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Knowledge Transfer Mechanisms Using Text Mining and Sentiment Analysis – Case in an Online Collaboration

Firmansyah DAVID
Institut Teknologi Padang

Nursyahrina NURSYAHRINA
Institut Teknologi Padang

Anna SYAHRANI
Institut Teknologi Padang

Putri MANDARANI
Institut Teknologi Padang

Dede Wira Trise PUTRA
Institut Teknologi Padang

Abstract: This study aims to test, examine, and validate text-based human-machine knowledge transfer (KT) by comparing it with human-human KT. The online discussion experiment was carried out via WhatsApp group chats. Chat sentiment was determined using text mining and sentiment analysis and then compared with the respondent's understanding of the knowledge obtained from interviews. The results have shown that human-machine KT is close to human-human KT. By analyzing the correlation coefficient between the two, it is proven that sentiment indicates an understanding of knowledge. Positive sentiment shows similar or in-line understanding between the source and recipient of knowledge and indicates the achievement of KT objectives. Neutral sentiment indicates incomprehension due to the failure of KT. Meanwhile, negative sentiment is ambiguous; it may indicate an incomprehension or a misunderstanding of the knowledge received. This study contributes to the area of knowledge and sentiments, showing that the effectiveness of text-based KT activity can be identified using the sentiment analysis approach.

Keywords: Human-machine, Knowledge transfer, Online, Sentiment analysis, Text mining

Introduction

Knowledge transfer (KT) disseminates knowledge, ideas, experiences, and skills between human agents (Duan et al., 2012). It continuously creates new knowledge (Nonaka et al., 1995) and improves the quality and productivity of knowledge (Becerra-Fernandez & Sabherwal, 2014). An example of a KT is online collaboration activities such as online discussions carried out using various media, such as social media, online communities or forums, and online learning platforms (Widyahastuti & Tjhin, 2018; Zhao et al., 2021; Ollesch et al., 2022; Shang et al., 2022). Social media is widely used because of its flexibility and multifunctionality with various modes of communication, and an example of a globally popular social media app is WhatsApp Messenger (Leng et al.,2013 ;Anireh & Amadi, 2020; Iqbal, 2022).

Social media is a source of written knowledge usually analyzed to research a topic. Social media analysis was carried out using text mining techniques and sentiment analysis methods, as has been done in previous studies (Kušen & Strembeck, 2018; Gorodnichenko et al., 2021; Liu & Liu, 2021; Perikos et al., 2021; Saura et al., 2022). Sentiment analysis, a.k.a. opinion mining, determines the sentiment polarity, i.e., positive, negative, or neutral, to understand the opinions and emotions contained in a text (Fimoza, 2021). Sentiment analysis is commonly used for various needs, e.g., to obtain business insights and analyze user satisfaction in the business field or to assist the decision-making process in an organization (Allahyari et al., 2017; Birjali et al., 2021).

KT is widely needed in various fields, however it's difficult to achieve because knowledge comes from various sources and most of them are tacit, i.e., personal knowledge obtained from individual experience involving intangible factors such as beliefs, perspectives, values, and intuition (Terra & Angeloni, 2003; Dubickis & Gaile-Sarkane, 2017; Narendra et al., 2017). Problems such as miscommunication, inconsistency, and misinformation frequently occur in the dissemination of information and knowledge (Kušen & Strembeck, 2018; Ragili et al., 2020; Sheehan et al., 2020; Zhao et al., 2021).

In recent years, several studies have discussed the dissemination of knowledge using the concept of sentiment, for example, to test tools or transfer media on online platforms. Testing and validation of KT are needed to evaluate and verify the effectiveness of knowledge dissemination (Levine & Gilbert, 1998) as well as to determine the validity of the methods, frameworks, tools, or media used whether knowledge is conveyed as it should be or not. (Cruz et al., 2018; Zhao et al., 2021; D’Orazio et al., 2022).

Existing studies generally examine KT in educational contexts (Huang et al., 2019; Ollesch et al., 2022; Wyeld et al., 2021) or professional work areas (Justin & Lim, 2013; Leng et al., 2013; Cruz et al., 2018; Zhao et al., 2021). The online platforms studied in KT-related research are generally online forms (Aji & Agichtein, 2010; Zhao et al., 2021; D’Orazio et al., 2022), online learning platforms (Huang et al., 2019; Ollesch et al., 2022), and social networking sites (Justin & Lim, 2013). However, from the existing studies, few discuss the use of social media as an intermediary in the transfer of human-machine knowledge in the wider context of online collaboration, especially chat mode social media apps such as the WhatsApp chat application, despite its worldwide popularity. Therefore, this study aims to test, examine, and validate text-based human-machine KT in the context of online collaboration.

Literature Review

Knowledge is formed when someone can find and understand patterns in the information and its implications (Uriarte, 2008). In other studies, Becerra-Fernandez & Sabherwal (2014) stated that knowledge is at the highest level in the knowledge hierarchy, above data and information, and knowledge is information that enables action and decision-making as well as information that has a specific purpose. Knowledge is either explicit or tacit (Terra & Angeloni, 2003; Uriarte, 2008; Dubickis & Gaile-Sarkane, 2017). Explicit knowledge can be easily expressed through words and can be disseminated in the form of guides, specifications, pictures, audio, videos, computer programs, etc. Meanwhile, tacit knowledge is personal and comes from individual experiences such as insight, intuition, and feelings of a person, making it harder to express, formulate, and disseminate (Becerra-Fernandez & Sabherwal, 2014).

KT is traditionally carried out directly, where the sources and targets of knowledge meet face-to-face at the same time and space (synchronous), as is applied to formal education (Gulau, 2021b). Ragili et al. (2020) studied the KT process that occurred in the library based on the activities of librarians and staff and found obstacles, i.e., problems in conveying and absorbing information, which ultimately led to miscommunication. They stated that it was caused by the dissemination of information, which is mainly done directly through informal discussions without documentation. In this study, we will use a machine as tool (online chat application) to analyze and optimize KT as the solution to problems in KT (Zhao et al., 2021; Ollesch et al., 2022).

The development of science and technology today allows the dissemination of information between humans without having to be in the same space and time (asynchronously) through various online media that can be accessed anywhere and anytime (Gulau, 2021a). Many studies have been conducted on the transfer of knowledge carried out using online media, tools, applications, or machines. Various intermediary tools or machines are examined and tested for their effectiveness in the process of disseminating information and knowledge. For example, a group awareness tool in a social media learning community with a wiki-like platform environment in the study conducted by Ollesch et al. (2022) was tested to prove its effectiveness in improving the quality of content and learning outcomes. This tool combines the visualization of the knowledge level (cognitive awareness) and friendliness level (emotional awareness) by analyzing the content of the text, the comments, and the sentiments. The test was carried out using experimental methods, and the results showed that the knowledge level information displayed had a good impact on the quality of the distributed knowledge content. While the friendliness level of information has a good impact on friendliness in the knowledge exchange process and indirectly has the potential to produce well-learning outcomes. In another study, the online health community on the social media platform Baidu was evaluated using the model proposed by Zhao et al. (2021). The sentiment analysis model applies a machine learning approach to detect misinformation contained in forums. Based on the research results, it is concluded that the proposed model is valid in detecting misinformation and text features related to behavior, giving better detection results than linguistic features. The two studies above turned out to involve the element of sentiment in testing social media as an intermediary for the dissemination of knowledge.

Sentiments or opinions are subjective expressions of human feelings towards particular things or events that can be used as indicators for various purposes and can be found in textual information such as conversational texts and comments (Justin & Lim, 2013). Huang et al. (2019) stated that sentiment plays an essential role in knowledge recipients' engagement and knowledge creation. Positive sentiment is expressed in statements that support or like an opinion. Negative sentiment is contained in a different statement, contradicts, or dislikes an opinion. While neutral sentiment exists when there is ambiguity, a feeling of indifference, and an unclear tendency, it often arises when positive or negative sentiments are absent or very small.

Previous studies in knowledge management have discussed the role of sentiment. Some of them use sentiment to build and validate designs or tools to improve the dissemination of information and knowledge, such as automated systems, frameworks, or learning models. Cruz et al. (2018) introduced an automated framework based on sentiment analysis to identify the level of trust between members of a global software development team. Sentiment analysis is performed automatically on team member interaction data on the online collaboration platform and versioning system, GitHub. Framework validation is done through a survey. This study successfully validates the proposed framework, which can provide better trust estimation than conventional automated models to improve communication, cooperation, and dissemination of information and knowledge in working groups.

Huang et al. (2019) examine interaction patterns and sentiment dynamics in the learning process by conducting learning experiments on an online discussion platform. The interaction patterns and learning sentiments were codified manually, then analyzed using latent semantic analysis and correlation analysis methods. Based on the results, a model with four learning phases is proposed, describing the dynamics of sentiment and changes in interaction in the learning process. This model contributes to asynchronous or online learning as a basis for advancing the dynamics of sentiment in the learning process and interaction of students involved.

D'Orazio et al. (2022) validated the automatic building maintenance request detection method that applies sentiment analysis techniques with a lexicon approach. The computerized management system uses email as a medium for delivering information related to maintenance requests. The results of the maintenance request severity classification using sentiment analysis are compared with manual annotations by humans, which is considered the gold standard, using contingency tables and correlation coefficients (classifications by machine vs human). Based on the results, automated detection with sentiment analysis can classify maintenance requests based on their severity and urgency, which increases efficiency and reduces the analysis effort of human agents as maintenance personnel when faced with large requests. However, sentiment analysis can only provide basic analysis to exclude less important requests, whereas further detection of which part is affected and where the problem is not possible to generate, like manual annotations made by humans.

All of the above studies examine KT in the context of online collaboration using social media as an intermediary machine (human-to-machine KT). They all involve an element of sentiment for various purposes, such as for methods of learning, testing, validation, and analysis, as well as for information visualization. The sentiment is used as a tool in KT research. For testing or validating human-machine KT intermediary media, the application of sentiment analysis methods is accompanied by manual research methods such as human manual annotations, interviews, and questionnaires as gold standard data collection methods (Cruz et al., 2018; D'Orazio et al., 2022). Machine and human interpretations are then compared (machine vs. human) with various comparative analysis techniques, e.g., contingency tables and correlation analysis (Huang et al., 2019; D'Orazio et al., 2022).
Several other studies examine how sentiment affects the dissemination of knowledge. Aji & Agichtein (2010) identified the effect of sentiment on the dynamics of knowledge sharing on the online collaboration site Yahoo! Answer. This study conducted manual sentiment analysis and calculation of the accumulated answers and votes received from time to time on several questions that expressed different sentiments. From the exploration results, it was found that sentiment may have a strong influence on the dynamics of knowledge distribution in collaboration forums, especially negative sentiments that evoke "negative bias".

Leng et al. (2013) studied the effect of sentiment on knowledge sharing among knowledge workers in virtual communities of practice through social networking sites. Questionnaires, interviews, and text and sentiment analysis were conducted to test several proposed hypotheses. From this research, it is evident that sentiment is positively related to knowledge sharing and affects the quantity of knowledge shared. On another occasion, Justin and Lim (2013) conducted a similar study to analyze employee performance improvements as implications of sentiment on social networking sites, which also proved the positive relationship between sentiment and the quality of knowledge and individual worker performance.

In another study, Huang et al. (2019) stated that in knowledge exchange and learning, positive sentiments (enjoyment, pride, hope) signify a proactive state and continuous participation, which can increase the quality and frequency of interactions. Negative sentiments (frustration, boredom, and anxiety) can have an impact on the lower learning process and KT but may increase self-motivation. While neutral sentiments indicate non-involvement in the process of learning and knowledge exchange.

Based on the literature review that has been carried out, especially regarding sentiment in KT, we propose that if the sentiment is positive, then KT is likely to be successful. If the sentiment is negative, then the knowledge is most likely received with the opposite understanding. Meanwhile, if the sentiment is neutral, then the knowledge is most likely not successfully transferred.

Method

Data

This study uses data from human-to-machine activities of KT in the form of chat data from the online chat application, WhatsApp, to build a sentiment classification model tool (hereinafter referred to as tool data) and validate KT. Tool data is obtained from the conversational data of eight founders of a digital start-up, consisting of 25 people, who provide a marketplace platform (hereinafter referred to as start-up A). In the conversation, the founders collaborated online to discuss the planning and implementation of a marketplace platform for buying and selling organic products. Of these eight founders, two of them come from IT circles, while the other six are from non-IT backgrounds, such as business people. In a start-up that provide IT platform, these two founders from IT circles usually become the main sources of knowledge, especially when exchanging knowledge in the area of IT.

The data for validation is chat data obtained from an online discussion experiment (hereinafter referred to as experiment data). This experiment replicates the KT activity of start-up A founders but is executed with different human agents. In addition, validation data is also obtained through direct interviews as a representation of human-human KT activities (hereinafter referred to as interview data). The interview data illustrates the understanding of the knowledge recipients of the knowledge conveyed through online discussion experiments. More details will be explained later in the section of experiment methods. Detailed information about the data can be seen in Table 1.

Table 1. Data source

Data	Source	Date obtained	Total data	Format	Purpose
Tool data	WhatsApp group chat from the eight founders of Start-up A	March 11, 2022	14,746 lines	text (.doc)	to build a tool for sentiment classification
Experiment data	WhatsApp group chat from eight participants of online discussion experiment	March 24-25, 2022	463 lines	text (.txt)	to validate human-machine KT
Interview data	Direct interviews with six (non-IT) participants regarding the level of understanding of the knowledge gained from the experiment.	March 26-28, 2022	60 answers	audio/video recordings (transcribed)	to validate human-machine KT

Modeling of the Sentiment Classification Tool

The sentiment classification model was built through several processes, as shown in Figure 1. These are modifications and combinations of the general sentiment analysis and text mining processes proposed by previous studies (Birjali et al., 2021; Fimoza, 2021). Tool data with the main language of Indonesian was obtained in a document file format (.docx), then the content was transferred to a text file (.txt) for further processing using Jupiter Notebook programs.

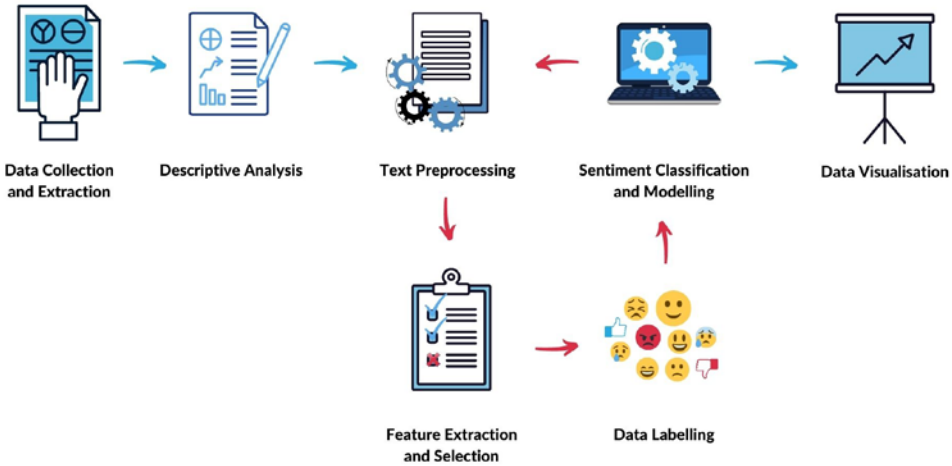

Figure 1. Sentiment classification modeling processes

In the extraction process, the data is tokenized to form separated chat data with the structure of timestamp, chat text, and sender name. Data not required for sentiment analysis, such as timestamps and sender names are excluded. Emojis contained in chat texts are first converted to text so that they can be included in text-based processing. The chat data is then saved into a comma-separated values (.csv) file for next processing. Furthermore, a descriptive analysis was carried out to get an overview of the data to be used, related to the size, dimensions, and characteristics of the data. The next stage is text preprocessing, to simplify chat data through a series of operations such as case folding, data cleansing, tokenization, stop words removal, stemming, and normalization, producing data in the form of simple term features. Then, feature extraction is conducted by calculating term frequency, Bag-of-words, and Term Frequency-Inverse Document Frequency (TF-IDF) to get the dominant feature. The feature list is selected by removing unnecessary terms (filtering). When obtained, chat data has not been categorized into any sentiment class, therefore it is necessary to carry out a labeling process to complete the data attributes needed in the sentiment analysis process. Labeling is carried out using the VADER (Valence Aware Dictionary for Sentiment Reasoning) method, as has been used in previous studies (Liu & Liu, 2021; D'Orazio et al., 2022). However, to be able to use this method, the chat data must first be translated into English. The translation is then performed collectively using the document translation feature in the Google Translate web application. Using VADER, the chat data was then labeled with one of three sentiment classes, i.e., positive, negative, and neutral, as applied in other studies (Liu & Liu, 2021; Muttineni & Deng, 2021).

The chat data that has been selected and labeled is then used for training and testing of the Multinomial Naive Bayes machine learning model for sentiment classification. This modeling phase combines several techniques described in several sources, including the processes of cross-validation and resampling data, training, testing, and evaluating the classification model (Abusalah, 2019; Birjali et al., 2021; Lyashenko & Jha, 2022; Olugbenga, 2022). The machine learning model that has been built is then used to analyze sentiment in the KT process. The results of the sentiment analysis are then supported by data visualization.

All data processing is carried out using the Jupyter Notebook programs in Python 3, utilizing data processing libraries such as pandas and NumPy, machine learning modeling libraries such as scikit-learn and imblearn, natural language processing libraries such as NLTK, and sastrawi (Indonesian only), data visualization libraries such as matplotlib and seaborn, and other Python libraries.

Experiments

In this study, experiments were designed to test and validate human-machine KT by comparing it with human-human KT. Here, we test and validate KT in online collaboration activities through the WhatsApp chat application. The experiment consisted of 2 activities, i.e., online group sharing and discussion as a representation of human-machine KT and interview as a representation of human-human KT. Through the experimental and interview methods, as also applied in previous studies (Justin & Lim, 2013; Leng et al., 2013). We obtained data from the human interpretation, which is to be used as a standard in the validation process.

The series of activities included is described by the experimental design, which can be seen in Figure 2. The topics of online discussion were 10 knowledge terms in the information technology (IT) world in the context of online collaboration, viz., online, online collaboration, IT startup, platform, cross-platform, marketplace, crypto, blockchain, crowdsourcing, and virtual enterprise. The group members, participants of the online discussion experiment, consisted of 8 people: 2 from IT circles and 6 others from non-IT circles, adjusted in such a way that it is similar to the conditions at start-up A, which is the source of the tool data. Two IT members become knowledge sources, while the other 6 non-IT members become KT targets or recipients. The group chat data generated from the experiment was then analyzed using the sentiment classification model developed.

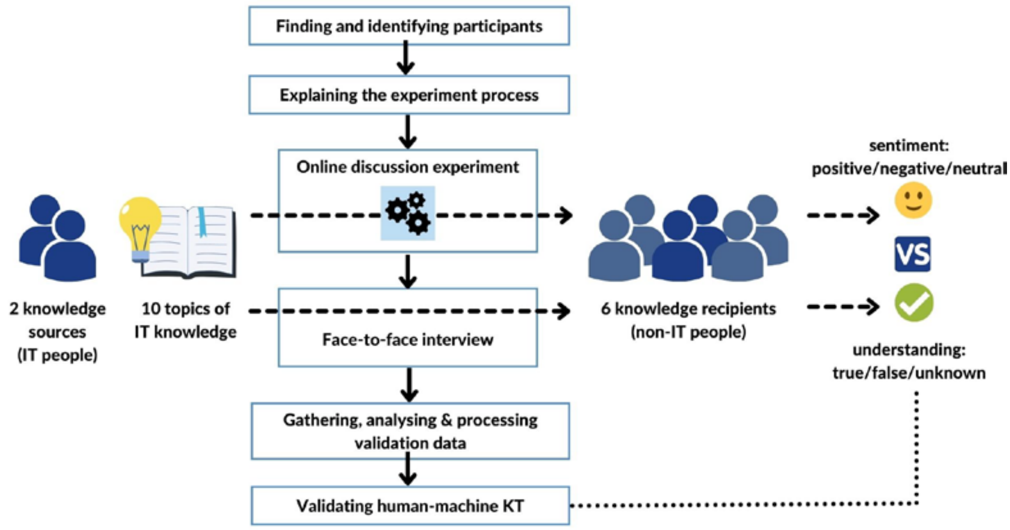

Figure 2. Experimental process design

The interviews were conducted by the same human agents and the same knowledge sources. The 2 IT members met with the 6 non-IT members in turn to re-investigate the knowledge recipients' understanding of the topics discussed in the online discussion. One IT member acted as the interviewer, asking one question on each topic (10 questions in total), with a detailed list of questions as can be seen in Table 2. While the others acted as observers who assess the level of understanding of non-IT members on certain topics, whether their level of understanding is in the true, false, or unknown categories.

Validation of human-machine KT was carried out by comparing KT activities through machines (human-machine) with direct KT between human agents (human-human); comparing knowledge received based on machine interpretation (tool) vs. human interpretation. This is done by comparing the sentiments of the respondents during online discussions (human-machine KT) and the level of understanding of the respondents from the results of the interview (human-machine KT). A contingency table and correlation coefficient were used (Howell, 2010; Zychlinski, 2018; Roflin & Zulvia, 2021) to determine the relationship between two variables in human-machine KT, i.e., sentiment and the level of understanding of knowledge. (Howell, 2010; Zychlinski, 2018; Roflin & Zulvia, 2021). Human-machine KT was validated regarding its success in transferring knowledge and the extent to which knowledge can be conveyed.

In addition to validation, experiment results were also used to examine the extent to which knowledge can be conveyed through human-machine KT. Has knowledge been successfully transferred to the knowledge level, or is it limited to the information level? This was carried out due to the differences in information and knowledge in terms of depth and complexity of understanding (Becerra-Fernandez & Sabherwal, 2014; Terra & Angeloni, 2003). This was conducted by examining the interview answers given by respondents who received knowledge. From the list of questions in Table 2, were the respondents able to answer the main questions and questions based on the keywords 'how' and 'why' with in-depth answers? Or did the respondents only briefly answer the alternative questions based on 'what' or yes-or-no questions without further explanation? This method corresponds to the differences in questions on the levels of information and knowledge mentioned in another study (Taylor, 2022).

Table 2. Interview topics and questions

Topics	Main question	Alternative questions
Online	Explain how you	What is online?
Online collaboration	understand each	What is an example of online collaboration?

Start-up IT	topic that has been	What is a start-up?
Platform	through online	What is an example of a platform?
Cross-platform	discussion. What did	What is an example of a cross-platform app?
Marketplace	you get from the	What makes marketplace and online store different?
Crypto	discussion regarding	Is it legal to use crypto in Indonesia? Why?
Blockchain	each topic?	What makes crypto and blockchain different?
Crowdsourcing		What is crowdsourcing?
Virtual enterprises		What are the characteristics of virtual enterprises?

Results and Discussion

Sentiment Classification Model

The development of a machine learning model for sentiment classification was carried out using group chat data on the WhatsApp application. The data used for the classification model training is group chat data with context around online collaboration, which consists of 14,746 lines of text. Before being used for model training, chat data goes through a series of processing as described in the section of sentiment classification tool modeling method. After going through the process, the remaining data consists of 8,021 rows of data. 80% of the data is then used for model training, and the rest is used in the testing process.

The classification model resulted has a balanced accuracy value of 78.94% and an F1 score of 81.41% for the test data. The confusion matrix from the test results can be seen in Figure 3. This value is still relatively low, and in the future, it can be improved by various model tuning techniques. This rather low metric value could be caused by the fact that the data is too unbalanced (the amount of negative chat data is very small compared to neutral and positive data). Another factor is that automatic labeling may give inaccurate results because it only depends on the sentiment value of the word in the dictionary (lexicon). Moreover, before being labeled, the data was first translated into English. This can affect the final accuracy. However, the accuracy of the resulting model is sufficient to be used in this study. This machine learning model becomes a tool that will later be used to analyze sentiment in the human-machine KT validation process.

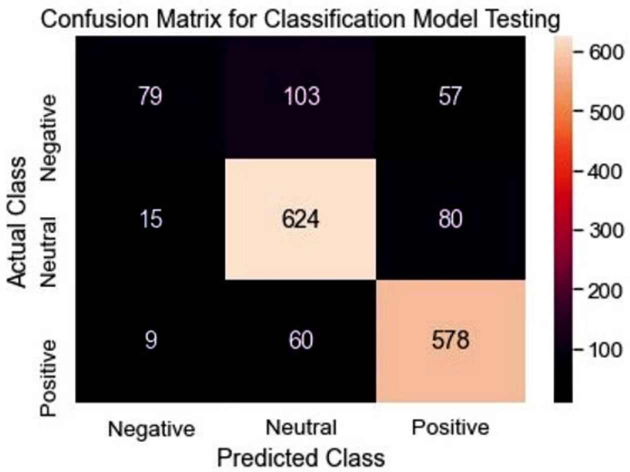

Figure 3. Confusion matrix of classification model testing

Experiment Results

The online discussion experiment generates chat data that will be used in the validation of human-machine KT. Experimental data was obtained from exporting WhatsApp chats to a text file, and the total data consisted of 463 lines of text. Furthermore, data extraction and text preprocessing were carried out, leaving 334 lines of data ready for further analysis. The chat data is then classified using the Multinomial Naive Bayes Classifier sentiment analysis model tool that has been developed previously. As can be seen in Figure 4, there are positive, negative, and neutral sentiments in the chat data resulting from this online discussion experiment. The three sentiments have been previously explained in other studies. Positive sentiment supports the quality of knowledge understanding; negative sentiment indicates a contradictory understanding; and neutral sentiment indicates indifference in the exchange of knowledge (Justin & Lim, 2013; Leng et al., 2013; Huang et al., 2019).

The majority of online discussions are neutral, which may indicate a lack of attention in the process of knowledge transfer, resulting in knowledge not being conveyed.

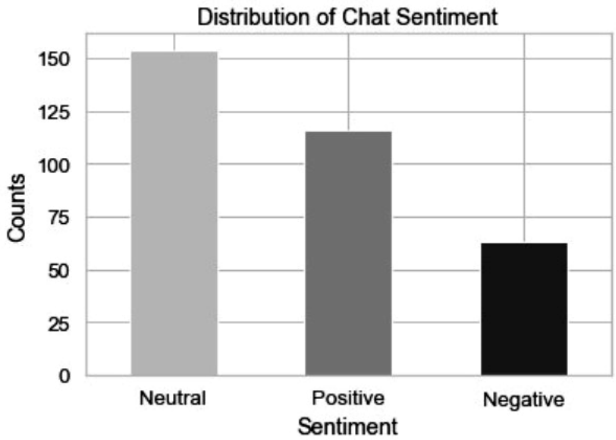

Figure 4. Distribution of chat sentiments

The classifications obtained using the machine learning model didn’t give good results if judged based on the basis of common sense by human agents, especially within the boundaries of the Indonesian language. For example, "paham", which means “understand”, is generally considered a positive sentiment in Indonesian, but neutral in English. This difference in perception can be caused by the labeling process carried out using the VADER library, which was created for English text analysis. Another example can be seen in the group chat data snippet from the sentiment classification results in Table 3.

Table 3. Snippet of chat sentiment classification results

Chat text (translated)	Sentiment class
in my opinion, online it is a device that is connected through a network	Neutral
if this one I've never heard of	Neutral
not really understand 😔	Neutral
I don't know sis :(	Negative
okay understand 👍	Positive

The next activity was to directly interview all respondents who had received knowledge. Of the total 60 questions (10 questions for each respondent), 35 of them could not be answered because the respondent didn’t know the answer or had forgotten it already. Most of the other questions were answered briefly, as can be seen in Table 4.

Table 4. Snippet of interview answers

Topics	Respondents’ answers (translated)
Online	Online is connected to a network.
	Online is an internet network.
Online collaboration	Online collaboration is when two people or groups are connected online.
Start-up IT	A startup is a new company.
	A start-up is a business that is run by a company in the industrial sector in a modern way.
Platform	An example of a platform is YouTube.
	The example is YouTube.
Cross-platform	Cross-platform is cross-lane.
Crypto	Crypto legality depends on government regulations.
	Not prohibited.
	Not allowed.
Blockchain	A blockchain is part of crypto, which is a database of the crypto transaction history.
Crowdsourcing	Crowdsourcing is a way for people to share information online.

When examining the list of questions in Table 2 and the answers in Table 4, we can see that respondents could only briefly answer alternative questions, i.e., 'what' or yes-or-no questions. Respondents didn’t understand the topic of discussion in detail and in-depth. Regarding the differences in knowledge levels described in other studies (Terra & Angeloni, 2003; Becerra-Fernandez & Sabherwal, 2014; Taylor, 2022). These findings suggest that in online discussions (human-machine KT) knowledge only reaches the recipient at the information level. KT through machine intermediaries has not been able to convey comprehensive and in-depth knowledge from one human agent to another. As has also been described in previous research (Terra & Angeloni, 2003). Machine intervention leads to limited knowledge transfer at the information level.

From the results of this interview, data about the level of understanding of knowledge recipients was obtained through the codification of respondents' answers, as shown in Table 5. The overall distribution of the data can be seen in Figure 5. Based on the bar plot, it is known that the majority of respondents still do not know or do not understand the knowledge topics that have been conveyed previously through online discussion experiments.

Table 5. Coding result of the interview answers

Source knowledge (translated)	Respondent's answer (translated)	Code
A marketplace is different from an online store. Marketplace provider companies facilitate operational activities such as website management and payment methods for several sellers, while in online stores, single sellers make transactions directly with buyers with no intermediaries.	In the marketplace, there are intermediaries between sellers and buyers, such as (for) cost issues. Meanwhile, in online stores, sellers directly send (goods) to buyers.	True
	Haven't found the difference yet. In my opinion (both things) are the same.	False
	Don't know; do not understand; forgot already	Unknown

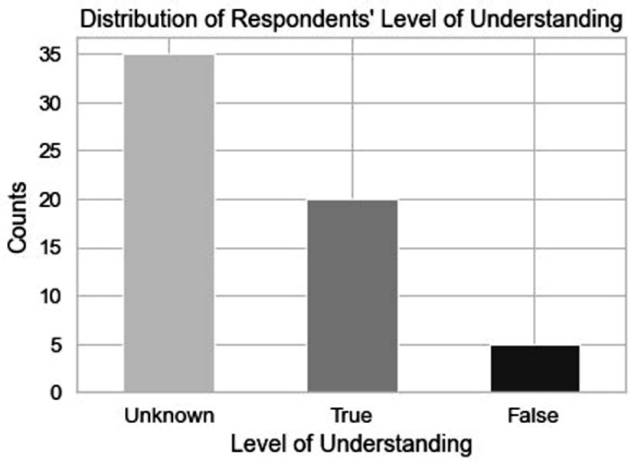

Figure 5. Distribution of respondents' level of understanding

Validation of Human-Machine Knowledge Transfer

Validation of human-machine KT was carried out by comparing the sentiments of the respondents during online discussions with the level of understanding of the respondents from the results of the interviews. The two experimental datasets were compared to see the relationship between the two types of KT. Sentiment class in online group chat data has a distribution similar to the level of understanding of respondents obtained from direct interviews, where there is one label with a very large amount of data (majority), one minority label, and another label right between the two. This can be seen by comparing the bar charts in Figure 4 and Figure 5.

Table 6. Comparison of machine and human interpretation of chat data

Chat text (translated)	Sentiment (by machine)	Understanding (by a human)
in my opinion, online it is a device that is connected through a network	Neutral	True
if this one I've never heard of	Neutral	Unknown
oo, it turns out that there are a lot of meanings to the word platform	Negative	Unknown
Isn't crypto like a stock game? Isn't it?	Negative	Unknown
So crowdsourcing is the method, while for the application on the website, that's how it is.	Positive	True

This proves that both types of KT give similar results. In other words, human-machine KT resembles or approaches human-human KT. From this resemblance, further analysis is carried out between the two KT variables, viz., sentiment and the level of understanding, because of the possibility of a relationship (correlation) between the two. To find out more about the relationship, sentiment data (interpreted by machine) and level of understanding data (interpreted by a human) are juxtaposed in a new analysis table, as can be seen in Table 6.

There is a gap between the amount of chat data (sentiment) and interview data (understanding). Therefore, the data included in the comparison table (Table 6) is only core chat sentiment data from non-IT respondents discussing the topic of knowledge. The respondent's understanding (during the chat) is adjusted to the results of the interview. Simply put, when discussing a topic, the respondent's level of understanding is assumed to be unknown before the source of knowledge conveys knowledge related to the topic, but after that, the respondent's level of understanding is assumed to be the same as the interview data on that topic. The comparison data is then quantified in the form of a contingency table or cross-tabulation (crosstab) and normalized based on sentiment data to show more clearly the relationship between sentiment data and level of understanding, as shown in Table 7.

Table 7. Cross-tabulation of sentiment and understanding (normalized)

Understanding	False	Unknown	True	Total
Sentiment				
Negative	0.077	**0.69**	0.23	1
Neutral	0.037	**0.63**	0.33	1
Positive	0.048	0.24	**0.71**	1

From the crosstab, it can be seen that the majority of negative and neutral sentiments are related to a lack of understanding of the knowledge transferred (unknown). Meanwhile, positive sentiment relates to the true level of understanding; that is, a similar or in-line understanding between the recipient and the source of knowledge. However, from this positive sentimental knowledge, not everything is understood. Only 71% of knowledge can be understood correctly; the rest is unknown and misunderstood (false). The relationship between variables can be seen through the distribution of data in the cross-tabulation, but how the relationship between the sentiment variable and the level of understanding based on existing standards is still not known for certain. A correlation matrix was made using Pearson's r formula to determine with certainty the relationship between each category of sentiment and the level of understanding.

Based on the correlation matrix in Figure 6 and the standard classification of correlation coefficients used (Schober et al., 2018). İt can be seen that positive sentiment is related to the true level of understanding with a moderate unidirectional proportional relationship (correlation coefficient 0.4 = moderate positive correlation), whereas negative and neutral sentiments were associated with the unknown level of understanding with a weak but definite proportional relationship (correlation coefficients 0.19 and 0.22 = weak positive correlation). Meanwhile, the relationship between negative sentiment and the false level of understanding in this study is very small (0.07 = negligible positive correlation) and can be ignored. However, negative sentiment might also mean a misunderstanding in KT. This shows the ambiguity of negative sentiment in text-based human-machine KT.

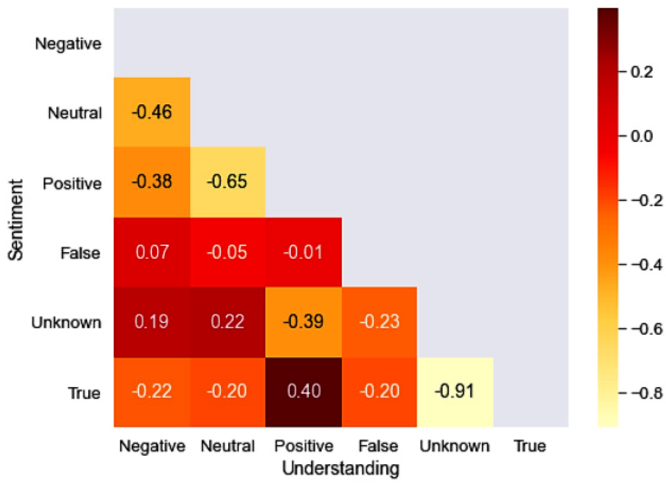

Figure 6. Pearson correlation matrix of sentiment data and level of understanding

Based on the results of the comparison and correlation analysis that have been carried out, it was found that in human-machine KT, sentiment is related to KT. This statement is quite similar to the results of research conducted by previous researchers who stated that sentiment greatly affects the quantity of knowledge disseminated online through social networking sites or social media (Aji & Agichtein, 2010; Leng et al., 2013).

Positive sentiment relates to the correct understanding and shows the success of KT, where the recipient of knowledge has a similar or in-line understanding with the source of knowledge. Neutral sentiment is related to incomprehension and shows the failure of KT, where knowledge is not conveyed at all to the target of knowledge transfer. While the negative sentiment is ambiguous, it can indicate incomprehension or misunderstanding. Misunderstandings can be in the form of different understandings or conflicting opinions between the recipient and the source of knowledge.

Based on the distribution of sentiment data in Figure 4, associated with previous findings regarding the correlation between sentiment and KT, it can be concluded that neutral sentiment data indicating incomprehension is more than positive sentiment data indicating correct understanding. In other words, there is still more knowledge that is not accepted than the knowledge that is properly accepted and understood. This shows that text-based KT via machine (human-machine KT) such as group discussions on online chat applications, has not been successful. KT is not achieved because the majority of knowledge fails to pass from the source to the transfer target.

As stated in the section of experiment results, KT through machines (human-machine KT) has approached or resembled direct KT (human-human KT) but machine intervention has limited the transmission of knowledge only at the information level. The validation results also prove that human-machine KT has not been effective in transferring knowledge between human agents. Whereas in reality, machines are very commonly applied and used in the dissemination of knowledge, i.e., social media applications, online chat applications, or chatbots. From these findings, we can finally conclude that there are deficiencies or gaps in knowledge management studies. This deficiency or gap can be overcome by combining the concepts of knowledge transfer and knowledge management with sentiment analysis, as we proposed through the validation method in this study.

Conclusion

As explained in the results and discussion section, this study proves that sentiment indicates knowledge transfer. It is evident that positive sentiment indicates that knowledge has been transferred successfully, neutral sentiment indicates that knowledge is not conveyed, and negative sentiment is found to have multiple meanings. Negative sentiments are proven to indicate that knowledge is received with contradictory understandings, but can also indicate the failure of knowledge transfer.

Recommendations

Although the aim of this study to test, examine, and validate human-machine KT has been achieved, there are some limitations and shortcomings. This research is only to test and validate, not to build an analytical tool that can be used directly by end-users. This research is limited to text-based human-machine KT and sentiment analysis on knowledge texts in the context of online collaboration. Further processing was only applied to knowledge in Indonesian, while knowledge in other languages is still included in data processing but is only considered as a collection of terms. The analysis was carried out purely on the knowledge text data and its sentiments without considering differences in age, gender, and background of the source and target of KT as research respondents. The analysis also does not consider other factors, such as prior knowledge and human behavior, in transferring knowledge.

Future research is advised to overcome the limitations of this study. For example, research to optimize KT by developing a KT machine that applies sentiment analysis. One of the ideas is to develop a chat application that can perform sentiment analysis so that during the KT process, users can find out in an instant whether KT was successful or not, through the sentiments displayed. Another idea is to develop a chatbot engine that can generate questions and conversational rules based on sentiment and user understanding. Further research related to testing and validation of human-machine KT can also be carried out, not only considering sentiment factors but also other factors such as prior knowledge and the behavior of human agents in transferring knowledge. Another recommendation for future research is to test the human-machine KT to determine the understanding of silent readers on a text-based online group platform. A sentiment-based approach, such as the solution given in this study, certainly cannot be used. This kind of research is very interesting to do because the silent reader did not give any response, so data-driven analysis could not be done.

Scientific Ethics Declaration

The authors declare that they are responsible for the scientific, ethical, and legal aspects of the paper published in EPSTEM.

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Author Information

Firmansyah David
Institut Teknologi Padang
Padang, Indonesia
Contact E-mail: *firman@itp.ac.id*

Nursyahrina Nursyahrina
Institut Teknologi Padang
Padang, Indonesia

Anna Syahrani
Institut Teknologi Padang
Padang, Indonesia

Putri Mandarani
Institut Teknologi Padang
Padang, Indonesia

Dede Wira Trise Putra
Institut Teknologi Padang
Padang, Indonesia

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