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Emotional Responses to Religious Conversion: Insights from Machine Learning

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Abstract
This study aims to understand the feelings of newly converted Muslims when they narrated their pre- and post-conversion using the Machine Learning model and qualitative approach. The data set analyzed in this paper comes from in-depth interviews with 12 mualaf/newly converted Muslims from various backgrounds. All recorded interviews were transcribed and filtered to remove any unnecessary or misaligned data to ensure that the data was fully aligned with the interview questions. To analyze emotional changes, we utilize natural language processing (NLP) algorithms, which enable us to extract and interpret emotional content from textual data sources, such as personal narratives. The analysis was performed in Google Colab and utilizing XLM-EMO, a fine-tuned multilingual emotion detection model that detects joy, anger, fear, and sadness emotions from text. The model was chosen because it supports Bahasa, as our interview was conducted in Bahasa. Furthermore, the model also has the best accuracy amongst its competitors, namely LS-EMO and UJ-Combi. The model also has great performance, with the overall average Macro-F1s for XLM-RoBERTa-large, XLM-RoBERTa-base, and XLM-Twitter-base are 0.86, 0.81, and 0.84. Furthermore, two psychologists compared emotion detection results from the XLM-EMO model to the raw input data, and an inductive content analysis was performed. This approach allowed us to identify the reasoning behind the emotions deemed pertinent and intriguing for our investigation. This study showed that Sadness is the most dominant emotion, constituting 46.67% of the total emotions in the pre-conversion context. On the other hand, joy emerges as the most dominant, constituting a substantial proportion of 57.73% among the emotions analyzed from post-conversion emotions data. Understanding the positive impact of religious conversion on emotions may inform mental health interventions and incorporate spiritual or religious elements into therapeutic approaches for individuals struggling with emotional issues, guiding individuals undergoing religious conversion and emphasizing the potential emotional benefits.

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INTRODUCTION

The connection between religiosity and physical and mental well-being is becoming more evident (Garssen et al., 2021; Milner et al., 2020). It appears that Muslims who follow Islamic teachings have better mental health than Muslims who do not (Koenig & Al Shohaib, 2019). In addition to impacting health outcomes, religion and spirituality appear to play a significant role in alleviating suffering (Lucchetti et al., 2021). Furthermore, there are statistically significant positive relationships between religiousness and psychological toughness (Al Eid et al., 2020). Religiosity is a complex construct that encompasses a wide range of beliefs (Chopra &

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Urolagin, 2020; Edelstein et al., 2020; Łowicki et al., 2022), practices, and experiences (Benoit, 2023; Heyen et al., 2021; Hwang et al., 2023; Lissitsa et al., 2023).

Numerous studies have found evidence that suggests religion may benefit mental health. Religious practices and beliefs, especially in the areas of anxiety, can improve mental health (Abdel-Khalek et al., 2019; Chen J. et al., 2021; Hermosilla et al., 2023); overall well-being (Cook, 2020; El-Awad et al., 2022; Nguyen, 2020), and self-esteem (Kielkiewicz et al., 2020; Soelton et al., 2020). The process by which variety someone switches their religious commitment is known as religious conversion. It profoundly transforms an individual's religious beliefs, practices, and affiliations. This process typically involves abandoning one religious faith or tradition to adopt another or embracing a different set of religious principles altogether (Streib, 2021). Religious conversion can result from a of circumstances, including personal experiences (Jones et al., 2022; Kéri, 2020; Meanley et al., 2020), religious teachings (Chen Y. & Dorairajoo, 2020; Iqbal et al., 2019), and social influences (Ouwehand et al., 2019; Timol, 2020). Religious conversion can be a transformative experience, leading to changes in an individual's beliefs, values, and behavior. It significantly impacts the mental health (Rajeshwar & Amore, 2019; Snook et al., 2019).

Prior research on religious conversion has frequently relied on qualitative interpretations (Snook et al., 2021; Wilkinson et al., 2021). The first (Casey, 2019) study of Muslim converts in the United States focuses on the form or structure of their conversion narratives rather than the causes or motives of conversion. The study discovered that stories of arising, stability, and a comeback are three distinct narrative structures used to explain conversion to Islam. These stories offer various perspectives on conceptualizing and expressing narratively conversion to Islam. The discussion focuses on the overlaps and disparities between these stories and how converts use them to demonstrate the truthfulness of their Muslim personas.

Similarly, Chen & Dorairajoo (2020), in his qualitative study, explores how American Muslim missionaries' da'wah (missionary work) People they interacted with were influenced to become Muslims. They point out that American Muslim da'wah was based on direct teaching of religious tenets and emphasizing faith through deeds or actions. This attracted non-Muslims to Islam and affected their conversion. Results are based on in-depth interviews conducted between June 2014 and May 2015 with fifty-nine Muslim converts within the United States.

Pusztai & Demeter-Karászi (2019) investigates whether religious transfer is best understood through a reproductionist or constructive angle. Previously, religious socialization was seen as adopting religious practices from the family. However, sociology's constructive and social community frameworks have challenged this view, arguing that religious socialization is more complex and dynamic. This paper presents a study of 18 qualitative interviews with young adults. The study found that religious socialization is a multidimensional phenomenon and that there are seven distinct types of religious socialization. These findings support the constructivist approach to religious socialization. Shestopalets (2021) analyzes female Islam convert in Ukraine as an extensive occurrence influenced by social, psychological, and cultural factors. According to the investigation of 21 cases based on reports in the media and personal interviews, intellectual motifs are the most common reason for conversion. However, marriage can also be a factor. Converts frequently go through significant personal transformations.

However, no study above examines the emotional change before and after religious conversion. Furthermore, utilizing Machine learning (ML) enables the study of religious conversion in a more quantitative, faster and handles big data with ease (Chi et al., 2023; Jiang et al., 2023; Milićević et al., 2023; Obelcz et al., 2023; Sayed et al., 2023; Wang et al., 2023). To find patterns in interview transcripts, ML algorithms can be trained, which can assist researchers in identifying important themes and topics (Jayachandran et al., 2023; Monaro et al., 2022; Mühling & Große-Bölting, 2023; Saiyed et al., 2022; Sofia et al., 2023).

Natural Language Processing (NLP) and Affective Computing rely heavily on the emotion detection (Bianchi et al., 2022). For this aim, numerous resources and models have been presented (Demszky et al., 2020; Nozza et al., 2017; Xia & Ding, 2019). These models can be used by social and computer scientists to better understand how individuals react to events (Huguet Cabot et al., 2020; Kleinberg et al., 2020; Verma et al., 2020). Nonetheless, multilingual approaches have proliferated throughout the domain, demonstrating excellent few-shot and zero-shot capabilities (Wu & Dredze, 2019). Processing interview data is a laborious and time-consuming process that ML can automate to improve efficiency. This entails labeling various passages in the transcript, such as the speaker's emotion or sentiment (Gu et al., 2023; Roegiers et al., 2022; Zahid & Campbell, 2023).

To our knowledge, this is the first study to examine religious conversion interview data using ML in companion with qualitative method. Analyzing interview data with ML has significant advantages, including efficient data processing, pattern recognition, and predictive modeling. ML can streamline initial data tasks, uncover hidden patterns, and predict future trends. However, it's crucial to recognize its limitations, such as the need for human interpretation and the potential for bias in models. These challenges are essential for harnessing the full potential of ML. Given the limitations and advantages of either qualitative methods or ML to provide new insights, this research's objectives are to offer a fresh understanding of the emotional changes that occur during religious conversion to a new religion and how machine learning may be used to qualitative interview data.

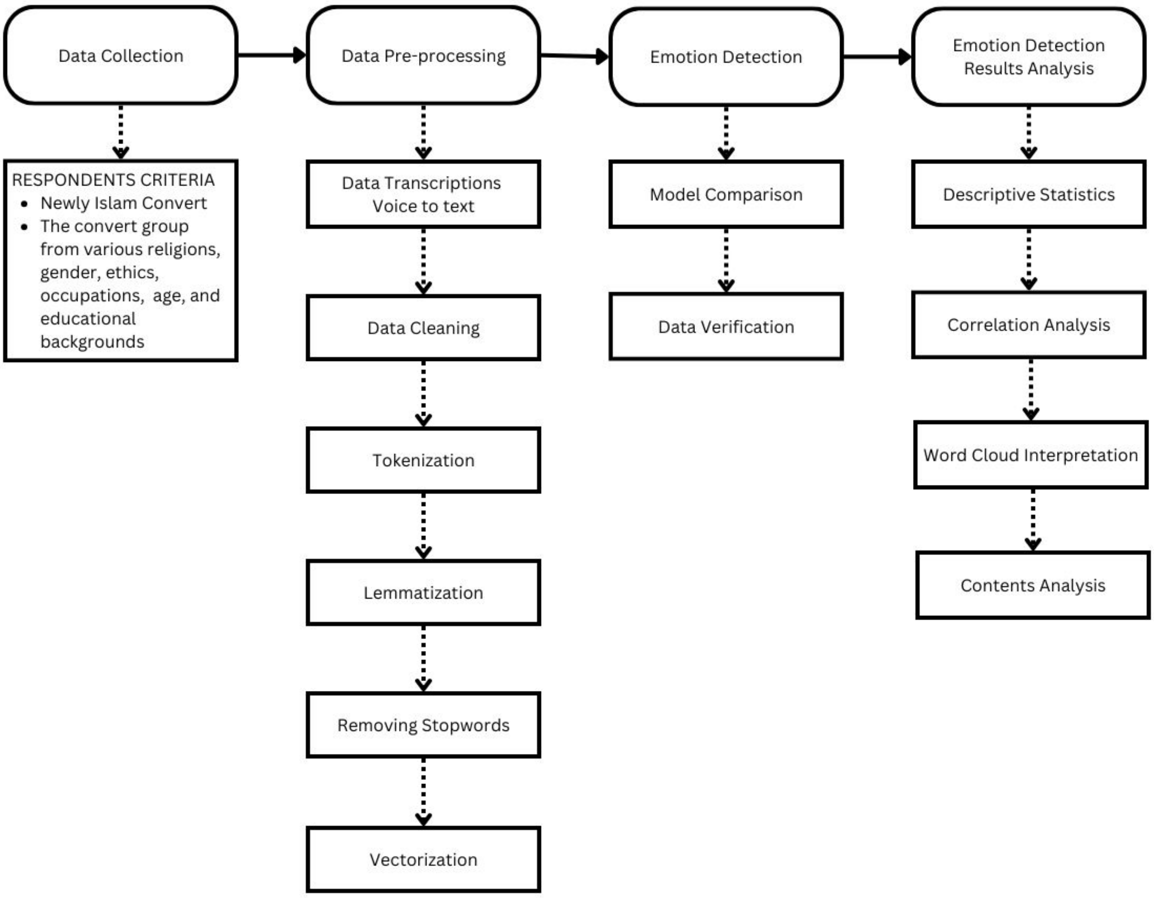

Figure 1. Research Design

METHODS

Research Design

This study used a novel approach to studying religious conversion to interpret the emotional changes that occur during conversion. We focused on the difference in the emotions expressed by people when they narrated their stories about their story before and after they became converts. Detailed research design is depicted in Figure 1.

Data Sets

The data set analyzed in this paper comes from in-depth interviews with 12 mualaf/ newly converted Muslims from various backgrounds. The detailed demographic information of participants can be seen in Table 2. We focused on their emotions when they narrated their stories about their lives before and after receiving hidayah (enlightenment). To obtain the necessary data, we formulated interview questions that consisted of: (1) What are their family, education, and social background to get detailed demographic data; (2) How did they make religious practices before and after they became convert; (3) How was their social life and the meaning of their lives before and after become a convert.

These question's formulations were to get their statement about their previous and current religious practices, social life, and their opinion about the meaning of their life to get their open-ended statement for ML analysis and reasoning for inductive content analysis. Interviews were recorded and transcribed. However, due to the open-ended nature of the interview questions, the data was cumbersome, redundant, and not aligned with the objective of the analysis. Therefore, the transcripts were filtered to eliminate all data that did not align with the main interview questions, such as the story about the interviewee's daily work routine, how proud they are of his job, how many kids they have, etc. The samples of interview data are shown in Table 1.

Data Transcription and Pre-Processing

All recorded interviews were transcribed and filtered to remove any unnecessary or misaligned data to ensure that the data was fully aligned with the interview questions. The data was then categorized into two groups: data that narrated events before the conversion and data that narrated events after the conversion. Afterward, data cleaning and Tokenization were performed. Tokenization is breaking up big blocks of text into smaller ones. Tokenization separates the original text into tokens, which are words and sentences. These tokens help with context understanding and NLP model development. Tokenization helps with language reading by evaluating the series of sentences. All the data that narrated events before and after the conversion was split into two lists and chunked into segments of no more than 500 words to ensure no more than 512 tokens per batch. This chunking was necessary because the machine learning model used in this study has a maximum token length of 512.

Once this text data is obtained, data cleaning is the next step. Data cleaning involves identifying and addressing issues like missing values, outliers, and inconsistencies in the text data. It ensures that the text is accurate and consistent for further processing. It also removes special characters. Tokenization is a fundamental step in natural language processing (NLP), where the text is divided into smaller units or tokens, typically words or sub-words. Tokenization helps break down the text into manageable pieces for analysis and modeling. Lemmatization is a linguistic process that reduces words to their base or dictionary form (lemma). It standardizes words to their root form, which can improve text analysis by reducing the dimensionality of the data and ensuring that related words are treated as equivalent. Removing stop words involves eliminating common words like "the," "and," and "in," which do not carry significant meaning in text analysis. Removing these stop words reduces noise in the data and focuses the analysis on more meaningful terms. Vectorization is the process of converting text data into numerical form. It's crucial for machine learning algorithms, which

Table 1. Interview data samples

Question	Answer
How was the beginning of your conversion story?	I was in elementary school when I was small. I was taught Islam from kindergarten, even when I used to call to prayer in the prayer room. I was born in 1962, so I graduated from junior high school in 1977. I told my parents if I continued, I would feel uncomfortable remaining in the Catholic religious school.
How were your previous religious practices?	In my opinion, the procedures for worship were too complicated; I thought that I wanted to do the worship quietly at home at that time.
What do you think is the meaning of life?	In my opinion, the provision(wealth) has been arranged. Fortune will not be changed from one person to another when we fulfill our obligations to Allah.

Table 2. Participants demographics information

No	Respondents	Gender/ Age	Ethnics	Previous Religions	Educational Backgrounds	Occupations
1	R1	F/44	Javanese	Christianity	Bachelor	Teacher
2	R2	M/54	Chinese	Christianity	Master	Lecturer
3	R3	F/56	Javanese	Catholic	Bachelor	Government Officials
4	R4	M/49	Javanese	Catholic	Bachelor	Security
5	R5	F/45	Javanese	Catholic	Highschool	House Wife
6	R6	F/65	Javanese	Christianity	Elementary School	Employee
7	R7	M/63	Javanese	Christianity	Bachelor	Government Officials
8	R8	F/24	Javanese	Catholic	Master	University Students
9	R9	F/45	Javanese	Buddhist	Elementary School	Shopkeeper
10	R10	M/70	Scotland	Christianity	Diploma	Government Officials
11	R11	F/44	Javanese	Catholic	Bachelor	Teacher
12	R12	M/33	Javanese	Christianity	Bachelor	Industrial Employee

Table 3. Indonesian label distribution

	Anger	Joy	Sadness	Fear
Indonesian	1100	1012	996	646

require numerical input. Techniques like one-hot encoding or word embeddings represent words or phrases as vectors, allowing algorithms to operate on the data effectively.

Used ML Models

The analysis was performed in Google Colab and utilizing XLM-EMO (Bianchi et al., 2022). This fine-tuned multilingual emotion detection model detects joy, anger, fear, and sadness emotions from text. This model is based on XLM-T (Barbieri et al., 2022), a multi-language model that performed well on multi-language emotion detection. The model was chosen because it supports Bahasa, as our interview was conducted in Bahasa. Furthermore, the model also has the best accuracy amongst its competitors, namely LS-EMO and UJ-Combi. The model also has great performance, which the overall average Macro-F1s for XLM-RoBERTa-large, XLM-RoBERTa-base, and XLM-Twitter-base are 0.86, 0.81, and 0.84 (Bianchi et al., 2022).

The Indonesian data sets (Saputri et al., 2018) label distributions are described in Table 3. The data shows that it is sufficient to be underlying data for model development. The distribution of data labels plays a pivotal role in shaping a model's performance and generalization capabilities. Data label distribution refers to the relative frequency or occurrence of different classes or categories within a labeled dataset. It is fundamental to consider when developing and training machine learning models for classification tasks. The label distribution directly impacts the model's ability to learn and make accurate predictions. The model consistently performs well across 19 languages (Bianchi et al., 2022). This makes it a valuable tool for emotion detection in low-resource languages with limited data.

Quantitative and Qualitative Analysis

The dataset offers abundant quantitative and qualitative data, which can be effectively utilized to comprehensively examine both pre- and post-conversion data. Data sets that narrated events before and after the conversion were split into two lists and chunked into segments of no more than 500 words to ensure no more than 512 tokens per seed. Data sets were exported to a CSV file and analyzed using the XLM-EMO model. To this end, the results were exported to Excel and evaluated by two psychologists to verify their accuracy. Psychologists compared emotion detection results from the XLM-EMO model to the raw input data. They validated whether the emotion detection results were valid or not.

The results were then analyzed using descriptive statistics. Quantitative analysis is conducted in two steps:(1) Descriptive Statistics and (2) Pearson's correlation analysis (Tijotob et al., 2023; Yuningsih et al., 2021). The equation used to analyze the emotions is presented in equation 1.

$$r = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum (x_i - \bar{x})^2 \sum (y_i - \bar{y})^2}}$$

r = correlation coefficient
x_i = values of the x-variable in a sample
x = mean of the valuesof x variable
y_i = values of the x-variable in a sample
y = mean of the valuesof y variable

Pearson's correlation analysis was employed to get a correlation analysis between emotions resulting from the ML model. The correlation analysis scores shed light on the direction and strength of these emotions' relationships with one another. A qualitative text analysis employing inductive methodologies Field (Kuckartz, 2013) was executed to get reasoning about emotions. We analyze the narratives and identify key themes, contexts, and patterns related to emotions (anger, fear, joy, sadness). We paid intense attention to the reasons behind experiences, emotions expressed, and any notable insights or perspectives in narratives. The analysis aims to identify recurring themes and patterns related to its associated emotions. The data is analyzed, applying a systematic approach to understand the underlying sentiments and experiences expressed in the narratives. This approach allowed us to identify the reasoning behind the emotions deemed pertinent and intriguing for our investigation.

RESULTS AND DISCUSSION

Results

This section shows the results of the analysis conducted on the data set described in section two to understand the feelings of newly converted Muslims when they narrated their

Table 4. Tokens and Batch Count

	Pre	Post
Tokens	3578	7461
Batch	60	98
Avg. Token/Batch	59	76

Table 5. Pre-Conversion Descriptive Statistics

Indicators	Anger	Fear	Joy	Sadness
Mean	0.039735	0.156360	0.513525	0.290381
Min	0.000463	0.001311	0.000952	0.002526
Max	0.367214	0.995535	0.994810	0.974176
Q1	0.003625	0.025145	0.180152	0.046613
Q3	0.029289	0.213329	0.902341	0.453409
IQR	0.025665	0.188184	0.722189	0.406795
Lower Limit	-0.034870	-0.257130	-0.903130	-0.563580
Upper Limit	0.067786	0.495604	1.985624	1.063602
Stdev	0.075363	0.213339	0.363250	0.270588

Table 6. Post-Conversion Descriptive Statistics

Indicators	Anger	Fear	Joy	Sadness
Mean	0.071922	0.176712	0.307547	0.443819
Min	0.000597	0.002187	0.004902	0.003063
Max	0.629928	0.765749	0.994154	0.960038
Q1	0.005673	0.041862	0.019846	0.228212
Q3	0.082187	0.225483	0.550504	0.713754
IQR	0.076514	0.183621	0.530658	0.485542
Lower Limit	-0.109098	-0.233569	-0.776142	-0.500100
Upper Limit	0.196958	0.500914	1.346491	1.442066
Stdev	0.123810	0.185493	0.324624	0.289443

Table 7. Most Showed Emotion per Batch Examples

Batch	Anger	Fear	Joy	Sadness	Most showed emotion
Batch1	0.00438510	0.02568073	0.74054730	0.22938685	joy
Batch2	0.05894279	0.12139444	0.55341905	0.26624373	joy
Batch3	0.00581822	0.06539550	0.21360156	0.71518475	sadness
Batch4	0.01835252	0.16440243	0.01819782	0.79904723	sadness
Batch5	0.00315047	0.02749892	0.10512365	0.86422688	sadness

pre- and post-conversion. To understand the extent to which feelings they express from the narrated story, narrated volumes were analyzed. Table 4 shows tokens and batch count.

Descriptive Statistics

The presented data in Table. 5 provides information on the emotion density of anger, fear, joy, and sadness in a pre-conversion context. The mean emotion densities for anger, fear, joy, and sadness are as follows: anger (0.039735), fear (0.15636), joy (0.513525), and sadness (0.290381). These values represent the average emotional intensity for each emotion category. The minimum emotion density values indicate the lowest observed levels of each emotion: anger (0.000463), fear (0.001311), joy (0.000952), and sadness (0.002526). Conversely, the maximum emotion density values represent the highest observed levels: anger (0.367214), fear (0.995535), joy (0.99481), and sadness (0.974176).

The first quartile (Q1) values, which are anger (0.003625), fear (0.025145), joy (0.180152), and sadness (0.003625), give insight into the lower range of emotion density (0.046613). Anger (0.029289), fear (0.213329), joy (0.902341), and sadness (0.029289) are the values in the third quartile (Q3) that represent the top range (0.453409). The range of data between the first and third quartiles is represented by the interquartile range (IQR), a measure of dispersion. The IQR values for these emotions are anger (0.025665), fear (0.188184), joy (0.722189), and sadness (0.025665). (0.406795). To find probable outliers, the lower and upper bounds are computed. These boundaries show the range of values that may be deemed extreme. The lower limits for these emotions are as follows: melancholy (-0.90313), joy (-0.03487), fear (-0.25713), and anger (-0.03487). (-0.56358). Anger (0.067786), fear (0.495604), joy (1.985624), and melancholy (0.067786) are the upper bounds (1.063602). The standard deviation (Stdev) quantifies data dispersion around the mean. Anger (0.075363), fear (0.213339), joy (0.36325), and melancholy (0.075363) are the respective standard deviations (0.270588), see table 5.

The Post-Conversion Descriptive Statistics are shown in Table. 6. The mean emotion densities for anger, fear, joy, and sadness are as follows: anger (0.071922), fear (0.176712), joy (0.307547), and sadness (0.443819). These values represent the average emotional intensity for each emotion category after the conversion. The minimum emotion density values indicate the lowest observed levels of each emotion: anger (0.000597), fear (0.002187), joy (0.004902), and sadness (0.003063). Conversely, the maximum emotion density values represent the highest observed levels: anger (0.629928), fear (0.765749), joy (0.994154), and sadness (0.960038). The Q1 values of anger (0.005673), fear (0.041862), joy (0.019846), and sadness (0.228212). The Q3: anger (0.082187), fear (0.225483), joy (0.550504), and sadness (0.713754).

The IQR values for these emotions are anger (0.076514), fear (0.183621), joy (0.530658), and sadness (0.076514). (0.485542). To find probable outliers, the lower and upper bounds are computed. These boundaries show the range of values that may be deemed extreme. The lower bounds for these emotions are anger (-0.109098), fear (-0.233569), joy (-0.776142), and sadness (-0.776142). (-0.500100). The upper limits are anger (0.196958), fear (0.500914), joy (1.346491), and sadness (1.442066). The standard deviation (Stdev) measures the dispersion of data around the mean. The standard deviations for anger, fear, joy, and sadness are anger (0.123810), fear (0.185493), joy (0.324624), and sadness (0.289443).

The data is depicted in Figure 1 and 2 represent the distribution of emotions within pre and post-conversion results, with each emotion expressed as a percentage. The result's composition is categorized into four primary emotions: anger, fear, joy, and sadness. The percentages assigned to each emotion indicate the relative prevalence of that emotion within the result.

In pre-conversion, emotion frequency data is depicted in Figure 1. Anger is present at a percentage of 5.00%. It appears to be the least prevalent emotion, making up a relatively small portion of the overall emotional distribution. Fear accounts for 11.67% of the emotions in the result. It shows a higher prevalence than anger but is still a minority emotion. Joy accounts for 36.67% of the total emotions, making it the second most prevalent emotion, see table 6.

It is significant but slightly less prevalent than sadness. Sadness is the most dominant emotion in this result, constituting 46.67% of the total emotions. This indicates that sadness is the most prevalent emotion in the pre-conversion context. To better understand the frequency percentage data, results samples were presented in Table 7.

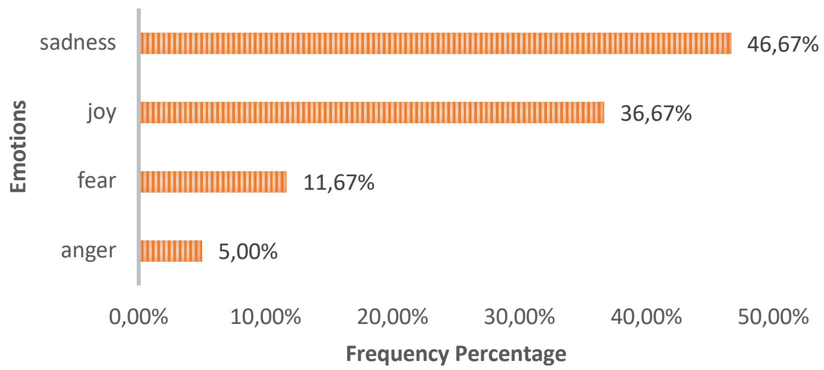

Figure 1. Highest Pre-Conversion Emotions Percentage

Among the emotions analyzed from the highest post-conversion emotions data depicted in Figure 2, joy emerges as the most dominant, constituting a proportion of 57.73%. This high percentage suggests a prevalent and pervasive experience of joy within the result. Sadness follows with a considerable proportion of 31.96%, indicating a significant presence of this emotion. Fear, with a percentage of 9.28%, appears to be relatively less prominent in comparison. Finally, anger exhibits the lowest prevalence within the result, representing merely 1.03%.

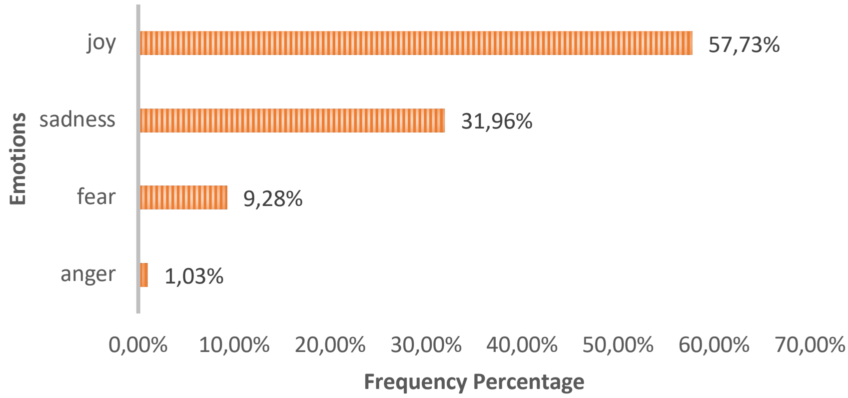

Figure 2. Highest Post-Conversion Emotions Percentage

To better understand the distribution of the data, heatmaps were produced in Figures 3 and 4. The heatmap of pre-conversion emotions in Figure 3 shows that sadness has become dominant. Despite having a slightly lower maximum frequency than sadness, joy is the second most prevalent emotion and has the brightest heatmap, indicating a higher emotion density. Anger had the lowest density of all the emotions expressed during the pre-conversion narrative, with fear coming in second. Darker colors represent the lower emotional density, while lighter hues represent the higher emotional density.

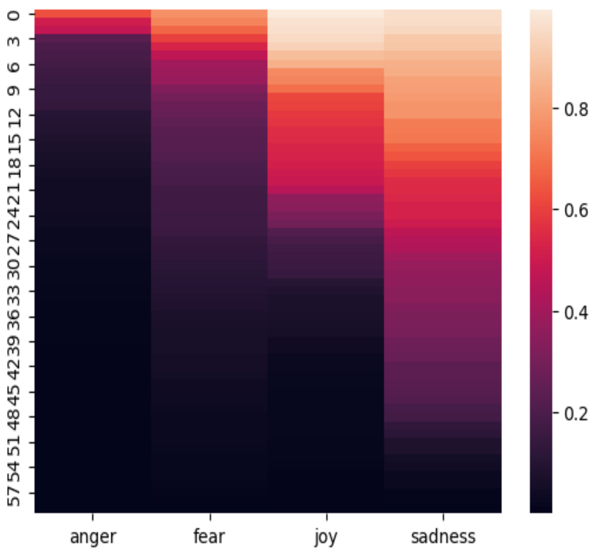

Figure 3. Pre-Conversion Distribution Heatmap

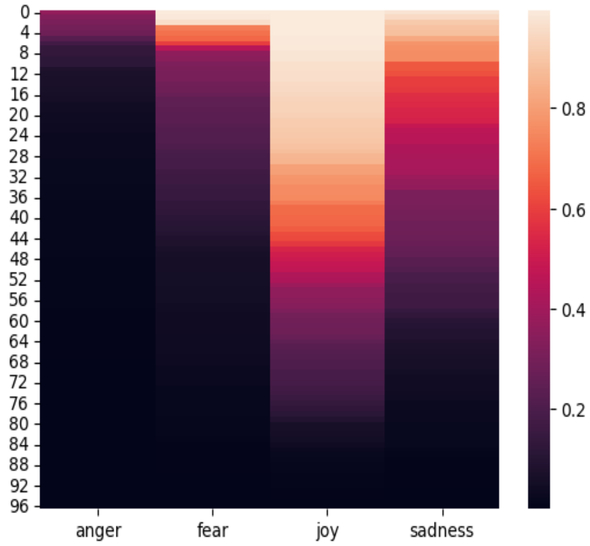

Figure 4. Post-Conversion Distribution Heatmap

Figure 4's post-conversion heatmap, which contrasts with the pre-conversion heatmap, reveals that happiness is the most prominent and brightly colored emotion. This shows that happiness is the highest density and frequency feeling, making it the main emotion displayed in post-conversion narration. Though it occurs much less frequently than joy, sadness has the second-highest density and frequency of all the emotions. Anger has the lowest density and frequency, with fear being somewhat similar to the pre-conversion data and not particularly prominent. This suggests that almost no anger was shown during pre- and post-conversion narration.

Correlation Analysis

The correlation heatmap is depicted in Figures. 5 and 6 present correlation scores between analyzed emotional states, specifically anger, fear, joy, and sadness. The correlation scores shed light on the direction and strength of these emotions' relationships with one another. Figure 7's pre-conversion correlation heatmap shows a weak positive correlation between anger and fear, with a correlation score 0.015. This suggests that there is a small degree of tendency for anger and fear to coexist. Anger and joy, on the other hand, have a correlation score of -0.33, which indicates a moderately negative correlation. Inferring that higher levels of one emotion correspond to lower levels of the other, anger and joy are more likely to be experienced as opposing emotional states. Anger and sadness have a correlation score of -0.07, which indicates a very slender negative correlation. As they are not strongly correlated, this implies little overall association between anger and sadness. Moving on to fear, there is a moderately negative correlation (correlation score of -0.38) between fear and joy. Joy decreases in direct proportion to levels of fear and vice versa. This finding suggests that fear and joy have a mildly negative relationship.

The correlation between fear and sadness is -0.22, which shows a shaky negative association. The conclusion that fear and sadness frequently go hand in hand, with higher levels of fear equating to lower levels of melancholy and vice versa, can be drawn from this. Last, the correlation value of -0.74 shows a high negative association between happiness and sadness. This shows that joy and sadness are exceedingly unlikely to coexist since larger levels of one emotion are linked to markedly lower levels of the other.

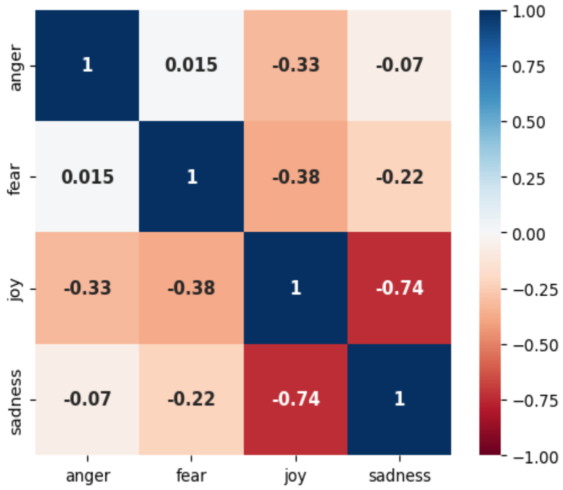

Figure 5. Pre-Conversion Correlation Heatmap

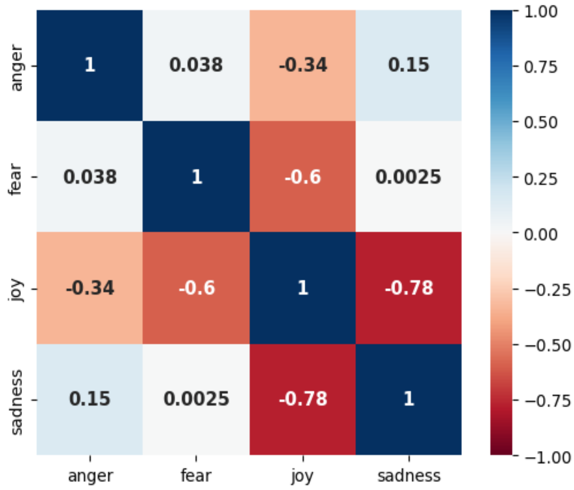

Figure 6. Post-Conversion Correlation Heatmap

The post-conversion correlation score between anger and fear is 0.038 in Figure 6, which suggests a tenuous positive link. This indicates a slight, tinier tendency for anger and fear to co-occur. It's vital to remember that this association is of a small scale and should not be taken literally. With a correlation coefficient of -0.34, anger and joy have a moderately unfavorable relationship. This suggests that joy and anger are frequently experienced as opposing emotional states. The intensity of one's anger increases, as do their levels of joy, and vice versa. This result suggests a higher link between anger and joy than the earlier results. With a correlation score of 0.15, anger and sadness have a marginally favorable relationship. This suggests a slight positive association between anger and sadness. However, the magnitude of this correlation is relatively small, implying that the relationship between anger and sadness may be weak.

Next, there is a moderate negative association between fear and joy, with a correlation score -0.6. This suggests that fear and joy are frequently felt as diametrically opposite emotions. One's level of joy and fear both increase in direct proportion to one another. This finding suggests that fear and joy have a moderately inverse relationship. Fear and sadness have a correlation score of 0.0025, indicating a weak positive correlation. This suggests that fear and sadness have a minimal relationship, with little association between these emotional states. Finally, the correlation score between joy and sadness is -0.78, indicating a strong inverse relationship. This finding implies that joy and sadness are extremely unlikely to coexist. Sadness decreases significantly as levels of joy rise, and vice versa. This correlation indicates a strong inverse relationship between joy and sadness.

Figure 5. Pre-Conversion Word Cloud

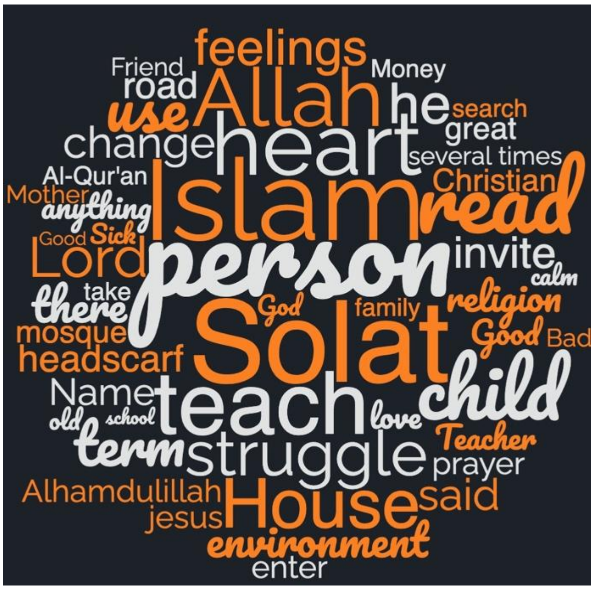

Figure 6. Post-Conversion Word Cloud

Wordcloud Interpretation

To extract qualitative insights from the narratives, world clouds for pre- and post-conversion showing words with strong and weak intensity have been produced in Figures. 5 and 6. These word clouds provide a quick overview of the main themes and sentiments expressed. The larger font sizes indicate their prominence within the results, and smaller font sizes suggest their lesser frequency and density.

Some of the prominent terms in the results include "person," "religion," "Islam," "church," and "old." These terms indicate a broad scope of subjects, ranging from personal identity and religious affiliations to age and spirituality. Additionally, words such as "teach," "read," and "educate" suggest a focus on imparting knowledge or engaging in intellectual activities. There are also specific religious terms like "Buddha," "Catholic," and "Christian," which show that the results come from a variety of religious backgrounds. "Al-Qur'an" and "prayer" also imply a relationship to Islamic principles and customs. The words "friend," "family," "grandma," and "father," among others, are also found in the results, suggesting the significance of interpersonal relationships and ties to one's family. Likewise, some words have a sense of time, such as "sooner or later," "Sunday," and "evening," which may refer to routines or activities that take place at specific times. Other terms that imply actions or movements include "submit," "move," and "enter."

On the word cloud depicted in Figure 6, one noteworthy term in the results is "Islam," "person," and "Salat" (Islamic prayer), which serves as a broad category encompassing belief systems and practices. The weight assigned to this term indicates its relevance within the results. Additionally, the term "invite" suggests extending an invitation, possibly in the context of welcoming individuals to explore or engage with religious teachings. Another prominent keyword is "teach," denoting the process of imparting knowledge or guidance. The high weight associated with this term signifies its significance in the results. It implies that acquiring and transmitting knowledge, particularly about religious matters, plays a crucial role. The results present specific religious terms, such as "Allah" and "Al-Qur'an," which are closely associated with Islam. These terms hold considerable weight, indicating their importance within the context. The mention of "Alhamdulillah" is a declaration of gratitude or praise commonly expressed by followers of Islam.

Furthermore, the word "child" is given a notable amount of weight, emphasizing the rearing and education of kids in a religious setting. The idea of guiding young people in questions of faith and spirituality is respected. The word "read" has a lot of weight, indicating the importance of literacy and reading in the religious context. This is probably due to the perception that reading promotes knowledge, comprehension, and religious reflection. The phrases "prayer," "mosque," "Solat," and other terms in the studied data also point to the significance of religious rites and practices. These words imply that places of prayer and collective worship are essential elements of religious life.

The word "heart" also has a high weight in the results, indicating that people may have a strong emotional and spiritual bond with their beliefs. The word "person," which appears numerous times and carries a substantial weight, is more evidence for this. This indicates that the convert may involve discussions with other people about their beliefs within the context of religion and education. Finally, the results also include terms such as "love," "environment," and "great," which may indicate positive sentiments associated with religious experiences, spiritual growth, and the broader community. It is worth noting that the results contain references to other religions, such as "Christian" and "Jesus," albeit with relatively lower weights. This indicates a comparative or inclusive perspective, acknowledging the presence of multiple religious traditions within the discussion.

Content Analysis

In this section, we analyze the narratives and identify key themes, contexts, and patterns related to emotions (anger, fear, joy, sadness). We paid intense attention to the reasons behind experiences, emotions expressed, and any notable insights or perspectives in narratives. The analysis aims to identify recurring themes and patterns related to its associated emotions. The data is analyzed, applying a systematic approach to understand the underlying sentiments and experiences expressed in the narratives. The score from the ML model filtered the data analyzed in this section. After that outlier was removed, only scores greater than Q3 were analyzed. We also consider the result from the pre- and post-conversion distribution heatmap from Figures. 3 and Figure 4.

Anger Pre-Conversion

Buddhist Influence:

One prominent theme is the mention of Buddhism and the role of following one's spouse in this religion. The narrator expresses frustration regarding the absence of Buddhism in their current location, stating that their father already had a house there.

Religious Discrimination:

Religious discrimination experienced by the narrator's friend, who belongs to the Islamic faith. The friend is reprimanded by their Islamic Religion teacher for participating in a Christmas party, leading the narrator to question the strictness of such religious rules.

Academic Pressure:

The result includes mentioning academic pressure related to learning Arabic in the afternoon. The narrator expresses dissatisfaction with violating this academic routine, suggesting frustration or anger towards the circumstances preventing them from pursuing their education effectively.

Consequences of Not Meeting Requirements:

Another theme identified in the result is not meeting academic requirements. The narrator mentions the possibility of receiving a warning and being dropped out if certain requirements are unmet.

Personal Conflicts:

There are indications of personal conflicts within the narratives, specifically concerning religious conversion. The narrator mentions their mother's conversion from Islam to Catholicism, met with emotional turmoil and resistance from their father. The narrator acknowledges their lack of happiness with the decision but states that they followed their husband's wishes.

Emotional Separation:

A prolonged absence from home, where the narrator's son and wife are sorely missed. This narrative conveys a sense of longing, sadness, and potentially anger or frustration towards the circumstances that led to the extended separation from loved ones.

Fear Pre-Conversion

Influence of Family:

The influence of family on religious choices, being invited by their father, and joining Islam as a result. However, there is an indication that if the father had not played a role in teaching them about Islam, they would not have pursued it.

Confidence in Faith:

The narrator credits their strong religious conviction to their Christian upbringing. They claim that their education in a Christian family gave them the gifts of faith and confidence.

Independent Decision-making:

The decision to convert to Islam was made personally without pressure. The narrator declares a wish to practice Islam alone, implying a sense of independence and autonomy.

Participation in Religious Practices:

The narrator's involvement in religious rituals explicitly alludes to going to church around Christmas. This story implies a willingness to partake in religious activities, which may be interpreted as a worry about missing out on significant rituals or traditions.

Lack of Interest and Confusion:

Despite being given knowledge and resources, there is a lack of enthusiasm for learning about Islam. The narrator claims not to be interested in learning more about Islam and instead bids them farewell and draws their focus to the church. This story raises the possibility of a fear of Islam or unfamiliarity.

Observing Grandmother's Prayer:

An incident where the narrator observes their grandmother praying and inquires about it. The grandmother responds by mentioning the recitation of "Al-Fatihah."

Joy Pre-Conversion

Discovery of Faith:

The discovery of faith and experiences with religious teachings, such as reading the Bible or the Quran, triggered a sense of interest and curiosity.

Personal Transformation:

Personal transformation and growth. Narratives mention becoming involved in religious activities, such as becoming an activist in the Church or studying to serve God.

Spiritual Exploration:

The spiritual exploration and learning about different religions. The narrators express excitement and interest in visiting meditation centers, reading about Buddhism, and encountering Hindu teachings.

Religious Upbringing:

Joy expression associated with a religious upbringing. The narrators mention being taught about Islam or Christianity from a young age, and some describe participating in religious activities, such as reciting the Quran or calling prayer.

Freedom of Choice:

The freedom to choose one's religious path. Narratives mention not wanting to follow one particular religion, instead embracing the ability to explore and appreciate various religious teachings.

Sadness Pre-Conversion

Religious Conflict and Disconnection:

The sadness expressed due to religious conflict and disconnection. Narrators describe feelings of unhappiness resulting from conflicts between different religious beliefs within their families or communities. Sadness and a sensation of being divided between several religious identities are evoked by the existence of different faiths and the ensuing divisions.

Lack of Spiritual Fulfillment:

Religious rituals or services that one has participated in without real commitment to the faith. Since the religious activities do not express their emotions or provide inner peace, this separation leaves them feeling empty and depressed.

Parental Absence and Lack of Support:

A sense of longing and sadness from their parents' absence or diminished availability. Because of this absence, they cannot receive direction and support from those who share their faith, which adds to their isolation and sorrow.

Inner Conflict and Compromise:

The parents' differing religious beliefs or converted to a different faith, leading to a sense of confusion and sadness. The narrators often feel torn between conflicting religious influences, causing inner turmoil and a lack of clarity.

Feeling Disconnected from Religion:

Childhood experiences of not caring about religion and not following any faith.

Anger Post-Conversion

Religious Comparison and Critique:

The narrators express frustration and anger as they try to find faults with Christianity and highlight what they perceive as the superiority of Islam. They question aspects of Christianity and express anger towards perceived contradictions or concepts that do not align with their beliefs.

Perception of Worship and Human Intervention:

The idea of worshiping humans or the concept of human intervention in religious scriptures. They express frustration and doubt when encountering elements in religious texts that they perceive as having been altered or influenced by human intervention.

Financial Aspects of Religion:

The narrators mention spending money on religion, such as giving alms or supporting religious developments. They express anger towards perceived imbalances or concerns about using money within religious contexts.

Factors Influencing Religious Conversion:

The conversion process highlights personal factors such as faith as a gift from God and external factors such as the influence of the environment or social factors. They express anger and acceptance towards these factors, recognizing that multiple influences may have influenced their decision to convert to Islam.

Fear Post-Conversion

Uncertainty and Curiosity:

Sometimes, they were uncertain and perplexed, doubting their comprehension of religious ideas and seeking clarification. They worry and panic over not understanding certain tenets of their religion, such as prayers or sacred texts, or about not knowing how to perform them.

Search for God and Identity:

When they first learned God existed and felt awe or anxiety in their early lives. They pose questions about God's nature to better understand and have a relationship with him.

Religious Education and Transformation:

They went through learning about Islam, attending Islamic institutions or classes, and speaking with religious leaders or teachers. They exhibit anxiety and concern about taking part in religious practices like prayer. Still, they also talk about how their education has transformed and brought them closer to Islam.

Doubt and Confusion:

The problematic circumstances when comparing Christian and Islamic principles. They show worry and perplex at apparent contradictions or differences between religious texts and Christian doctrines.

Emotional and Social Impact:

Their unease and worry are exacerbated by their strained relationships with their parents and their disagreements and arguments. They show concern over the potential effects of their conversion to Islam on their relationships and position in their families or social circles.

Joy Post-Conversion

Spiritual Fulfillment and Peace:

The experiences of converting to Islam and the subsequent positive effects on their lives.

Community and Support:

The supportive and welcoming communities, interactions with Muslim neighbors, friends, and acquaintances who provided information, guidance, and encouragement.

Religious Education and Growth:

Engaging in Islamic studies, attending Islamic schools or classes, and learning to read the Quran.

Prayer and Worship:

The commitment to regular prayer and the joy they experience when engaging in congregational prayers or reciting the Quran. Prayer and worship are tranquility, contentment, and a deep connection with Allah.

Gratitude and Sustenance:

The appreciation for the blessings in their lives, including having sufficient food, clothing, and livelihood. They attribute their joy and contentment to their faith and believe that fulfilling their obligations to Allah leads to blessings and sustenance.

Sadness Post-Conversion

Spiritual Search and Doubt:

Spiritual journeys and struggle to find answers to existential questions. Feelings of doubt, confusion, and a sense of something missing in their lives. The sadness over their previous beliefs raises questions about Christianity and its teachings, particularly in comparison to Islam.

Emotional Turmoil and Conflict:

The stories recall disputes and arguments with their parents over their religious preferences, adding to anxiety and discomfort at home. Their disagreements with family members impact their emotional well-being, which adds to their general sadness.

Learning and Adaptation Challenges:

The challenges faced during learning and adapting to Islam. Struggles with understanding and correctly performing prayers, reading the Quran, and adapting to new religious practices. The difficulties encountered in religious education contribute to their sadness and frustration.

Striving for Personal Growth:

Desire for personal growth and trying to be better Muslims, learn more about Islam, enhance understanding, and faithfully obey Allah's precepts. Sense of responsibility and a desire to fulfill their religious obligations despite the difficulties and personal sacrifices that may be required.

Discussion

Comparing our results with related approaches is a challenging task. Most studies use qualitative interpretation methods for specific cases or contexts. In general, important findings are obtained by interpreting the results of ML analyses. Therefore, it is difficult to carry out a fair comparison. The discussion in the following aims to assess whether the results observed in different studies are more or less in line with the findings we obtained with our analysis. To do this, we will discuss the similarities and differences between our approach and those used in other studies.

Emotion detection from text using machine learning techniques is a valuable tool, but it has some limitations. One limitation is that the meaning of words and phrases can change depending on the context in which they are used. This can make it difficult for models to identify the intended emotional state accurately. Additionally, cultural and linguistic differences can affect the accuracy of emotion detection, as emotions are expressed differently in different cultures and languages. Another limitation is that models may not be able to detect the nuanced blend of multiple emotions in text. For example, a text could express happiness and sadness; the model might only identify one.

Additionally, models may not be able to recognize sarcasm, irony, or humor, which can lead to misinterpretations. Finally, models may be unable to capture the depth and subtlety of emotions, which can be highly individualized and nuanced. Despite these limitations, text-based emotion detection is a valuable tool that can be used for various purposes. As the technology continues to develop, the accuracy of text-based emotion detection is expected to improve. To overcome the limitation, this study employed a verification procedure from two psychologists to verify the accuracy of emotions resulting from the model by comparing it with the input text. Furthermore, this study employed inductive content analyses to gain reasoning underlying expressed emotions.

Our findings are aligned with those reported in (Thong et al., 2023), that emotional change occurred through religious conversion. The purpose of this mixed-method study was to investigate how the kinship-based belief of Indigenous Temiar was affected by the globalizing world religions and to what extent this affected their emotional and mental states. Data was collected through semi-structured interviews, transcripted, translated into English, and then back-translated for psycholinguistic coding. Sundararajan (2020), Schubert Word Count and Linguistic Inquiry and Word Count were used to analyze the linguistic elements that implement the phenomenological profiles of participants' thoughts and emotions. The findings showed that the traditional Temiar and Temiar-Muslim groups had retained a large portion of the strong-ties cognitive styles of their ancestor niche. Compared to their counterparts, Temiar-Christians used more "experience-distant modes" of emotional expression (like intellectualization). Our study uses the same data collection method, but in our case, the analysis was conducted using the ML model.

Rahim & Inayati (2023) studied the phenomenon of religious conversion among parents in Kaliagung Hamlet, Kendalrejo Village, Tegaldlimo, Banyuwangi, focusing on the factors behind its occurrence and the methods used by converts to instill Islamic education values in their children. Adopting a descriptive qualitative approach, the researchers employed multiple data collection methods, including observation, interviews, and documentation. The sample for this research was selected through purposive sampling. Subsequently, a qualitative descriptive analysis technique was employed to analyze the written and oral data obtained from the informants, aiming to comprehensively describe the observed phenomena. The findings reveal that the factors contributing to religious conversion among parents in this community can be categorized as internal and external. Islamic religious education emphasizes the installation of faith and worship in children, encompassing values such as faith in Allah, angels, Allah's books, messengers, the Last Day, and qada' and qadar. Additionally, the values of worship entail teaching the Qur'an, prayer, zakat, fasting, and pilgrimage. Parents practicing religious conversion employ motivation, personal example setting, and habit formation to transmit Islamic education values to their children. Similar to our analysis, the result shows that emotional change occurred through religious conversion. However, different analysis methods are used.

Stronge et al. (2021) aimed to investigate the longitudinal changes in personality traits before and after religious conversion and deconversion from Christianity, utilizing a representative national sample of New Zealand adults over nine years (2009-2017). The data collection method involved gathering information from a large sample size of 31,604 individuals. Piecewise latent growth models (Harring et al., 2021) were employed to analyze the data and assess the longitudinal changes in the Big Five personality traits and Honesty-Humility. The results indicated that there were no significant personality changes observed before conversion or after deconversion. However, following conversion, there were observed increases in Honesty-Humility, Conscientiousness, and Neuroticism. Before deconversion, individuals exhibited higher levels of Honesty-Humility and lower levels of Agreeableness. These findings suggest that religious conversion triggers changes in character, particularly in terms of increased modesty and greed avoidance. Similar to what we have done, religious conversion affects changes in character, even though two different analyses are used. This discussion section results show that the ML model could be used as an alternative way to analyze qualitative data. Its result was satisfactory, less time-consuming, and easy to interpret.

This study has implications for growing knowledge regarding the relationship between religion and emotional well-being. It suggests that religious conversion may serve as a psychological coping mechanism, potentially enhancing emotional resilience and providing a sense of purpose. The findings can enrich the theoretical underpinnings of religious studies by highlighting the emotional aspect of religious conversion. Furthermore, the study may shed light on the role of religious communities in providing social support and fostering a sense of belonging, which can positively affect emotions. Understanding the positive impact of religious conversion on emotions may inform mental health interventions and incorporate spiritual or religious elements into therapeutic approaches for individuals struggling with emotional issues, guiding individuals undergoing religious conversion and emphasizing the potential emotional benefits.

Certain limitations and potential directions for further study are acknowledged. To begin, although there are machine learning models capable of analyzing emotions from voice data, their usage is accompanied by certain limitations and computing power requirements, leading to more time-consuming and costly processes. Because of this, the analysis was limited to text data. Emotions expressed in a text can be highly subjective and context-dependent. Textual expressions of emotions often involve figurative language, idioms, or metaphors, which can be difficult for ML models to interpret accurately. Emotions like sarcasm or irony can be challenging to detect accurately from text and may be present in discussions related to religious conversion. ML models may struggle to distinguish between genuine emotions and sarcastic expressions. Nevertheless, this research contributes to a deeper understanding of the complex relationship between religion and emotions by combining the ML and qualitative approaches, emphasizing the need for further investigation into how various religious doctrines and practices influence emotional experiences. To increase the accuracy of ML results, gathering well-structured data, especially in written language, becomes essential for achieving accurate results.

CONCLUSION

This paper presents a study that offers fresh perspectives on emotional transformations occurring during religious conversion and the potential application of machine learning in analyzing qualitative interview data in companion with qualitative methods. Based on an ML and qualitative analysis of emotional transformations during religious conversion suggested that religious conversion can enhance emotional resilience and purpose. It also highlights the role of religious communities in providing social support and fostering a sense of belonging. This study showed that Sadness is the most dominant emotion, constituting 46.67% of the total emotions in the pre-conversion context. On the other hand, joy emerges as the most dominant, constituting a substantial proportion of 57.73% among the emotions analyzed from post-conversion emotions data. Understanding this can inform mental health interventions and therapeutic approaches. Nevertheless, certain limitations and potential directions for further study should be acknowledged. First, due to the limitations of the ML model used, the analysis was limited to text data. As a result, gathering well-structured data, especially in written language, becomes essential for achieving accurate results. Secondly, although there are ML models capable of analyzing emotions from voice data, their usage is accompanied by certain limitations and demanding computing power requirements, leading to more time-consuming and costly processes.

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AUTHOR CONTRIBUTION STATEMENT

All authors have read and approved the final version of the manuscript.

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