The Contradictions Between the Learning Mechanism of Llms and L2 Learners' Knowledge Construction Process and Its Influence on SLA

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Abstract. In recent years, Large Language Models (LLMs) have achieved great success, with many L2 learners and educational institutions beginning to explore the utilization of LLMs in facilitating Second Language Acquisition (SLA). However, the integration of LLMs in the SLA framework comes along with numerous risks. Many recent studies have compared the different learning mechanisms of LLMs and L2 learners from diverse perspectives, but few of them linked such differences with the influence of LLMs on SLA. Utilizing the literature review method, this article mainly draws on Processability Theory (PT) and Complex Dynamic Systems Theory (CDST) and pays special attention to the chatbot in an oral English practicing scenario. By reflecting and comparing the learning mechanisms of LLMs and L2 learners, this article sheds light on the influence of their different learning mechanisms on SLA and identifies several challenges related to safety, ethics, and society. To handle these challenges and promote the effective utilization of LLMs among teachers and students, this article provides the following recommendations: upgrading models, improving transparency, adopting a human-centered approach, enhancing users' capacity, and strengthening government supervision, etc.

Keywords: Large Language Models, Second Language Acquisition, Computational Learning.

1. Introduction

LLMs have influenced scientific research and daily life with their unparalleled capabilities in language processing. Such influence is especially prominent in the field of SLA. Several models have emerged in recent years, including generative pre-trained transformers (GPTs), BERT, ChatGPT, etc.

In the past few decades, there were numerous articles focusing on both SLA and the training process of LLMs. There is a consensus that LLMs acquire a new language in a totally different way from humans, which can be illuminated by existing theories. There are quite a few researchers who argue that, in terms of acquisition, LLMs have their limitations and can only learn the form, instead of acquiring the meaning of a language like humans. This can be an account for why phenomena like hallucination can be observed.

The contradictions between the learning mechanisms of the two can affect SLA greatly. From a positive perspective, such contradictions pave the way for deeper research and new perspectives in SLA research. They can greatly change the learning mode of a second language by providing paradigms of new learning methodology or acting as a teaching aid as well. From a negative perspective, new researches call for attention to applications of LLMs and their social impacts, with issues related to security, ethics, society, etc., coming into the limelight [1].

Therefore, the contradictions between the learning mechanisms of LLMs and human learners deserve attention because LLMs' integration into the SLA field is an inevitable trend and can impose great impacts both positively and negatively. It is of great importance to explore the ways to take advantage of LLMs in the SLA framework for the sake of the well-being of individuals and society.

This article aims to expose the contradictions between the learning mechanism of LLMs and L2 learners' language development and its influence on SLA, then provide corresponding recommendations according to the influences to facilitate better application of LLMs in the SLA field. It will contain 5 sections, with section 2 reviewing the SLA mechanism of humans, section 3 shedding light on contradictions, section 4 exposing possible challenges, and proposing reasonable recommendations to integrate LLMs into SLA frameworks.

2. L2 Learner's Knowledge Construction Process: Basic Theories

2.1 Gradualness: Processability Theory (PT)

L2 learners acquire a language on the basis of mental understanding. They acquire certain structural options only when the psychological processing resources are available. Therefore, human language learning is a gradual process, especially for L2 learners who need to reverse the structural hypotheses of their native languages.

Processibility Theory, which was developed by Pienemann, provides a convincing explanation of the developmental stage of SLA from a psychological and cognitive perspective. The core point of PT is that the developmental route of SLA depends on the architecture of the human language processor [2].

The learning process is incremental as there is a hierarchy of processing resources [2]. This hierarchy can provide a predictable sequence of SLA development, from word to subordinate clause. Specifically, L2 learners are constrained by their native language in the early stages. Due to the difference in initial structural hypotheses, L2 learners may bypass or experience a relatively slow development when acquiring certain structures.

To illustrate the profound and long-lasting influence of those early structural hypotheses in the SLA process, the concept "Generative Entrenchment" is introduced [2]. As long as these early hypotheses are entrenched, they will strongly interfere with later stages of SLA.

2.2 Variability: Complex Dynamic Systems Theory (CDST)

From the perspective of the temporal dimension, the learning process of L2 learners depicts significant variability, containing numerous moderating variables. Phenomena like the butterfly effect, variation are vivid examples.

As the fatal result of the merger of Complex Theory (CT) and Dynamic System Theory (DST), CDST is an overarching framework that views language learning as a complex, dynamic, and non-linear system [3]. CT-for-SLA mainly focuses on the relevance of language use to learner language development [3]. Complex nonlinear systems contain multiple interdependent components, and the whole is better than the sum of those components. DST-for-SLA is a theory focusing on change, suggesting that SLA is a system developing through the interaction between the internal (brain) and external resources (social and cultural) [3]. These resources limit learners' carrying ability, leading to uneven development.

2.3 Individual Differences: Other Perspectives

The L2 acquisition process is linked with individual differences in both physical and mental aspects, taking the complexity of "human" into consideration.

Drawing on a neural perspective, Van Hell summarized some major insights. Firstly, different levels of auditory processing are linked to the outcome of SLA. Secondly, the cortical functional networks can affect SLA. Causal relations between particular brain regions and SLA will be an imperative future direction [4]. Finally, variability in L2 processing is partially associated with variability in L1 processing [4]. Incorporating sociolinguistic and sociocultural approaches, personal social network (PSN) analysis and social network analysis are utilized to explore how (inter)individual variability shapes the process and outcome of SLA. Such variability can change the neural signatures associated with a multitude of language processes.

The framework of "learner individual differences" developed by Lightbown and Spada mainly considered five interactional factors: intelligence, aptitude, motivation, personality, and learner preference [5]. Firstly, intelligence refers to verbal IQ, which is more related to the ability to master the rules of language (like grammar, reading) rather than communicate or interact in real life.

Secondly, aptitude may impose different levels of impact through interaction with numerous factors like instructional methods, age, etc, still emphasizing that its impact will be debilitated in implicit instruction and communication tasks. Thirdly, motivation contains different elements and types, modulating the impact of aptitude, intelligence, etc, on SLA. Moreover, the research about personality went beyond the dichotomy of extrovert and introvert, taking cultural or social background into consideration. Finally, preference is related to the growth track. For instance, Chinese students place more emphasis on reading and listening practice than speaking and writing. Most of the practice is in the form of exercises instead of communicative interaction.

3. The Logical Mechanism of AI Algorithms: Contradictions and Impacts

3.1 The Mechanism of LLM Learning

Firstly, LLMs learn a language mainly through a certain training pattern, especially the transformer (self-attention). Operating on three layers (input, computing, output), LLMs can model contextual dependencies. The learning mechanism can be explained by statistics. That is, LLMs can automatically acquire the so-called rules of language by inputting large-scale text data.

On the input layer, the words are tokenized through Causal Language Models (CLMs) or Pretrained Language Models (PLMs) [6]. Then these tokens experience an "embedding" process, represented as low-dimensional continuous vectors.

On the computing layer, contextualized embeddings are achieved through a self-attention network [6]. First, each word is encoded according to its position and query(Q), key(K), and value(V) of each token are generated. Subsequently, the similarity scores are calculated by an attention mechanism to indicate how closely related a pair of words is and generate a graph of weighted representation. In this process, multiple-head attention pays attention to different kinds of relationships among words at the same time. After that, the output attention layer needs to pass through a feed-forward network to make the information more abstract and expressive. Finally, after residual connections and layer normalization, layers are stacked to capture richer relationships among words.

On the output layer, vectors generated by the decoder are passed through a linear layer and an activation function (Softmax), projecting the representation of each position into a distribution of probability of each word in the vocabulary as a preparation for the prediction of the next word [6].

Secondly, LLMs mostly behave as unsupervised multitask learners through task-conditioning. They can form tasks based on original texts without the need for manual annotation, which can be shown in some advanced learning patterns like language modelling (LM).

LM aims at next-word prediction, is an unsupervised distribution estimator, capturing diverse structures and task descriptions in an illimitable corpus [7]. Initially, when the natural language prompt (NLP) tasks that are expressed in the format of task+text-to-text appear in the training corpus, LLMs are capable of learning them incidentally. Then, a larger capacity of the LM can result in a higher success ratio of zero-shot task transfer, displaying a scale effect.

Apart from these, other variables like the scale of model capacity and data diversity matter.

3.2 The Contradictions between LLM Learning Modes and SLA

There is a consensus that LLMs perform well and develop quickly in functional tasks like translation and extraction. The core of the contradiction between LLM learning and SLA is " Did LLM acquire meaning like humans?". In other words, did they understand? The learning path of LLM is completely different from the path of human language acquisition.

Firstly, the learning pattern of LLMs is much simpler and direct than L2 learners. LLMs' learning is not constrained to physical limitations and mainly relies on a single path, while SLA is more complex, containing several stages and influenced by internal and external factors. Such a difference can be analyzed through a classic framework proposed by Tinbergen [7]. In the ontogeny aspect, SLA is a process of gradual development containing several variables like critical period effects, while the training of LLMs is a disposable process that modifies the paradigm by learning a large-scale corpus.

As for the mechanism, SLA relies on several complex mechanisms, such as the neural system, working memory, attention, social interaction feedback, etc. The knowledge construction process is not only about things like word choice or correct sentence, but also about meaning construction, intention identification, and context handling. In contrast, the LLM learning process is mostly based on prediction training and word embedding, heavily depending on the optimization of algorithms instead of understanding the meaning.

Secondly, even though the amount of L2 learners' input is much smaller than that of LLMs, L2 learners' understanding of language is much deeper than that of LLMs. That is, LLMs are not able to acquire "meaning" like L2 learners and cannot use language like humans in society. Bender& Koller (2020) argue that the prediction training of LM is purely a form of task in which LLMs are trained to focus on the distribution possibility [8]. Despite learning from a large-scale text corpus, they lack signals of communicative intention, feedback, or interaction of the real world, etc. In contrast, the input of humans is relatively little, yet it is connected with the real world deeply. L2 learners tend to acquire language in a communicative environment by being exposed to diverse input. Apart from these arguments, hallucinations and the mechanistic opacity of LLMs are evidence of false understanding [9].

4. Toward Integrating SLA and AI: Recommendations

4.1 Challenges Brought by LLMs

Although LLMs have the potential to enhance SLA efficiency, there are practical and ethical flaws that may hinder them from being further integrated into the educational environment.

Initially, the teaching of LLM cannot guarantee the quality of learners' second language acquisition. Take LLM-driven chatbots as an example, although they can create a more relaxed environment to release L2 learners' anxiety, they have several flaws in terms of teaching quality. Firstly, since LLM is not good at connecting the language to real life, the naturalness of dialogue as well as the authenticity of communicative context may be doubtful [1]. Users may communicate smoothly in oral practice, but cannot interact with native speakers. Over-reliance on LLM-driven chatbots can probably undermine autonomous judgment abilities and interpersonal communication skills. Secondly, the speech recognition of LLM-driven chatbots is sometimes inadequate. Consequently, the accuracy of their pronunciation correction is sometimes doubtful, and their feedback may lack sufficient detail.

Furthermore, given that language is a humanities discipline closely intertwined with society and culture, social challenges must also be taken into consideration. Although LLMs can prominently improve the efficiency of teaching as well as change the role of teachers, the relatively low adoption rate reflects society's distrust of LLM involvement in teaching indirectly [10]. Firstly, technical challenges like high costs and hallucination diminish the credibility of LLMs. Secondly, legal loopholes blur the boundaries of responsibilities for illegal conduct during the utilization of LLMs. When LLMs mark assignments and provide feedback, the privacy and data security of L2 learners cannot be guaranteed. When LLMs generate teaching materials such as lecture notes, the generated content may raise issues concerning copyright and academic integrity (plagiarism, cheating). Thirdly, inadequate institutional frameworks pose fairness challenges during the introduction of LLMs. Significant disparities exist in access to LLMs among schools and students across different regions and resource backgrounds, exacerbating educational inequalities. Fourthly, the mature collaboration mode of teachers and LLMs has not been developed yet, and the efficacy of the utilization of LLMs in teaching scenarios needs more empirical evidence.

4.2 Practical Ways to Handle Challenges

Firstly, efforts can be made from the perspective of upgrading models. Not only should the computational resource be reduced to enhance the efficiency of the model, but LLMs should also incorporate more modalities (speech, vision, etc.) to enrich the learning experience [10]. For instance, future chatbot design should enhance multi-turn interactions and address affective dimensions such as learners' motivation [1].

Secondly, open-source and transparency should be encouraged for the sake of better adaptation in diverse educational settings [11]. In this way, researchers, teachers, and other stakeholders are enabled to access and verify the internal mechanisms of models and systems, enhancing the credibility of LLMs and facilitating collaborative improvement. Such improvement can enable LLMs to build trust among students, parents, and teachers since the basis of the feedback or decision-making process is transparent and can be understood [10].

Thirdly, the study of LLMs should adopt human-centred approaches, encouraging the participation of users and stakeholders [11]. Long-lasting impacts of LLMs should be examined in real classrooms and long-term practices, taking the adaptation to diverse cultural settings into account [1].

Last but not least, the user's effort should also be highlighted, including teachers and students. Teachers should be further trained to master both conceptual knowledge (the nature of LLMs, their capabilities and limitations) and practical skills (applying LLMs in real contexts) [12]. In practical application, teachers are supposed to act as facilitators, integrating chatbox practice with speaking activities in class [1]. Students should learn how to use LLM-based tools as a complement to classroom learning. Schools and educational authorities should take the responsibility to ensure supportive resources, guidelines, and institutional frameworks, providing a more favourable environment for the adaptation of LLMs in education.

5. Conclusion

This article provided several recommendations to handle the challenges hindering the effective utilization of LLMs in SLA, including upgrading models, improving transparency, adopting a human-centered approach, enhancing users' capacity, and strengthening government supervision. These challenges are brought by the different learning mechanisms of LLMs and L2 learners in terms of SLA, which can be explained by the following facts. While the outcome of L2 learners is related to mental understanding capacity, individual differences, etc., LLMs mainly rely on a statistical method by inputting numerous texts and calculating the probability. Firstly, such a training process of LLMs is much simpler and direct than L2 learners, raising the question of credibility. Secondly, LLMs can only learn the "meaning" in form and cannot use language as well as humans in practical interactions in specific settings, leading to questions about the effectiveness.

This study not only deepens the understanding of the influence on SLA of the different learning mechanisms of LLMs and L2 learners and contributes to the effective integration of LLMs in the SLA framework, but also calls for the joint efforts of developers and users to handle the challenges and help LLMs reach their full potential in the SLA field. In the future, the way to enhance the performance of LLMs in communicative tasks is worth studying, which may lead to the finding of new training methods to avoid current risks.

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