

ON THE PROMISE OF A NON-WESTERN LLM: THE CASE OF EZUMEZU LOGIC

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Abstract

In this exploratory paper, I consider Ezumezu, a formal non-Western logic invented by Jonathan O. Chimakonam, and I take OpenAI's GPT-5 as a broad paradigm of modern Large Language Model (LLM) capabilities. I examine the three supplementary laws of thought in Ezumezu logic, and find that GPT-5 is capable of reasoning only in alignment with the third supplementary law, Onona-etiti. In the case of Njikoka, I find that GPT-5 is entirely incapable of reasoning in accordance with the principle, and in the case of Nmekoka, it is capable of reasoning in accordance with the principle (curiously) only when prompted in the English language, and not when prompted in Igbo. I take a brief survey of the field to show that LLMs are not capable of logical reasoning, and frame this inability in terms of Raymond Cattell's distinction between crystallised intelligence and fluid intelligence, showing that LLMs are highly proficient at the former, yet poor at the latter (a finding atypical of *human* cognitive patterns). I show that, therefore, in order to create a non-Western LLM that can effectively reason in Ezumezu logic, a neuro-symbolic framework is required, and I suggest the use of external symbolic executors as a good potential architecture. I note that such a future project would represent the first attempt at an LLM-based system designed specifically to reason in a non-Western logic.

Keywords: Large language models (LLMs), logic, philosophy, artificial African reasoner, neuro-Symbolic

Introduction: A Brief History

Large Language Models (LLMs) are the shiny new thing in the world of Artificial Intelligence (AI). They represent a kind of computational model trained on vast amounts of natural language data as their parameters. LLMs are used to generate and analyse natural language across many different fields (QI 2024). A general interest in LLMs quickly formed after the release of 'ChatGPT', OpenAI's generative AI chatbot, in 2022 (OPENAI 2022). The history of LLMs begins much earlier, however, with the not-so-large language model behind the chatbot 'Eliza', designed by Joseph Weizenbaum at MIT in the 1960s (WEIZENBAUM 1966), and the development of Long Short-Term Memory (LSTM) recurrent neural networks (RNNs) by Sepp Hochreiter and Jürgen Schmidhuber in 1997 (HOCHREITER & SCHMIDHUBER 1997). The real turning point that defines our current era of artificial intelligence came in 2017 at the NeurIPS conference, when Google researchers introduced their 'transformer' architecture, which uses a self-attention mechanism, in their paper 'Attention is All You Need' (VASWANI n.d.n. 2017).

The rest is history, as they say, but history in the making. The value of the transformer-LLM architecture has not been exhausted, nor has it been exhaustively implemented. There remains a serious question, however, about the extent to which LLMs can reason logically. Much research has been performed here (see for example, SCHLEGEL, PAVLOV, & PRATT-

HARTMANN 2022; (HAN n.d.n. 2025; YAN n.d.n. 2024), yet no research has been done to determine whether LLMs can reason in accordance with logics of a non-Western origin, despite increasing interest in this area and in the comparisons between Western logic and non-Western logics [see (SCHUMANN 2025)]. Importantly, Aabid Karim n.d.n. (2025) found that LLMs struggle with mathematical reasoning across cultural contexts, even when the mathematical structure remains identical. They discovered that LLMs with exposure to the relevant cultural contexts, and yet zero mathematical training, could often outperform mathematically proficient larger models on questions in which the mathematical problem is culturally situated.

The aim of this paper is to explore whether modern Large Language Models (LLMs), in particular OpenAI's GPT-5, can reason within a formal non-Western logic like Ezumezu, a system formulated by Jonathan O. Chimakonam. In the first section, I will examine Ezumezu logic and its three supplementary laws of thought: Onona-etiti, Njikoka, and Nmekoka. The second section will consist of various prompts designed to test GPT-5's ability to reason in accordance with the three supplementary laws of thought in Ezumezu logic. I will show that the responses to these prompts demonstrate that GPT-5 can reason only in accordance with the third supplementary law, Onona-etiti. I will show that GPT-5 is entirely unable to reason in alignment with the supplementary law of Njikoka, and can only reason in accordance with the supplementary law of Nmekoka, curiously, when prompted in English and not in Igbo. In the third and fourth sections, I will briefly survey the field to show that LLMs are incapable of logical reasoning, framing this inability in terms of Raymond Cattell's distinction between crystallized intelligence and fluid intelligence, and showing that LLMs excel at the former but are poor at the latter (a finding atypical of human cognitive patterns). My final section will argue that creating a non-Western LLM capable of effectively reasoning in Ezumezu logic requires a neuro-symbolic framework, and I will propose external symbolic executors as a promising potential architecture. I will note that such a future project would be the first attempt at an LLM-based system designed specifically to reason within a non-Western logic.

Introducing Ezumezu Logic

The question poses itself: since LLMs seem to be poor reasoners even in a Western context using Western logics, ought we expect that LLMs such as GPT-5, being trained primarily on Western data, will be even worse at reasoning in *non-Western* logics? The case in mind is that of Ezumezu, a formal logic created by Jonathan O. Chimakonam. Ezumezu is a three-valued logic possessing, in addition to 'truth' and 'falsity', a third value called 'ezumezu'. Ezumezu is called an *African* logic, but, as is well-known to its progenitor and proponents, African philosophy is not a monolith but a menagerie of distinct and diverse perspectives. As such, it is particularly relevant to note that Ezumezu reflects a broadly Igbo tradition (CHIMAKONAM 2014), with ezumezu (the third value) meaning both *true and false*; as opposed to neither true nor false in Jan Łukasiewicz's Aristotelian-inspired logic (ŁUKASIEWICZ 1920).

In Ezumezu logic, there are three additional laws to supplement the three traditional Western 'laws of thought.'¹ These additional laws are: Njikoka, Nmekoka and Onona-etiti. Now, there are issues that are left largely unexamined in a post-colonial context, such as whether the three traditional Western laws of thought are even capable of exhaustively capturing *Western* reasoning itself. Emmanuel Ofuasia and Lucky Ogbonnaya (2022) nod towards this problem, noting A.N. Whitehead's own doubt regarding this. However, for the purposes of this paper, I shall let this particular issue pass over in silence.

¹ N.B. The traditional Western 'laws of thought' are as follows: (1) The law of identity: 'Whatever is, is.' (2) The law of non-contradiction: 'Nothing can both be and not be.' (3) The law of excluded middle: 'Everything must either be or not be' (RUSSELL 1912[2001], 47).

The first law, Njikoka, is formulated as $(T) A \uparrow (T) A \mid \rightarrow (T) (A \wedge B)$ in the metatheory of Ezumezu. This reads as ‘A is true iff A is true wedge-implies A and B is true’² (CHIMAKONAM 2019, 100). The idea behind Njikoka is that variable A is true only in the company of another variable, B, and is heavily tied to the communitarian nature of African societies (CHIMAKONAM 2014, 10).

The second supplementary law, Nmekoka, is also very much conceived in terms of group dynamics, and is formalised as $(T \mid \supset F) = C$, meaning ‘C is or equals a complement of T and F’³, where ‘C’ is the third value, ‘ezumezu’ (CHIMAKONAM 2019, 100). Chimakonam asserts that the truth values (T) and (F) are mutually complementary in (C), yet a definition of (C) as merely $(T) \wedge (F)$ would be an error, because in (C) the “two values (T), (F) are mutually complementary, each losing itself to the group in the form of perfect synthesis”, and “the individual identities of the two contraries have been lost in the new perfect synthesis” (CHIMAKONAM 2014, 11)⁴. We might call this principle, in English, “subsumption”. The whole subsumes the qualities of the individuals in a group context.

The final supplementary law in Ezumezu logic is that of Onona-etiti, which is formalised as: $(T) A \wedge (T) \sim A$ or $(T) A \wedge (F) A$ and is designed to account for intermediary values where a proposition is not altogether true, nor altogether false (CHIMAKONAM 2019, 100). Chimakonam describes this principle as the ‘included middle’, as opposed to the ‘excluded middle’ law in traditional Western logic. Indeed, he asserts that “the Aristotelian law of excluded middle posits that either a thing is or it is not”, which therefore “exclude[s] the middle position which is the possibility of a thing being and not being at the same time” (CHIMAKONAM 2014, 11). However, the supplementary law Onona-etiti is more clearly defined in comparison with the Western law of non-contradiction, rather than the law of excluded middle (LEM). For, although the LEM does form a disjunct, as Chimakonam notes, the salient point here is that according to the LEM, there is no additional truth value to which a variable may adhere. For example, the LEM states that either A is true, or A is false – this being as opposed to some alternative middle value (of which, ezumezu ‘(C)’ would be a candidate), but that middle value does not have to be ‘the possibility of being and not being at the same time’, as Chimakonam asserts (CHIMAKONAM 2014, 11), but could also be a value such as ‘neither’ or ‘meaningless’ etc.

On the contrary, the law of non-contradiction explicitly states that a proposition cannot be both true and false, that something cannot both be and not be. Thus, since Onona-etiti explicitly states that something *can*, in fact, be both true and false, ‘that a thing could be and not be at the same time’ (CHIMAKONAM 2014, 12), it seems that this final supplementary law is more relevantly presented as an addendum to the law of non-contradiction, rather than the law of excluded middle.

With all this now in mind, it will be helpful to take GPT-5 (via ChatGPT) as a paradigm of the current state of the art in LLMs, in order to test its ability to reason in Ezumezu logic.

² It should be noted that wedge-implication is not intended as a substitute for the material conditional, or as a stylistic alternative; in Ezumezu logic, $\mid \rightarrow$ means that a contextual condition must also hold in the case of the conditional (CHIMAKONAM 2019, 101). An example to demonstrate this would be something like ‘R $\mid \rightarrow$ U’, so ‘iff it is raining, then I will bring my umbrella’, which is true in normal life conditions. However, if, for instance, the rain is due to a hurricane and one flees their home out of last-minute necessity, it is clear that one will not bring their umbrella. Acknowledgement of this fact is not a rebuke of the principle ‘R $\mid \rightarrow$ U’, because wedge-implication makes explicit conditionals’ social contexts and intended scopes of relevance (which may well be culturally bound).

³ Chimakonam introduces a further notation, $\mid \supset$, meaning ‘complementation’ (CHIMAKONAM 2019, 100)

⁴ It should be noted that in ‘Ezumezu: A System of Logic for African Philosophy and Studies’ (CHIMAKONAM 2019, 160), it is stated that the value, ezumezu, does not represent a “perfect synthesis” in the Hegelian sense, as complementary values can disintegrate and be later recovered.

Below are some prompts and GPT-5's responses, based on the thrust of the three supplementary laws of thought in Ezumezu logic.

Ability of GPT-5 to Reason in Ezumezu Logic⁵

Since Ezumezu logic largely reflects an Igbo worldview, the prompts are asked in Igbo⁶ (via a translation of the prompt into Igbo). To test GPT-5's ability to handle the law, Njikoka, I asked it this prompt in Igbo: "Enye onye 'A' na onye 'B' so n'otu egwuregwu, 'C', bu nkwuputa "A bu onye mmeri naani ma o buru na A na B bu ndi mmeri" bu eziokwu?", which translates to "Given person 'A' and person 'B' are part of a sports team, 'C', is the statement "A is a winner if and only if A and B are winners" true?". GPT-5 responded that "Nkwuputa ahụ abụghị tautology (o bughị eziokwu n'oge niile), ma o bu eziokwu naani ma o buru na A na B abuo meriri, ma o bu ha abuo anaghị imeri".

This translates into English roughly as "[T]he statement is not a tautology (not true at all times), but it is true only if both A and B win, or neither of them wins", and GPT-5 gives an explanation in terms of truth tables (even drawing them diagrammatically), and describes the statement in our query, "A bu onye mmeri naani ma o buru na A na B bu ndi mmeri" ("A is a winner if and only if A and B are both winners") as being of the logical form " $A \leftrightarrow (A \wedge B)$ " (even with no further prompt than what is detailed above). Two things are clear from this response. Firstly, GPT-5 is biased towards Western modes of logic, as demonstrated by its construction of a truth table in order to assess a stripped-down version of the statement in Western classical propositional logic. Secondly, GPT-5 is unable to reason in accordance with the law of Njikoka in the Igbo language, as it is ignorant of the key group aspect of the question asked, even though this group context was made explicit.

When the question is asked in English, GPT-5 responds in much the same way, rendering the statement "A is a winner if and only if A and B are both winners" as " $W(A) \Leftrightarrow (W(A) \wedge W(B))$ ", and concluding that: "The statement "A is a winner if and only if A and B are both winners" is not true in general. It is only true in situations where A is not a winner, or both A and B are winners". This is concerning because, given the explicit group context given, GPT-5 should have realised that being part of team 'C' was a salient feature of the question. If A and B are part of the same team, C, then necessarily A can only be a winner if B is also a winner. This is a simple logic puzzle that GPT-5 fails to solve because it contrives the logical content into a counterproductively simplified format.

Secondly, I test GPT-5 in the context of the supplementary law, Nmekoka. Nmekoka is slightly more difficult to verbalise in order to make it amenable to LLM interpretation. As noted earlier, the law states that truth and falsity complement one another to form a new value, ezumezu. In (CHIMAKONAM 2014), it is stated that the law may be formalised as '(C) A' (meaning that A is ezumezu). This is distinct from $(T) \wedge (F)$, or indeed (T) and $\sim(T)$, for in Nmekoka the individual truth values (T) and (F) lose themselves in the group "in the form of perfect synthesis", and "have come together to produce "C" such that we no longer talk of (T) or (F) " (CHIMAKONAM 2014, 11).

Therefore, contrary to our Njikoka prompt, in which a truth value at the individual level is tied to another truth value in virtue of a group, a prompt for Nmekoka needs to reflect the truth value of a proposition being true, and also being false, at the individual level, but being ezumezu at the group level. I asked GPT-5 "O buru na onye 'A' nwere obi nkpari, onye 'B' nwee obioma, ma ha abuo noro n'otu 'C', otu ahụ abụ otu nkpari, obioma, ma o bu ezumezu?", which means, "If person 'A' is rude, and person 'B' is kind, and they form group 'C', is that group rude, kind, or ezumezu [both/combined]?".

⁵ This prompting occurred in early November of 2025.

⁶ N.B. GPT-5's responses often demonstrate poor command of the Igbo language.

GPT-5 struggled to conceive of the answer as being anything other than a binary value or a tug-of-war between two binary values. GPT-5 concluded: “Otu ahụ 'C' ga-abụ ezumezu, ma ọ bụrụ na onye ojoo na onye oma di n’otu ahụ enweghi otu ndumodu ma ọ bu ike ha adighi iche. Ma ọ bụrụ na otu n’ime ha nwere ike karịa, agwà nke otu ahụ ga-agbaso onye ahụ”, meaning: “Group 'C' will be ezumezu if the good person and the bad person in the group have the same level of influence or power. But if one of them is more powerful, the character of the group will follow that person”. Thus, although GPT-5 did indeed answer “ezumezu”, it is clear that this answer was based on a kind of conflict between two individuals that is yet unresolved, rather than a perfect harmony as is the case in Ezumezu logic and traditional African thought. GPT-5 clearly struggled to answer that these contradictory values may merge and complement within a group, rather than one always vanquishing the other, or both holding in equal and opposing proportions.

Curiously, as part of its response, GPT-5 asked, in Igbo, whether the conversation could be continued in English, further demonstrating its difficulty reasoning in an African, non-Western context/language. When asked in English: “If person 'A' is rude, and person 'B' is kind, and they form group 'C', is that group rude, kind, or both/combined?”, GPT-5 was actually able to answer in a much more varied way, giving multiple suggestions, and being generally more flexible in its response as compared to its previous Igbo-language one. GPT-5 made the important point that “collective traits aren’t simple averages”, and that the quality of the group will “emerge” as a result of a broader social dynamic. This is, in a way, the very essence of Nmekoka, a principle based on Igbo reasoning patterns, which makes it even more perplexing that GPT-5 is seemingly able to reason in a manner more analogous to African modes of thought when discussing the question in English, than in the relevant context language of Igbo.

Finally, I test GPT-5 on Onona-etiti, which is the principle that both p and $\sim p$ may be true: that a proposition may not be altogether true, nor altogether false (CHIMAKONAM 2019, 100). Take a classic example of vagueness: a man who is balding and thus difficult to classify as either bald or not bald. In Ezumezu logic, we may say that the man is both bald and not bald, or that it is true that the man is bald and also true that the man is not bald. I prompt GPT-5 in Igbo, “Ọ bụrụ na otu nwoke nwere ụfọdụ ntutu, ma nwekwaa ebe ụfọdụ ntutu na-adighi ofuma, ọ nwere nkwocha, ma ọ bu na o nweghi nkwocha, ka ọ bu na onwere ha abuo?”, which in English means “If a man has some hair, but there are also areas in which the hair is sparse, is he bald, or is he not bald, or is he both bald and not bald?”.

GPT-5 responds: “N’otu mkpuru okwu: Onye ahụ nwere nkwocha akuku, ọ bughị nkwocha kpamkpam ma ọ bughikwa onye na-enweghi nkwocha.” Which translates to “In one sentence: The person has partial baldness — he is not completely bald, and he is not someone with no baldness at all.” It seems, then, that GPT-5 is quite capable of reasoning in accordance with Onona-etiti in Igbo, and does not attempt to classify the solution as definitively one option or its negation. In fact, when prompted further with “Yabu, ọ bu n’onwere nkwocha ma onwekwaghị nkwocha?” (“So is he both bald and not bald?”), GPT-5 responds: “Ee, n’uzo ezi uche, ọ bu ma nkwocha ma ọ bughị nkwocha.” Which translates to: “Yes, in a reasonable sense, he is both bald and not bald”.

This is a far cry from the English-language response. When prompted in English, GPT-5 responds: “This is a classic example of vagueness — specifically the sorites paradox about the word bald. The short answer is: He is not fully bald, because he still has some hair. He is not fully “not-bald”, because some areas are sparse. But he is not literally both bald and not bald at the same time.” In fact, when further prompted again with “So is he both bald and not bald?”, GPT-5 replied: “He is not literally both bald and not bald at the same time — that would violate classical logic.” In the case of Onona-etiti, therefore, there is a huge difference between how GPT-5 reasons in English and how it reasons in Igbo. In English, GPT-5 explicitly

maintains adherence to classical logic rules, whereas in Igbo, GPT-5 happily accepts the legitimacy of Onona-etiti and does not seek to defend the law of non-contradiction.

Can LLMs Reason Logically?

The inconsistencies between GPT-5's abilities to reason in accordance with the three additional laws of thought in Ezumezu logic are extremely telling. With respect to the first supplementary law, Njikoka, GPT-5 was equally incapable of reasoning in accordance with the law in both Igbo and English, and in both cases constructed contrived classical Western logic formulations of the question given, ignoring the important group context, and deriving incorrect results, despite the simplicity of the question. Importantly, the answer to the question is, arguably, the same in both an Igbo and an English-language context; "A is a winner if and only if A and B are both winners" is true because of the group context outlined. The poor ability of the LLM to heed key information contained within the question (that person 'A' and person 'B' are part of a sports team, 'C') implies that GPT-5 struggles to reason logically in an abstract group context.

In the case of Nmekoka, GPT-5 answered in a very straightforward manner when asked in Igbo, and adhered to classical Western logic principles, asserting that the group will be rude if the rude person wins out, or kind if the kind person wins out, but will be ezumezu if both people hold equal power or sway over the group. This is not really what is intended by Nmekoka, however, for Nmekoka refers to the harmony that occurs when opposing qualities complement each other in a group context. Yet, unexpectedly, when prompted separately in English, GPT-5 answered in a way that *did* reflect Nmekoka, asserting that group dynamics are complex and are not merely "averages" over the qualities of the individuals that make up the group, and that the qualities of the group will "emerge" as a result of these broader interactions. This is much more in line with Nmekoka than the dry response given when prompted in Igbo.

Somewhat bizarrely, therefore, GPT-5 is able to reason in a manner reflective of Nmekoka when prompted in English, and yet is incapable when prompted in Igbo. This may indicate two related points. Firstly, Nmekoka may be reflective of natural language reasoning patterns more broadly, not just in an African/Igbo context. Secondly, since LLMs like GPT-5 are trained on natural language data, the difference between the responses given in English and in Igbo may be the result of more extensive training of the LLM on English language text versus Igbo text. In that way, GPT-5 may be better able to 'reason' in line with Nmekoka in English simply because it knows natural language reasoning patterns better in English than it does in Igbo.

With respect to Onona-etiti, GPT-5 was able to reason well in Igbo. Onona-etiti is the principle that p and $\sim p$ may be true concurrently, that a proposition and its negation may both be true. GPT-5 responded to our given prompt that the man is partially bald, and, when prompted further, attested that "in a reasonable sense, [the man] is both bald and not bald". This latter point can be taken as a direct affirmation of the rule of Onona-etiti. Conversely, when prompted in English, GPT-5 stated that "[the man] is not literally both bald and not bald at the same time" and when prompted further, declared that the man cannot be both bald and not bald at the same time, for "that would violate classical logic". For Onona-etiti, then, the respective responses generated by GPT-5 do conform to what we would expect from an LLM: it will act according to African logic when prompted in an African language and according to Western logic when prompted in a Western language.

The Reasoning Problem

The problems that GPT-5 faces with respect to reasoning in Ezumezu logic appear, then, to relate to the first two supplementary laws of thought, Njikoka, and Nmekoka. GPT-5 is unable to handle reasoning prompts in accordance with Njikoka in neither Igbo nor English. Couple

this with the fact that the answer to the question is arguably true in Western natural language reasoning patterns, as well as Igbo ones, and it appears that GPT-5's inability to reason in accordance with Njikoka reflects a broader poor ability of the LLM to reason. Conversely, the fact that GPT-5 can reason in accordance with Nmekoka in English, but not in Igbo, could be an issue on the training side. An LLM that can reason in Ezumezu logic must overcome these two issues.

There is a large body of evidence suggesting that Large Language Models are incapable of genuine reasoning. (WANG n.d.n.. 2024) find that LLMs struggle to reason with rules. (HAZRA n.d.n. 2025, 1) found that, when testing LLMs on 3-SAT problems, LLMs "are incapable of performing true reasoning". (GERBER & EYBERS 2025) found that all but two of the LLMs they tested failed a basic logical inference test given to them based upon an ontology with an inconsistent concept. They did find, however, that the latest LLMs had progressed "significantly" in their logical reasoning capabilities, which could potentially be due to increased/improved training.

Fengxiang Cheng n.d.n. (2025) find that LLMs can, in fact, be "empowered" to reason, but that this ability requires a symbolic component, such as external solvers. They find that, without this symbolic element, LLMs struggle with even basic logical reasoning, noting that the state-of-the-art question answering LLM, Macaw, will answer in the affirmative to "Is a magpie a bird?" and "Does a bird have wings?". Yet will answer the follow-up question "Does a magpie have wings?" in the negative (CHENG n.d.n. 2025, 10400).

Clearly, then, LLMs are something quite peculiar. Human intelligence is often considered a holistic metric⁷. Psychologist Raymond Cattell parsed intelligence into two broad categories, namely: fluid intelligence and crystallised intelligence (CATTELL 1943). In brief, fluid intelligence is that which can be called 'raw' problem-solving power, whereas crystallised intelligence refers to the ability to use learned knowledge to solve tasks such as recalling information. Fluid intelligence and Crystallised intelligence are distinct but highly correlated measures in humans (SCHIPOLOWSKI, WILHELM & SCHROEDERS 2014). Yet, LLMs are an unusual case because they are now paradigmatic of the very term *artificial intelligence*, and yet they show an enormous cleft between their crystallised intelligence and their fluid intelligence.

LLMs can be said to be extremely skewed towards crystallised intelligence. In fact, their great strength comes from their enormous power as a form of artificial crystallised intelligence (hereafter ACI), which can recall facts no single person could ever memorise, even over a lifetime. It is the very basis of how transformer-LLMs operate that they produce outputs derived from vast amounts of training data (see YILDIRIM & PAUL 2024). Since the datasets that major LLMs such as GPT-5 are trained upon represent a large subset of the entire corpus of human-written knowledge, their ability as ACIs is incredible, and they are far and away superior to humans in this regard. Yet, simultaneously, results show that even *colossal* large language models' fluid intelligence is far worse than that of a single competent human being (see MALEK n.d.n. 2025; WILLIAMS & HUCKLE 2024). Therefore, despite their triumphs as ACIs, LLMs cannot be considered genuine examples of artificial fluid intelligence (AFI hereafter).

Indeed, Yue Yang n.d.n. (2026) found that in a benchmark of 36 abstract reasoning tasks, across four cognitive levels, LLMs (including both general LLMs and reasoning LLMs) behave competently in low-level cognition tasks, but seriously struggle in high-level cognition tasks. The researchers found that LLMs show difficulty with generalisation as complexity grows, demonstrating that current LLMs lack human-like fluid intelligence, as humans are capable of extrapolating the same principles between different examples, irrespective of the

⁷ See (HUANG n.d.n. 2024) for an extrapolation of this idea into a robotics framework.

relative difficulties of those tasks. Conversely, it should be noted that David Ilić and Gilles E. Gignac (2024) found that a human-like positive manifold exists between LLMs' performances on 12 cognitive tests aligned with fluid reasoning (Gf), domain-specific knowledge (Gkn), reading/writing (Grw), and quantitative knowledge (Gq). The authors conclude, therefore, that LLMs possess a general factor of ability over all intelligence tasks, which, like with human cognitive abilities, they say represents a common underlying ability to process information and solve problems.

I would like to push back against the idea that large language models share an underlying quasi 'g-factor' (COLOM, JUNG & HAIER 2006), as this would contradict all of the aforementioned research to the contrary, as well as the results from prompting GPT-5 in this paper (especially in the cases of Njikoka and Nmekoka). The findings of David Ilić and Gilles E. Gignac (2024) are likely the result of insufficient scaling of the difficulties of the tasks given. Indeed, since LLMs learn reasoning patterns from their training data, it is completely expected that LLMs, which are better at writing and knowledge, will also be better at reasoning, as they will likely have been trained more extensively. However, we should expect that this relationship will not be linear as the complexity of the tasks increases. LLMs will struggle much more with the increase in difficulty on reasoning-based tasks than they will on knowledge and writing-based tasks.

Towards LLMs that Can Reason in Ezumezu Logic

To return, then, to the issue of LLMs reasoning in Ezumezu logic, it is clear that LLMs are superb ACIs, but extremely poor AFIs. It is not to be expected, therefore, that LLMs will reason well in *any* logic. Nevertheless, GPT-5 did well at reasoning in accordance with Onona-etiti, and, naturally, we can only expect that this ability is coming from the training side. With respect to Njikoka and Nmekoka, there appear to be two sets of potential solutions. GPT-5's inability to reason in accordance with Nmekoka seems to come, most relevantly, from the (lack of) training side also. If the LLM was trained more extensively on Igbo data relating to group characteristics, then we would expect it to answer this question in the manner in which it did when prompted in English, which *was* in accordance with the principle of Nmekoka.

On the contrary, the Njikoka prompt reveals a general issue with logical reasoning possessed by the LLM, since GPT-5 was unable to answer correctly in neither Igbo, nor English, and yet the answer to the question would likely be deemed the same in both a Western and an African context. The LLM seemed to be unable to handle prompts relating to Njikoka because of the added caveat of group adherence/identity, which the model did not identify as a salient feature of the question, despite this fact being obvious to any human interpreter. Deriving an LLM that can act in accordance with Njikoka and, therefore, Ezumezu logic as a whole, will require a specialised neuro-symbolic framework that is capable of overcoming the difficulties that large language models show in answering logic/reasoning problems.

For directions for future research, a potential framework that might be particularly well-suited to Ezumezu logic is the use of external symbolic executors, which have already been used to great effect in the domain of theory of mind (ToM) reasoning (TANG & BELLE 2024), another closely-related area in which LLMs currently struggle. One could utilise a similar methodology to create an Ezumezu-based external symbolic executor focused on the principle of Njikoka, thereby allowing LLMs to reason in accordance with this crucial first supplementary law of thought in Ezumezu logic.

Then, if enough Igbo training data is utilised such to patch the gaps between English and Igbo language reasoning in Nmekoka, the result would be an LLM that is capable of reasoning in a non-Western logic, the very first of its kind. Even if the training-side solution to the problems faced by LLMs when reasoning in accordance with Nmekoka is not forthcoming, the principle of Nmekoka could also be implemented into the external symbolic executor.

Assuming that GPT-5's ability to reason in Onona-etiti is sufficient (and shared by other state-of-the-art LLMs), then the resultant neuro-symbolic architecture would represent a novel and capable artificial African reasoner.

Conclusion

The creation of a neuro-symbolic framework to allow LLMs to reason in accordance with a non-Western logic is a project that is now long overdue. Ezumezu, being well-defined and articulable, represents an ideal logic with which to achieve this. Since GPT-5 currently represents an industry standard in the field of AI and LLMs, and yet is incapable of reasoning in accordance with two of the three supplementary laws of thought in Ezumezu, there is strong justification for the creation of a neuro-symbolic framework that will allow for rigorous logical reasoning in accordance with this prominent African logic. Since the evidence discussed makes it abundantly clear that LLMs cannot reason logically, that is to say, they are not AFIs, it will be important to augment them with something that can. External symbolic executors represent an ideal methodology for achieving this, allowing us to keep an intact LLM and to overlay an additional 'filter' on top of it. To patch the gaps revealed by GPT-5, such an external symbolic executor would need to be based upon the first two supplementary laws of Nmekoka and (especially) Njikoka. It would then represent the world's first LLM-based architecture for reasoning in a non-Western logic.

Declarations

*The author declares no conflict of interest or ethical issues for this work.

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