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Sentiment Analysis Based on Questionnaires: A Case Study on the Use of Induction Stove

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ABSTRACT: Indonesia's reliance on subsidized Liquefied Petroleum Gas (LPG) for household cooking places a significant burden on the national energy subsidy budget and increases dependence on imported fossil fuels. As part of the clean energy transition strategy, the Indonesian government has promoted the conversion from LPG stoves to electric induction stoves. However, public acceptance and actual post-use experiences at the household level remain diverse and insufficiently examined empirically. This study aims to analyze public sentiment toward induction stove use based on post-adoption user reviews to identify factors that encourage interest and reveal existing adoption barriers.

This study employs a machine learning–based sentiment analysis approach using primary data collected through open-ended questionnaires distributed to induction stove users. A total of 265 valid textual responses were analyzed. Text preprocessing was conducted using Python with the NLTK and Sastrawi libraries, including data cleaning, case folding, tokenization, stopword removal, stemming, and duplicate removal. Sentiment classification was performed using the Term Frequency–Inverse Document Frequency (TF-IDF) method and the Naive Bayes algorithm, while WordCloud visualization was applied to identify dominant keywords.

The results indicate a relatively balanced sentiment distribution, with positive sentiment accounting for 33.6%, neutral sentiment 32.5%, and negative sentiment 34.0%. Positive sentiment is mainly associated with energy efficiency, safety, and ease of use, whereas negative sentiment is driven by concerns regarding initial costs and electricity dependence. Neutral sentiment reflects an evaluative phase among users. These findings provide empirical insights to support user-oriented policies and strategies for accelerating the sustainable adoption of induction stove technology in Indonesia's clean energy transition.

KEYWORDS: Clean Energy Transition, Induction Stove Adoption, Machine Learning, Sentiment Analysis, User Experience.

INTRODUCTION

Indonesia currently faces considerable challenges in managing energy subsidies, particularly subsidies for Liquefied Petroleum Gas (LPG), which remains the primary cooking fuel for most households. Government subsidies have made LPG relatively affordable and accessible, leading to its widespread use across all segments of society. However, this dependence places a significant burden on the State Budget (APBN), mainly due to the increasing reliance on LPG imports. Data from the Central Statistics Agency (BPS) shows that the value of LPG imports in 2021 increased significantly compared to 2020 [1]. In the same year, government spending on LPG subsidies reached around USD 4.9 billion, with a total import volume of 6.2 million tons [2]. This situation underscores the urgency of reducing dependence on LPG while improving national energy efficiency.

The transition from subsidized LPG gas stoves to electric induction stoves is one of the main strategies in Indonesia's clean energy transition efforts, which aim to reduce dependence on imported fossil fuels and pressure on the energy subsidy budget. Induction stoves are positioned as a more energy-efficient, safer, and environmentally friendly cooking technology, in line with national targets for cleaner energy use and long-term emission reductions [3]. The Indonesian government, through various pilot projects, is encouraging the adoption of induction stove in households, such as the LPG to induction stove conversion program, which targets millions of households by 2025 [4]. However, the actual adoption rate and user experience at the household level still show significant diversity and challenges, including perceptions of cost, ease of use, and technological readiness, which have not been fully understood empirically in the Indonesian context [5]. Therefore, empirical studies based on user reviews are important to understand users' actual evaluations of induction stove after using them in daily cooking activities, as a basis for identifying factors that influence the acceptance of this technology in society.

One of the strategies implemented by the Indonesian government to overcome this problem is energy substitution, particularly through efforts to convert LPG stoves to induction stoves. Among the various alternatives available, induction stoves are currently considered the most viable replacement for LPG stoves [6]. This policy direction is also supported by the condition of the national electricity system. PT Perusahaan Listrik Negara (PLN) (Persero) reports that Indonesia has excess electricity reserves of more than 30 percent, which is one of the main considerations in implementing the program to convert LPG stoves to induction stoves. In addition, PLN is also developing a number of new power plants with a total planned capacity of around 35,000 MW, thereby opening up further opportunities for optimizing electricity utilization [7]. This condition provides a strategic opportunity to reduce the energy subsidy burden while utilizing excess electricity capacity.

From an environmental and sustainability perspective, the transition from LPG to induction stove is in line with Indonesia's long-term energy policy objectives. Members of the National Energy Council (DEN) emphasize that the adoption of induction stove supports cleaner and more environmentally friendly energy use. Additionally, this initiative is expected to contribute to reducing LPG imports and supporting the achievement of the national target of utilizing 25 percent new and renewable energy (EBT) by 2025 [3]. Induction stove also have other advantages, including higher energy efficiency and no direct air pollutant emissions, thereby potentially improving indoor air quality and public health [8].

Following up on these considerations, the Indonesian government, through PT PLN (Persero), officially launched a program to convert LPG stoves to induction stoves in 2021. This program was initially implemented as a pilot project in Bali and Surakarta, which began in June 2022, involving 1,000 beneficiary households. The pilot project includes the distribution of induction stoves along with compatible cooking equipment, the installation of supporting electrical devices, and the provision of additional electricity capacity tailored to the needs of induction stoves without affecting the electricity tariff per kWh. [9]. However, the adoption rate of induction stove is still relatively limited. Public concerns about the stability of electricity supply, network coverage disparities, and the perception that induction stove are difficult to operate have led to resistance and mixed responses from the public [10]. The actual adoption rate and user experience at the household level still show significant diversity and challenges, including perceptions of cost, ease of use, and technological readiness, which have not been fully understood empirically in the Indonesian context [5]. Therefore, empirical studies based on user reviews are important to understand users' actual evaluations of induction stove after using them in daily cooking activities, as a basis for identifying factors that influence the acceptance of this technology in society.

In many studies on technology adoption, research tends to focus on pre-adoption factors such as usage intentions and initial factors that influence a person to try a new technology using models such as TAM and UTAUT. However, these studies often only capture users' perceptions before actual use and do not explore how those perceptions change after users actually interact with the technology in their daily lives. Other studies show that long-term usage experiences and user evaluations of products or services play an important role in determining satisfaction, loyalty, and intent to continue using the technology, especially when actual experiences may differ from initial expectations (e.g., user evaluations of quality, benefits, and long-term experience issues) [11].

In the context of user reviews themselves, research in consumer literature has shown that online reviews or user feedback provide valuable insights into perceptions of benefits and user experiences, which can influence subsequent consumer decisions and shape information adoption and credibility in decisions to purchase new technology or products [10, 12, 13, 14]. Therefore, it is important to utilize user reviews as a source of empirical data that not only describes initial perceptions but also actual post-use experiences, so as to reveal the functional and emotional factors that influence the acceptance and sustainability of induction stove use in Indonesia.

These diverse public responses underscore the importance of understanding public perceptions in determining the success of projects carried out by the government. In recent years, project management literature has increasingly recognized that public opinion and user satisfaction are key factors that influence project quality and long-term sustainability [15]. Collecting public feedback allows stakeholders to identify potential problems, manage risks, and improve project outcomes. However, conventional methods of measuring public opinion, such as surveys and interviews, often require significant costs, take a long time, and have limited coverage.

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In the context of Industry 4.0, sentiment analysis has emerged as an alternative approach to analyzing public opinion in a more dynamic way and with a wider reach [16]. Sentiment can be defined as the views, attitudes, or opinions expressed by individuals toward a particular issue or policy [17]. Sentiment analysis is a computational technique used to identify and classify opinions contained in text data to determine the sentiment orientation of the author [18]. This approach combines Natural Language Processing (NLP), text analysis, and computational methods to automatically extract emotional information and attitudes from text [19]. Sentiment analysis has been widely applied in various fields, including election prediction [20], infrastructure project evaluation [15], analyzing responses to government policies, and measuring customer satisfaction [19].

To examine users' real experiences more systematically, this study utilizes sentiment analysis of user reviews collected through a questionnaire with an open-ended question: "Menurut anda, apa yang dapat meningkatkan minat masyarakat dalam menggunakan kompor induksi?" Sentiment analysis allows researchers to extract users' opinion trends, attitudes, and emotional evaluations from unstructured text data in a quantitative and measurable manner. This approach has been widely used in technology and energy studies to identify public perceptions, barriers to adoption, and factors driving technology acceptance based on actual user experiences, which often cannot be optimally captured through closed-ended questions or Likert scale surveys alone [21, 22].

Furthermore, the use of open-ended questions in collecting review data provides space for respondents to freely express their views, thereby capturing both the functional and emotional dimensions related to the use of induction stove, such as perceptions of efficiency, safety, cost, and ease of use. However, the diverse and unstructured nature of text data requires an analysis method that can process this information effectively. Therefore, machine learning-based sentiment analysis was chosen in this study because it has been proven to be able to classify user opinions into positive, neutral, and negative sentiment categories with a good level of accuracy, especially in high-dimensional text data such as user reviews [23, 24].

By analyzing the sentiment of post-use user reviews, this study focuses not only on initial intentions or perceptions prior to adoption, but also on actual user evaluations after direct interaction with induction stove in daily cooking activities. This approach is expected to provide a more comprehensive empirical contribution to understanding the factors that can increase public interest in induction stove, as well as identifying the main obstacles still felt by users. The findings of this study are expected to provide relevant input for policymakers, manufacturers, and relevant stakeholders in designing more effective induction stove adoption strategies that are user-experience oriented and sustainable in supporting Indonesia's clean energy transition agenda.

METHODOLOGY

In the context of the LPG stove to induction stove conversion program implemented by PT PLN (Persero), understanding public sentiment is a very important aspect in improving project quality and community acceptance. The success of this initiative is not only determined by technical and infrastructure readiness, but also by how the policy is perceived and accepted by the community. Therefore, this study integrates sentiment analysis as a supporting approach to evaluate public perception of the induction stove conversion program. Through sentiment analysis, this study aims to provide additional contextual insights that complement the main analytical framework, assist stakeholders in identifying areas for improvement, and support a more informed decision-making process. Ultimately, the integration of public sentiment in project evaluation is expected to contribute to the development of more effective, sustainable, and socially acceptable energy transition initiatives in Indonesia.

1. Research framework

   This study aims to analyze public sentiment towards user experiences with induction stove. The research framework, consists of three main stages, namely data collection, data preprocessing, and data analysis. In the data collection stage, public opinion was obtained through a questionnaire containing open-ended questions about respondents' experiences and perceptions in using induction stove. The use of open-ended questions allows respondents to express their opinions freely and contextually, so that the resulting text data is richer and more representative for analysis using a text-based sentiment analysis approach [21].

   The data preprocessing stage was carried out to clean and standardize the text data in order to reduce noise and improve data quality before further analysis. The preprocessing process is a crucial stage in sentiment analysis because the quality of text data greatly affects the performance of the classification model [22]. The preprocessing stages applied in this study include data cleaning, case folding, tokenization, stopword removal, stemming, and duplicate data removal.

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In the data analysis stage, this study applied a machine learning-based sentiment analysis approach to classify respondents' opinions into three sentiment categories, namely positive, neutral, and negative. Text feature representation was performed using the Term Frequency–Inverse Document Frequency (TF-IDF) method, which is commonly used in sentiment analysis to capture the level of importance of a word in a document [24]. Next, the sentiment classification process was carried out using the Naive Bayes algorithm, which is known to be effective and efficient in handling high-dimensional text data [23]. The sentiment classification results are then analyzed descriptively to identify dominant sentiment trends and gain a more comprehensive understanding of public perceptions of the experience of using induction stove.

2. Data Collection

   Data collection in this study was conducted using questionnaires distributed to respondents to obtain public opinion regarding their experiences with induction stove. The questionnaire was designed in the form of 21 to allow respondents to freely express their opinions, experiences, and perceptions without being limited by specific answer choices. This approach was chosen because it was able to capture the respondents' perspectives in a more in-depth and contextual manner compared to closed questions.

   The questionnaire was distributed online to respondents who had used or had experience with induction stove. From the data collection process, 265 open-ended answers were obtained, which were declared valid and used as research data. All respondent answers became a source of text data that was analyzed in the sentiment analysis stage.

   The data used in this study is primary data obtained directly from respondents. To maintain research ethics, the identity of respondents is kept confidential and all data is used solely for academic purposes. The text data from the questionnaire was then processed and analyzed to identify public sentiment trends regarding experiences with using induction stove.

3. Data Preprocessing

   The data obtained was then preprocessed to remove nonstandard terms or elements. The preprocessing stage is a very important initial step before the data is further analyzed in the sentiment classification process, as it aims to improve data quality and analysis accuracy [22]. In this study, data preprocessing was performed using the Python programming language with the help of the Natural Language Toolkit (NLTK) and Sastrawi libraries. This process includes removing irrelevant elements and normalizing the text so that the data is ready for further analysis [24]. The preprocessing stages carried out are as follows.

   a. Data Cleaning

      This step is done by removing unnecessary elements in the text data, such as user names, links, or special characters, as well as normalizing the text to standardize the writing format.

   b. Case Folding

      Case folding aims to convert all letters in the text to lowercase to avoid differences in meaning due to variations in the use of uppercase and lowercase letters.

   c. Tokenisasi

      Tokenization is the process of separating text into units of words (tokens). This stage is carried out by breaking sentences or text into words based on specific separators, thereby facilitating the subsequent analysis process.

   d. Deletion Stopword

      Stopwords are words that do not contribute significantly to the meaning of a text. The process of removing stopwords is done to eliminate irrelevant words so that only important words are retained in the analysis.

   e. Stemming

      Stemming is the process of converting words to their base form by removing prefixes and suffixes. The purpose of this stage is to simplify words so that variations of words with the same meaning can be treated uniformly.

   f. Deletion of Duplicate Data

      The final stage in preprocessing is to remove duplicate text data to avoid repetition of information that could affect the sentiment analysis results. All stages of data preprocessing are carried out before feature extraction and sentiment classification using a machine learning approach.

RESULTS

1. Sentiment Analysis Result

The results of sentiment analysis of 265 text data from respondents' opinions regarding their experiences using induction stove show that public sentiment is divided into three categories: positive, neutral, and negative. Sentiment classification was performed using a machine learning approach with TF-IDF feature representation and the Naive Bayes algorithm, which is known to be effective in handling [23].

Based on the classification results, positive sentiment was the most dominant category, followed by neutral sentiment, while negative sentiment had a relatively smaller proportion. The dominance of positive sentiment indicates that, in general, respondents have a good perception of the use of induction stove. This is in line with previous research findings which state that machine learning-based sentiment analysis is able to effectively capture public opinion trends from unstructured text data [21].

The positive sentiment that emerged in this study was generally related to respondents' perceptions of the energy efficiency, ease of use, and safety aspects of induction stove. Respondents tended to rate induction stove as practical, modern, and safer than conventional stove. These findings support the results of the study [22], which states that positive opinions in sentiment analysis often correlate with perceptions of ease and benefits of using a technology.

The neutral sentiments in this study largely reflect respondents' opinions that are informative or descriptive in nature without showing strong emotional tendencies. Respondents in this category generally expressed objective views, such as the need to adjust cooking habits or limitations in supporting infrastructure. Meanwhile, negative sentiment was more related to perceptions of the initial cost of purchasing an induction stove and dependence on electricity, which are still considered major barriers to the adoption of this technology. These findings are in line with the study [24] which states that economic and infrastructure constraints are often the main factors in the emergence of negative sentiment towards new technologies. The following are the results of the data preprocessing stage to sentiment analysis, which are displayed in Table 1.

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Table 1 Sentiment Analysis Results

index	Menurut anda, apa yang dapat meningkatkan minat masyarakat dalam menggunakan kompor induksi?	tokenized_text	clean_Menurut anda, apa yang dapat meningkatkan minat masyarakat dalam menggunakan kompor induksi?	tokenized	no_stopword	stemmed	final_text	sentiment	predicted_sentiment
0	harga dan manfaat dari kompor induksi dapat meningkatkan minat masyarakat dalam menggunakan kompor induksi	harga,dan,manfaat,dari,kompor,induksi,dapat,meningkatkan,minat,masyarakat,dalam,menggunakan,kompor,induksi	harga dan manfaat dari kompor induksi dapat meningkatkan minat masyarakat dalam menggunakan kompor induksi	harga,dan,manfaat,dari,kompor,induksi,dapat,meningkatkan,minat,masyarakat,dalam,menggunakan,kompor,induksi	harga,manfaat,kompor,induksi,meningkatkan,minat,masyarakat,kompor,induksi	harga,manfaat,kompor,induksi,tingkat,minat,masyarakat,kompor,induksi	harga manfaat kompor induksi tingkat minat masyarakat kompor induksi	-1	0
1	Melalui edukasi dan promosi tentang manfaatnya, seperti keamanan, kemudahan perawatan dll	Melalui,edukasi,dan,promosi,tentang,manfaatnya,,,seperti,keamanan,,,kemudahan,perawatan,dll	melalui edukasi dan promosi tentang manfaatnya seperti keamanan kemudahan perawatan dll	melalui,edukasi,dan,promosi,tentang,manfaatnya,seperti,keamanan,kemudahan,perawatan,dll	edukasi,promosi,manfaatnya,keamanan,kemudahan,perawatan,dll	edukasi,promosi,manfaat,aman,mudah,awat,dll	edukasi promosi manfaat aman mudah awat dll	1	1
2	promosi tentang manfaatnya, seperti keamanan, kemudahan	promosi,tentang,manfaatnya,,,seperti,keamanan,,,kemudahan	promosi tentang manfaatnya seperti keamanan kemudahan	promosi,tentang,manfaatnya,seperti,keamanan,kemudahan	promosi,manfaatnya,keamanan,kemudahan	promosi,manfaat,aman,mudah	promosi manfaat aman mudah	0	0
3	promosi tentang manfaatnya,keamanannya	promosi,tentang,manfaatnya,,,keamanannya	promosi tentang manfaatnyakeamanannya	promosi,tentang,manfaatnyakeamanannya	promosi,manfaatnya keamanannya	promosi,manfaatnya keamanannya	promosi manfaatnyakeamanannya	-1	-1
4	Desain yang menarik dan Fitur yang lengkap	Desain,yang,menarik,dan,Fitur,yang,lengkap	desain yang menarik dan fitur yang lengkap	desain,yang,menarik,dan,fitur,yang,lengkap	desain,menarik,fitur,lengkap	desain,tarik,fitur,lengkap	desain tarik fitur lengkap	1	1

2. WordCloud Analysis

To reinforce the results of the sentiment analysis, this study also uses WordCloud visualization to identify the words that appear most frequently in each sentiment category. WordCloud is used as an exploratory tool to visually describe word occurrence patterns and facilitate the interpretation of dominant topics in text data [25].

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The WordCloud of the overall data shows that the most dominant words are related to price, electricity, economy, safety, and practicality. This indicates that respondents' perceptions of induction stove are greatly influenced by considerations of energy efficiency and cost of use. This visualization reinforces the sentiment analysis results, which show that functional benefits are a major factor in shaping positive public perceptions.

In the positive sentiment WordCloud, words such as economical, safe, practical, and efficient appear in larger sizes than other words. This indicates that efficiency and safety factors are the main reasons driving respondents' interest in using induction stove. This finding is consistent with previous research stating that perceived usefulness and perceived ease of use play an important role in shaping positive attitudes toward technology adoption [26].

Conversely, the WordCloud of negative sentiments is dominated by words such as expensive and electricity. This shows that the initial cost barrier and dependence on electricity supply are still the main obstacles to increasing public interest in the use of induction stove. This finding is consistent with the results of the study [21] which states that negative sentiment in text data often represents economic and technical barriers to technology adoption.

The neutral sentiment WordCloud displays words that are more informative and descriptive, reflecting respondents' opinions without strong emotional tendencies. This shows that some respondents are still in the consideration stage and need additional information before forming a clearer attitude towards the use of induction stove. Here is a word cloud visualization of each sentiment analysis.

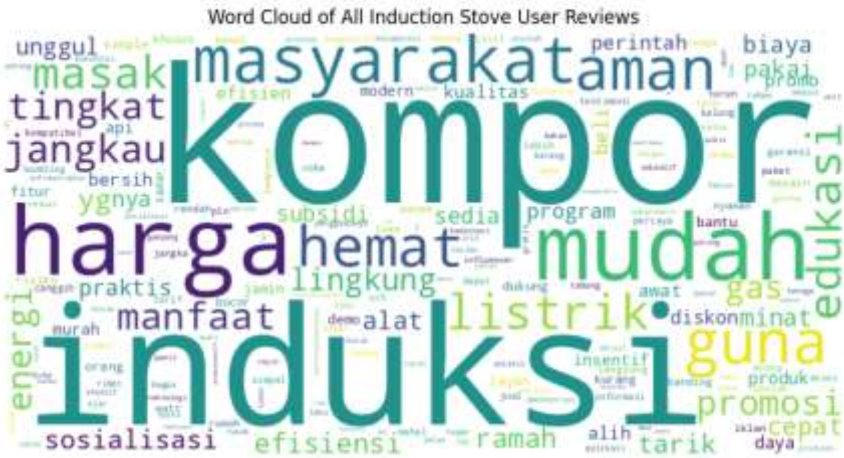

Figure 1 Wordcloud of All Induction Stove User Reviews

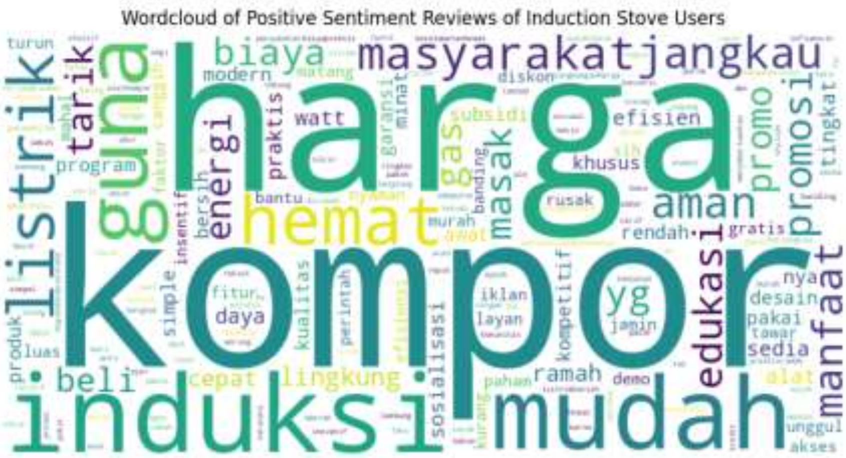

Figure 2 Wordcloud of Positive Sentiment Reviews of Induction Stove Users

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Figure 3 Wordcloud of Neutral Sentiment Reviews of Induction Stove Users

Figure 4 Wordcloud of Negative Sentiment Reviews of Induction Stove Users

DISCUSSION

Based on the sentiment distribution results, out of a total of 265 respondents analyzed, positive and neutral sentiments dominated public perception of induction stove use, with a relatively balanced number of respondents and higher than negative sentiments. Meanwhile, negative sentiment had a lower number, although it still showed a proportion that could not be ignored. This distribution indicates that most respondents did not show strong rejection of induction stove, but rather were on the spectrum of acceptance to the stage of further evaluation and consideration.

The dominance of positive sentiment reflects that the benefits of induction stove, such as energy efficiency, safety, and ease of use, have been felt tangibly by most users. This shows that actual usage experience can reinforce positive perceptions of this technology, which may have previously been perceived only theoretically or based on preliminary information. This finding is in line with the literature which states that post-use experiences play an important role in shaping positive attitudes and the sustainability of technology adoption, especially when functional benefits can be felt directly by users [22].

On the other hand, the proportion of neutral sentiments, which is also quite large, indicates that there are still groups of users who have not yet fully formed a clear attitude towards the use of induction stove. This neutral sentiment can be interpreted as an indication of an adaptation process, limited usage experience, or dependence on external factors such as the readiness of electrical infrastructure and cooking habits. This condition suggests that improving the quality of information, usage education, and technical support has the potential to shift neutral sentiment to positive sentiment in the future.

Although smaller in number, the existence of negative sentiment remains an important finding because it reflects real barriers perceived by users, particularly related to the initial cost of purchasing an induction stove and dependence on electricity supply. This negative sentiment shows that economic and infrastructure aspects remain crucial factors that can hinder wider adoption, even though the perceived benefits have been recognized by most respondents. Therefore, the results of this sentiment distribution confirm that strategies to increase induction stove adoption should not only emphasize the benefits of the technology, but also be accompanied by supporting policies that can reduce cost barriers and improve the reliability of energy infrastructure.

Overall, the distribution of sentiment, which is dominated by positive and neutral sentiment, shows that public acceptance of induction stove is in a transitional stage towards wider adoption. Quantitative analysis of sentiment combined with qualitative analysis through WordCloud provides a more comprehensive picture of public perception, while also confirming the effectiveness of machine learning-based sentiment analysis in assessing user opinions [22]. Figure 5 below shows a comparison of positive, neutral, and negative sentiment proportions among induction stove users.

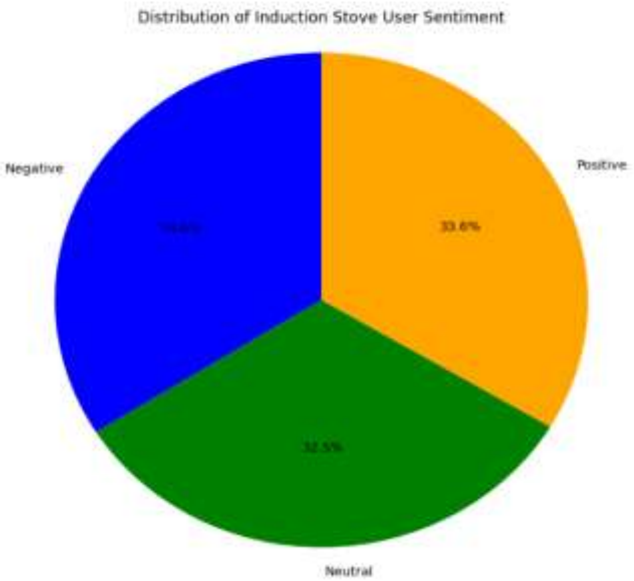

Figure 5 Comparison of Positive, Neutral, and Negative Sentiment Proportions Among Induction Stove Users

Figure 5 shows that the distribution of user sentiment toward the use of induction stoves is relatively balanced between positive, neutral, and negative sentiments. Positive sentiment has a proportion of 33.6%, reflecting public acceptance of induction stoves as a cooking technology that is considered efficient, safe, and modern. This positive perception is generally related to ease of use, safety aspects, and potential long-term energy savings, as also indicated by the dominance of positive words in the WordCloud visualization.

On the other hand, neutral sentiment, which reached 32.5%, indicates that some respondents are still in the evaluative stage or do not yet have sufficient experience to form a clear attitude towards induction stoves. This condition shows that even though induction stove technology is already known, there is still a need for increased literacy, socialization, and guidance on usage so that the public can feel its benefits optimally. This finding is in line with the literature on technology adoption, which states that neutral attitudes often arise during the transition phase from technology introduction to sustainable use.

Meanwhile, the proportion of negative sentiment at 34.0% indicates that there are real barriers to the adoption of induction stoves at the household level. These negative sentiments are mainly related to perceptions of high initial costs, concerns about electricity consumption, and limited electrical infrastructure in some areas. Although the proportion is not absolutely dominant, these findings confirm that economic factors and the readiness of support systems are still crucial issues that need to be addressed to encourage wider adoption.

Overall, this relatively balanced distribution of sentiment indicates that induction stove adoption in Indonesia is in the early-to-middle adoption phase, where acceptance is beginning to form but is still accompanied by resistance and doubt. Therefore, the results of this sentiment analysis provide a strong empirical basis for the formulation of policies and intervention strategies, particularly in the areas of user education, economic incentives, and improving the reliability of electrical infrastructure to accelerate the transition to more sustainable cooking technologies.

CONCLUSION

This study presents a sentiment analysis of Indonesian users' perceptions of induction stove based on review data collected through open-ended questionnaires. The analysis results show that positive and neutral sentiments dominate respondents' opinions, while negative sentiments account for a smaller proportion. These findings indicate that, in general, users do not show strong rejection of induction stove, although the level of acceptance is still in the evaluation and adaptation stage.

Positive sentiment is mainly related to perceptions of energy efficiency, safety, and ease of use, while negative sentiment is generally related to the initial cost of the device and dependence on electricity supply. WordCloud visualization reinforces these results by identifying the keywords that appear most frequently in each sentiment category, providing a clearer understanding of the main factors that shape user opinion.

The main contribution of this study lies in the use of machine learning-based sentiment analysis to examine post-use experiences with induction stove using open-ended questionnaire data. This approach enables the systematic measurement of public perceptions from unstructured text data and provides an empirical picture of user sentiment trends toward induction stove technology in Indonesia.

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