai dari asisten virtual seperti Siri dan Google Assistant hingga sistem rekomendasi di platform seperti Netflix dan Amazon. AI memungkinkan mesin untuk belajar dari data, mengenali pola, dan membuat keputusan dengan sedikit intervensi manusia. Dalam aplikasi sehari-hari, AI digunakan untuk meningkatkan efisiensi dan kenyamanan pengguna. Misalnya, algoritma pencarian Google menggunakan AI untuk memberikan hasil yang paling relevan dengan pertanyaan pengguna. Di media sosial, AI digunakan untuk mempersonalisasi umpan berita berdasarkan preferensi pengguna dan interaksi sebelumnya. [Doc 2] Dalam industri transportasi, mobil otonom menggunakan AI untuk memproses data dari sensor dan kamera untuk menavigasi jalan secara aman. Ini melibatkan teknik pembelajaran mendalam (deep learning) dan jaringan saraf tiruan (neural networks) untuk mengenali	kecerdasan buatan (ai) telah menjadi bagian integral dari kehidupan sehari - hari kita, mulai dari asisten virtual seperti siri dan google assistant hingga sistem rekomendasi di platform seperti netflix dan amazon. ai memungkinkan mesin untuk belajar dari data, mengenali pola, dan membuat keputusan dengan sedikit intervensi manusia.	kecerdasan buatan (ai) telah menjadi bagian integral dari kehidupan sehari - hari. ai memungkinkan mesin belajar dari data, mengenali pola, dan membuat keputusan dengan sedikit intervensi manusia.

Type	Articles	Bert2Bert	Bert2Bert+Xtreme
	objek di sekitar kendaraan dan membuat keputusan mengemudi yang tepat. AI juga digunakan dalam aplikasi navigasi seperti Google Maps untuk memberikan rute tercepat berdasarkan kondisi lalu lintas terkini.		
2-Doc	[Doc 1] Blockchain adalah teknologi yang mendasari mata uang kripto seperti Bitcoin, tetapi aplikasinya melampaui dunia keuangan. Pada intinya, blockchain adalah buku besar terdistribusi yang aman dan transparan, memungkinkan transaksi untuk dicatat dalam cara yang tidak dapat diubah dan dapat diaudit. Di sektor keuangan, blockchain telah merevolusi cara orang melakukan transaksi, dengan menyediakan alternatif yang lebih aman dan efisien daripada sistem perbankan tradisional. Transaksi yang dilakukan melalui blockchain dapat diselesaikan lebih cepat dan dengan biaya lebih rendah, tanpa perlu perantara. [Doc 2] Di luar keuangan, blockchain memiliki potensi besar untuk mengubah berbagai industri. Dalam rantai pasokan, teknologi ini dapat digunakan untuk melacak pergerakan barang dari pabrik hingga konsumen akhir, memastikan transparansi dan keaslian produk. Hal	pada intinya, blockchain adalah buku besar terdistribusi yang aman dan transparan, memungkinkan transaksi untuk dicatat dalam cara yang tidak dapat diubah dan dapat diaudit.	teknologi yang mendasari uang bitco seperti bitcoin telah melampaui dunia keuangan. pada intinya, blockchain adalah buku besar terdistribusi yang aman dan transparan.

Type	Articles	Bert2Bert	Bert2Bert+Xtreme
	ini sangat penting dalam industri seperti makanan dan obat-obatan, di mana keamanan dan kualitas produk adalah prioritas utama. Dengan blockchain, semua pihak yang terlibat dalam rantai pasokan dapat melihat riwayat produk dan memastikan bahwa standar kepatuhan terpenuhi.		
3-Doc	[Doc 1] Kecerdasan Buatan (Artificial Intelligence/AI) telah berkembang dari sekadar konsep dalam fiksi ilmiah menjadi kekuatan transformasi yang membentuk dunia modern. Ide awal tentang AI, seperti teori Alan Turing, meletakkan dasar bagi mesin yang dapat meniru kecerdasan manusia. Selama beberapa dekade, kemajuan dalam daya komputasi, ketersediaan data, dan algoritma mendorong AI menjadi aplikasi praktis seperti pemrosesan bahasa alami, pengenalan gambar, dan sistem otonom. Saat ini, AI memengaruhi berbagai industri, mulai dari kesehatan hingga keuangan, mendorong inovasi sekaligus memunculkan pertanyaan tentang etika dan dampak sosial.	kemampuan mesin yang ditunjukkan manusia memiliki rentang informasi yang luas dan teknologi dalam negeri, tak diragukan selama ini sebagai dampak globalisasi. dengan perubahan luar biasa di dunia dan di antaranya adalah perkembangan ekonomi serta informatika melalui komputer dan otak,	perjalanan cerdas dan cepat adalah gabungan dari daya ungkit manusia. pengembangan kecerdasan itu dipengaruhi oleh adanya empat faktor : penemuan, pemberdayaan, tangggapan, dan pelanggaran etika dan lingkungan. ai - 123 dan masukan manusia menciptakan keh miram dalam keseimbangan global.

Type	Articles	Bert2Bert	Bert2Bert+Xtreme
	[Doc 2] Evolusi AI ditandai oleh tonggak-tonggak penting yang mencerminkan kecerdikan dan ketekunan manusia. Dari penciptaan jaringan saraf pertama pada tahun 1950-an hingga munculnya pembelajaran mesin pada tahun 1980-an, setiap era membawa terobosan yang mendefinisikan ulang kemungkinan-kemungkinan baru. Abad ke-21 menyaksikan pertumbuhan eksponensial dengan hadirnya pembelajaran mendalam (deep learning) dan model AI generatif seperti GPT dan DALL-E, yang merevolusi tugas-tugas kreatif dan analitis. Seiring AI terus berkembang, potensinya untuk mengatasi tantangan global dan meningkatkan kemampuan manusia menjadi janji sekaligus tanggung jawab. [Doc 3] Perjalanan Kecerdasan Buatan (AI) mencerminkan perubahan luar biasa dalam peran teknologi di masyarakat, dari mengotomatisasi tugas-tugas berulang hingga meningkatkan kreativitas dan pemecahan masalah manusia. Dimulai dengan sistem berbasis aturan pada pertengahan abad ke-20, AI telah berkembang menjadi alat yang kuat yang digerakkan oleh pembelajaran mesin dan jaringan saraf. Inovasi seperti ChatGPT dan kendaraan otonom menunjukkan potensi AI	mikrobialuas... apa yang mendorong si penemu? ternyata peran mereka masih lebih penting. Summary Gabungan 2 (IndoBERT-Xtreme): perkembangan teknologi informasi membutuhkan tindakan yang cepat untuk mengubah sikap dan bertindak di berbagai lapisan masyarakat. misalnya, para mahasiswa harus mengembangkan kesiapan mereka secara klinis dan dapat melakukan tantangan dengan teknologi baru. halo khan.	

Type	Articles	Bert2Bert	Bert2Bert+Xtreme
	untuk merevolusi industri dan mendefinisikan ulang pengalaman manusia. Namun, seiring dengan meningkatnya pengaruhnya, muncul pula kekhawatiran tentang privasi, bias, dan penggantian pekerjaan, sehingga pengembangan AI yang bertanggung jawab menjadi hal yang penting untuk masa depan yang berkelanjutan.		
3-Doc	[Doc 1] Integrasi machine learning dengan blockchain membuka peluang baru dalam meningkatkan keamanan data. Algoritma machine learning dapat digunakan untuk mendeteksi anomali atau aktivitas mencurigakan dalam jaringan blockchain, sehingga mencegah potensi serangan. Di sisi lain, blockchain memberikan transparansi dan auditabilitas pada proses machine learning, menciptakan ekosistem yang aman dan dapat dipercaya. Kolaborasi ini akan menjadi fondasi bagi infrastruktur digital yang lebih kuat di masa depan. [Doc 2] Machine learning dapat membantu mempercepat proses yang terjadi dalam blockchain, seperti validasi transaksi dan konsensus jaringan. Dengan menganalisis pola data secara cepat dan efisien, algoritma machine learning mampu mengurangi waktu yang	sistem romi learning membuka peluang untuk meningkatkan keamanan data. memetakan jaringan blockchain, sehingga mencegah potensi serangan. tapi perlu dilakukan untuk mendeteksi terdeteksinya logged voice atau aktivitas mencurigakan dalam jaringan ratchain di sisi	integrasi machine learning dengan blockchain membuka peluang baru untuk teknologi di masa depan. tentu, bekerjasama dengan mesin tersebut adalah cara jitu untuk menemukan dicuri dan menghindarkan potensi serangan. demikian, mengapa terjadi masalah terbesar dalam komputer t.?

Type	Articles	Bert2Bert	Bert2Bert+Xtreme
	diperlukan untuk memproses transaksi dalam jaringan blockchain. Teknologi ini juga dapat diimplementasikan untuk memprediksi kinerja jaringan, mengoptimalkan penggunaan sumber daya, dan meningkatkan skala sistem blockchain secara keseluruhan. [Doc 3] Kombinasi machine learning dan blockchain memiliki potensi besar untuk menyelesaikan tantangan kompleks dalam berbagai industri. Contohnya, dalam rantai pasok, blockchain menyediakan transparansi data, sementara machine learning memproses informasi untuk memberikan wawasan yang mendalam. Selain itu, integrasi ini dapat digunakan untuk menciptakan kontrak pintar yang lebih adaptif, yang secara otomatis menyesuaikan kondisi berdasarkan analisis data real-time. Kolaborasi ini akan mendorong inovasi teknologi ke level yang lebih tinggi.	lain. dan mengalirkan informasi pada heal..	

Appendix E

Examples of the Results on Recommendation System

No	Students Id	Students Name	Recommendation Results				
			Topics Recommended by The System	**Recall**	**Precision**	**F1-Score**	**MAE**
1	1217050001	ABDULLAH AMALI AL GHASYIYAH ARRIDHUANI	1. STANDAR KOMPRESI GAMBAR / CITRA 2. SISTEM PENYIARAN DIGITAL (Standar televisi digital, Teknologi berbagai sistem televisi digital, Model bisnis televisi digital, TV 3D dan Free Viewpoint) 3. Representasi Audio 4. MULTIMEDIA STREAMING (Jaringan multimedia, Multimedia streaming, Playout buffer, Distribusi konten multimedia) 5. STANDAR KOMPRESI AUDIO	0.5	1	0.67	1.22
2	1217050003	AGUNG ISKANDAR YUDA	1. STANDAR KOMPRESI GAMBAR / CITRA	0.67	1	0.8	1.24

No	Students Id	Students Name	Recommendation Results				
			Topics Recommended by The System	Recall	Precision	F1-Score	MAE
			2. SOCIAL MEDIA SHARING (Representative Social Media Services, User-Generated Media Content Sharing, Media Propagation in Online Social Networks) 3. SISTEM PENYIARAN DIGITAL (Standar televisi digital, Teknologi berbagai sistem televisi digital, Model bisnis televisi digital, TV 3D dan Free Viewpoint) 4. Konsep Sistem Multimedia 5. Representasi Audio 6. STANDAR KOMPRESI VIDEO (Ragam standar kompresi video, Karakteristik sistem kompresi video, Intraframe dan Interframe coding) 7. STANDAR KOMPRESI AUDIO				
3	1217050004	ALDRIAN RIZKI KUSUMA	1. STANDAR KOMPRESI GAMBAR / CITRA	0.67	1	0.8	1.18

No	Students Id	Students Name	Recommendation Results				
			Topics Recommended by The System	Recall	Precision	F1-Score	MAE
			2. SOCIAL MEDIA SHARING (Representative Social Media Services, User-Generated Media Content Sharing, Media Propagation in Online Social Networks) 3. STANDAR KOMPRESI VIDEO (Ragam standar kompresi video, Karakteristik sistem kompresi video, Intraframe dan Interframe coding) 4. MULTIMEDIA STREAMING (Jaringan multimedia, Multimedia streaming, Playout buffer, Distribusi konten multimedia) 5. Representasi Audio 6. STANDAR KOMPRESI AUDIO				
4	1217050005	ALFAN FADHIL BAIHAQI	1. MULTIMEDIA STREAMING (Jaringan multimedia, Multimedia streaming, Playout buffer, Distribusi konten multimedia)	0.67	1	0.8	1.11

No	Students Id	Students Name	Recommendation Results				
			Topics Recommended by The System	Recall	Precision	F1-Score	MAE
			2. STANDAR KOMPRESI VIDEO (Ragam standar kompresi video, Karakteristik sistem kompresi video, Intraframe dan Interframe coding) 3. STANDAR KOMPRESI AUDIO				
5	1217050007	ALIKA PUTIE SYADRINA	1. STANDAR KOMPRESI GAMBAR / CITRA 2. SISTEM PENYIARAN DIGITAL (Standar televisi digital, Teknologi berbagai sistem televisi digital, Model bisnis televisi digital, TV 3D dan Free Viewpoint) 3. Konsep Sistem Multimedia 4. MULTIMEDIA STREAMING (Jaringan multimedia, Multimedia streaming, Playout buffer, Distribusi konten multimedia) 5. Representasi Audio	0.6	1	0.75	0.61

No	Students Id	Students Name	Recommendation Results				
			Topics Recommended by The System	Recall	Precision	F1-Score	MAE
			6. STANDAR KOMPRESI VIDEO (Ragam standar kompresi video, Karakteristik sistem kompresi video, Intraframe dan Interframe coding)				
6	1217050008	ALYA KUSUMA WARDHANI	1. STANDAR KOMPRESI GAMBAR / CITRA 2. SISTEM PENYIARAN DIGITAL (Standar televisi digital, Teknologi berbagai sistem televisi digital, Model bisnis televisi digital, TV 3D dan Free Viewpoint) 3. SOCIAL MEDIA SHARING (Representative Social Media Services, User-Generated Media Content Sharing, Media Propagation in Online Social Networks)	0.67	1	0.8	0.48

No	Students Id	Students Name	Recommendation Results				
			Topics Recommended by The System	Recall	Precision	F1-Score	MAE
			4. MULTIMEDIA STREAMING (Jaringan multimedia, Multimedia streaming, Playout buffer, Distribusi konten multimedia) 5. Representasi Audio 6. STANDAR KOMPRESI VIDEO (Ragam standar kompresi video, Karakteristik sistem kompresi video, Intraframe dan Interframe coding) 7. STANDAR KOMPRESI AUDIO				
7	1217050009	ALYSSA DIVAIRA	1. STANDAR KOMPRESI GAMBAR / CITRA 2. MULTIMEDIA STREAMING (Jaringan multimedia, Multimedia streaming, Playout buffer, Distribusi konten multimedia) 3. Representasi Audio 4. STANDAR KOMPRESI VIDEO (Ragam standar kompresi video, Karakteristik sistem	0.5	1	0.67	1.01

No	Students Id	Students Name	Recommendation Results				
			Topics Recommended by The System	Recall	Precision	F1-Score	MAE
			kompresi video, Intraframe dan Interframe coding) 5. STANDAR KOMPRESI AUDIO				
8	1217050010	ANDHIKA EKA PUTRA SUTRISNO	1. STANDAR KOMPRESI GAMBAR / CITRA 2. SOCIAL MEDIA SHARING (Representative Social Media Services, User-Generated Media Content Sharing, Media Propagation in Online Social Networks) 3. SISTEM PENYIARAN DIGITAL (Standar televisi digital, Teknologi berbagai sistem televisi digital, Model bisnis televisi digital, TV 3D dan Free Viewpoint) 4. Konsep Sistem Multimedia 5. Representasi Audio	0.67	1	0.8	0.95

No	Students Id	Students Name	Recommendation Results				
			Topics Recommended by The System	Recall	Precision	F1-Score	MAE
			6. MULTIMEDIA STREAMING (Jaringan multimedia, Multimedia streaming, Playout buffer, Distribusi konten multimedia) 7. STANDAR KOMPRESI AUDIO 8. STANDAR KOMPRESI VIDEO (Ragam standar kompresi video, Karakteristik sistem kompresi video, Intraframe dan Interframe coding)				
9	1217050011	ANDHIKA MALIK	1. STANDAR KOMPRESI GAMBAR / CITRA 2. SISTEM PENYIARAN DIGITAL (Standar televisi digital, Teknologi berbagai sistem televisi digital, Model bisnis televisi digital, TV 3D dan Free Viewpoint) 3. SOCIAL MEDIA SHARING (Representative Social Media Services, User-	0.6	1	0.75	1.69

No	Students Id	Students Name	Recommendation Results				
			Topics Recommended by The System	Recall	Precision	F1-Score	MAE
			Generated Media Content Sharing, Media Propagation in Online Social Networks) 4. Konsep Sistem Multimedia 5. MULTIMEDIA STREAMING (Jaringan multimedia, Multimedia streaming, Playout buffer, Distribusi konten multimedia) 6. STANDAR KOMPRESI VIDEO (Ragam standar kompresi video, Karakteristik sistem kompresi video, Intraframe dan Interframe coding) 7. Representasi Audio 8. STANDAR KOMPRESI AUDIO				
10	1217050012	ANDHIKA PUTRA GEFADRI	1. STANDAR KOMPRESI GAMBAR / CITRA 2. Konsep Sistem Multimedia	0.67	1	0.8	0.88

No	Students Id	Students Name	Recommendation Results				
			Topics Recommended by The System	Recall	Precision	F1-Score	MAE
			3. MULTIMEDIA STREAMING (Jaringan multimedia, Multimedia streaming, Playout buffer, Distribusi konten multimedia) 4. Representasi Audio 5. STANDAR KOMPRESI VIDEO (Ragam standar kompresi video, Karakteristik sistem kompresi video, Intraframe dan Interframe coding) 6. STANDAR KOMPRESI AUDIO				
11	1217050014	ANIS MUBAROKAH	1. STANDAR KOMPRESI GAMBAR / CITRA 2. SISTEM PENYIARAN DIGITAL (Standar televisi digital, Teknologi berbagai sistem televisi digital, Model bisnis televisi digital, TV 3D dan Free Viewpoint) 3. SOCIAL MEDIA SHARING (Representative Social Media Services, User-	0.6	1	0.75	0.19

No	Students Id	Students Name	Recommendation Results				
			Topics Recommended by The System	Recall	Precision	F1-Score	MAE
			Generated Media Content Sharing, Media Propagation in Online Social Networks) 4. Representasi Audio 5. MULTIMEDIA STREAMING (Jaringan multimedia, Multimedia streaming, Playout buffer, Distribusi konten multimedia) 6. STANDAR KOMPRESI VIDEO (Ragam standar kompresi video, Karakteristik sistem kompresi video, Intraframe dan Interframe coding) 7. STANDAR KOMPRESI AUDIO				
12	1217050015	ANISSA TRI LAHITANI	1. STANDAR KOMPRESI GAMBAR / CITRA 2. Representasi Audio 3. STANDAR KOMPRESI VIDEO (Ragam standar kompresi video, Karakteristik sistem	0.5	1	0.67	1.22

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<tr><td></td><td></td><td></td><td>kompresi video, Intraframe dan Interframe coding)
4. STANDAR KOMPRESI AUDIO</td><td></td><td></td><td></td><td></td></tr>
<tr><td>13</td><td>1217050016</td><td>ANNISA SABILLAH</td><td>1. STANDAR KOMPRESI GAMBAR / CITRA
2. SOCIAL MEDIA SHARING (Representative Social Media Services, User-Generated Media Content Sharing, Media Propagation in Online Social Networks)
3. SISTEM PENYIARAN DIGITAL (Standar televisi digital, Teknologi berbagai sistem televisi digital, Model bisnis televisi digital, TV 3D dan Free Viewpoint)
4. Konsep Sistem Multimedia
5. Representasi Audio</td><td>0.5</td><td>1</td><td>0.67</td><td>0.86</td></tr>
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No	Students Id	Students Name	Recommendation Results				
			Topics Recommended by The System	Recall	Precision	F1-Score	MAE
			6. MULTIMEDIA STREAMING (Jaringan multimedia, Multimedia streaming, Playout buffer, Distribusi konten multimedia) 7. STANDAR KOMPRESI VIDEO (Ragam standar kompresi video, Karakteristik sistem kompresi video, Intraframe dan Interframe coding) 8. STANDAR KOMPRESI AUDIO				
14	1217050017	ANSYARULLAH	1. STANDAR KOMPRESI GAMBAR / CITRA 2. SISTEM PENYIARAN DIGITAL (Standar televisi digital, Teknologi berbagai sistem televisi digital, Model bisnis televisi digital, TV 3D dan Free Viewpoint) 3. SOCIAL MEDIA SHARING (Representative Social Media Services, User-	0.67	1	0.8	1.18

No	Students Id	Students Name	Recommendation Results				
			Topics Recommended by The System	Recall	Precision	F1-Score	MAE
			Generated Media Content Sharing, Media Propagation in Online Social Networks) 4. Konsep Sistem Multimedia 5. Representasi Audio 6. MULTIMEDIA STREAMING (Jaringan multimedia, Multimedia streaming, Playout buffer, Distribusi konten multimedia) 7. STANDAR KOMPRESI AUDIO				
15	1217050018	APRIAN NUR ROHMAN	1. SOCIAL MEDIA SHARING (Representative Social Media Services, User-Generated Media Content Sharing, Media Propagation in Online Social Networks) 2. SISTEM PENYIARAN DIGITAL (Standar televisi digital, Teknologi berbagai sistem televisi digital, Model bisnis televisi digital, TV 3D dan Free Viewpoint) 3. Konsep Sistem Multimedia	0.5	1	0.67	0.38

No	Students Id	Students Name	Recommendation Results				
			Topics Recommended by The System	Recall	Precision	F1-Score	MAE
			4. Representasi Audio 5. STANDAR KOMPRESI VIDEO (Ragam standar kompresi video, Karakteristik sistem kompresi video, Intraframe dan Interframe coding) 6. STANDAR KOMPRESI AUDIO				
16	1217050019	ARDIAN MALIK MUHARAM	1. SISTEM PENYIARAN DIGITAL (Standar televisi digital, Teknologi berbagai sistem televisi digital, Model bisnis televisi digital, TV 3D dan Free Viewpoint) 2. MULTIMEDIA STREAMING (Jaringan multimedia, Multimedia streaming, Playout buffer, Distribusi konten multimedia) 3. Representasi Audio 4. STANDAR KOMPRESI VIDEO (Ragam standar kompresi video, Karakteristik sistem	0.5	1	0.67	0.07

No	Students Id	Students Name	Recommendation Results				
			Topics Recommended by The System	Recall	Precision	F1-Score	MAE
			kompresi video, Intraframe dan Interframe coding) 5. STANDAR KOMPRESI AUDIO				
17	1217050021	ARIFIN NURMUHAMMAD SYARIFUDIN	1. SOCIAL MEDIA SHARING (Representative Social Media Services, User-Generated Media Content Sharing, Media Propagation in Online Social Networks) 2. MULTIMEDIA STREAMING (Jaringan multimedia, Multimedia streaming, Playout buffer, Distribusi konten multimedia) 3. Representasi Audio 4. STANDAR KOMPRESI AUDIO 5. STANDAR KOMPRESI VIDEO (Ragam standar kompresi video, Karakteristik sistem kompresi video, Intraframe dan Interframe coding)	0.5	1	0.67	1.06

No	Students Id	Students Name	Recommendation Results				
			Topics Recommended by The System	Recall	Precision	F1-Score	MAE
18	1217050022	ARIH ADILAH HASAN CIPADUNG	1. SOCIAL MEDIA SHARING (Representative Social Media Services, User-Generated Media Content Sharing, Media Propagation in Online Social Networks) 2. SISTEM PENYIARAN DIGITAL (Standar televisi digital, Teknologi berbagai sistem televisi digital, Model bisnis televisi digital, TV 3D dan Free Viewpoint) 3. Konsep Sistem Multimedia 4. MULTIMEDIA STREAMING (Jaringan multimedia, Multimedia streaming, Playout buffer, Distribusi konten multimedia) 5. STANDAR KOMPRESI VIDEO (Ragam standar kompresi video, Karakteristik sistem kompresi video, Intraframe dan Interframe coding) 6. Representasi Audio	0.6	1	0.75	1.3

No	Students Id	Students Name	Recommendation Results				
			Topics Recommended by The System	Recall	Precision	F1-Score	MAE
			7. STANDAR KOMPRESI AUDIO				
19	1217050025	ATHIF ZHARFAN SETIAWAN	1. STANDAR KOMPRESI GAMBAR / CITRA 2. SISTEM PENYIARAN DIGITAL (Standar televisi digital, Teknologi berbagai sistem televisi digital, Model bisnis televisi digital, TV 3D dan Free Viewpoint) 3. SOCIAL MEDIA SHARING (Representative Social Media Services, User-Generated Media Content Sharing, Media Propagation in Online Social Networks) 4. Konsep Sistem Multimedia 5. Representasi Audio 6. MULTIMEDIA STREAMING (Jaringan multimedia, Multimedia streaming, Playout buffer, Distribusi konten multimedia) 7. STANDAR KOMPRESI AUDIO	0.67	1	0.8	0.58

No	Students Id	Students Name	Recommendation Results				
			Topics Recommended by The System	Recall	Precision	F1-Score	MAE
			8. STANDAR KOMPRESI VIDEO (Ragam standar kompresi video, Karakteristik sistem kompresi video, Intraframe dan Interframe coding)				
20	1217050026	BAYU SEPTIAN	1. STANDAR KOMPRESI GAMBAR / CITRA 2. SOCIAL MEDIA SHARING (Representative Social Media Services, User-Generated Media Content Sharing, Media Propagation in Online Social Networks) 3. SISTEM PENYIARAN DIGITAL (Standar televisi digital, Teknologi berbagai sistem televisi digital, Model bisnis televisi digital, TV 3D dan Free Viewpoint) 4. Konsep Sistem Multimedia 5. Representasi Audio	0.5	1	0.67	0.94

No	Students Id	Students Name	Recommendation Results				
			Topics Recommended by The System	Recall	Precision	F1-Score	MAE
			6. MULTIMEDIA STREAMING (Jaringan multimedia, Multimedia streaming, Playout buffer, Distribusi konten multimedia) 7. STANDAR KOMPRESI AUDIO 8. STANDAR KOMPRESI VIDEO (Ragam standar kompresi video, Karakteristik sistem kompresi video, Intraframe dan Interframe coding)				
21	1217050027	BINTANG NURFIRDAUS SUWARDI	1. STANDAR KOMPRESI GAMBAR / CITRA 2. SISTEM PENYIARAN DIGITAL (Standar televisi digital, Teknologi berbagai sistem televisi digital, Model bisnis televisi digital, TV 3D dan Free Viewpoint) 3. SOCIAL MEDIA SHARING (Representative Social Media Services, User-	0.5	1	0.67	1.05

No	Students Id	Students Name	Recommendation Results				
			Topics Recommended by The System	Recall	Precision	F1-Score	MAE
			Generated Media Content Sharing, Media Propagation in Online Social Networks) 4. Konsep Sistem Multimedia 5. MULTIMEDIA STREAMING (Jaringan multimedia, Multimedia streaming, Playout buffer, Distribusi konten multimedia) 6. STANDAR KOMPRESI VIDEO (Ragam standar kompresi video, Karakteristik sistem kompresi video, Intraframe dan Interframe coding) 7. Representasi Audio 8. STANDAR KOMPRESI AUDIO				
22	1217050028	CINDY OKTAVIAN	1. SISTEM PENYIARAN DIGITAL (Standar televisi digital, Teknologi berbagai sistem televisi digital, Model bisnis televisi digital, TV 3D dan Free Viewpoint)	0.67	1	0.8	1.63

No	Students Id	Students Name	Recommendation Results				
			Topics Recommended by The System	Recall	Precision	F1-Score	MAE
			2. MULTIMEDIA STREAMING (Jaringan multimedia, Multimedia streaming, Playout buffer, Distribusi konten multimedia) 3. STANDAR KOMPRESI VIDEO (Ragam standar kompresi video, Karakteristik sistem kompresi video, Intraframe dan Interframe coding) 4. STANDAR KOMPRESI AUDIO				
23	1217050029	DAFFA RHAUDA FADILLAH	1. STANDAR KOMPRESI GAMBAR / CITRA 2. SOCIAL MEDIA SHARING (Representative Social Media Services, User-Generated Media Content Sharing, Media Propagation in Online Social Networks) 3. SISTEM PENYIARAN DIGITAL (Standar televisi digital, Teknologi berbagai sistem	0.5	1	0.67	1.39

No	Students Id	Students Name	Recommendation Results				
			Topics Recommended by The System	Recall	Precision	F1-Score	MAE
			televisi digital, Model bisnis televisi digital, TV 3D dan Free Viewpoint) 4. Konsep Sistem Multimedia 5. MULTIMEDIA STREAMING (Jaringan multimedia, Multimedia streaming, Playout buffer, Distribusi konten multimedia) 6. Representasi Audio 7. STANDAR KOMPRESI VIDEO (Ragam standar kompresi video, Karakteristik sistem kompresi video, Intraframe dan Interframe coding) 8. STANDAR KOMPRESI AUDIO				
24	1217050031	DARRYL NAUFAL ARDIAZ	1. STANDAR KOMPRESI GAMBAR / CITRA 2. SOCIAL MEDIA SHARING (Representative Social Media Services, User-	0.5	1	0.67	1.28

No	Students Id	Students Name	Recommendation Results				
			Topics Recommended by The System	Recall	Precision	F1-Score	MAE
			Generated Media Content Sharing, Media Propagation in Online Social Networks) 3. SISTEM PENYIARAN DIGITAL (Standar televisi digital, Teknologi berbagai sistem televisi digital, Model bisnis televisi digital, TV 3D dan Free Viewpoint) 4. Konsep Sistem Multimedia 5. STANDAR KOMPRESI VIDEO (Ragam standar kompresi video, Karakteristik sistem kompresi video, Intraframe dan Interframe coding) 6. MULTIMEDIA STREAMING (Jaringan multimedia, Multimedia streaming, Playout buffer, Distribusi konten multimedia) 7. Representasi Audio 8. STANDAR KOMPRESI AUDIO				

No	Students Id	Students Name	Recommendation Results				
			Topics Recommended by The System	Recall	Precision	F1-Score	MAE
25	1217050034	DESI AINUL AMELIA	1. STANDAR KOMPRESI GAMBAR / CITRA 2. SISTEM PENYIARAN DIGITAL (Standar televisi digital, Teknologi berbagai sistem televisi digital, Model bisnis televisi digital, TV 3D dan Free Viewpoint) 3. SOCIAL MEDIA SHARING (Representative Social Media Services, User-Generated Media Content Sharing, Media Propagation in Online Social Networks) 4. Konsep Sistem Multimedia 5. Representasi Audio 6. STANDAR KOMPRESI VIDEO (Ragam standar kompresi video, Karakteristik sistem kompresi video, Intraframe dan Interframe coding)	0.6	1	0.75	0.88

No	Students Id	Students Name	Recommendation Results				
			Topics Recommended by The System	Recall	Precision	F1-Score	MAE
			7. MULTIMEDIA STREAMING (Jaringan multimedia, Multimedia streaming, Playout buffer, Distribusi konten multimedia) 8. STANDAR KOMPRESI AUDIO				
26	1217050035	DEWI ANGGITA YULIANTI	1. STANDAR KOMPRESI GAMBAR / CITRA 2. SISTEM PENYIARAN DIGITAL (Standar televisi digital, Teknologi berbagai sistem televisi digital, Model bisnis televisi digital, TV 3D dan Free Viewpoint) 3. SOCIAL MEDIA SHARING (Representative Social Media Services, User-Generated Media Content Sharing, Media Propagation in Online Social Networks) 4. Konsep Sistem Multimedia	0.67	1	0.8	0.96

No	Students Id	Students Name	Recommendation Results				
			Topics Recommended by The System	Recall	Precision	F1-Score	MAE
			5. MULTIMEDIA STREAMING (Jaringan multimedia, Multimedia streaming, Playout buffer, Distribusi konten multimedia) 6. Representasi Audio 7. STANDAR KOMPRESI AUDIO				
27	1217050036	DHEA LISTIA APRIYANTI	1. STANDAR KOMPRESI GAMBAR / CITRA 2. SISTEM PENYIARAN DIGITAL (Standar televisi digital, Teknologi berbagai sistem televisi digital, Model bisnis televisi digital, TV 3D dan Free Viewpoint) 3. SOCIAL MEDIA SHARING (Representative Social Media Services, User-Generated Media Content Sharing, Media Propagation in Online Social Networks) 4. Representasi Audio	0.6	1	0.75	1.18

No	Students Id	Students Name	Recommendation Results				
			Topics Recommended by The System	Recall	Precision	F1-Score	MAE
			5. STANDAR KOMPRESI VIDEO (Ragam standar kompresi video, Karakteristik sistem kompresi video, Intraframe dan Interframe coding) 6. MULTIMEDIA STREAMING (Jaringan multimedia, Multimedia streaming, Playout buffer, Distribusi konten multimedia) 7. STANDAR KOMPRESI AUDIO				
28	1217050037	DIAN SAPUTRA	1. STANDAR KOMPRESI GAMBAR / CITRA 2. SISTEM PENYIARAN DIGITAL (Standar televisi digital, Teknologi berbagai sistem televisi digital, Model bisnis televisi digital, TV 3D dan Free Viewpoint) 3. SOCIAL MEDIA SHARING (Representative Social Media Services, User-	0.67	1	0.8	1.18

No	Students Id	Students Name	Recommendation Results				
			Topics Recommended by The System	Recall	Precision	F1-Score	MAE
			Generated Media Content Sharing, Media Propagation in Online Social Networks) 4. STANDAR KOMPRESI VIDEO (Ragam standar kompresi video, Karakteristik sistem kompresi video, Intraframe dan Interframe coding) 5. Representasi Audio 6. STANDAR KOMPRESI AUDIO				
29	1217050038	DIAZ MUHAMAD AZHAR AZQIA	1. STANDAR KOMPRESI GAMBAR / CITRA 2. SOCIAL MEDIA SHARING (Representative Social Media Services, User-Generated Media Content Sharing, Media Propagation in Online Social Networks) 3. MULTIMEDIA STREAMING (Jaringan multimedia, Multimedia streaming, Playout buffer, Distribusi konten multimedia)	0.67	1	0.8	0.9

No	Students Id	Students Name	Recommendation Results				
			Topics Recommended by The System	Recall	Precision	F1-Score	MAE
			4. Representasi Audio 5. STANDAR KOMPRESI VIDEO (Ragam standar kompresi video, Karakteristik sistem kompresi video, Intraframe dan Interframe coding)				
30	1217050039	DIKA RIZQI AKBARIs	1. STANDAR KOMPRESI GAMBAR / CITRA 2. SOCIAL MEDIA SHARING (Representative Social Media Services, User-Generated Media Content Sharing, Media Propagation in Online Social Networks) 3. SISTEM PENYIARAN DIGITAL (Standar televisi digital, Teknologi berbagai sistem televisi digital, Model bisnis televisi digital, TV 3D dan Free Viewpoint) 4. Konsep Sistem Multimedia	0.67	1	0.8	0.13

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<tr><td></td><td></td><td></td><td>5. MULTIMEDIA STREAMING (Jaringan multimedia, Multimedia streaming, Playout buffer, Distribusi konten multimedia)
6. Representasi Audio
7. STANDAR KOMPRESI VIDEO (Ragam standar kompresi video, Karakteristik sistem kompresi video, Intraframe dan Interframe coding)
8. STANDAR KOMPRESI AUDIO</td><td></td><td></td><td></td><td></td></tr>
<tr><td>31</td><td>1217050040</td><td>DILA NUR ILAHIYAH</td><td>1. STANDAR KOMPRESI GAMBAR / CITRA
2. SISTEM PENYIARAN DIGITAL (Standar televisi digital, Teknologi berbagai sistem televisi digital, Model bisnis televisi digital, TV 3D dan Free Viewpoint)
3. SOCIAL MEDIA SHARING (Representative Social Media Services, User-</td><td>0.5</td><td>1</td><td>0.67</td><td>0.87</td></tr>
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No	Students Id	Students Name	Recommendation Results				
			Topics Recommended by The System	Recall	Precision	F1-Score	MAE
			Generated Media Content Sharing, Media Propagation in Online Social Networks) 4. Konsep Sistem Multimedia 5. Representasi Audio 6. MULTIMEDIA STREAMING (Jaringan multimedia, Multimedia streaming, Playout buffer, Distribusi konten multimedia) 7. STANDAR KOMPRESI VIDEO (Ragam standar kompresi video, Karakteristik sistem kompresi video, Intraframe dan Interframe coding) 8. STANDAR KOMPRESI AUDIO				

Appendix F

List of Publication

Muharam, A. F., Gerhana, Y. A., Maylawati, D. S., Ramdhani, M. A., & Rahman, T. K. A. (2025). Enhancing Abstractive Multi-Document Summarization with Bert2Bert Model for Indonesian Language. *JISKA (Jurnal Informatika Sunan Kalijaga)*, *10*(1), 110–121. https://doi.org/10.14421/jiska.2025.10.1.110-121