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Develop A Hybrid Recommendation System to Optimize Knowledge Utilization: A Case Study of an Indonesia Telecommunication Company

Richard Alberto and Rizal Kurniawan

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Abstract - **With rapid industrial digitalization, companies need to strengthen core competences and digital talents within organizations to achieve competitive advantage. Companies have been developing digital knowledge management practices for acquisition, inventory, transfer, etc. But, to achieve a successful knowledge diffusion, increasing knowledge stock alone isn't enough. As the knowledge stock increases, user choice for learning is also increasing. Reliable recommendation system is required as the selecting knowledge to learn in repository grows more complex. Ideal competences for each position need to be addressed as the company has done assessment for their ideal workforce. Meanwhile, every knowledge user has their own preferences which can be seen from registered preferences and learning history. Hybrid recommendation approaches from content based filtering and collaborative filtering can be utilized to address these issues. Finally, to complete this study of knowledge utilization optimization using machine learning, we will use knowledge stock, and human capital development data from Telkom Indonesia to develop a more personal and efficient knowledge platform. The proposed model can be used as a basis for further development of knowledge management platforms.**

Keywords - **Knowledge Management; Knowledge Utilization; Recommender System; Machine Learning;**

I. INTRODUCTION

A. Background

Digital industry is growing fast and competition has become fiercer than before. Companies have to face new challenges and adapt to survive in the industry. Indonesia Ministry of Communication and Information Technology in 2021 stated that in the next 15 years, Indonesia needs 600.000 new digital talents each year. Nair [9] stated that at least 50% of companies are experiencing a significant gap of digital talent, and 60% of them have difficulties to compete. Because of these issues, companies need to strengthen their competencies, especially related to digital talent.

To strengthen core competencies, aside from digitalization of business processes, companies need to rely on knowledge management and integration, and use information technology to assist company's knowledge activities [7]. Growth of knowledge stock is also important to increase knowledge diffusion capacity and increase innovation performance. With these concerns, companies need to strengthen their knowledge stock from both quality and quantity perspective [15]. PT XYZ, the biggest telecommunication company in Indonesia, has been developing a digital knowledge management system (KMS) for years. In the last 3 years, knowledge utilization is declining significantly. Company is concerned with this issue as knowledge platform utilization is an important indicator of knowledge management implementation.

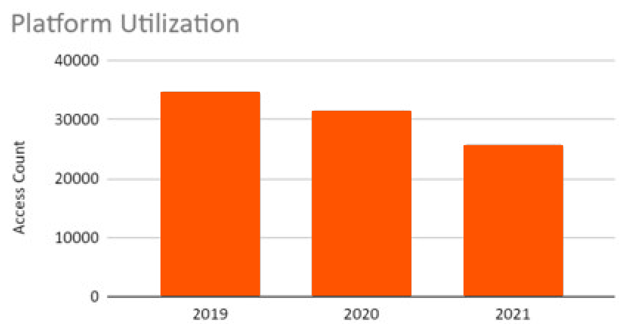

Fig. 1. PT XYZ knowledge utilization trend

PT XYZ is trying to address declining knowledge utilization issues by developing a new knowledge platform which accommodates multimedia knowledge such as text articles, videos, audios, and courses as a repository. Platform which adopts a social media system like this can improve knowledge utilization by covering informal knowledge formats [10]. This change is deployed to accommodate information technology and knowledge gaps with recommendations at the right time, right person and right format. This approach is expected to increase employee participation and result in higher knowledge utilization.

The following section discusses how to propose to build an efficient KM. The objective of this research is to develop a conceptual model of a knowledge recommendation system that can accommodate company and knowledge user needs of knowledge. This approach is expected to increase the company's knowledge utilization, as PT XYZ has set a target of 10% increase this year. This also aligns with the agenda of the Indonesian government to build digital talent for digital industry acceleration.

B. Literature Review

Generally, knowledge management (KM) can be described as defined as performing the activities involved in discovering, capturing, sharing, and applying knowledge so as to enhance the impact of knowledge on goal achievement in organizations [3]. As the time goes, management perspective has shifted from scientific management invented by Frederick W. Taylor to knowledge economy and knowledge management. These changes affect companies' perspective of employees from "economic man" to "intellectual man" as represented by Peter Drucker [2].

Chen [2] explains that innovation area for knowledge management should be based on 3 areas: the first is emphasize emotional interaction to develop knowledge creation model further, the second is emphasize digital drive, and use advanced digital technology including network technology, to create an efficient knowledge management, the third is to sublimate the pursuit of philosophy from objective pursuit to subjective pursuit, the pursuit of meaning, the pursuit of value, and the pursuit of happiness. Align with focus on KM innovation areas, Wu [14] in their research on Chinese companies divided into 3 development phases; KM 1.0, KM 2.0, and KM 3.0. Table 1 explains the characteristics of each phase and their focus of function.

Table 1 - THREE GENERATION OF KNOWLEDGE MANAGEMENT

	KM 1.0	KM 2.0	KM 3.0
Practice Mode	*Capitalization*	*Contextualization*	*Intellectualization*
Characteristics	Knowledge management within the organizations	Global knowledge transferring	Artificial intelligence (AI)-enabled knowledge management
Research Focus	Knowledge creation, sharing, and storage process within organizations	Improve the efficiency of global knowledge transfer and cooperation through information technologies	Deep mining and micro mechanisms of the knowledge creation process driven by AI

PT XYZ has been developing its ideal Knowledge Management. Figure 2 explains the PT XYZ framework of KM. Emphasize digital drive and advanced digital technology are deployed to support the KM process. The main technology is a knowledge platform which can accommodate various formats. Wang et al. [13] explains how AI-enabled KM can increase utilization of knowledge and become the focus of KM research in the future. AI can assist knowledge acquisition, control knowledge activities, and identify potential needs that can't be accommodated by traditional KM. As companies shift their focus from how to efficiently manage and promote knowledge, to utilize big data and global knowledge to the company's benefit.

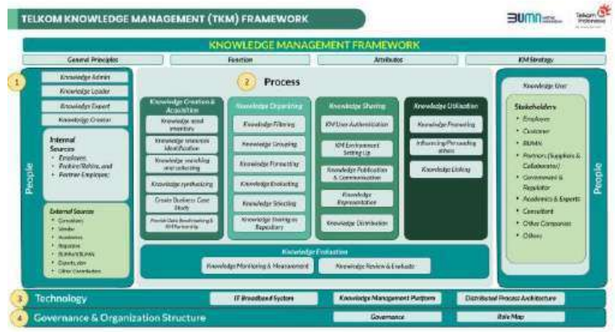

Fig. 2. Existing knowledge management framework

Knowledge stocks feature is regulated by human capital development at PT XYZ. Knowledge needs of the company are identified and listed in the competency's framework. Competencies divided into leadership and technical/ professional competences with core values as their center. PT XYZ also has job architecture which is inseparable with competences framework and complement to each other development. These two frameworks give opportunity for the company to make further improvement on their business processes.

One of the future trends of AI-enabled KM stated by Wang et al [13] is designing personalized knowledge recommendation systems. In the past differentiated knowledge was hardly measured, now it can be measured with AI. Personalized recommendation systems can adjust knowledge recommendation based on data selection from user profile, navigation, history, and other online factors. Machine learning as an application of AI can analyze such data to predict the most fitting knowledge for users [4]. According to the PT XYZ case, we identified two main subjects who need to be measured: knowledge creator and knowledge user. With the main objective of knowledge-promoting, all knowledge processes will be included. There are 2 well-known recommendation system practices; the first is collaborative filtering is a method to give recommendations based on correlation between user and knowledge, in other word filtering knowledge based on other user's utilization or rating. The second is content based filtering, a method to classify similar knowledge considering user preferences, and then recommend different knowledge with same attributes [1].

These practices to build personalized knowledge recommendation is important to achieve efficient KM. Wang et al. [13] added that meeting individual needs alone isn't enough, management has to deal with organization level needs, such as organizational strategic goals. That said, multi-agent needs have to be considered. According to the PT XYZ case, there are two different agent perspectives; the first is a management plan to develop human capital, which is a top-down approach. The second is user history and pre-registered preferences which is a bottom-up approach.

II. METHODOLOGY

A. Machine Learning Development

In this research, we adopt machine learning development phases. There are 6 main phases of machine learning development identified by Maass & Storey [8]. Conceptual models should map business goals to data requirements. Data required is supplied by existing databases and data mining from business processes. This research focuses on developing conceptual models for understanding the problems and proposed solutions. The process of data collection and the following steps are excluded for further research after data mining technology for various formats is deployed.

First phase of machine learning is problem understanding. This phase includes problem statements and descriptions. Complex environment demands a manager to identify critical factors for decision making. Machine learning is applied to decision problems to develop better decision making. In the KM system, problems of declining knowledge utilization are identified. Knowledge utilization is described as the access count of knowledge documents uploaded to a knowledge platform by knowledge users.

Hypothesis is developed based on identified problems. Knowledge experts and managers examine existing conditions of the company to identify important factors involved. This hypothesis then is used as a problem statement.

Problem statement is then analyzed if it can be translated into a predictive model, and is feasible to be solved. During problem analysis, relevant documents are included. Competence directory and job architecture is analyzed as a company's perspective of talent development. Knowledge management playbook and knowledge platform reports are analyzed from a knowledge development perspective.

B. Conceptual Model

Johnson [6] defined conceptual model is the model of solution proposed that the researcher wants users to understand. A Model is developed by studying literature with the aim to create common understanding between the designer and users. Parush [11] added that conceptual models can be different based on the degrees of freedom given to the user in accomplishing tasks and achieving goals. Following this, typologies of conceptual models can be divided into two main categories: sequential and structured, nonsequential and unstructured.

In this phase, we develop a conceptual model based on solutions for problems stated and defined from the previous step. Conceptual models are developed based on the existing framework of knowledge management and recommendation system development phases.

III. RESULTS

A. Problem Understandings

Knowledge utilization, represented by total count of knowledge platform access, is on a declining trend in the last 3 years. This is the main problem defined in knowledge management, and specifically the problem which this research is trying to address.

Management has described that accessing documents has become more difficult as the repository holds thousands of documents of knowledge. This hypothesis is supported by the fact that most of the documents in the repository are left unaccessed and also the existing classification is based on general categories, despite the competence's framework has been developed.

Solution for more efficient knowledge management, specifically knowledge platform is needed for this issue. PT XYZ has set a target to increase knowledge utilization by 10% at the end of 2022. An increasing trend is expected to happen in following years. Speaking of knowledge utilization, the company has developed a job architecture to classify its 23.756 employees into 3 job families, 12 job functions and 57 job roles. Competency framework is also developed to list competences needed by telecommunication companies, consisting of 2 types; leadership competencies and technical/professional competences. Competencies also act as complementary in supporting a job position for individuals to perform their work. Every job is expected to master 9-12 competencies which are prioritized based on business needs.

To conclude this problem understanding, we develop solutions based on the company's (top-down) and user (bottom-up) interests. Therefore, as stated in the knowledge management framework, we identified 3 components that should be involved; knowledge expert, knowledge user, and knowledge creator. Recommendation system with a machine learning approach will be developed to make better user experience when accessing knowledge platform. To accommodate multi-agent interests, a hybrid recommendation system is selected to combine collaborative filtering and content-based filtering.

B. Data Collection

Data collection will be conducted from various data sources. Data collection is based on data requirements to solve the problem. User profile, company's goal of competences development, knowledge data, and external references to build terms dataset.

Profile data to represent knowledge user interests, is collected from knowledge platform database and supported by other databases if needed. Data of competences accessed will be used for content-based filtering. Competence attributes of viewed documents are recorded and will be processed to match algorithm requirements. Media preferences for each user are represented by format attributes from access history. At last timestamp of access is recorded for adjustment of notification for follow up of recommendation calculation.

Knowledge experts create a competencies framework and assign ideal competences to each job role. This competency mapping data will be used for recommendation system, specifically collaborative filtering. Every employee is assigned to a job role. Ideal competences for each job role have different importance to each other, therefore weight is added as strength score. Data required from knowledge experts is a list of employees with a job role attribute and list of job roles with ideal competences as attribute and their weighted importance. At the time this research is conducted, knowledge experts are working on human capital data to assign job family, job function and job role attributes to employee data.

Knowledge creators play an important role to supply the fulfillment of knowledge stock. Data requirements for this representation will be collected from the knowledge repository. Knowledge stock of PT XYZ consists of many formats/media like; text article, video, and audio. Due to the complexity advanced data mining is required. Company needs to extract terms contained from various kinds of sources; plain text, audio to text, photos to text, and video to text. Unfortunately, PT XYZ is developing data mining technology for this use case and will be available in the near future.

Next step is data engineering, with the aim to decrease model complexity. We describe this process as pre-processing. Terms without any significant meaning to competences are removed, such as; like, to, from, with, etc.

C. Collaborative Filtering

Collaborative filtering is a recommendation system with an objective to give suggestions based on user correlation with knowledge. In this case knowledge is represented by competences. Company's goal is addressed in this recommendation system. Data of competencies mapping is used as score, and weight is added to enhance the priority.

Aside from the company's objective for competencies development, user objectives are accommodated. Knowledge platform has features to collect user preferred competences. These preferences can be aligned or different from a company's mapping of a given job role.

We use model-based type algorithms because competences mapping and user preferences can be dynamic as the time goes. SVD is used for matrix factorization techniques to decrease dimension. Equation (1) explains SVD key function to decompose into three other matrices:

$$X = U \times S \times V^T \qquad (1)$$

X is M x N utility matrix; U is a M x R matrix that shows relationship between user and competences as knowledge attributes. V is a R x N that shows similarity of knowledge and competences included. and S is a R x R matrix that shows the strength of each competence in knowledge. Each row of matrix represents a user, and each column represents knowledge.

D. Content Based Filtering

The aim of content-based filtering in KM is to classify knowledge based on their attributes. In this case attribute is competencies contained inside a knowledge document. The result is different recommendations of knowledge with similar competencies.

User needs of knowledge may vary for each individual. Historical data is recorded, in addition user favorite competences are pre-registered to enhance user data accuracy. This combination then is used as a user representation vector.

We use data mining on words for each knowledge document for the TF-IDF algorithm. Every word has weight added to determine its value to each competency. Weight in TF-IDF indicates how rare and significant each word is to a competency. Term TF (total frequency) is the frequency of a word appearing in a document. This means if the word frequently appears, the weight will be larger. Then we will add normalization for TF score using the length of the document. Equation of TF-IDF is described in equation (2) with N (Tx , Dy) is the total count of a word x (Tx) in a document (Dy), where N(Py) is the count of all words.

$$TF(T_{xy}) = \frac{N(T_x, D_y)}{N(P_y)} \qquad (2)$$

To address the different importance of each word in a competence, a weight for each word needs to be determined. IDF is using the scarcity rate of a word in the entire knowledge stock. Equation (3) explains IDF calculation where N(D) is total count of documents in knowledge repository, and N(D,Tx) is total count of documents contain the word x

$$IDF(T_x) = \log\left(\frac{N(D)}{N(D, T_x)}\right) \qquad (3)$$

Therefore, the TF-IDF equation (4) will determine score for each word in each competences, with normalization:

$$\mathrm{TF}-\mathrm{IDF}(\mathrm{T}_{xy}) = \mathrm{TF}(\mathrm{T}_x) \times \log10\left(\frac{\mathrm{N(D)}}{\mathrm{N(D,T_x)}}\right) \tag{4}$$

User representation will be determined by historical data of media (format) of knowledge, and competences of documents accessed. These data will be weighted and calculated using for user competency rating. We obtained both representation of the user and knowledge with TF-IDF score for knowledge and rating score for user. Cosine similarity approach equation (5) is used to calculate the similarity of these representation vectors:

$$\cos = \frac{A.B}{\|A\|.\|B\|} \tag{5}$$

For better understanding of this recommendation system, table 2 will serve as example of expected result of knowledge score of each document for this recommendation system:

Table 2 - EXAMPLE OF EXPECTED RESULTS

	Service Planning	User Support	Marketing Strategy
Document 1	0.015	0.030	0.097
Document 2	0.031	0.258	0.015
Document 3	0.174	0.075	0.059

E. Hybrid Recommendation System

Combination of two recommendation system methods is used to get advantages of both methods. Afoudi [1] explains there are 5 hybridization methods listed in table III. This research uses a weighted method, as top down and bottom-up approaches both are identically important.

Table 3 - KNOWN HYBRID RECOMMENDATION METHOD

Hybridization Method	Service Planning
Weighted	The scores of different recommendation systems combinec together to produce a single recommendation.
Switching	Depending on current situation, the system switches between recommendation techniques.
Mixed	Recommendation from several different recommenders are presented at the same time
Cascade	One recommender refines the recommendations given by another.
Feature Augmentation	Output from one technique is used as an input feature to another.

F. Conceptual Model

We developed a conceptual model in a swim lane diagram for the proposed solution to solve the knowledge utilization problem. Conceptual model starts from 3 components identified from the company's knowledge management framework. Development process is divided into 7 lanes. First lane is the knowledge workers component involved. Second lane is data sources related to knowledge workers for data collection purposes. Third lane contains data pre-processing for each data collected.

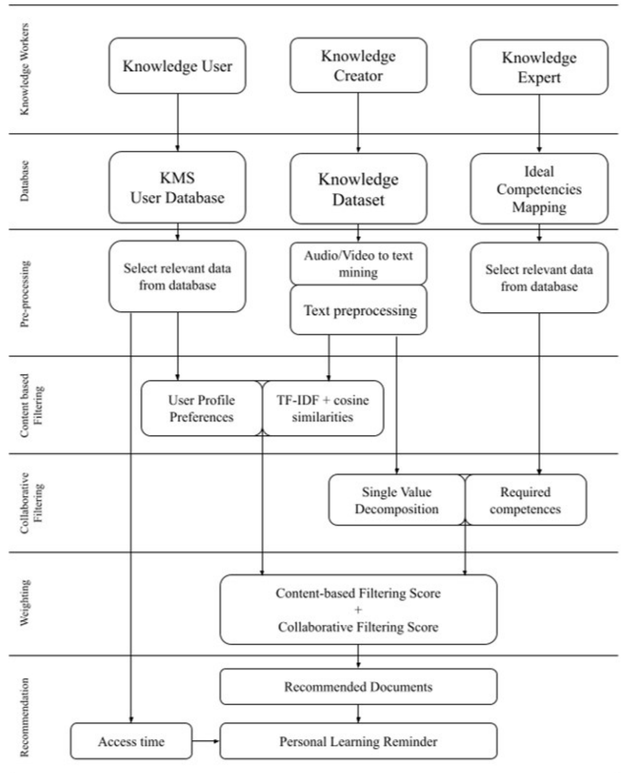

Fig. 3. Proposed recommendation system model

The following lanes consist of technical machine learning algorithms and the follow up solution to reach knowledge users. Fourth lane explains content-based filtering recommendation system to accommodate knowledge user interests. Combining user profile based on history and score of every competence in each knowledge document to calculate their similarity. Fifth lane explains collaborative filtering to cover the company's goal of employee competencies development. Adjusted with user's registered competences preferences. Combination of content based filtering and collaborative filtering as hybrid recommendation systems is explained in the sixth lane. Weighted method will be used to combine the scores from both algorithms. The last lane explains the follow-up process to actively reach knowledge users based on their access time of knowledge platform.

IV. DISCUSSION

This research result is a conceptual model for knowledge utilization optimization. Only the early phases of machine learning development are covered, because of PT XYZ existing condition. With a broad data source from cross division within the company, this research has developed a model for integration of Therefore this research will serve as guidance for further research about knowledge management especially for organizations with similar backgrounds.

This research is trying to address the incoming challenge of knowledge management. Machine learning development method is deployed to make personalized knowledge platforms, and hybrid combination is deployed to cover multi-agent purposes. Research about evaluation of recommendation relevance to user needs has to be done. Furthermore, evaluation to determine whether multi-agent purposes solutions can be done properly with existing models.

V. CONCLUSION

PT XYZ as the biggest telecommunication company in Indonesia is growing fast despite operating in uncertain conditions. One of the company's focus is to develop digital talent to tackle upcoming challenges. This mission is facing a threat of knowledge utilization decline. Furthermore, this trend can affect company performance if it continues to happen for a long term. As defined by Dong & Yu [3] that advancement of IT such as cloud computing, machine learning, big data and AI have been refining KM practices for years, PT XYZ expects machine learning implementation is able to improve knowledge utilization. The company has set a target to increase knowledge utilization by 10% at the end of the year, and hope this trend continues for the following years.

One managerial implication that can be derived from this study is the implementation of machine learning for understand and improve knowledge utilization despite of its complexity is worth exploring. The conceptual model describe how machine learning implementation is developed and adjusted based on company's condition and needs. Therefore, while development methods are similar, implementation in each field can be unique to each other. Management also needs to measure and compare the effectiveness for each deployment project based on proposed model such as the result of this study.

This research can be used as guidance for further research on knowledge management, or implementation of machine learning specifically recommendation systems in other areas. Data from various sources has to be integrated and prepared ahead of time to cover multi objectives within the company. Finally, efficient implementation should be deployed by a personalized system to match various individual needs, and brings out the hidden potential of the company's knowledge.

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