LlaMA for Sentiment Analysis in Self-Care Applications: A Case Study with Life Energy

Inácio L. Souza Filho; Maryane C. Lima; Anderson I. M. Ripardo; Jessyca A. Bessa; Wedja J.G.Costa; Jermana L. Moraes.

***Abstract*—In recent years, self-care, and well-being have received growing attention, reflecting the importance in maintaining mental and emotional health amid the complexities of modern life. In this context, Life Energy emerges as an innovative tool designed to foster personal reflection and strengthen interpersonal connections. Structured around interactive tasks that explore physical, mental, and social dimensions, the instrument allows individuals to engage in a journey of self-discovery. The integration of emerging technologies, such as Artificial Intelligence, has further expanded the possibilities for mental health promotion through personalized interventions. This study presents the application of the LLaMA model for sentiment analysis within the Life Energy instrument, aiming to interpret user input, assess emotional states, and generate introspective questions. The proposed Life Energy Sentiment Model (LESM) was evaluated using both the Life Energy dataset and two public benchmark datasets: Amazon and IMDB reviews. The results for the Life Energy data were promising, especially regarding the generation of introspective questions that support user self-reflection. In the public datasets, the LESM achieved high performance, with accuracy, recall, and F1-scores all greater than 0.95, demonstrating its robustness and generalization capability across domains. These findings highlight the potential of combining large language models and structured self-care tools to create intelligent systems that promote emotional insight and personal development.**

***Index Terms*—Self-awareness, Well-being, Sentiment Analysis, Large Language Models (LLMs) LLaMA, Artificial Intelligence and Human-Centered AI.**

I. Introduction

In recent years, the pursuit of self-awareness, self-care, and well-being has gained significant prominence in contemporary society, also driven by advances in technological tools that allow for personal monitoring and personalized and individualized experiences. Innovative and smart tools have been developed to help individuals on this journey. Among them, there is Life Energy [1], an instrument developed to promote deep reflections on oneself and interpersonal relationships. It consists of 81 tasks that address relational situations involving physical, mental and social tasks. This instrument allows individuals to begin their journey of self-knowledge based on intrapersonal and interpersonal.

Technological advances have driven the development of self-care tools based on Artificial Intelligence, using Large Language Models (LLMs) such as Ollama, ChatGPT and others [2], [3]. These applications not only encourage the creation of healthy daily habits, but also perform intelligent sentiment analyses, adapting suggestions and reflections in a personalized, sensitive and effective way [4].

There are some attempts in the literature to apply LLMs to sentiment analysis. However, these studies are limited to some specific tasks within a specific area and consider different models, datasets, and scenarios in experiments [5]–[7]. So far, it is not entirely clear existing large language models can be leveraged for sentiment analysis remains unclear [2]. This study aims to address this gap by providing empirical evidence of the feasibility and effectiveness of using the LLaMa model applied to the Life Energy instrument to analyze sentiments and provide introspective questions aligned to the individual needs of each user. To validate the performance of the proposed Life Energy Sentiment Model (LESM), we use public sentiment analysis datasets, IMDB [8] and Amazon Review [9], and compare the proposed model with two models available in the literature [10], [11].

II. Life Energy instrument

The Life Energy instrument consists of 81 tasks featuring relational situations that involve tasks with physical, mental, and social activities for the user to develop. These tasks are organized into three pillars: the relationship with oneself, the relationship with others, and the relationship with the whole. Each pillar of the Life Energy instrument is explored through six essential linking points, which encompass the full spectrum of human experience and form a cohesive framework for personal growth and self-discovery [1].

The first pillar — the relationship with oneself — focuses on Linking Points that include the physical (health and body care), spiritual (search for meaning and transcendence), emotional (internal emotions and feelings), financial (relationship with material resources and prosperity), professional (career and accomplishments at work), and intellectual (mental and cognitive development). The second pillar — the relationship with others — explores Linking Points related to relationships with parents (family bonds and influences), spouses (intimacy and partnership), children (parental responsibility and love), friends (friendship and companionship), subordinates (leadership and people management), and partners (professional and collaborative connections).

The third pillar — the relationship with the whole — explores Linking Points that include the familiar (family

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TABLE I: Distribution of Linking Points in the three pillars of Life Energy.

Relationship with oneself	Relationship with others	Relationship with the Whole
Physical	Friends	Social
Financial	Partners	Institutional
Professional	Parents	Life Processes
Intellectual	Subordinates	Ethical Principles
Emotional	Children	Family
Spiritual	Spouses	Finitude

system dynamics), social (community and societal participation), institutional (relationship with organizations and social structures), life processes (navigating life's phases and transitions), ethical principles (reflection on values and morals), and finitude (contemplation of temporality and mortality). The Table I shows the three Life Energy pillars and their respective linking points.

III. Related Work

A study was conducted to evaluate the reliability, consistency, and quality of seven state-of-the-art language models (LLMs), including variants of OpenAI's GPT-4, Gemini, LLaMA, and Mixtral, against human annotators for tasks such as sentiment analysis, political leaning, emotional intensity, and sarcasm detection. The results indicate that LLMs demonstrate high reliability in sentiment analysis and political leaning assessments, exhibiting higher internal consistency than human annotators [12].

Among the evaluated models, the LLaMA model, developed by Meta AI, stands out for its advanced capabilities in natural language understanding, positioning it as a particularly relevant tool for applications that demand deep contextual interpretation, such as sentiment analysis [13], [14].

In recent years, LLaMA has emerged as a promising tool in the field of sentiment analysis, primarily due to its capacity to capture both semantic and contextual subtleties within textual data [15]. This ability enhances the precision of emotional state classification, allowing for a more refined understanding of user sentiment. Compared to traditional Natural Language Processing (NLP) models, Large Language Models (LLMs) like LLaMA offer a significant advantage in interpreting nuanced emotional expressions, leading to more accurate and meaningful sentiment evaluations [14].

Building on these strengths, recent research has applied LLaMA to more specialized sentiment analysis tasks, such as sentiment intensity regression, which assigns numerical values to represent the strength of a sentiment, thereby increasing the granularity and accuracy of emotional assessments in text [13]. Additionally, LLaMA has been employed in Aspect-Based Sentiment Analysis (ABSA), enabling the identification of sentiments tied to specific aspects within a broader topic [16].

The integration of LLaMA in the Life Energy instrument aims to refine sentiment analysis, offering a more personalized user experience. LLaMA excels at handling ambiguities and generating deeper insights into user emotions, providing a robust foundation for evaluating sentiment and promoting self-awareness and self-care. [16].

IV. Methodology

The LESM methodology begins with a task suggested to the user from the Life Energy dataset. The user can choose to either engage with the task and provide feedback or ignore it. If the user decides to proceed, he/she is required to submit three hierarchically ranked and justified responses `Input Data` (the user's text responses). These responses serve as input to the LLaMA model through a customized prompt structure (Ollama LLM Prompt - a specially designed prompt format for this application), which analyzes the content and returns a JSON-formatted string (a structured data format with the analysis results) containing a generated sentiment — such as Happiness, Sadness, Confusion, Excitement, Frustration, Gratitude, Calmness, or Curiosity — along with a key introspective question designed to guide the user's self-reflection process. Additionally, the model generates visual representations, such as a wave chart, to analyze the user's emotional behavior `JSON Process-Chart Generate` (the processing step that transforms the raw output into structured data). The entire methodological flow described above is illustrated in 1.

In addition, the LESM was evaluated using the Groq API, a cloud-based AI inference service designed for high-performance execution of large language models. The API provides efficient access to pre-trained models, enabling rapid deployment and evaluation without extensive computational requirements. This approach ensures that model inference is optimized, leveraging Groq's infrastructure without requiring specialized local hardware. Each input consisted of a textual review, and the model's predicted sentiment was compared against the ground truth labels [17]. Performance metrics such as accuracy, precision, recall, and F1-score were calculated to facilitate comparisons with existing models from the literature.

A. Datasets

LESM has not been assessed using the Life Energy dataset, as it is not annotated by experts. Moreover, the nature of sentiment analysis in this context is inherently subjective and not strictly binary, involving varying degrees of emotional intensity and, most importantly, the generation of introspective questions tailored to the user's personal reflection. Due to these characteristics, the Life Energy data are not suitable for conventional validation procedures. Therefore, two publicly available and expert-annotated dataset, based on binary sentiment classification, were selected to validate the LESM,

which are 1) Amazon Reviews [18], available on link [1], which comprises user-generated reviews of products from the Amazon platform, and 2) the IMDb Movie Reviews dataset [19], available on link[2], which contains 50,000 movie reviews labeled with positive or negative sentiments.

These publicly datasets were selected for testing due to their widespread use in sentiment analysis research and their clear binary sentiment classifications. Notably, the sentiment distribution in both datasets is balanced, with a 50%-50% division between positive and negative samples. This ensures that the evaluation remains unbiased towards any particular sentiment category.

Several studies have used these datasets for sentiment analysis using various machine learning and deep learning models. The Amazon dataset was used for sentiment analysis using word embeddings and recurrent neural network (RNN) variants, machine learning and deep learning models [18], [20]. Meanwhile, the IMDb dataset has been used for sentiment analysis applied to various computational intelligence techniques, such as convolutional neural networks (CNNs) and transformer-based models [19].

Although the model was not formally evaluated using the Life Energy dataset, it was applied within the Life Energy dataset to illustrate its practical use. This application allowed for a qualitative demonstration of the model's capabilities in a real-world context, showcasing how it can generate emotional insights and guide self-reflection, even though these outputs are not suitable for traditional performance metrics.

B. Sentiment Analysis With LlaMa

As illustrated in Figure 1, the first step of the Sentiment Analysis with LLaMA process involves analyzing the `Input Data`, which consist of three user-generated responses that are both justified and hierarchically ranked in relation to a specific task from the Life Energy instrument. These string-formatted inputs serve as the contextual foundation for the subsequent stages, establishing the interpretive framework within the proposed methodology.

Still on Figure 1, in `Generate Response`, the input data are processed in conjunction with the `Ollama LLM Prompt`, a prompt architecture specifically designed for this project. A key part of this step is the integration with `Ollama LLM Prompt`, which maintains a bidirectional connection with the `Generate Response` step. `Ollama LLM` acts as an advanced language model that assists in generating the user's sentiment and the introspective question. The integration of the language model plays a critical role in enhancing the system's capacity to interpret nuanced user inputs and support meaningful self-reflection.

The `Generate Response` step produces two key outputs: `temp_file_name` (a temporary file used to store generated visualizations) and `string_json`. The former refers to a temporary file used to store the generated visualizations,

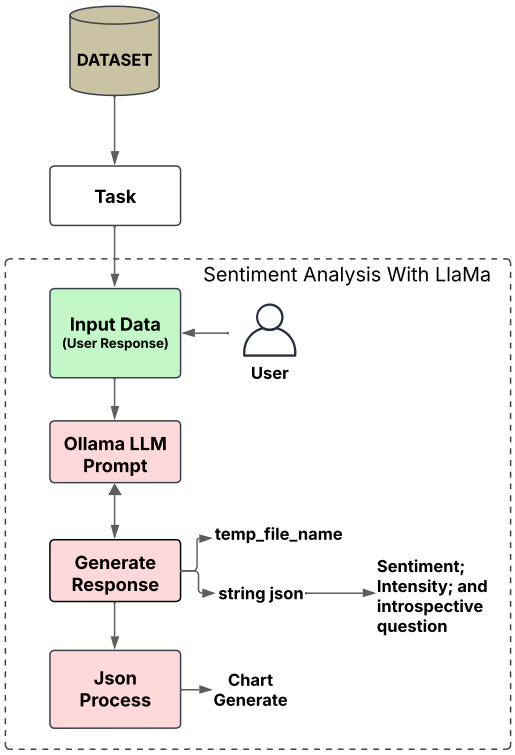

Fig. 1: Flowchart of the methodology adopted in this work.

functioning as a transient repository. The latter is a structured JSON-formatted string that encapsulates the generated sentiment, its associated intensity, and the corresponding introspective question. This structured format ensures clarity and consistency, facilitating future integration with applications and enabling further analytical processing.

The data proceed to the `Json Process` stage. In this phase, the outputs from the `Ollama LLM Prompt` and `Generate Response` are refined and structured to meet the specific requirements of the project. This includes the removal of irrelevant content and the transformation of textual outputs into a dictionary-like structure. The responses are then organized in JSON format, facilitating standardized data handling, integration with external applications, and interoperability across different system components. This structured formatting ensures consistency, clarity, and readiness for the subsequent stages of analysis and visualization.

In the `Generate Chart` phase, the processed data are used to create visual representations, such as the wave chart, that model the user's emotional dynamics over time. It is important to note that this chart is not intended for direct user visualization; rather, it serves as internal feedback for the `Ollama LLM Prompt`, supporting its ability to infer behavioral patterns and user's emotional profile.

This dynamic process fosters a balanced user experience, ensuring emotional variety while enhancing self-awareness and resilience.

[1]https://www.kaggle.com/datasets/kritanjalijain/amazon-reviews

[2]https://www.kaggle.com/datasets/lakshmi25npathi/imdb-dataset-of-50k-movie-reviews/data

TABLE II: Performance comparison with benchmarked models from previous works

Dataset	Model	Accuracy	Precision	Recall	F1 Score
IMDB	LLaMa 3.3 70b (proposed)	**0.9529**	**0.9565**	**0.9489**	**0.9527**
IMDB	Multi-channel CNN+LSTM+attention [10]	0.9413	-	-	-
Amazon	LLaMa (proposed)	**0.9526**	**0.9745**	**0.9295**	**0.9514**
Amazon	CNN [11]	0.9000	0.9000	0.9000	0.9000

V. Experimental study

This section presents the results obtained from two complementary evaluation strategies. First, we provide illustrative examples from the Life Energy instrument to demonstrate how the LESM interprets user input. Second, we report the quantitative evaluation of the model using two publicly available sentiment analysis datasets, Amazon and IMDB Reviews, annotated with binary labels, enabling comparison with established models in the literature. Together, these results offer a comprehensive view of the LESM interpretive capabilities and overall performance.

A. Results in Life Energy Instrument

Although the Life Energy dataset was not used for formal evaluation due to the absence of expert annotations and the inherently subjective, non-binary nature of the emotional responses, it was employed to demonstrate the practical application of the LESM. The examples presented below illustrate how the model interprets user input, captures varying degrees of emotional intensity, and generates tailored introspective questions. These qualitative results highlight the LESM ability to support self-reflection, even in the absence of conventional ground truth labels.

Figure 2 illustrates three examples of interaction between a user and the LESM. In each case, it is possible to observe the identification of the predominant sentiment, its associated intensity, and the introspective question generated automatically. The model's outputs are directly linked to the text entered by the user, reflecting the connection between the language used and the detected sentiment. Additionally, the introspective question aims to stimulate future moments of personal reflection and self-awareness in the user.

B. Results in public Datasets

The results, summarized in Table II, present a comprehensive comparison between the LESM and benchmark models reported in the literature, which are selected due to their relevance to literature. The performance of the LESM demonstrate not only matches, but in several aspects surpasses existing sentiment analysis models in the literature.

For the IMDB dataset, the selected benchmark model reported only the accuracy metric, in which the LESM outperformed it by 1.2%. However, the absence of other essential metrics, crucial for a more comprehensive performance analysis, limits the ability to fully compare the models. In contrast, for the Amazon dataset, the LESM outperformed the benchmark across all evaluated metrics, with improvements ranging from 3% to approximately 8%.

The consistent performance across both datasets highlights the model's enhanced ability to capture relevant patterns across different data and generalize effectively, demonstrating its robustness and superiority over selected benchmarks.

VI. Discussion

One of the most significant strengths of the LESM lies in its ability to generalize effectively without requiring retraining on multiple datasets, unlike traditional models that demand extensive task-specific training and high computational resources to achieve optimal performance [21]. Once pretrained, the LLaMA-based architecture can be efficiently fine-tuned with smaller datasets for specific tasks [22].

The LESM leverages the inherent capabilities of the LLaMa, which are not only reduces the time and resources needed for deployment but also enhances the model's flexibility, allowing it to adapt seamlessly to varying user inputs and behavioral patterns [23]. This adaptability is crucial for maintaining the relevance and effectiveness of recommendations in a dynamic user environment.

The sentiment analysis component of the LESM, powered by the LLaMa architecture, demonstrates high accuracy and a nuanced understanding of user emotions. As shown in Table II, the LESM, which leverages advanced natural language processing techniques, achieves superior performance metrics compared to other approaches that primarily rely on deep learning architectures and convolutional neural networks for sentiment classification. This leads us to believe that the use of LLaMa in the LESM exemplifies a more streamlined and adaptable approach, without compromising accuracy or performance [23].

Its lack of requirement for pre-training, coupled with high adaptability, renders the LESM a highly effective and user-centric application. These attributes collectively contribute to its potential as a powerful tool for enhancing self-care and self-awareness, offering a personalized and engaging experience that is both scientifically grounded and intuitively designed.

VII. Conclusion

This study offers a comprehensive theoretical and practical framework that bridges traditional self-reflection practices with modern artificial intelligence techniques. By integrating the Life Energy instrument, a tool grounded in personal introspection, with the LLaMA language model, the Life Energy Sentiment Model (LESM) was developed to interpret user emotions and generate tailored introspective questions.

The model's strong performance on benchmark sentiment analysis datasets validates its technical robustness, while

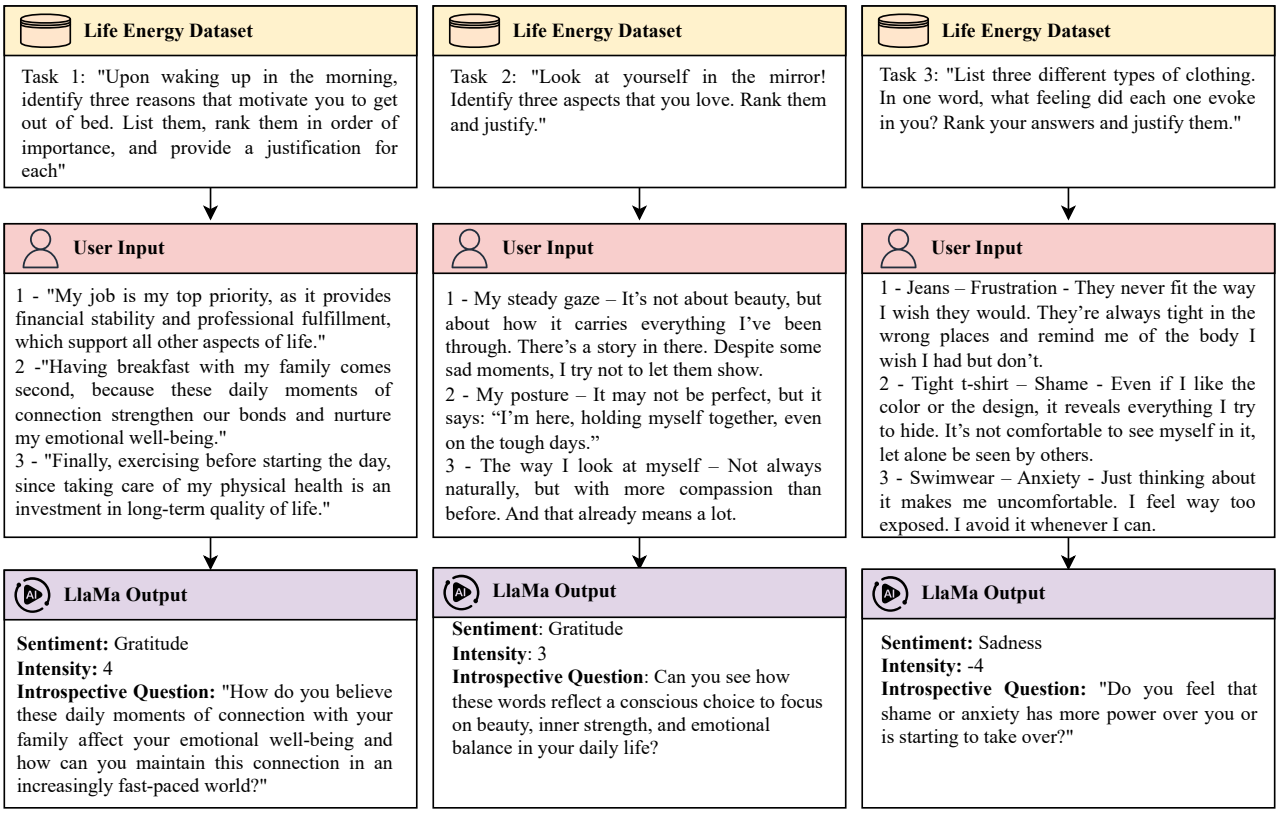

Fig. 2: Examples of user interaction with the prosposed model.

its application within the Life Energy self-care framework showcases its practical value in supporting self-reflection and personal growth. These findings highlight the potential of a multidisciplinary methodology that synthesizes classical psychological insights with contemporary computational methods.

For future work, we could explore the integration of multimodal inputs, such as voice, facial expressions, or physiological signals, to provide a richer and more holistic emotional analysis. Furthermore, longitudinal studies examining the long-term impact of LESM-generated introspective questions on users' self-awareness and well-being would offer valuable insights into the effectiveness and sustainability of AI-assisted self-reflection tools.

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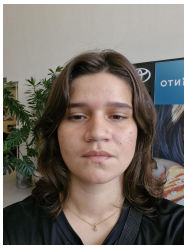

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