Neutrosophic Sentiment Analysis Method Based on NeutroAlgebra for the Evaluation of M-Learning as a Quechua Learning Instrument

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Abstract. This study focuses on assessing the efficacy of m-learning as a tool for learning Quechua. It uses a unique method of sentiment neutrosophic sentiment analysis, which is based on neutroAlgebra. In the current scenario, where the use of mobile platforms for learning indigenous languages is gaining significance, there is a noticeable absence of methods that can effectively handle the intricate and uncertain nature of users' perceptions towards these systems. Existing literature provides limited solutions that effectively integrate mathematical precision with the ability to recognize and respond to emotions and ambiguous opinions. This article addresses the lack of methodology by utilizing neu-troAlgebra to process and analyze sentiment data. This approach enables a more comprehensive and profound comprehension of the user experience. The study's findings indicate that utilizing neutroAlgebra for neutrosophic sentiment analysis is a highly efficient method for comprehending the intricate and uncertain nature of users' perceptions regarding Quechua m-learning. The findings emphasize that this methodology not only enables a more accurate and thorough evaluation of the tool, but also provides valuable insights to enhance the design and implementation of educational strategies in indigenous languages. The study makes two main contributions. Firstly, it presents a novel theoretical and methodological framework for evaluating m-learning in situations with a high level of uncertainty. Secondly, it proposes practical applications that have the potential to greatly enhance the teaching and learning of Quechua and other minority languages in digital settings and the implemetation in Orange data mining tool.

Keywords: M-Learning, Mobile Platforms, Neutroalgebra, Prospector, Sentiment Analysis, of Indigenous Languages.

1 Introduction

M-learning, also known as mobile learning, has significantly transformed the process of imparting and acquiring knowledge in the 21st century, particularly in educational settings with restricted access to physical resources [1]. Teaching indigenous languages, like Quechua, encounters distinctive obstacles within this context. These challenges arise from the necessity to safeguard the language's integrity while also accommodating advancements in technology [2]. This study aims to assess the efficacy of m-learning as a Quechua teaching and learning tool, employing a novel neutrosophic sentiment analysis approach grounded in neutroalgebra. The significance of this research resides in its capacity to offer a methodology that addresses the intricacy of emotional data and the uncertainty inherent in users' perspectives, thereby providing a more precise and comprehensive assessment.

The preservation and instruction of indigenous languages have historically posed a substantial obstacle, primarily due to limited resources, the dwindling number of native speakers, and the inadequate incorporation of these languages into contemporary educational systems [3]. Nevertheless, due to the proliferation of mobile technology and the growing availability of digital devices, m-learning has emerged as a feasible solution to tackle these difficulties. Although m-learning has been widely used in various contexts, its potential in the teaching of indigenous languages like Quechua has not been fully investigated. The need to assess the efficacy of educational technology in specific linguistic contexts is highlighted by recent advancements in this field and the increasing focus on preserving endangered languages [4]. The main issue that this study aims to solve is the absence of a strong and scientifically rigorous method for assessing the effectiveness of m-learning in the instruction of Quechua, taking into account the intricacies and uncertainties associated with users' perceptions. While there are studies examining the utilization of mobile technologies in education, the majority of them fail to sufficiently consider the diversity of users' emotions and opinions, as well as the uncertainty that arises from interacting with technology [5]. This literature gap prompts the research question: How can a neutrosophic sentiment analysis, utilizing neutroAlgebra [6], be employed to accurately assess the effectiveness of m-learning as a Quechua teaching-learning tool?

Hence, the objective of this study is two-fold. The primary objective is to create and implement a neutrosophic sentiment analysis technique utilizing neutroAlgebra[6]. This method is specifically designed to accurately capture the intricate and uncertain nature of users' perceptions regarding Quechua m-learning. Additionally, it seeks to assess the efficacy of this educational instrument in terms of its capacity to instruct and safeguard the Quechua language, thereby offering a pioneering method that can be duplicated in the instruction of other native languages. The objectives outlined in this article align with the research question and will be thoroughly examined. Their exploration will contribute to the advancement of theory and educational practice in the field of Indigenous languages.

2 Preliminaries

2.1 M-Learning Or Mobile Learning.

M-learning, also known as mobile learning, has become a highly innovative tool in the 21st century education field, providing unparalleled flexibility in accessing knowledge. In a society where technology has infiltrated all facets of everyday existence, m-learning holds the potential to revolutionize not just the timing and location of our learning, but also the manner in which it occurs. Nevertheless, this phenomenon is not devoid of challenges and criticism, which gives rise to a crucial and intricate discourse regarding its actual influence on education. Is m-learning a passing trend or a fundamental shift in education? This question is currently being discussed, and any attempt to answer it must go beyond shallow compliments and explore the profound and complex consequences it entails. M-learning allows for equal access to knowledge by removing geographical and temporal constraints that have historically restricted education [8]. It is presented as an inclusive tool that is particularly advantageous for individuals residing in rural areas or facing barriers that prevent them from accessing traditional educational institutions. Moreover, the capacity to customize learning based on individual speed and requirements is one of the most significant benefits of m-learning. Nevertheless, the process of democratization can be deceptive due to the lack of universal access to technology and the persistent existence of digital disparities, which restrict the availability of this form of communication in numerous global regions. The issue of unequal access to mobile devices and connectivity persists as a significant barrier that must not be overlooked.

M-learning, from a pedagogical perspective, brings forth novel dynamics that have the potential to enhance the educational experience, but also present notable obstacles. M-learning has successfully enhanced interactivity, gamification, and collaborative learning. Nevertheless, the potential for shallowness in education cannot be disregarded when emphasizing the utilization of appealing applications and platforms that lack scholarly rigor. Convenient access to information can result in fragmented learning, where the depth of comprehension is compromised in favor of acquiring a large quantity of knowledge quickly. However, it is crucial to take into account the cognitive effects that mobile learning (m-learning) can have on students. Prolonged exposure to mobile devices and the necessity to allocate attention to multiple tasks can impact concentration and the efficacy of learning [9].

M-learning provides substantial flexibility by allowing learning to take place at any time and in any location. However, the absence of a structured framework can pose difficulties in cultivating efficient study habits and time management skills. This highlights the significance of self-discipline and self-regulation for students, while simultaneously redefining the role of teachers from providers of knowledge to facilitators of learning. Nevertheless, this transition gives rise to apprehensions regarding the preservation of educational excellence in settings with limited in-person interaction, emphasizing the necessity for ongoing teacher education and adjustment to emerging technologies. It is imperative for institutions to allocate resources and provide assistance for this transition, as not all educators are adequately equipped to handle these changes [10].

The influence of mobile learning goes beyond just students and teachers, as it has the potential to reshape traditional educational models and raise concerns about sustainability and fairness within the broader educational system. Integrating mobile technologies into curricula for education must be done carefully to ensure that educational goals are not compromised. Moreover, the growing reliance on technology may impede the acquisition of essential abilities such as analytical reasoning and problem-solving. M-learning should serve as a supplement to, rather than a substitute for, traditional education, guaranteeing that students acquire a comprehensive range of skills. Consistently assessing and adopting a critical mindset towards the utilization of educational technologies are crucial in order to maximize the advantages of mobile learning, while simultaneously tackling its obstacles and guaranteeing equal opportunities for all students[11].

2.2 Neutroalgebra generated by combining function in Prospector

For a given natural number $n > 0$, NeutroGroup is defined from the Prospector combinator function. Prospector is the well-known expert system used to model mining problems [12]. The NeutroGroup set consists of all integers between $-n$ and n plus the symbolic element I to represent indeterminacy. This is $NG_5 = \{-5, -4, -3, -2, -1, 0, 1, 2, 3, 4, 5, I\}$and $\oplus_5$is used. This is defined according to the following Cayley table:

Table 1. Cayley table corresponding to $\oplus_5$. Source: [13].

$\oplus_5$	-5	-4	-3	-2	-1	0	Io	1	2	3	4	5
-5	-5	-5	-5	-5	-5	-5	-5	-5	-5	-5	-5	I
-4	-5	-5	-5	-5	-4	-4	-4	-4	-3	-2	0	5
-3	-5	-5	-4	-4	-4	-3	-3	-2	-1	0	2	5
-2	-5	-5	-4	-3	-3	-2	-2	-1	0	1	3	5
-1	-5	-4	-4	-3	-2	-1	-1	0	1	2	4	5
0	-5	-4	-3	-2	-1	0	I	1	2	3	4	5
I	-5	-4	-3	-2	-1	I	I	I	I	I	I	I
1	-5	-4	-2	-1	0	1	I	2	3	4	4	5
2	-5	-3	-1	0	1	2	I	3	3	4	5	5
3	-5	-2	0	1	2	3	I	4	4	4	5	5
4	-5	0	2	3	4	4	I	4	5	5	5	5
5	Io	5	5	5	5	5	Io	5	5	5	5	5

$\oplus_5$ satisfies the properties of commutativity and associativity and has 0 as a null element. Furthermore, it satisfies each each of the following properties [13]:

- If $x, y < 0$t hen $x \oplus_5 y \leq min(x, y)$,
- If $x, y > 0$ then $x \oplus_5 y \geq max(x, y)$,
- If $x < 0$ and $y > 0$or if $x > 0$and $y < 0$, then we have $min(x, y) \leq x \oplus_5 y \leq max(x, y)$.
- $\forall x \in G, x \oplus_5 0 = x$.
- $(-5) \oplus_5 5 = 5 \oplus_5 (-5) = I$.

3 Materials and Methods

The following steps outline the process for gathering and processing opinions:

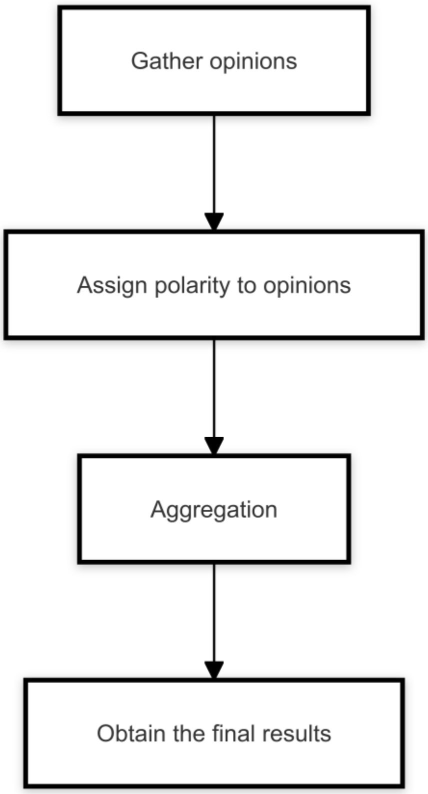

Figure 1. Flowchart of the sentiment analysis method based on neutroAlgebra

Step 1 Gather opinions: Gather opinions from a group of experts $P = \{p_1, p_2, \ldots, p_l\}$, in short, informal texts about aspects/variables to evaluate $V = \{v_1, v_2, \ldots, v_n\}$.

Step 2 Assign polarity to opinions: Each variable (i) is associated with polarity $v_{ij} \rightarrow x_{ij}$, based on a modification on the sentiment analysis algorithm to give values on a discrete scale from -5 to 5. "I" is assigned to indicate the text's unintelligibility

Step 3 Aggregation: For each person and each variable aggregate

$$x_{total,i} = x_{i,1} \oplus_5 x_{i,2} \oplus_5 x_{i,3}, \ldots, \oplus_5 x_{i,n} \quad (1)$$

Step 4 **Obtain the final results**:**.** To obtain the final results, we have a group of people whose opinion is studied. Let's call this set of people by $P = \{p_1, p_2, \cdots, p_l\}$, so that the values are taken into account, $x_{total,i}$ it is the total value of the ith variable,

for the i^{th} variable we obtain the final result That is, the arithmetic mean of each of the variables is calculated.

$$\bar{x}_{total,i} = \frac{\sum_{j=1}^{l} x_{total,i,j}}{l} \quad (2)$$

Where l is the number of experts

In this process, the examination of opinions and perceptions is conducted using neutrosophic theory [14, 15, 16], which takes into account the degrees of positivity, negativity, and indeterminacy. This method not only captures explicit emotions, such as positive and negative ones, but also takes into account those that are neutral or unclear, thereby achieving a more precise evaluation and enhanced comprehension of how these aspects are perceived in the organizational setting [17, 18].

This technique, which is highly efficient for analyzing brief and casual texts, as explained in the aforementioned method, necessitates the identification of a group of words that are categorized as positive, negative, or neutral. Each word is assigned a strength value ranging from -5 to 5, or labeled as indeterminate. Indeterminacy arises when it is impossible to interpret the person's thoughts regarding the subject at hand, either due to unclear language or incomprehensibility. Moreover, there are instances where a text may contain both highly positive (+5) and highly negative (-5) evaluations for the same variable, resulting in a contradictory and indeterminate classification marked with the letter I [19]. The indeterminacy in this situation can arise from various sources, as demonstrated by the PROSPECTOR expert system [20]. This system assesses the level of evidence provided by an expert on a specific aspect, and it reveals that maximum evidence is found in opposite directions for two different aspects.

This method facilitates the classification of terms associated with the analyzed variables into three categories: Positive, Negative, or Neutral, based on linguistic values. Each term is assigned a value ranging from -5 to 5, or even I, based on the magnitude of its positive or negative charge.

The implementation was developed using the Orange platform, utilizing the "Multilingual Sentiment" [21] widget for lexicon-based sentiment analysis. The processed texts were classified on a discrete scale from -5 to 5, where -5 indicates extremely negative sentiment and 5 indicates extremely positive sentiment. (Figure 2). A Python script was employed to map continuous sentiment values to the desired scale

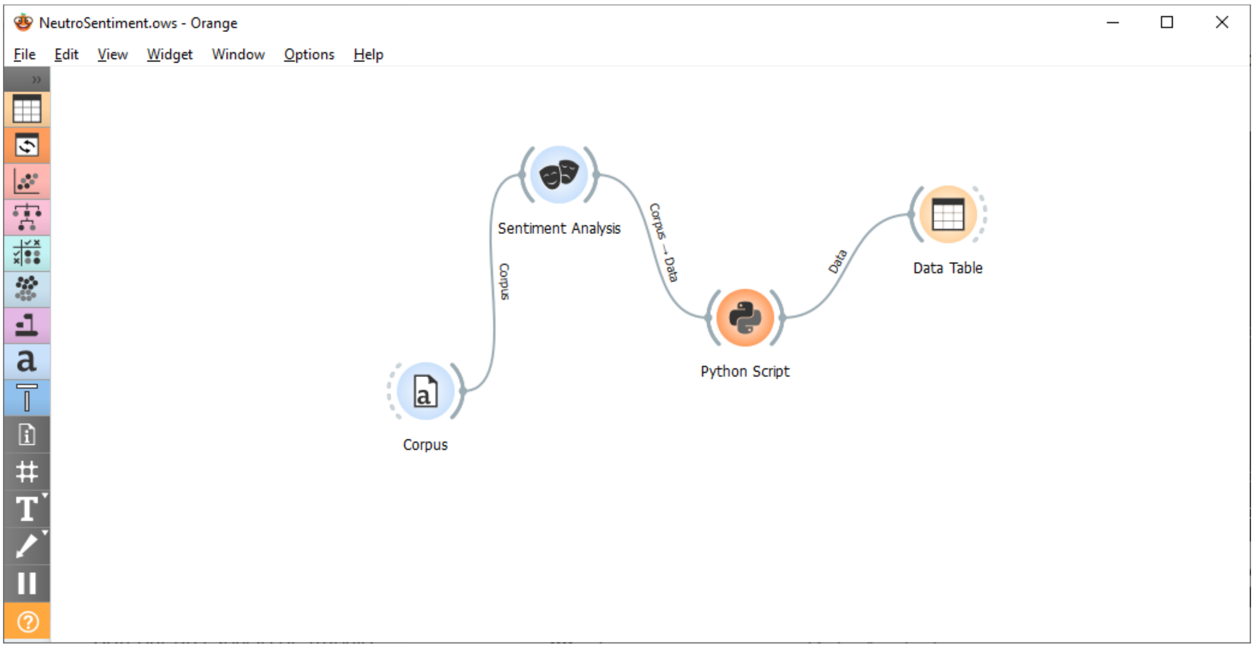

Figure 2. Sentiment Analysis Workflow in Orange.

Additionally, logic was implemented to detect unintelligible texts, defined as those with evident syntactic or semantic issues. In such cases, a special value "I" was assigned to indicate the text's unintelligibility[22]. This approach effectively classified texts, integrating standard sentiment analysis with the handling of exceptional cases within a single platform.

1. Case Study.

To evaluate the effectiveness of m-learning as a tool for teaching and learning Quechua, an approach based on sentiment analysis using neutrosophy is used. The methodology used considers different aspects related to the perception of educators and linguistic anthropologists about m-learning. Below are the steps and calculations carried out in this case.

Step 1: Definition of Variables and Aspects to Evaluate

The aspects to evaluate to measure the effectiveness of m-learning in teaching Quechua are the following:

1. **Accessibility**: Ease of accessing learning materials.
2. **Interactivity**: Degree to which m- learning facilitates the interaction between the content and the user.
3. **Relevance of Content**: Relevance of educational content for learning Quechua.
4. **Ease of Use**: Simplicity of the interface and ease of navigation.
5. **Motivation**: Capacity of m-learning to maintain the interest and motivation of the student.
6. **Learning Efficiency**: Speed with which students acquire new knowledge.
7. **Technical Support**: Quality of support available to resolve technical problems.
8. **Personalization**: Possibility of adapting the content to the individual needs of the students.
9. **Quality of Resources**: Quality and accuracy of the teaching resources available.
10. **Content Update**: Frequency with which materials are updated.
11. **Social Interaction**: Opportunities to interact with other students and educators.
12. **Feedback**: Availability and usefulness of the feedback provided.

Step 2: Data Collection

An open-ended questionnaire was carried out among 15 indigenous language educators and linguistic anthropologists, who evaluated each aspect of m-learning with comments expressed anonymously to ensure sincerity

Answers are processed using Orange pipeline shown in Figure 1. A scale from -5 to 5, where -5 indicates a very negative evaluation, 0 a neutral evaluation, and 5 a very positive. The fragments of survey results are shown in Table 1.

Table 2: Selected Evaluations of M-Learning Aspects by 15 Educators and Linguistic Anthropologists

Aspect	Educator 1	Educator 2	Educator 3	...	Educator 15
Accessibility	4	3	5	...	2
Interactivity	3	2	4	...	3
Content Relevance	5	4	5	...	4
Ease of Use	3	3	2	...	4
Motivation	4	4	5	...	3
Learning Efficiency	3	2	4	...	2

Aspect	Educator 1	Educator 2	Educator 3	...	Educator 15
Technical Support	-1	I	3	...	2
Personalization	4	3	4	...	5
Resource Quality	5	4	4	...	4
Content Update	3	0	3	...	3
Social Interaction	2	3	2	...	3
Feedback	4	3	5	...	4

Step 3: Calculation of Average Values and Evaluation of sentiments.

For each variable evaluated, the total value is calculated using the neutrosophic aggregation operation. This operation is performed by adding the values of each evaluation.

$$x_{total,i} = x_{i1} \oplus_5 x_{i2} \oplus_5 \dots \oplus_5 x_{i15} \quad (3)$$

It is calculated:

$$\bar{x}_{total,i} = \frac{\sum_{j=1}^{15} x_{total,i,j}}{15} \quad (4)$$

the total number of evaluators is 15 in this case.

Table 3: Average Evaluation Values of Aspects of M-Learning.

Aspect	Average Value
Accessibility	3.33
Interactivity	2.67
Content Relevance	4.33
Ease of Use	3.00
Motivation	3.73
Learning Efficiency	2.80
Technical Support	2.53
Personalization	4.00

Aspect	Average Value
Resource Quality	4.27
Content Update	2.87
Social Interaction	2.73
Feedback	4.00

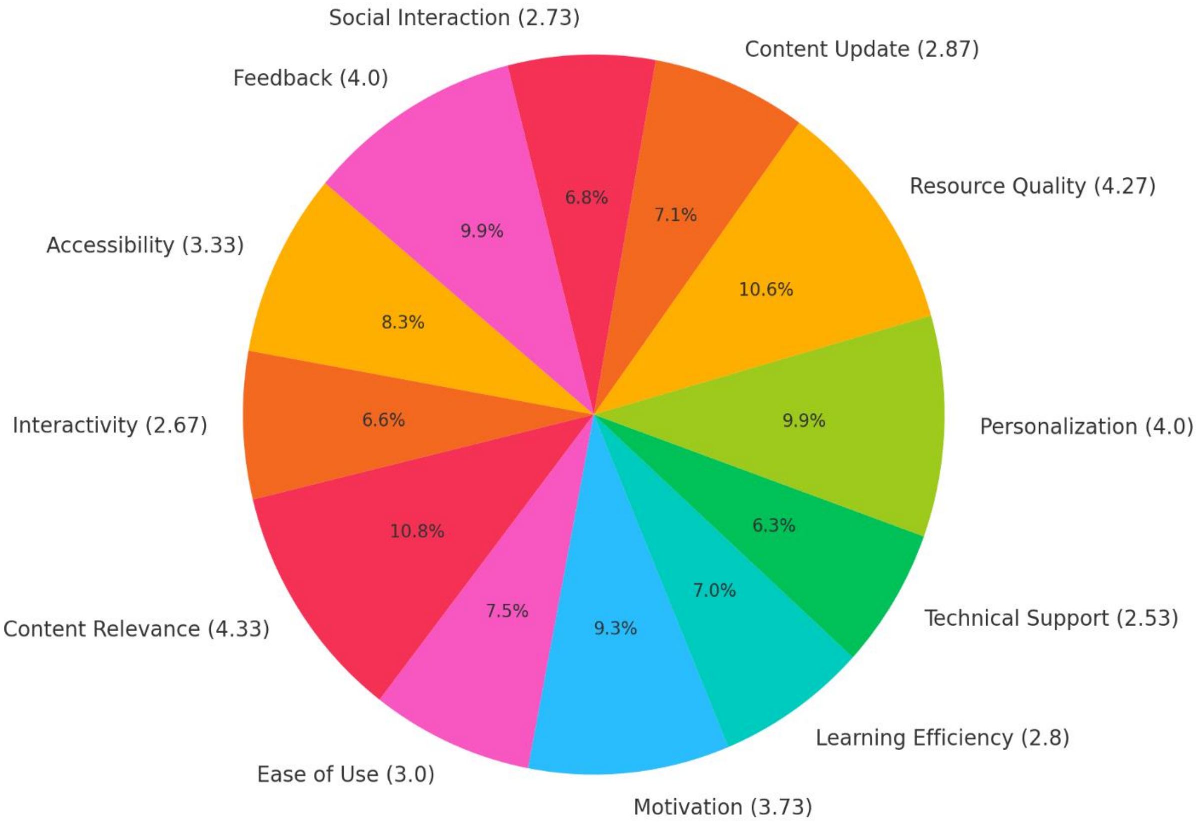

Figure 3. Average Evaluation Values of Aspects of M- Learning.

The average values obtained in the m-learning evaluation reflect diverse perceptions among linguistic educators and anthropologists. Aspects with higher scores, such as **Relevance of Content** and **Quality of Resources** , indicate a positive perception of the ability of m-learning to provide relevant and high-quality materials for teaching Quechua. On the other hand, aspects such as **Technical Support** and **Social Interaction** show lower scores, suggesting areas that could benefit from significant improvements. This analysis provides a detailed vision of the perception of m-learning as an educational tool for Quechua. The data reveals strengths in the relevance and quality of content while highlighting critical areas that require attention, especially in terms of technical support and social interaction opportunities. These findings can guide the future development of m-learning to maximize its effectiveness and better suit the needs of Quechua educators and students. The results obtained in this research highlight the perception of educators and linguistic anthropologists about m-learning as a tool for teaching Quechua. The average values obtained reflect a diverse range of opinions, with highest scores in aspects such as Relevance of Content (4.33) and Quality of Resources (4.27). In contrast, aspects such as Technical Support (2.53) and Social Interaction (2.73) obtain considerably lower evaluations.

The results indicate that m-learning is positively perceived in terms of the pertinence and excellence of educational content for acquiring Quechua language skills, consistent with prior studies that highlight the significance of content quality in m-learning platforms. Nevertheless, the study emphasizes the shortcomings in technical assistance and social engagement, which are essential for user contentment and the overall efficacy of mobile learning. When interpreting the results, it is important to take into account the study's limitations, such as the small sample size and the subjective nature of evaluating certain aspects. To improve the effectiveness of m-learning in Quechua teaching, it is crucial to address these shortcomings. Future research should focus on developing strategies to improve technical support and social interaction. Additionally, it is important to investigate the underlying causes of any anomalies found in the platform's implementation.

Conclusion

The study assessed the effectiveness of m-learning as a pedagogical tool for teaching Quechua, uncovering both advantages and disadvantages of this approach. The content's relevance and the quality of resources were positively perceived, with high average ratings in these aspects. Nevertheless, technical support and social interaction received negative evaluations, highlighting the need for substantial improvement in these areas. The significance of these findings lies in their ability to inform the creation of m-learning platforms for Quechua, specifically in improving technical assistance and fostering social engagement. This has the potential to enhance the overall efficiency and accessibility of m-learning for educators and students alike.

The study has made significant contributions to the field of digital education. It has laid the groundwork for future research and the creation of educational tools that are specifically designed for teaching indigenous languages. It emphasizes the significance of a thorough assessment that takes into account both the favorable and unfavorable aspects of m-learning. Nevertheless, it is important to recognize the limitations of the study, such as the small number of participants and the possibility of subjective assessment in certain areas. Future research should investigate alternative and complementary approaches to mobile learning (m-learning), increase the sample size to ensure a more representative analysis, and examine specific strategies to enhance technical support and social interaction on these platforms. Furthermore, it is worth considering the utilization of alternative sentiment analysis algorithms to enhance and validate the results.

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