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at the Level of the Sentence:
Automated Translation
and the Global South

**Human-Centred AI
in the Translation Industry.
Questions on Ethics,
Creativity and Sustainability**

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Reading Political Economy at the Level of the Sentence: Automated Translation and the Global South

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Abstract: Automated translation is being touted as revolutionizing inter-lingual communication on a global scale. Models such as Google Translate and DeepL are claimed to show a high accuracy rate in translating between certain languages, often to the extent of surpassing human-level performances. However, automated translation between most of the world's languages, primarily those from the Global South, does not exhibit a consistently high standard accuracy rate. The reason for this disparity is discussed only superficially by the creators of these models. It is either claimed to be the result of the limited online presence of these languages or is written off as a symptom of these languages' inherent complexities. This article attempts to understand the underlying structures that constitute this inequality in the field of automated translation. In light of world-systems analysis, this article argues that the underperformance of automated translation technology in certain languages is a systematic project of subordination of the Global South. It delineates the chain of processes, starting with European colonialism, that led up to the modern-day invention of automated translation, to examine

how this inequality was at the core of global events, although it has always been branded as organic. This article then shows how this new ‘milestone’ of automated translation also becomes a device that operates to propagate the ideologies of the dominant structures of power.

Keywords: Automated translation, Global South, Underdevelopment, AI.

1 Introduction

Translation has become an indispensable part of everyday social interactions in an unprecedented manner since the introduction of automated translation.¹ The new phase of machine translation technology has revolutionized communication in the globalized world, be it one-on-one interactions at an airport in a metropolis, mediated by Google Translate or the ‘See Translation’ option appearing under comments sections on Instagram posts and stories. Advancement of artificial intelligence (AI) in general, and automated translation in particular, have become the center of both academic discourses and everyday conversations alike. However, most of these discussions seem to address automated translation as merely a tool that assists in interlingual communication. Consequently, the structures of power inherent in the automation of translation are mostly left out of the conversation. This is alarming, since translation has historically been used by political entities to maintain their power.

From the oldest translations of texts available to us from ancient Greece and Egypt through the Middle Ages, the colo-

1 I am grateful for my advisor, Dr. Hosam Aboul-Ela, for serving as my first interlocutor and offering insightful feedback on the first draft of this article. I also extend special thanks to my colleagues at the University of Houston—Seth Uzman, Kaitlin Rizzo, and Sara Kaplan-Cunningham—for their thoughtful engagement with the ideas and their generous assistance with copyediting.

nial era, and the neo-colonial period we are in, translation has been predominantly used as a political tool (cf. Álvarez Rodríguez/Vidal 1996, Niranjana 1992, Valdeón/Calafat 2020, Bassnett/Trivedi 2002, Aboul-Ela 2018). Much like the production of translation, the development of machine translation also became a priority of major political powers from its very beginning. The United States' investment of 20 million USD in machine translation and related research in the 1950s and 1960s, as well as similar trends in the United Kingdom, France, Japan, and the Soviet Union, support this claim (cf. Somers 1998: 140). Recent developments in the field of automated translation, therefore, cannot be presumed to be free from these structures of power. This article is an attempt to understand how automated translation functions on a global scale as a tool that reifies the inequalities of the global political economy and the uneven development across multiple spatial scales and social spheres.

2 The State of Automated Translation

Conversations on translation often stumble on the question of its future in a world characterized by a boom in automated translation technology. Are translators going to be out of jobs due to the expansion of automated translation models that use advanced neural networks, translate between languages faster, and translate between languages few human translators work with? The impulse to ask these questions stems from an age-old anxiety that machines and technology are going to replace humans. Even though the professional translation industry is showing a reliance on automated translation, the possibility of a large-scale replacement of humans in the field seems far-fetched. Moreover, each time a new technology is introduced, even in the event of its success, it creates new roles and oppor-

tunities. In this case, for example, some studies show an increase in the demand for translators in the past several years due to the boom in streaming media globally (cf. Deck 2021). This is also true in the case of literary translations due to the growing interest in world literature. As a literary translator, my own response, whenever these questions inevitably come up in question-and-answer sessions and discussions, is that I do not share the anxiety of translation machines replacing me. This is based on two different yet loosely connected reasons.

First, as Thierry Poibeau (2022: 6018) argues, automated translation, despite its claims of “human parity” and “super-human performance,” is not yet capable of carrying out translations independently in any language in a way that satisfies the needs of the readers of the translation. Poibeau maintains that these claims

are reproduced in the media for a general audience without much care, as if [automated translation] was a solved task, at least between some languages, whereas it is clear that performance varies a lot from one domain to the other, or from one type of text to the other. (Poibeau 2022: 6018).

Human supervision is still required in producing any valid automated translation—known as human-in-loop machine translations. Andrew, addressing the efforts to automate subtitle translations in streaming platforms, says: “In some instances, machine learning is currently used to generate a first-draft translation, which is then edited or disregarded by a human subtitler as they see fit” (Deck 2021: n.p.) This may indicate that the translator’s role is evolving with the advent of automated translation, but never becoming insignificant. Despite the claims of automated translation technology being revolutionary, its unreliability prevails, which is a characteristic of contemporary AI technology by and large. Gary Marcus makes a humorous observation about the reality of the current state

of AI while talking about PaLM-SayCan, which uses language models in a robot: “Imagine that you want to put your grandpa in bed, and you want to tell the robot to do that, and three quarters of the time it does that and one quarter time it drops your grandpa” (Marcus 2022: 23’50). So long as the probability of such mishaps is unavoidable, the technology will remain unreliable, deemed to be used in areas of lower stake. The unreliability of these translations is stated as disclaimers on websites that use automated translation (US Navy, Department of State). Additionally, when it comes to literary translations, there is an added expectation of creativity. Automated translation relies on statistical datasets and functions by finding patterns among them, which means it can only reproduce what already exists and can only make predictions based on the prominent patterns available in the dataset (cf. Lewis 2024). According to Guerberof-Arenas and Toral (2022: 184), creativity, understood as something that “involves novelty and acceptability,” is something neural machine translation systems are still not capable of. That is to say that automated translation cannot create something novel while staying within the parameters of the acceptable language use. The authors conclude that human translators produce translations without assistance more creatively, whereas machine translations and post-editing methods fail to reach the standard benchmark (cf. *ibid.*: 25–26).

The second reason comes down to the languages I work with. I have been translating primarily between two languages from the Global South, Arabic and Malayalam; languages that do not follow the same pace of advancement as languages from the Global North when it comes to automated translation. The terminology used for signifying this difference is “low-resource languages” (LSL) and “high-resource languages” (HSL) (Ranathunga et al. 2023: 2). Considering Poibeau’s claim that automated translation between “high-re-

source languages” itself does not meet human standards, it is clear that translations between an HRL and a LRL, or two LLRs, have a long way to go. A study published in 2014—in which the researchers used Google Translate to translate ten most commonly used medical statements from English to 26 languages—shows that the accuracy of translations from English and Western European languages was 74%, whereas for English and African languages it was 45% and for English and Asian languages 46%. In comparison, Swahili had only a 10% accuracy rate, whereas Portuguese had 90% (cf. Patil/Davies 2014). Ten years later, in 2024, western European languages are still at the top of this hierarchy, while Asian and African languages remain at the bottom (cf. Evans 2024). This does not mean the past decade was a stagnant period in the field of automated translation research. The technology claims to have made unprecedented progress by moving from statistical machine translation (SMT) to neural machine translation (NMT) in 2015, and with Google deploying its more advanced version of the neural machine translation model called Google’s neural machine translation (GNMT) in 2016 (cf. Wang et al. 2022). In 2016, Google’s model claimed to reduce the errors by 60% compared to earlier phrase-based machine translation (PBMT) on several language pairs (cf. Wu et al. 2016). However, the pairs that show highest accuracy are Germanic and Romance languages, whereas the only non-European language considered in the research, Chinese, improved to a lesser degree (cf. Wu et al. 2016: 19). What this reveals is that despite the claims of the projected goal of supporting all the languages in the world (cf. WSJ 2024: 08’10), automated translation is still biased against the languages from the Global South, and translation between them is not going to reach the benchmark standard in a foreseeable future.

The problem of inaccuracy is further complicated when automated translation is used in translating texts between two non-English languages, especially from the Global South. With very few exceptions, Google Translate uses English as a pivot language to translate between two non-English languages (cf. WSJ 2024: 04'30; Benjamin 2019: n.p.). To translate a text from Tamil to Malayalam, two closely related languages, for example, Google Translate translates it from Tamil to English first, and then from English to Malayalam. Given the low accuracy rates in translating between English and non-European languages, a two-step translation means doubling the chances of inaccuracies. These inaccuracies are not the result of the inherent 'untranslatability' between these languages, but due to the incapacity of automated translation tools, which rely on English as the universal mediator between them, even when translating between two closely related languages. These machines continue to be widely used, though they do not provide caveats admitting their inefficiency in providing reliable translations. They are trained to instantly give translations of any verbal text fed into their system, between any languages available to them.

3 The Problems of Universal Translatability in Automated Translation

The state of automated translation reiterates one of Emily Apter's twenty theses on translation in *Translation Zone: A New Comparative Literature* (2006): "Everything is translatable" (Apter 2006: xi). Though contradictory to Apter's first thesis, "Nothing is translatable," the claim of universal translatability of "everything into everything else" is a reflection on the state of translation on the Internet (ibid.: xi, 227). The chapter with the same title begins with a statement on how the "explosion of world language usage on the Internet" has transformed

translation theory; “[i]nstead of fixating mournfully on the supposition that nothing is translatable (the original is always and inevitably lost in translation), translation studies increasingly explores the possibility that everything is translatable” (ibid.: 226). Apter then explains how “technological literacy” contributes to this universal translatability by producing a “linguistic marketplace, bringing the languages of the world into colloquy” (ibid.). Apter’s observations on “pan-translatability” include the translation of “data, language, matter, information, [and] aesthetic expression” (ibid.: 240). However, her argument also presents the limitations of such a space, as she rightly identifies how the language on the Internet—which she calls “Netlish”—as “the expressionism of global capitalism,” that reinforces the hegemony of English (ibid.: 228). Despite this, Apter sees possibilities in the entry of non-Western languages into the Internet as this is causing an erosion of the hegemony of English (ibid.: 229). Almost two decades after Apter made this statement, we are bound to see her skepticism of Netlish becoming increasingly prominent. The imperfections of the automated translations still remain a reality, with a major difference of them being masqueraded by superficial fluency. These machines are created in a way that privileges the readability and fluency of the output (cf. Rothwell et al. 2023: 105). In Justin Joque’s words, this system “favors production over quality control” (Joque 2022: 139). That is the reason why they tend to provide translations even to words and phrases that they are unaware of. My experiences of typing gibberish in Malayalam into Google Translate always yielded fluent sentences in English. There is a wide gap emerging between the governing principles related to accuracy and fidelity in human translation compared to automated translation.

Indeed, discussions in translation studies moved away from concerns about *mistranslations* and *bad translations*, as the

proliferation of the discourses around culture and politics in translation changed the understanding of translation. While earlier translation was seen as a direct rendering of words from one language to another, now the prevailing idea is that translation is a context-bound act that gives the translator plenty of choices to choose from. The instability of the source text (cf. Emmerich 2017) or the translation's inability to give back the original (cf. Venuti 2019) were also premises for such an understanding. However, the ideas of 'accuracy' and 'faithfulness' are still indispensable to the process of translation, and they find expression in the theoretical discourses very prominently. Gayatri Chakravorty Spivak's (1993: 180) notion of translation as "the most intimate act of reading" and of the necessity of "surrendering to the text" illustrates an extreme case of fidelity in translation. Lawrence Venuti (2019: 8), whose hermeneutic method of translation was instrumental in shifting the discussions away from ideas of "equivalence" and "accuracy," and provided new ways of producing as well as reading translation, cites "semantic correspondence" and "stylistic approximation" as valuable and achievable goals in translation. Additionally, Venuti's (1995: 1) critique of the "regime of fluency" and the subsequent "invisibility" of the translator in English as symptomatic of the "imperialistic and xenophobic" attitudes prevalent in the UK and the US (ibid.: 13) points out that hegemonic power influences the methods of translations. If privileging fluency while maintaining semantic correspondence can itself be problematic in a human translation, the current state of automated translation that disregards standards of accuracy creates a crisis.

Since AI-based models used for automated translation focus on producing translations that sound fluent in the target language, they not only misrepresent ideas but also make the mistakes "difficult to spot" (Rothwell et al. 2023: 105). In other

words, they focus on creating an illusion of accurate translation, rather than creating accurate translations. And if the person using the technology is not fluent in both languages—which is not the case most of the time—such illusions of accuracy lead to a wider acceptability of these technologies. Additionally, the way the performances of translation machines is explained conveniently hides the fact that they follow any ideology. Instead, they are presumed to be innocently reflecting the state of present technology to the best of their abilities, and merely attempting to create the translations based on the statistics and data available to them. An awareness of the underlying principles of the machines—both at the micro-level of producing the translations as well at the macro-level of promoting certain prejudices through them—becomes necessary.

An awareness of the disparity between the ideology of automated translation and human translation leads to the necessity of inventing new frameworks to address the crises in translation. The necessity of such frameworks hinges on the fundamental difference between a human translator and a translation machine. An average literary or professional translator who has been engaging in translating between Malayalam to Tamil will possess the same level of competence as a translator translating from Spanish to English. Their awareness of the syntax and diction of the languages they work with will not be considerably different. They will presumably possess an awareness of the cultural and political context in which the translation is taking place and will be capable of producing translations that do not vary considerably in terms of their quality. Even when the number of translations is limited between these languages, they meet a certain standard of accuracy. The translation machines, on the other hand, have constituted a situation where the quality of translation has been predetermined to a certain extent. That is, a text translated from a European language is going to

exhibit greater accuracy compared to a text translated from an African language. Here, the very semantic field created by the new technology is systematically imposing a hierarchy of languages that are involved in the translation process—both the ones that actively participate in translation and the ones left out of the process—and increases the gap between them. To understand the reasons for the aforementioned disparity, we will have to approach the emergence of automated translation with a sharper and more global theoretical lens.

4 The Ideology of the Machines

Considering the financial investment required for developing any of these translation models, it is relevant to consider the motivating economic logic. Translation has been a defining factor in global trade, and multinational companies have relied on localization processes using human translators for several decades (cf. Doherty 2016). Therefore, the development of new machine translation technology cannot be separated from the aspirations of capital. Proposing the method of AI realism to make sense of the current situation, Holly Lewis underscores the necessity of understanding these models as

not just commodities or platforms, but the unfolding outcome of the systemic logic of embedded material social relations. Large language models are created for the purpose of profit maximization and trained on the data that humans have generated, ideologically, as subjects making sense of their lives within capitalist social relations. (Lewis 2024: n.p.)

Joque, in his extensive study of the ideological underpinnings of the AI, argues: “while algorithms and machine learning may change the speed and nature of computation, they are ultimately bound to reproduce extant societal systems of valuation and violence” (Joque 2022: 14). Approaching discussions on auto-

mated translation technologies from the vantage point of them having an ideological backbone rather than them being systems that work based on pure statistics and probabilities enables us to go beyond discussions on the *experiences* of automated translation and examine all corners of this phenomenon.

I emphasize *experiences* here, given the prominent profile of AI in popular culture in recent years and the fantasies projected onto the technology's efficacy. This runs the risk of being generalized as a global experience, whereas these experiences are limited to a minority—considering the primary beneficiaries are English language speakers—when taken at a global scale. The attitude celebrating the development of translation technology reiterates one of the *original* flaws of development theory; the hyper-focus on the most developed and glittery side while ignoring the areas that do not adequately benefit from this development. Additionally, the experiences also conceal the problems of the inner mechanisms of these technologies that do not get enough attention in the mainstream discourses. As Joque (2022: 58) argues, the machine learning systems solidify extant social systems “in ways that are potentially more insidious and harder to resist, presenting their outputs as objective facts.” It is high time we opened conversations not only about the unequal pace at which automated translation is growing across languages but also about the underlying structures that facilitate such unequal development.

World-systems analysis gives a conceptual framework for understanding the impact of this technological development by taking the whole world as its unit of study and focusing on the structural time—particularly Fernand Braudel's idea of “longue durée”—and using a “unidisciplinary approach” in studying this total social system (Wallerstein 2004: 19). The productions—and correspondingly states that own them—are divided primarily into cores and peripheries, where the surplus-

value constantly flow from the peripheries to the core (cf. *ibid.*: 12). Since the automated translation sector is controlled by what Wallerstein calls “quasi-monopolies” (*ibid.*: 28), they constitute a core-like production, which, given the mechanism of these machines, in effect assert the hegemony of the languages and ideology that the producers represent. In fact, information technology is arguably the most prominent core-like production of our time. By virtue of it being a technology that deals with information—that controls, manipulates, censors, and amplifies information—it is proven to be capable of doing the job its proponents want it to do. Examining the growth of automated translation on a world scale and ‘longue durée’ reveals some of the layers of such a process.

5 The Negative Impacts of Contemporary Automated Translation Technology

As explained earlier, the disparity in the quality of translation across languages is not their original condition. An average qualified translator in any pair of languages will be as competent as their counterpart in some other languages. This entails that the underdevelopment of neural machine translation systems that handle the languages from the Global South is also not their original condition, but a result of systematic subordination. Since more languages from the South have been introduced to Google Translate, there is a consensus that languages from the Global South are slowly catching up in the automated translation scene and there will be a time when all these languages will be able to provide equally good translations. However, this is a delusion because this ever-growing disparity in the distribution of resources is a fundamental characteristic of the capitalist system. What we need to reiterate, therefore, is that the sophistication in automated translation between Eu-

ropean languages is not the result of the organic progression of world events. They are the outcome of the systematic ways in which the capitalist economy historically privileged certain languages and helped them dominate, which assured their prominence in the field of translation as well. This is evident in English playing the role of the universal mediator in neural machine translation when it comes to translating between two non-English languages. Here, Google Translate and DeepL must rely on the translatability of English on more than one level to produce a translation. This very process maintains the hegemony of English on the global stage, making the language indispensable. This is comparable to the domination of English on the global translation market as well as in the world literature debate, which also is reflective of the role of English in the global political economy (cf. Mufti 2016).

A common justification for the better performance of automated translation in certain languages compared to others is their wide presence on the internet (cf. Evans 2024, Schoening 2023). As mentioned earlier, researchers of AI categorize languages as low-resource languages (LSL) and high-resource languages (HSL) based on the availability of “linguistic resources, e.g. grammars, POS taggers, corpora” on the internet (Karakanta et al. 2018: 168). While these categories are perhaps useful in understanding the present state of automated translation technology, a proper understanding of what *constitutes* the categories is also imperative, especially since the gap between these languages is massive. A recent study shows more than 55% of all websites globally use English as their primary language, even though English speakers are less than 5% of the global population (cf. Brandom 2023: n.p.). Russian, Spanish, German, French, and Japanese are next in that line, with 22% of the online presence (cf. *ibid.*). As there is a clear pattern emerging upon observing the internet occupancy of these languages, it

will also not be adequate to reduce the reason for this imbalance to 'online presence,' or 'un/availability,' since they have been determined by political economy: Rather, this could be understood as a way the system conceals the actuality of the events.

The direct relationship between online presence and political economy explains how the Global South has been systematically marginalized in the cyber world. The imbalances are further widened with each step in the development of technology. To give one example, the digitalization of printed texts was a turning point in the history of machine learning since it enabled an unprecedented amount of data to enter the internet. However, objective character recognition (OCR) software is still not fully developed to read many of the languages from the Global South, because this software is trained primarily to read the Roman alphabet. This prevents much of the already existing data in these languages from entering the internet. It goes without saying that this is also tied to the political economy of these languages, and it is preposterous to frame the situation as one concerning 'unavailability' without qualifying the situation, which obscures the relationship between the systems that created these hierarchies and the actors that benefit from them. Moreover, the dominance of these languages on the internet becomes a steppingstone for maintaining their hegemony in the long run. Discussions on AI technology often mention that AI models use a massive number of texts and documents available on the internet in machine learning processes. GPT-4 has reportedly been trained on 570 GB of datasets and these statistics are highlighted and celebrated to explain the 'magic' of AI (cf. Lammertyn 2024: n.p.). If these machines are trained on data available on the internet, and they produce more data and expand within the internet; that means, automated translation, and AI, by and large, are perpetuating

these imbalances in an unprecedented manner. As Brandom (2023: n.p.) puts it: “we’re already building the same imbalance into technology’s next frontier: artificial intelligence.”

Although online presence corresponds to the performance of automated translation in certain languages, the mere availability of data does not necessarily solve the problem. A data curation process identifies, collects, cleans, and processes data. Though the methods or criteria of this data curation process are either arbitrary or not available to the public, we can infer that this process is a potential tool for reifying the imbalances addressed in this article, especially since each of the steps involved in data curation requires financial investment. In data identification and collection, for example, the criteria can be based on cost-effective processes that will also meet the standard demand and profitability. HRLs get an upper hand in data identification and collection since they are considerably easier to process and more profitable due to the easy availability of data, but also because data curation in an under-resourced language will require specialists in those languages, which means more investment. There is also a projected concern of “clean data” when it comes to building any foundational model, which makes the developers either rely on the clean data sets that are already available or clean the datasets that have been collected (cf. Lewis 2024). Some use “low-paid human annotators” and even AI models to clean data (ibid.: n.p.). Data cleaning, therefore, is a gate-keeping mechanism that is aimed to ensure that the data used in machine learning is accurate. However, the political economy also plays a role in data cleaning, for the reasons mentioned above, and even if the data is available on the internet, it will not become the priority in machine learning given the current state of the field.

The rhetoric of HRLs and LRLs also risks these qualifiers being associated with the merit of these languages. There al-

ready exist discussions about how the complexity of the languages from the Global South is one of the reasons why they are not performing well in automated translation. A blog post on the accuracy of Google Translate considers “unique linguistic complexities less typical for European languages” in addition to the “unavailability” of data as the reason for Google Translate’s failure in translating Asian languages (cf. Schoening 2023: n.p.). Such claims reinforce the colonial attitude of constituting languages that are ‘illegible’ to machines. Certain languages are perceived as too foreign, rare, and exotic, which apparently makes translation between them impossible, especially when discussed in comparison to the success of automated translation in other languages. The reason why translations from French into English are, relatively speaking, easier and more accurate than translations from Telugu is then understood as due to Telugu’s ‘complexity,’ and not due to a translation machine’s incapacity or lack of sophistication. Any iterations of understanding this issue as a result of a lack of investments in developing models that can translate among these ‘complex’ languages is conveniently left out of the discussion. Moreover, given the fact that no languages are inherently complex, since the speakers of these languages learn to use them from childhood, the claim of their complexity should in return challenge the claims of ‘intelligence’ of AI models. What can be inferred here is that the claim of the ‘complexity’ of these languages is a way to not address the political economy of this process. We can go a step further and say the incapacity of automated translation tools in translating certain languages (which, as discussed, is a result of a chain of choices) is itself a method of creating an ‘illegible’ and ‘untranslatable’ other.

6 Conclusion

Translation, by being a concept that has universal application, helps understand systems of relations across the globe. Literary translations, for example, reveal the complex socio-political and cultural relationships between the literary traditions that interact through linguistic transfers. Put another way, the unique relationship between the two traditions that engage in a translation will be reflected in the way this literary exchange takes place, which an analysis of these texts will reveal. This article has been an attempt to apply the same logic to automated translation to understand the underlying structures that determine the process. What it has revealed is a unilateral relationship between English and other languages, in the guise of universal applicability of the technology across languages. Pivoting through English even to translate between closely related languages, with very few exceptions, is itself a symptom of that. The hegemony of English in automated translation systems and its subsequent relationship with other languages reflect the political economy of the world we live in. The current state of technology is made to preserve this hegemony, perpetuate the hierarchy, and increase the imbalances. It makes exaggerated claims, such as the super-human performance of automated translation tools, misleading the users in thinking about their capabilities, whereas it fails to provide *acceptable* translations in the vast majority of languages it claims to translate between. When a discussion on the imbalances across the lines of languages comes up, it is written off as a result of their limited online presence or inherent complexity, without addressing the reasons for this or attempting to execute a plan that will decrease the gap. As a first step in solving this problem, we need to understand the problem for what it is, which this article identifies as its primary goal. The current state of automated

translation is built on the premises of global capitalism, which seeks to perpetuate relationships of inequality. We need automated translation models that acknowledge this and work towards fixing the problems that are outcomes of centuries of systematic subordination.

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