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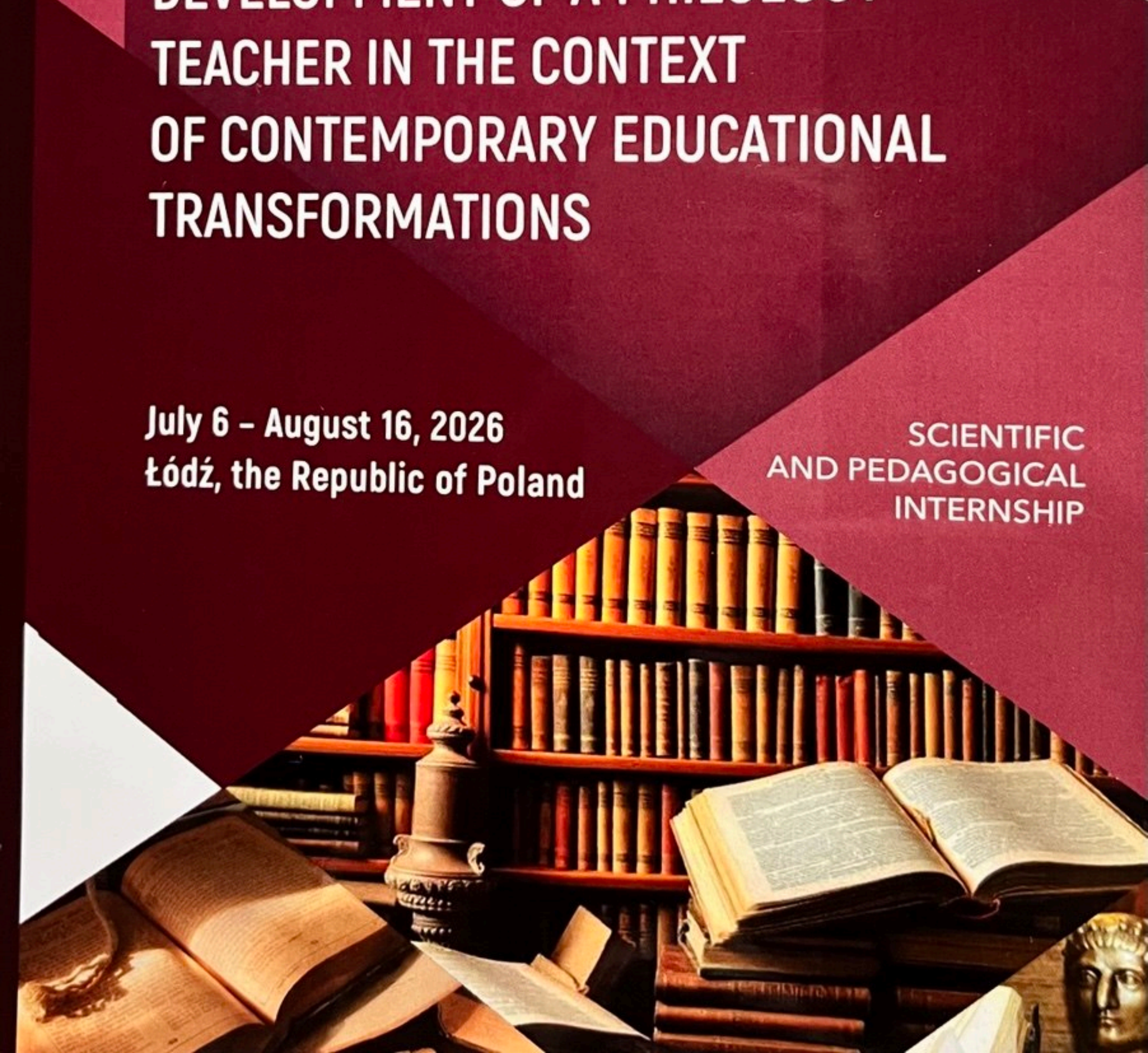
UCZELNIA NAUK SPOŁECZNYCH

PERSONAL AND PROFESSIONAL DEVELOPMENT OF A PHILOLOGY TEACHER IN THE CONTEXT OF CONTEMPORARY EDUCATIONAL TRANSFORMATIONS

July 6 – August 16, 2026
Łódź, the Republic of Poland

SCIENTIFIC AND PEDAGOGICAL INTERNSHIP



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Academy of Social Sciences

Scientific and pedagogical internship

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THE COMPUTATIONAL TURN IN TRANSLATION STUDIES: METHODOLOGICAL SHIFTS FROM CORPUS LINGUISTICS TO AI-DRIVEN ANALYTICS

Shkarban I. V.
Candidate of Philological Sciences,
Associate Professor at the English Language
and Communication Department,
Borys Grinchenko Kyiv Metropolitan University
Kyiv, Ukraine

Translation and Interpreting Studies have undergone a series of profound methodological transitions over the past several decades, evolving from traditional descriptive and qualitative analyses of individual texts relied on normative stylistic frameworks, exemplified by Yan Fu's classic tripartite principle of faithfulness, expressiveness, and elegance [7, p. 215], to large-scale, automated, and predictive computational modelling. The introduction of digitised, machine-readable corpora allowed scholars to transition from prescriptive, intuitive evaluations of translated texts to descriptive, data-supported analyses of translation universals, such as simplification, explicitation, and normalisation [1]. Recently, the proliferation of Large Language Models (LLMs) and advanced neural architectures has catalysed a "computational turn", fundamentally altering both the ontology of translation and the methodologies used to study it [1; 5, p. 183].

As the volume of digital data has grown exponentially, the limitations of traditional corpus linguistics have become increasingly evident. This traditional approach primarily relied on retrospective, single-factor statistical methods, such as relative frequency counts and basic dispersion measures, which were insufficient for capturing the complex, multidimensional nature of

cross-linguistic phenomena. The subsequent integration of Natural Language Processing (NLP), machine learning, and more recently Generative Artificial Intelligence (GenAI) and Large Language Models (LLMs), has facilitated a shift from static corpus-based analyses to dynamic AI-powered translation analytics, with an emphasis on predictive quality assessment, cognitive ergonomics, and automated reporting [3, p. 5873].

The operational efficiency and linguistic accuracy of contemporary neural architectures are significantly influenced by token dynamics and resource limitations. In their examination of LLM translational failures, Qian and Scherrer (2026) introduced the Token Activation Rate (TAR), a metric that measures how effectively an LLM leverages language-specific tokens within its vocabulary during the generation process. Their findings revealed that when models translate into low-resource target languages, TAR values decline sharply. This constriction of vocabulary correlates directly with a decrease in translation quality, as indicated by COMET scores. To counteract these vocabulary constraints, reasoning and generative models tend to produce a considerably higher volume of tokens per sentence, which not only increases computational latency but also heightens the risk of semantic hallucinations [6].

In light of the pressing need for accessible multilingual communication during humanitarian emergencies, Castaldo et al. (2026) proposed domain-adaptive translation pipelines that aim to simplify translated content using LLMs. Their methodology employs preference optimization techniques to align model outputs with the Common European Framework of Reference for Languages (CEFR) A2 proficiency level, ensuring that translated information remains comprehensible to users with limited language skills. The study illustrates that controlled linguistic simplification can improve the clarity and accessibility of critical messages without sacrificing essential content. By merging domain adaptation with readability-

focused optimisation, the proposed framework underscores the potential of AI-driven translation systems to facilitate effective communication in crisis situations, where timely and understandable information is vital for public safety and response [2].

A critical evaluation of the computational turn reveals a structural tension between technological determinism, the belief that automated systems will inevitably replace human translation, and the social technology perspective, which argues that human agency, institutional policy, and pedagogical design ultimately guide how tools are used. The academic and public discourse on translation technology frequently swings between alarmist predictions of professional obsolescence and corporate-driven claims of human-machine parity. As Monzó-Nebot and Dastyar (2025) argue in their sociological analysis of digital interpreting practices, technology-driven environments are far from socially neutral. Remote, platform-mediated translation systems, algorithmic labour management, and automated performance monitoring introduce specific socio-economic pressures. These digital frameworks can easily reinforce existing inequalities, limit the professional visibility of human translators, and reduce complex cultural mediation to a mechanical post-editing task [3, p. 5880].

In addition, AI-driven analytics in translation has evolved beyond merely generating target text; it now includes the systemic, automated evaluation of behavioural translation workflows, cognitive loads, structural fidelity, and semantic granularity. By employing deep analytics, researchers can quantify stylistic drift, predict post-editing efforts, and structurally evaluate localised texts. The theoretical framework of AI translation analytics is built on Deep Learning-based Semantic Estimation and Automated Translation Quality Assessment (TQA). In contemporary practice, translation analytics leverages transformer architectures to analyse multi-level linguistic

and visual data concurrently, rather than relying exclusively on human peer review [3, p. 5875–5884].

Large Language Models (LLMs) now actively generate diagnostic metadata related to translation fluency, cultural context, and error categorisation. This development has transformed TQA from a static, post-completion review into a dynamic computational pipeline, providing researchers with detailed insights into linguistic anomalies across legal, medical, and technical genres [4]. A central tension identified in contemporary translation analytics revolves around genre-specific performance. In rigid, domain-specific fields like legal and technical documentation, AI-driven analytics and generation models demonstrate remarkable fidelity, sometimes exhibiting fewer syntactic mistakes than unassisted human translators in routine technical drafts [4]. This occurs because legal and technical texts heavily favour semantic predictability and structured terminological networks. However, contrastive studies highlight that AI models lack the socio-cultural lived experience necessary to decode implicit intent, subtext, and regional idioms. Consequently, while AI translation analytics tools excel at identifying overt grammatical errors, they struggle to interpret ideological or poetic nuances, reinforcing the consensus that entirely automated pipelines fall short in tasks requiring literary finesse or highly sensitive transcreation [4; 5].

The findings of the study demonstrate that AI-driven analytics has fundamentally reshaped the landscape of translation research and practice, allowing for unprecedented levels of scalability, automation, and data-driven evaluation. Advances in Neural Machine Translation (NMT) and Large Language Models (LLMs) have significantly enhanced translation fluency and analytical capabilities, enabling researchers to explore linguistic patterns, quality indicators, and translation processes with a precision previously unattainable. However, evidence from quantitative linguistics and translationese research indicates that machine-generated translations increasingly

display a distinct linguistic profile characterised by lexical standardisation, reduced stylistic variability, and simplified syntactic structures [4; 6]. While these traits may enhance consistency and readability, they raise concerns about the preservation of linguistic richness, creativity, and cultural specificity.

Beyond linguistic considerations, the widespread adoption of AI technologies is reshaping the translation professional ecosystem. The growing reliance on automated systems affects translators' workflows, cognitive engagement, professional autonomy, and labour market conditions, presenting new ethical and socio-economic challenges for the discipline. These developments suggest that the future of translation cannot be understood solely through technological performance metrics but must also consider the human dimensions of intercultural communication [5]. Therefore, the sustainable advancement of AI-driven translation analytics requires a collaborative rather than substitutional paradigm. The strength of machine learning lies in its ability to process vast quantities of multilingual data, identify patterns, and support decision-making. In contrast, human translators contribute contextual awareness, ethical judgment, cultural competence, and critical interpretation. Future research and professional practice should prioritize integrated human-AI frameworks that balance computational efficiency with linguistic accuracy, cultural sensitivity, and communicative responsibility.

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