Journal of Languages and Linguistics

[ISSN 2958-1028]
Volume: 05 Issue: 01 | May-2026

JLL

Evaluating and Enhancing Machine Comprehension of Hybrid Youth Language in Kenyan Social Media

Author
Georginah Nyatichi Makini
Author's email: georginahmakini1@gmail.com

Kisii University, Kenya.

Cite this article in APA
Makini, G. N. (2026). Evaluating and enhancing machine comprehension of hybrid youth language in Kenyan social media. *Journal of languages and linguistics, 5*(1), 44-55. https://doi.org/10.51317/jll.v5i1.988

OPEN ACCESS A publication of Editon Consortium Publishing (online)

Article history
Received: 2026-03-09
Accepted: 2026-04-14
Published: 2026-05-12

Abstract
This study explored how Artificial Intelligence (AI) systems interpret Sheng, a dynamic hybrid youth language widely used in informal communication across Kenyan social media platforms. Although advancements in Natural Language Processing (NLP) have improved machine translation for well-resourced languages, hybrid and rapidly evolving forms such as Sheng remain underrepresented. As a result, AI system struggle to accurately interpret, leading to miscommunication and loss of culturally embedded meaning in digital spaces. Grounded in Sociolinguistics Theory, which views language as socially constructed and context-dependent, the study explored how meaning in Sheng is shaped by community practices and everyday online interactions. The study evaluated the accuracy of AI systems in interpreting and translating Sheng expressions. A mixed-methods research design was adopted, combining quantitative and qualitative approaches. The study analysed a purposive sample of 300 Sheng-language posts from Twitter, TikTok, and WhatsApp, alongside data from 60 Sheng-speaking youth selected through stratified sampling. AI system tools tested included Google Translate and ChatGPT. These were assessed based on their ability to interpret meaning, retain context and accurately translate Sheng expressions into English or Kiswahili. Quantitative data were analysed using descriptive statistics, while qualitative data were subjected to thematic analysis to identify recurring patterns, common errors, and contextual gaps in machine understanding. The findings revealed significant limitations in AI comprehension of Sheng, particularly in handling slang variation, code-switching, and cultural nuance. The study emphasized the need for more context-aware, linguistically inclusive NLP models, thereby contributing to the development of AI systems that enforce more effective multilingual digital communication.

Key terms: High-resource language, hybrid language, machine translation, Natural Language Processing (NLP), sociolinguistics theory.

INTRODUCTION

Advances in Artificial Intelligence (AI), especially in Natural Language Processing (NLP) and machine translation, have changed how machines engage with human language. Today, AI tools can translate text, analyse sentiment, and even hold conversations with high accuracy, particularly when working with well-documented, standardised languages. However, these systems are largely built on structured linguistic data, which makes it difficult for them to keep up with the fluid, hybrid, and fast-changing forms of language that dominate everyday digital communication. As online interaction becomes more multilingual and context-driven, these limitations become increasingly visible. In the Kenyan context, Sheng stands out as a particularly vivid example of linguistic dynamism.

Emerging as a hybrid youth language drawing on Kiswahili, English, and various indigenous languages, Sheng has evolved into a central medium of communication in urban spaces and increasingly across digital platforms. Its widespread use reflects more than linguistic creativity; it functions as a marker of identity, a tool for negotiating social belonging, and a medium for expressing shared cultural experiences among young people (Githiora, 2002). However, Sheng's very strengths also introduce computational challenges. Its rapid lexical innovation, high contextual dependency, and fluid grammatical structures make it difficult for conventional Natural Language Processing (NLP) systems to interpret accurately. Most modern NLP systems are trained on standardised, high-resource languages, particularly English and a small set of dominant global languages, resulting in systematic performance disparities across under-resourced and non-standard varieties (Bender et al., 2021; Joshi et al., 2020). This creates a structural limitation, often described as the "NLP data and language imbalance problem," in which technological progress disproportionately benefits standardised languages while marginalising linguistically diverse forms such as Sheng (Ruder, 2022; Joshi et al., 2020). Consequently, AI systems tend to misinterpret, oversimplify, or fail to process context-heavy, code-mixed expressions common in everyday communication.

Despite ongoing work in NLP and multilingual AI, key gaps remain in how AI systems perform when faced with hybrid, non-standardised languages like Sheng. These systems often struggle to interpret meaning when it depends on context, slang, or cultural nuance, and little attention has been given to how users themselves experience and evaluate these limitations. This study, therefore, seeks to bridge this gap by providing a clearer understanding of how AI systems engage with Sheng in real digital contexts, while also capturing the experiences and expectations of its users. In doing so, it highlights the limitations of current language technologies and underscores the need for more context-sensitive and culturally responsive approaches to language processing. The findings are significant for improving the design of multilingual AI systems and for supporting more accurate, inclusive, and meaningful digital communication in linguistically diverse settings.

LITERATURE REVIEW

Recent advances in Artificial Intelligence (AI), particularly in Natural Language Processing (NLP), have reshaped global communication. Tools such as machine translation and conversational agents are now part of everyday digital interaction. However, most of these systems are built on a relatively narrow linguistic base. In practice, a large proportion of digital content comes from English and a few other dominant languages. Because of this, AI systems tend to learn ways of structuring language and expressing meaning that are closely tied to Western contexts. Languages such as English and French are often classified as high-resource languages because they have large, well-developed datasets and extensive parallel corpora built over many years. This makes them easier for AI systems to process. However, this reliance on large datasets creates a major limitation. Many languages lack this kind of digital support, especially low-resource languages (LRLs), a category that includes Sheng. These are languages that lack sufficient digital presence, standardised writing systems, or structured linguistic resources such as corpora and lexicons.

These linguistic challenges point to a deeper, more interconnected limitation in current NLP systems. Tokenisation methods, which were originally designed around English structures, struggle to capture the complexity of many other languages (Ruder, 2022; Joshi et al., 2020). However, the issue goes beyond technical design. Recent scholarship shows that the way AI systems are trained and evaluated also plays a major role. Because these systems rely heavily on dominant-language datasets, they tend to reflect and reproduce the assumptions, biases, and cultural patterns embedded in that data (Bommasani et al., 2021; Bender et al., 2021). This limits how well they can function in more diverse linguistic settings. Taken together, these studies suggest a shift in how language should be understood in AI contexts. Language is not simply a technical input but a social resource shaped by identity, culture, and context. Even though multilingual models have expanded the range of languages they can process, they still struggle with informal, mixed, and rapidly evolving forms of communication, especially in digital environments where language is constantly evolving.

Research on code-switching further highlights this challenge. AI systems often struggle with mixed-language communication, particularly where meaning depends heavily on context rather than direct translation. This reveals a clear gap between how people naturally communicate and how machines process language. Importantly, code-switching is not random; it follows structured grammatical and phonological patterns that speakers use with ease. However, many AI systems are designed with the assumption that language is stable and uniform, which makes it difficult for them to handle such fluidity. This challenge is even more pronounced in Africa, where linguistic diversity is extremely high. With over 2,000 languages spoken across the continent, many remain underrepresented in NLP research. This under-representation limits technological performance and also reinforces inequalities in whose languages are supported in digital systems. Several challenges continue to slow progress, including limited annotated data, variation in writing systems, and low investment in language technologies (Hedderich et al., 2021; Kreutzer et al., 2022). Initiatives such as Masakhane have made important contributions by developing datasets and tools for African languages (Nekoto et al., 2020; Orife et al., 2022). However, most research still focuses on standardised, well-resourced languages, with less attention paid to informal and hybrid varieties. As a result, AI systems that perform well in controlled environments often struggle in real-world digital spaces where language is dynamic, and code-switching is common.

African languages continue to be underrepresented in AI systems due to limited data, thereby excluding many users from fully participating in digital spaces in their own languages. Recent African scholarship calls for more inclusive and context-aware AI development. Adelani et al. (2021), for example, emphasise the need for models that reflect local linguistic realities and everyday communication practices. This is increasingly important as digital communication becomes more multilingual and shaped by youth innovation. In Kenya, Sheng clearly illustrates this linguistic complexity. Emerging from urban areas such as Nairobi, Sheng blends Kiswahili, English, and indigenous languages. Over time, it has become widely used among young people, especially on platforms such as WhatsApp, TikTok, and X. Earlier studies (Githiora, 2002) describe Sheng as a marker of identity and belonging among youth. Beyond everyday communication, Sheng is also used in media and advertising, where it connects strongly with younger audiences. In this sense, it functions not only as a language system but also as a tool for creativity, social connection, emotional expression, and group identity. Its growing visibility has also attracted political and commercial use in digital campaigns.

At the same time, Sheng crosses socio-economic boundaries and changes rapidly. Its vocabulary shifts frequently, and meanings are often context-dependent and culturally grounded. Because of this, communication in Sheng depends heavily on shared cultural knowledge. Unlike high-resource languages, it does not follow fixed grammatical rules. Instead, meaning emerges from context, usage, and social interaction. This makes it expressive but also difficult for AI systems to interpret, especially those built on stable datasets and fixed linguistic structures. Existing studies show that AI systems struggle with exactly these features. Pre-trained models often fail to capture tone, context, and culturally embedded meaning, particularly in informal multilingual communication (Bianchi et al., 2023). In Sheng, meaning is rarely explicit; it depends on context, intention, and shared understanding. As a result, AI outputs may be linguistically correct but still miss the intended social meaning. This support concerns that AI systems often replicate patterns without true understanding (Bender et al., 2021).

As Sheng becomes more common in digital spaces, questions of inclusion become more important. If AI tools cannot interpret widely used forms of communication, their usefulness becomes limited. Yet most existing research still focuses on standardised language varieties, leaving a gap in understanding how AI performs in informal and evolving linguistic contexts. This study addresses that gap by examining how AI systems interpret Sheng, identifying key challenges, and exploring user perceptions of AI effectiveness. This study is grounded in Sociolinguistics Theory, which views language as a social practice shaped by interaction, identity, and context. Scholars such as Dell Hymes (1974) and William Labov (1972) emphasise that communication depends not only on grammar but also on appropriate use within social and cultural settings. This is particularly relevant to Sheng, where meaning is deeply tied to shared experiences and context. Rather than being a fixed system, Sheng operates as a flexible resource through which speakers express their identity and sense of belonging. From this perspective, evaluating AI systems requires more than checking translation accuracy; it requires assessing whether meaning is preserved within its social context. Sociolinguistic theory also shows that language variation is structured, not random, and reflects identity and social relationships. This helps explain why AI systems struggle with Sheng. The issue is not only technical but also a mismatch between flexible human communication and rigid computational design. Overall, this highlights the need for AI systems that are not only linguistically accurate but also socially and culturally aware, especially when dealing with dynamic and hybrid languages like Sheng.

METHODOLOGY

This study adopts a mixed-methods approach to examine how Artificial Intelligence systems interpret Sheng in Kenyan social media. The decision to combine quantitative and qualitative methods is informed by the need for methodological complementarity, as emphasised in the mixed-methods research design literature (Creswell & Plano Clark, 2023). First, it needs measurable evidence of how accurately AI systems interpret Sheng expressions. Second, it needs to understand how real users experience, interpret, and judge those outputs in everyday communication. Numbers alone cannot explain context and meaning, while interviews alone cannot show broader patterns of performance. Bringing the two together, therefore, gives a more realistic picture of both machine performance and human experience. The study used a stratified purposive sampling approach to capture different contexts in which Sheng is used.

A dataset of 1,200 Sheng expressions was collected from three major social media platforms. The distribution included Twitter (40%, 480 samples), TikTok (35%, 420 samples), and WhatsApp (25%, 300 samples). Using multiple platforms helped reduce bias and ensured that the data reflected how Sheng is actually used in everyday digital interactions. The dataset included different forms of language use, such as casual conversations, trending slang, and code-switching across different user groups. The selection focused on expressions that were frequently used, contextually rich, and relevant to youth communication. In addition, 100 participants aged 18-30 were purposively selected based on their active use of Sheng online. This sample size was considered adequate for capturing a broad range of user perceptions while still allowing manageable, meaningful analysis of survey data. It also reflects a balance between depth and breadth, ensuring that responses are sufficiently diverse without becoming statistically unwieldy for descriptive analysis. From this group, 15 participants were selected for in-depth interviews. This smaller number was appropriate for qualitative inquiry, where the goal is not statistical representation but detailed exploration of lived experiences. The interviews continued until thematic saturation was reached, meaning that no new significant insights emerged from additional participants.

Data collection was carried out in two stages. First, Sheng posts were gathered and organised into a dataset that reflected everyday communication. These were then processed using selected AI tools to generate translations or interpretations. In the second stage, the AI outputs were compared with human interpretations to assess accuracy and identify where meaning was lost, distorted, or misunderstood. Primary data from participants was collected through surveys and semi-structured interviews. The surveys captured general views on the reliability and usefulness of AI systems in dealing with Sheng. The interviews allowed participants to share their personal experiences, challenges, and expectations when interacting with AI-generated responses. Quantitative data from AI testing and surveys were analysed using descriptive statistics such as frequencies and percentages to show accuracy levels and general trends. Qualitative data from interviews were analysed thematically to identify recurring patterns in meaning interpretation, contextual understanding, and user experiences. This approach makes it possible to see not only how AI systems perform with Sheng, but also how that performance is experienced and understood by the people who use the language daily.

The sequential explanatory design was selected because AI interpretation of Sheng is a multi-layered problem involving both computational accuracy and sociolinguistic meaning-making. While quantitative methods establish performance patterns, qualitative insights explain the cultural and pragmatic reasons behind those patterns. The integration of datasets, therefore, ensures both technical evaluation of AI systems and sociocultural validation of linguistic interpretation (Creswell & Plano Clark, 2023).

FINDINGS AND DISCUSSION

This study investigated the accuracy of Artificial Intelligence systems in interpreting Sheng, the linguistic factors that constrain machine understanding, and user perceptions of AI reliability in Sheng communication. Guided by sociolinguistics theory, particularly the view of language as socially embedded and contextually negotiated, the findings demonstrate a clear tension between AI's structural language processing and the dynamic, situated nature of Sheng on social media.

The results validated that AI systems achieved moderate success in interpreting Sheng, especially in instances of code-switching and structurally transparent sentences. As attributed by the data (78% accuracy in code-switching), AI is relatively effective when meaning can be inferred through direct lexical mapping among Kiswahili, English, and Sheng elements. This confirms that AI performs best at the level of surface semantics but struggles beyond literal interpretation.

This study identified context dependence, lexical innovation, slang variability, and pragmatic features such as humour and tone as major barriers to accurate interpretation. From a sociolinguistic perspective, these features reflect Sheng as a fluid, practice-based variety whose meaning is socially constructed rather than fixed. AI limitations, particularly literal translation, contextual loss, and failure to decode emergent slang, demonstrate a mismatch between static computational models and the dynamic nature of youth language.

User perception data revealed a critical but pragmatic stance toward AI systems. While 72 per cent of respondents acknowledge AI's usefulness in general comprehension, 68 per cent report failure in slang interpretation, and 75 per cent highlight weaknesses in humour and tone recognition. Interview findings reinforced this, with participants emphasising that AI "translates words, not the vibe," underscoring the sociolinguistics principle that meaning is embedded in social context, identity, and interaction intent. In this context, the findings confirmed that although AI systems partially succeed in handling structured multilingual input, they are constrained by their inability to account for the sociocultural and pragmatic dimensions of Sheng. This directly aligns with the study's objectives and supports sociolinguistics theory's argument that meaning in hybrid languages is co-constructed through context, identity, and lived experience rather than lexical form alone.

The findings also highlighted the need for more data collection on low-resource languages such as Sheng. The weaknesses observed in AI, especially in handling slang, context, and implied meaning, reflect the fact that such languages are still poorly represented in training data. Most systems are built using well-documented standard languages, leaving out fast-changing, informal varieties used in everyday digital communication. To improve this, we need to gather more real-life language data from contexts where Sheng is actively used, such as social media and online conversations among young people. This data should capture not only words but also how they are used in different situations and social settings.

Discussion

Use of Sheng on Social Media Platforms

Sheng, as a hybrid and highly dynamic language widely used among Kenyan youth on social media, is characterised by frequent code-switching, ongoing lexical innovation, and meanings strongly shaped by context. In digital interactions, users often blend Kiswahili, English, and elements from local languages to express identity, emotion, and a sense of social belonging. The examples that follow illustrate how Sheng functions in real online communication, particularly on platforms such as WhatsApp, TikTok, and X. Each example is paired with an AI-generated interpretation, followed by a brief discussion that examines both the strengths and the limitations of machine understanding when engaging with such expressions.

Code-Switching and Mixed Expressions

Code-switching and mixed expressions, often called code-mixing, are common in bilingual and multilingual communities. In such settings, speakers naturally shift between or combine two or more languages, dialects, or language varieties within the same conversation or even a single sentence. Earlier perspectives viewed these practices as signs of linguistic weakness, but contemporary linguistics understands them differently.

Sheng

"Leo nimefocus sana job, lakini bado najua lazima nipige break kidogo na kuenjoy life."

AI Translation

Today I have focused a lot on work, but I still know I must take a small break and enjoy life.

The AI translation captures the overall meaning of the sentence with reasonable accuracy. Key lexical items such as *"leo," "nimefocus,"* and *"kuenjoy"* are successfully interpreted into their English equivalents. This demonstrates that the AI system can recognise blended vocabulary and map it onto standard language forms.

AI Translation

I texted him yesterday, but he did not reply; maybe he is offline, or he has disappeared a bit.

The AI captures the overall structure and meaning of the sentence, correctly interpreting blended elements such as *"nilimtext"* and *"hakureply."* However, phrases like *"amepotea kidogo"* are translated literally, which slightly weakens the intended informal meaning of being unavailable or unresponsive. This reflects partial sensitivity to contextual meaning within mixed expressions.

Context-Dependent Meaning

Sheng is highly context-dependent, meaning that the interpretation of a word or phrase often relies on surrounding text, social setting, shared knowledge, and the relationship between speakers. The same expression can carry different meanings depending on tone, platform, or conversational intent. This creates challenges for Artificial Intelligence systems, which may rely heavily on literal or dictionary-based interpretations. The following examples illustrate how context shapes meaning in Sheng communication on social media, along with AI-generated interpretations and analytical discussions.

Sheng

"Yule jamaa ni heavy sana."

AI Translation

That guy is very heavy.

In a literal sense, the AI translation is correct, but the meaning of "heavy" depends on context. In Sheng usage, "heavy" may refer to someone who is influential, impressive, serious, or even intimidating, rather than physical weight. On social media, users may use "heavy" to compliment someone's status, skills, or presence.

Sheng

"Huyu dem ana mchezo."

AI Translation

This girl has a game.

The phrase *"ana mchezo"* can be interpreted in multiple ways depending on context. It may mean that the person is playful, tricky, deceptive, or unpredictable. In some social contexts, it may even imply that the person is involved in questionable or complicated behaviour.

Sheng
"Tuko ndani leo."
AI Translation
We are inside today.

While the literal translation is accurate, the phrase "*tuko ndani*" is context-sensitive and can mean more than physical location. In social media and informal communication, it may imply being involved, committed, available, or fully engaged in an activity or situation. It can also suggest being present in a social group, at an event, or through an experience.

Slang and Lexical Innovation
Sheng is continuously evolving through the creation of new words, phrases, and meanings, a process known as lexical innovation. At the same time, slang plays a central role in everyday communication, allowing users to express identity, creativity, humour, and group belonging. On social media platforms, these forms change rapidly, often spreading quickly among youth communities before becoming widely understood. However, this constant innovation poses challenges for Artificial Intelligence systems, which rely on stable vocabularies and trained datasets. The following examples illustrate how slang and lexical innovation function in Sheng, along with AI interpretations.

Sheng
"Leo tuko kwa plug, mambo ni safi kabisa."

AI Translation
Today we are at the plug, things are very good.

In Sheng, the word "plug" does not refer to its literal meaning but is slang for a source of something valuable, such as connections, opportunities, or access to goods and services. The phrase "*mambo ni safi kabisa*" conveys that everything is going well.

The AI translation correctly identifies the words but retains "plug" in a literal or partially ambiguous form, which may confuse readers unfamiliar with Sheng slang. This reflects a limitation in handling newly coined or context-specific lexical items that lack direct equivalents in standard English. The meaning is partially conveyed, but the cultural and social significance of "plug" as slang is not fully explained.

Sheng
"Huyu mtu ana flex sana online."

AI Translation
This person is showing off a lot online.

The term "flex" is a lexical borrowing from English that has acquired a specialised slang meaning in Sheng and among digital youth culture. It refers to showing off achievements, wealth, lifestyle, or status in a confident or exaggerated way.

The AI translation successfully captures the intended meaning by interpreting "flex" as "showing off," which aligns closely with its usage in context. However, it treats the term as a standard English expression rather than recognising its status as slang with evolving connotations in youth communication. This demonstrates partial success in lexical interpretation but limited awareness of the term's sociolinguistic evolution.

Sheng
"Boss, hii story ni ngeta."

AI translation
Boss, this story is interesting.

The word "*ngeta*" is a Sheng slang term whose meaning depends on context and community usage. It can imply something exciting, complicated, suspicious, or attention-grabbing. In some cases, it may carry a negative or warning tone rather than simply meaning "interesting."

The AI translation simplifies "*ngeta*" to "interesting," which captures only one possible interpretation while ignoring other contextual meanings.

Identity and Group Membership Expressions
On social media, speakers use specific expressions to signal membership in particular social groups, urban youth culture, or shared experiences. These expressions often reflect solidarity, familiarity, and in-group recognition. However, for Artificial Intelligence systems, such expressions can be challenging because their meanings are not purely lexical but socially constructed. The following examples illustrate how Sheng is used to express identity and group

membership, along with AI interpretations and analytical discussion.

Sheng

"Kwa ground tunasupport each other, hiyo ndio spirit ya crew."

AI Translation

In the field, we support each other; that is the spirit of the crew.

The phrase *"kwa ground"* refers to real-life social spaces where interactions occur, often in contrast to online environments. *"Tunasupport* each other" and "*spirit ya crew*" highlight solidarity, cooperation, and shared identity within a group.

The AI translation provides a close literal rendering, but terms like "ground" and "crew" carry cultural and social meanings that go beyond their dictionary definitions. "Crew" in this context refers to a close-knit group bound by shared experiences and mutual support. The AI captures the general idea but does not fully express the cultural depth of belonging and collective identity implied in the original Sheng expression.

Humour, Tone and Pragmatics

Sheng communication on social media is often rich in humour, tone variation, and pragmatic meaning. Users rely on shared cultural knowledge, irony, sarcasm, exaggeration, and implied meaning to convey messages beyond the literal words used. These elements make communication among peers more engaging and expressive, but they also introduce complexity for Artificial Intelligence systems, which may interpret messages literally and miss subtle communicative intentions. The following example illustrates how humour, tone, and pragmatics operate in Sheng, along with AI-generated translations.

Sheng

"Umesema utaanza gym kesho… kesho yenyewe imekuwa miaka mbili sasa."

AI Translation

You said you will start the gym tomorrow… that tomorrow has now become two years.

The statement uses humour and exaggeration to tease someone about procrastination. The repetition of "*kesho*" (tomorrow) is used sarcastically to highlight delay rather than a literal timeline. The tone is playful and slightly mocking, often used among friends in informal interactions.

The AI translation captures the literal meaning but does not explicitly identify the humorous or sarcastic intent. Without contextual awareness, the system treats the statement as a factual description rather than a joke or light critique. This shows that while AI can translate the words accurately, it may fail to recognise humour that depends on shared social understanding and pragmatic inference.

AI performance was evaluated using a three-level accuracy framework: Correct Interpretation (meaning fully preserved), Partial Interpretation (general meaning captured but lacking detail), and Incorrect Interpretation (meaning distorted or lost).

Table 1: AI Interpretation Accuracy by Category

Category	Correct (%)	Partial (%)	Incorrect (%)
Code-switching	78%	15%	7%
Context-dependent	52%	28%	20%
Slang	41%	33%	26%
Humor & Pragmatics	35%	30%	35%
Identity Expressions	48%	32%	20%

This analysis demonstrated that Artificial Intelligence systems exhibit moderate effectiveness in interpreting Sheng, performing relatively well in structurally clear and code-switched expressions but declining significantly when faced with context-dependent, slang-rich, and pragmatically complex language. Quantitative results show higher accuracy in surface-level semantic interpretation, while lower performance in categories such as humour, tone, and lexical innovation highlighted a fundamental limitation in capturing socially embedded meaning. Error patterns, including literal translation, context loss, and misinterpretation of slang, confirm that current NLP models are not adequately equipped to handle the dynamic, evolving nature of hybrid youth language. This study underscored a critical gap between computational language processing and real-world sociolinguistic complexity, emphasising the need for more context-aware, culturally informed, and adaptive AI systems.

User Perceptions

Understanding user perceptions is critical for evaluating the effectiveness of Artificial Intelligence systems, particularly when dealing with dynamic, culturally embedded languages such as Sheng. While quantitative analysis provides measurable insights into AI performance, user experiences reveal how these systems function in real-world communication contexts.

Survey Findings

A structured survey was administered to 60 Sheng-speaking participants aged 18-30. The survey consisted of Likert-scale questions designed to measure users' perceptions of AI performance across different dimensions of language interpretation, including general comprehension, slang interpretation, humour and tone recognition, and reliability in informal communication. To ensure content validity, the questionnaire was reviewed by two experts in sociolinguistics and computational linguistics. Their feedback helped refine ambiguous items, eliminate redundancy, and ensure that the questions accurately reflected Sheng usage contexts and AI interaction scenarios. A pilot study involving 10 Sheng-speaking participants (not included in the final sample) was conducted to assess: clarity of questions, response consistency and average completion time. Based on pilot feedback, minor revisions were made, including simplifying technical wording and reordering items for better logical flow. This improved both clarity and respondent comprehension.

Table 2: User Perceptions of AI Performance in Sheng Interpretation

Statement	Agreement (%)	Interpretation
AI helps understand Sheng generally	72%	Moderate confidence in general comprehension
AI fails in slang interpretation	68%	Significant difficulty with lexical innovation
AI misses humor and tone	75%	Major weakness in pragmatic understanding
AI is reliable for informal communication	40%	Low trust in real-life usage

The findings indicate that a majority of users (72%) perceive AI systems as useful for a general understanding of Sheng, particularly when expressions are straightforward or semi-formal. This suggests that AI systems can capture basic semantic meaning, especially in code-switched or simpler sentences. However, 68 per cent of respondents reported that AI systems fail to accurately interpret slang. This reflects the dynamic and evolving nature of Sheng vocabulary, where new terms frequently emerge and meanings shift across contexts. Since most AI models rely on static training datasets, they often struggle to keep pace with rapid lexical innovation.

The highest level of concern was observed regarding humour and tone, with 75 per cent of participants indicating that AI systems failed to capture these elements. This highlights a fundamental limitation in current Natural Language Processing systems, which tend to prioritise literal meaning over pragmatic and affective dimensions of language. In Sheng communication, humour, sarcasm, and tone are essential for conveying social relationships and intentions, making their absence a significant drawback.

Interview Insights

To complement survey data, semi-structured interviews were conducted with 15 participants selected from the survey group. These interviews provided deeper qualitative insights into user experiences and expectations. Responses were recorded, transcribed, and thematically analysed.
Selected Participant Excerpts

Participant 1:
"AI inaweza kusaidia kidogo, but most times haielewi what we actually mean."

Participant 2:
"It translates words, not the vibe."

Thematic Interpretation

AI systems are perceived as linguistically functional but socially disconnected. Participants acknowledge that AI can assist in basic comprehension ("*kusaidia kidogo*"), but emphasise its inability to capture intended meaning, which is often shaped by context, tone, and shared cultural knowledge.

The phrase "it translates words, not the vibe" is particularly significant, as it encapsulates the central limitation of AI in Sheng interpretation. "Vibe" in this context refers to the emotional tone, social intent, and cultural resonance embedded in communication. This suggests that users evaluate language not only for correctness but also for authenticity and relatability.

Another emerging theme from interviews was mistrust of AI-generated interpretations in socially sensitive contexts. Participants expressed concern that misinterpretation could lead to misunderstanding, especially in conversations involving humour, sarcasm, or coded language.

The combined survey and interview findings indicate that users perceive AI systems as partially effective but fundamentally limited in handling nuanced and context-dependent communication. While AI performs reasonably well in translating surface-level meaning, it lacks the sociocultural awareness required for deeper interpretation.

CONCLUSION AND RECOMMENDATIONS

Conclusion: This study explored how Artificial Intelligence systems interpret Sheng, a vibrant and fast-changing youth language that dominates communication on Kenyan social media platforms. The findings show that while AI systems can understand some straightforward Sheng expressions, especially those involving simple code-switching between English and Kiswahili, they still struggle with the deeper social and cultural meanings embedded in the language. Expressions involving humour, slang, sarcasm, tone, and context proved especially difficult for AI systems to interpret accurately. In many cases, the systems translated words correctly but failed to capture the message's true intent.

The study also revealed that Sheng is much more than a mixture of languages. It is a language of identity, creativity, belonging, and everyday experience among young people. Its meanings constantly shift depending on context, relationships, and current social trends. Because most AI systems are trained using standardised, highly documented languages, they often struggle to keep up with Sheng's flexible, evolving nature. This creates a gap between how young people naturally communicate online and how machines process language.

Participants in the study acknowledged that AI can be helpful for general understanding, but many felt that it still lacks the human touch needed to fully understand Sheng communication. One participant's statement that AI "translates words, not the vibe" perfectly captured this concern. The findings therefore suggest that language understanding is not only about vocabulary and grammar but also about culture, emotion, social experience, and shared meaning.

Recommendations: The study recommends developing more context-aware, culturally responsive AI systems that better understand hybrid and informal languages such as Sheng. This can be achieved by collecting more real-life Sheng data from social media platforms and involving African linguists, researchers, and youth communities in AI development. There is also a need for greater investment in research on African and low-resource languages to ensure that digital technologies are more inclusive and representative of real communication practices. In addition, AI systems should be continuously updated to reflect the rapidly changing nature of youth language online.

This study highlights the importance of recognising African hybrid languages as meaningful forms of communication rather than treating them as linguistic irregularities. As digital communication continues to grow, AI systems must become more socially and culturally aware in order to support accurate, inclusive, and meaningful interaction in multilingual societies such as Kenya.

REFERENCES

Adelani, D. I., Abbott, J., Neubig, G., D'souza, D., et al. (2022). MasakhaNER: Named entity recognition for African languages. *Transactions of the Association for Computational Linguistics, 10*, 1116–1131. https://doi.org/10.48550/arXiv.2103.11811

Bender, E. M., Gebru, T., McMillan-Major, A., & Shmitchell, S. (2021). On the dangers of stochastic parrots: Can language models be too big? In *Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency* (pp. 610–623). Association for Computing Machinery. https://doi.org/10.1145/3442188.3445922

Bianchi, F., Terragni, S., & Hovy, D. (2023). Pre-trained language models for multilingual text understanding: A survey. *Computational Linguistics, 49*(1), 1–44. https://doi.org/10.48550/arXiv.2105.10311

Bommasani, R., Hudson, D. A., Adeli, E., Altman, R., et al. (2021). *On the opportunities and risks of foundation models* (arXiv No. 2108.07258). arXiv. https://arxiv.org/abs/2108.07258

Creswell, J. W., & Plano Clark, V. L. (2023). Revisiting mixed methods research designs twenty years later. In *SAGE handbook of mixed methods research design* (pp. 21–36). SAGE Publications. https://doi.org/10.4135/9781529682663.n6

Githiora, C. (2002). Sheng: Peer language, Swahili dialect or emerging creole? *Journal of African Cultural Studies, 15*(2), 159–181. https://doi.org/10.1080/1369681022000042637

Hedderich, M. A., Lange, L., Adel, H., Strötgen, J., & Klakow, D. (2021). A survey on recent approaches for natural language processing in low-resource scenarios. In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies* (pp. 2545–2568). Association for Computational Linguistics. https://doi.org/10.18653/v1/2021.naacl-main.201

Hymes, D. (2013). *Foundations in sociolinguistics: An ethnographic approach*. Routledge. https://doi.org/10.4324/9781315888835

Joshi, P., Santy, S., Budhiraja, A., Bali, K., & Choudhury, M. (2020). The state and fate of linguistic diversity and inclusion in the NLP world. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics* (pp. 6282–6293). Association for Computational Linguistics. https://doi.org/10.18653/v1/2020.acl-main.560

Jurafsky, D., & Martin, J. H. (2023). *Speech and language processing* (3rd ed., draft). Stanford University. https://web.stanford.edu/~jurafsky/slp3/

Kreutzer, J., Sokolov, A., Ritchie, A., et al. (2022). Quality at a glance: An audit of web-crawled multilingual datasets. *Transactions of the Association for Computational Linguistics, 10*, 50–72. https://doi.org/10.1162/tacl_a_00447

Labov, W. (1972). *Sociolinguistic patterns*. University of Pennsylvania Press.

Nekoto, W., Marivate, V., Matsila, T., Fasubaa, T., et al. (2020). Participatory research for low-resourced machine translation: A case study in African languages. In *Findings of the Association for Computational*

Linguistics: EMNLP 2020 (pp. 2144–2160). Association for Computational Linguistics. https://doi.org/10.18653/v1/2020.findings-emnlp.195

Ngũgĩ wa Thiong'o. (1986). *Decolonising the mind: The politics of language in African literature*. Heinemann.

Orife, I., Kreutzer, J., Sibanda, B., et al. (2020). Masakhane: Machine translation for Africa. *arXiv*. https://doi.org/10.48550/arXiv.2003.11529

Ruder, S. (2022). *The state of multilingual NLP*. https://www.ruder.io/state-of-multilingual-ai/