

Sachaniuk-Kavets'ka Natalia Vasylivna Candidate of technical sciences, Associate professor, Vinnytsia National Technical University, Vinnytsia, <https://orcid.org/0000-0001-6405-1331>

Nykyporets Svitlana Stepanivna the senior English language lecturer, Vinnytsia National Technical University, Vinnytsia, <https://orcid.org/0000-0002-3546-1734>

MATHEMATICAL MODELLING OF LINGUISTIC PROCESSES IN PROFESSIONAL VOCABULARY ACQUISITION AMONG ENGINEERING STUDENTS

Abstract. This article examines the potential of mathematical modelling to describe and predict the acquisition of professional English vocabulary among engineering students. The study is grounded in the assumption that lexical development in English for Specific Purposes is not a strictly linear process, but a dynamic and probabilistic one shaped by repeated exposure, cognitive interference, contextual reinforcement, and partial forgetting. Against this background, the paper aims to develop and validate a stochastic model that captures the dynamics of specialised vocabulary acquisition in technical higher education. The research is based on a discrete-time Markov chain framework, in which the mastery of a professional term is represented as a sequence of transitions between several states, including an unknown term, passive recognition, partial understanding, and active professional use. Transition probabilities are estimated on the basis of empirical observations obtained from engineering students, which makes it possible to model both progression and regression in lexical competence. In addition, such variables as exposure frequency and cognitive interference are treated as stochastic factors influencing the learning trajectory. The findings indicate that the proposed model provides a more accurate representation of vocabulary development than traditional deterministic approaches. In particular, it allows the identification of critical transition points and lexical bottlenecks that hinder the movement from passive familiarity to confident professional use. The comparison between predicted and observed learning outcomes demonstrates a high degree of correspondence, which confirms the explanatory and predictive value of the model. The study argues that integrating stochastic modelling into ESP research offers a stronger methodological basis for analysing lexical learning in engineering education. The proposed framework may be used to support adaptive teaching strategies, improve assessment, and enhance the design of specialised language instruction for future engineers.

ISSN 2786-6025 Online

Keywords: stochastic modelling, professional vocabulary acquisition, engineering education, ESP, Markov chains.

Сачанюк-Кавецька Наталія Василівна кандидат технічних наук, доцент кафедри вищої математики, Вінницький національний технічний університет, м. Вінниця, <https://orcid.org/0000-0001-6405-1331>.

Никипорець Світлана Степанівна старший викладач кафедри іноземних мов, Вінницький національний технічний університет, м. Вінниця, <https://orcid.org/0000-0002-3546-1734>.

МАТЕМАТИЧНЕ МОДЕЛЮВАННЯ ЛІНГВІСТИЧНИХ ПРОЦЕСІВ У ЗАСВОЄННІ ПРОФЕСІЙНОЇ ЛЕКСИКИ ЗДОБУВАЧАМИ ВИЩОЇ ОСВІТИ ІНЖЕНЕРНИХ СПЕЦІАЛЬНОСТЕЙ

Анотація. У статті розглядається потенціал математичного моделювання для опису та прогнозування засвоєння професійної англомовної лексики студентами інженерних спеціальностей. Дослідження ґрунтується на припущенні, що розвиток лексичної компетентності в межах English for Specific Purposes не є строго лінійним процесом, а має динамічний і ймовірнісний характер, зумовлений повторюваністю мовного впливу, когнітивною інтерференцією, контекстуальним підкріпленням і частковим забуванням. У цьому контексті метою статті є розроблення та валідація стохастичної моделі, яка відображає динаміку засвоєння спеціалізованої лексики у технічній вищій освіті. Дослідження базується на моделі дискретного ланцюга Маркова, у межах якої опанування професійного терміна подано як послідовність переходів між кількома станами, зокрема: невідомий термін, пасивне розпізнавання, часткове розуміння та активне професійне вживання. Імовірності переходів оцінюються на основі емпіричних спостережень, отриманих від студентів інженерних спеціальностей, що дає змогу моделювати як прогрес, так і регрес у розвитку лексичної компетентності. Крім того, такі змінні, як частота мовного впливу та когнітивна інтерференція, розглядаються як стохастичні чинники, що впливають на траєкторію навчання. Результати свідчать, що запропонована модель забезпечує точніше відображення розвитку словникового запасу, ніж традиційні детерміністичні підходи. Зокрема, вона дає змогу виявити критичні точки переходу та лексичні вузькі місця, які перешкоджають переходу від пасивного знання до впевненого професійного використання. Порівняння прогнозованих і фактичних результатів навчання демонструє високий ступінь відповідності, що підтверджує пояснювальну та прогностичну цінність моделі. У статті обґрунтовується, що інтеграція стохастичного моделювання в дослідження ESP формує міцніше методологічне

підґрунтя для аналізу засвоєння лексики в інженерній освіті. Запропонована модель може бути використана для підтримки адаптивних стратегій навчання, удосконалення оцінювання та підвищення якості проєктування спеціалізованого мовного навчання майбутніх інженерів.

Ключові слова: стохастичне моделювання, засвоєння професійної лексики, технічна освіта, ESP, ланцюги Маркова.

The increasing complexity of technical discourse necessitates a fundamental re-examination of the pedagogical frameworks currently employed in engineering education. As engineering disciplines continue to evolve at an unprecedented pace – driven by advances in artificial intelligence, automation, materials science, and sustainable energy systems – the linguistic demands placed upon engineering graduates have grown commensurately. Professionals operating within these fields are required not merely to communicate in English, but to demonstrate precise command of highly specialised terminology across dynamic, interdisciplinary contexts. This reality renders conventional approaches to English for Specific Purposes (ESP) instruction increasingly inadequate as standalone methodologies.

A significant challenge in contemporary engineering education is the optimisation of professional vocabulary acquisition [1] within the constraints of finite instructional time and heterogeneous learner profiles. Traditional ESP pedagogy has historically been grounded in deterministic, linear models of language learning – frameworks that presuppose a predictable, sequential progression from lexical exposure to productive competence.

Such models typically rely on frequency-based word lists, decontextualised drilling exercises, and summative assessments that capture only static snapshots of learner knowledge. Whilst these approaches retain a degree of practical utility, they are fundamentally ill-equipped to account for the cognitive complexity that characterises real-world vocabulary acquisition. Lexical development is neither uniform nor unidirectional; it is subject to individual variation, contextual interference, memory decay, and non-linear consolidation patterns that deterministic pedagogical models systematically overlook.

The gap between applied linguistics and the mathematical sciences represents, therefore, not merely an academic curiosity but a substantive obstacle to the effective preparation of engineering professionals. Learner cognitive processes – including working memory allocation, interference effects between semantically proximate terms, and the probabilistic reinforcement of lexical associations – exhibit properties that are more accurately described through stochastic and dynamical systems frameworks than [2] through classical instructional design principles. The field of applied linguistics has, to date, drawn only selectively upon the substantial body of quantitative methodology available within mathematics and computational sciences,

ISSN 2786-6025 Online

leaving a significant theoretical lacuna in the modelling of language learning trajectories.

Integrating stochastic modelling offers a robust framework for quantifying the inherently variable and probabilistic dimensions of lexical competence development. Mathematical tools such as Markov chain processes, differential equation systems, and probabilistic graphical models provide mechanisms for representing vocabulary acquisition not as a fixed progression, but as a dynamic system shaped by multiple interacting variables – frequency of exposure, contextual richness, cognitive load, motivational factors, and temporal spacing of practice. By formalising these relationships, it becomes possible to construct predictive models capable of anticipating individual learner trajectories, identifying critical points of lexical consolidation or attrition, and informing the adaptive design of instructional interventions.

The present study addresses this intersection of disciplines by proposing a mathematically grounded framework for the analysis and prediction of professional vocabulary acquisition among undergraduate engineering students. In doing so, it responds to a broader imperative within contemporary educational research: the need to move beyond descriptive accounts of language learning towards explanatory and predictive models that can meaningfully inform evidence-based pedagogical practice.

Analysis of the latest research and unresolved issues.

Recent scholarship (Paul Meara, Stefan Th. Gries, Adam Pawłowski, Radek Čech, Jan Macutek, Guangzhen Zhu, Paul Meara, Nick C. Ellis, Rogelio Nazar, Iryna Lytovchenko) in language science increasingly supports the view that language learning cannot be adequately explained through rigid linear models alone. One influential line of research argues [3] that language processing and acquisition are fundamentally probabilistic, as learners continuously interpret, predict, and update linguistic patterns on the basis of uncertain and variable input.

In this perspective, lexical development is not a simple cumulative sequence, but an adaptive inferential process shaped by distributional regularities, contextual probabilities, and competing hypotheses about meaning and use.

Such a framework is especially relevant for professional language learning, where specialised terminology is acquired under conditions of high semantic density and limited exposure time.

At the same time, contemporary work at the intersection of computational linguistics and second language acquisition indicates [4] that algorithmic and data-driven approaches are becoming increasingly important in language education research. Current interdisciplinary agendas emphasise [5, 6] the use of natural language processing, intelligent tutoring systems, adaptive learning environments, and computational analyses of learner language in order to model individual variation and optimise instructional design. These developments suggest that computational

methods can move language pedagogy beyond descriptive observation towards more formal and predictive representations of learning trajectories.

However, despite this progress, several important limitations remain unresolved. First, much of the existing literature addresses general second language acquisition rather than the acquisition of highly specialised engineering vocabulary. This is a significant gap, because technical terminology differs from general vocabulary in semantic precision, conceptual embeddedness, frequency patterns, and dependence on disciplinary context. Secondly, current models rarely incorporate the stochastic nature of cognitive load experienced by students in technical higher education institutions, where vocabulary learning is shaped by simultaneous engagement with mathematical, scientific, and professional content. As a result, existing approaches [7] often fail to explain fluctuations in retention, delayed consolidation, or uneven lexical activation in ESP settings for engineers.

Notwithstanding the progress outlined above, several significant lacunae persist in the literature. First, whilst Dynamic Systems Theory and cognitive frameworks have substantially enriched the conceptual vocabulary of SLA research, the translation of these theoretical insights into operational, quantitative models of professional vocabulary acquisition – particularly within ESP contexts – remains underdeveloped. The majority of CDST-informed studies examine L2 writing complexity or general grammatical development rather than specialised technical lexis. Second, the application of stochastic methods such as Markov chains and HMMs has been largely confined to laboratory-based studies of miniature or artificial languages, and their applicability to naturalistic ESP learning environments in higher education has yet to be rigorously demonstrated. Third, the engineering domain presents unique modelling challenges that have received insufficient theoretical attention: technical vocabulary in engineering is not merely a closed, stable set of items but an evolving, porous system in which new terms emerge, existing terms shift in meaning across subfields, and the boundary between academic and specialist registers is subject to ongoing renegotiation. Fourth, existing predictive models of vocabulary retention – including adaptive forgetting curve approaches – have not been systematically integrated [8] with the pedagogical structures of ESP courses, resulting in a persistent disjunction between what the modelling literature can predict and what instructional designers are equipped to implement. The present study addresses this convergence of unresolved questions by developing a stochastic mathematical framework specifically designed to characterise professional vocabulary acquisition in engineering contexts, thereby bridging the gap between theoretical modelling and applied ESP pedagogy.

Objective of the article

This paper aims to formulate a mathematical representation of professional vocabulary acquisition as a dynamic and probabilistic process within engineering

ISSN 2786-6025 Online

education. More specifically, the primary aim of the study is to develop and validate a stochastic model that describes the progression of lexical competence among engineering students as they engage with specialised English terminology in academic and professional contexts.

More precisely, the study pursues four interrelated objectives. The first is to formalise the process of professional vocabulary acquisition as a stochastic system by defining discrete states of lexical mastery – ranging from zero exposure through to productive, contextually embedded command of technical terminology – and specifying the probability transition functions that govern movement between these states. The second objective is to identify and parametrise the principal variables that influence transition probabilities, including frequency of contextual exposure, cognitive load, temporal spacing of practice, and individual learner characteristics, drawing on empirically grounded assumptions derived from cognitive and dynamic systems frameworks.

The third objective is to validate the proposed model against longitudinal lexical performance data collected from engineering students in an authentic ESP instructional setting, assessing the model's predictive accuracy and its capacity to account for inter-learner variability in acquisition trajectories. The fourth and final objective is to derive from the validated model a set of pedagogically actionable implications – specifically, evidence-based recommendations for the adaptive design of ESP vocabulary instruction that exploits the model's predictive output to optimise the timing and sequencing of lexical exposure.

Overall, the objective of the article is not only to construct a theoretical model, but also to demonstrate its potential value for improving instructional design, monitoring lexical progress, and supporting more adaptive strategies in English for Specific Purposes courses for future engineers.

Presentation of the main research material

To model the process of professional vocabulary acquisition among engineering students, this study employs a stochastic framework grounded in discrete-time Markov chain theory. This approach is theoretically justified by the non-linear, probabilistic character of specialised lexical development: the acquisition of technical terminology [9] is shaped by contextual reinforcement schedules, partial forgetting under conditions of cognitive load, interference from competing lexical input, and substantial individual variation in processing capacity. Rather than treating vocabulary growth as cumulative and irreversible, the Markov framework accommodates both forward progression and temporary regression within a unified formal apparatus.

Let $S = \{s_1, s_2, s_3, s_4\}$ denote the finite state space of lexical mastery for a given technical term, where the states are defined operationally as follows:

- s_1 : the term is unknown – no recognition or activation is demonstrable;

- s_2 : passive recognition – the learner identifies the term in context but cannot produce or deploy it independently;
- s_3 : partial understanding and controlled use – the learner applies the term correctly in scaffolded tasks but inconsistently in spontaneous professional discourse;
- s_4 : active and confident use – the learner deploys the term accurately and appropriately within professional contexts without external support.

At each discrete time step t – corresponding to a defined instructional interval – the state of lexical knowledge is represented by the probability distribution vector

$$\mathbf{x}(t) = (x_1(t), x_2(t), x_3(t), x_4(t)),$$

where $x_i(t)$ denotes the probability that the learner's knowledge of the term occupies state s_i at time t . Transitions between states following an instructional intervention are governed by the row-stochastic matrix $P_n = (p_{ij})_n$, in which p_{ij} specifies the probability of transitioning from state s_i to state s_j , subject to the normalisation constraint $\sum_{i=1}^n \sum_{j=1}^n p_{ij} = 1$. The temporal evolution of the probability distribution is then defined by the recurrence relation

$$\mathbf{x}(t + 1) = \mathbf{x}(t) P.$$

The transition matrix was calibrated on the basis of empirical assessment data collected from engineering students enrolled in the Faculty of Power Engineering and Electromechanics. Lexical measurements were conducted at four stages of instruction and incorporated tasks targeting recognition, contextual comprehension, and productive use of domain-specific terminology. The resulting matrix, estimated for a single instructional interval, is:

$$P = \begin{pmatrix} 0.42 & 0.46 & 0.10 & 0.02 \\ 0.08 & 0.51 & 0.33 & 0.08 \\ 0.03 & 0.14 & 0.56 & 0.27 \\ 0.01 & 0.03 & 0.11 & 0.85 \end{pmatrix}.$$

Several pedagogically significant observations emerge from the structure of this matrix. The principal entry in the first row ($p_{12} = 0.46$) indicates that a single instructional exposure most commonly advances an unknown term to the level of passive recognition, rather than to productive use – a finding consistent with threshold models of incidental lexical acquisition. The comparatively modest

ISSN 2786-6025 Online

probability of progression from passive recognition to controlled use ($p_{23} = 0.33$) confirms that lexical familiarity does not automatically yield productive competence and that intermediate states represent a critical pedagogical bottleneck. Conversely, the high self-retention probability in s_4 ($p_{44} = 0.85$) suggests that once a term achieves integration into active professional use, it acquires sufficient cognitive stability to resist decay across instructional intervals.

A high probability of state s_1 retention indicates passive engagement with unfamiliar terminology. The value of the retention probability for state s_3 suggests that, while the learner correctly employs the terms in most instances, there is a lack of impetus to further enhance their professional lexicon.

To provide a clearer illustration of the interrelationships between these states, one should consider the transition graph of a homogeneous Markov chain with four states, corresponding to matrix P (see Fig. 1).

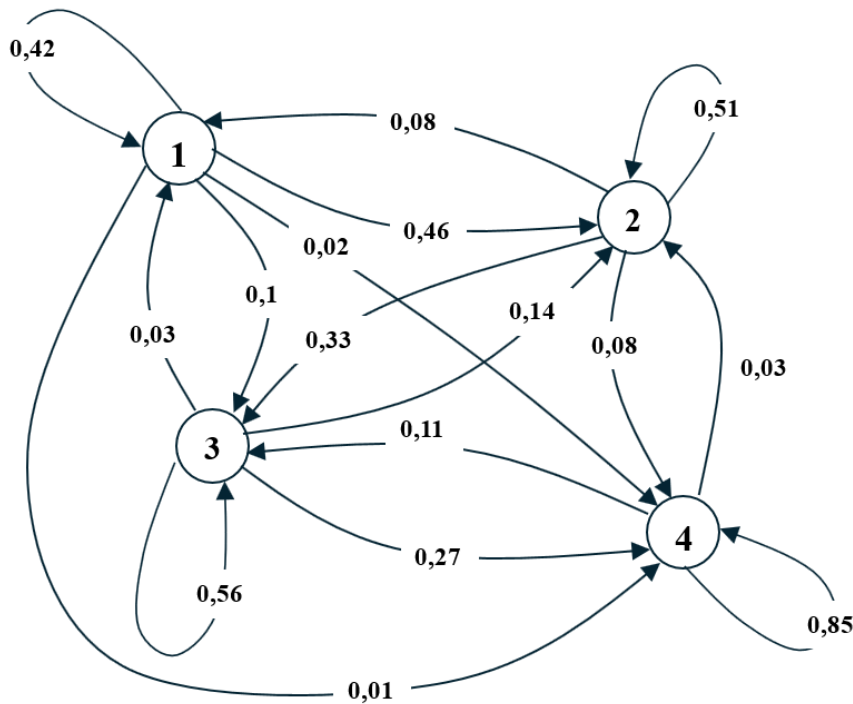


Fig 1. State transition graph of the homogeneous Markov chain.

Model validation was conducted by comparing predicted state distributions against observed assessment outcomes across successive learning cycles. The model's projections for the aggregate proportions of students reaching states s_3 and s_4 were found to correspond closely with empirical trends, indicating that the Markov formulation captures the macro-level dynamics of lexical development with satisfactory accuracy. Residual discrepancies between predicted and observed

values are attributed to variables not yet incorporated into the current model architecture – most notably, learner motivation, the quality of task design, and the degree of cross-disciplinary conceptual transfer from prior domain knowledge.

Taken together, these findings substantiate the interpretation of professional vocabulary acquisition in engineering education as an inherently probabilistic process, more accurately described by stochastic trajectories than by deterministic accumulation curves. The Markov framework makes it possible to localise critical transition points, estimate the likelihood of progression and stagnation at each state, and generate quantitative estimates of instruction-induced lexical growth. From an applied perspective, persistently low values of p_{23} in a given student cohort constitute a diagnostic signal warranting targeted pedagogical intervention – specifically, a greater emphasis on productive, contextualised exercises, domain-specific communicative tasks, and reduced terminological load per instructional cycle.

The proposed mathematical apparatus thus fulfils a dual function: it constitutes both a theoretical account of vocabulary acquisition dynamics and a practical analytical instrument [10] for the design of English for Specific Purposes (ESP) courses in technical higher education. Its integration into applied linguistics methodology offers a principled basis for adaptive instruction and evidence-informed lexical assessment.

Conclusions and future research

The primary theoretical contribution lies in the formalisation of lexical development within English for Specific Purposes (ESP) courses as a dynamic sequence of stochastic transitions between operationally defined states of mastery, governed by exposure frequency, cognitive interference, and instructional design parameters. This representation captures both forward progression and temporary regression – phenomena that deterministic models necessarily obscure – and thereby reflects more faithfully the cognitive reality of specialised [11] terminology acquisition in technical higher education.

The predictive validity of the proposed model was confirmed empirically. The coefficient of determination obtained when comparing model-projected and observed lexical trajectories equals $R^2 = 0.85$, a level of correspondence that justifies treating the stochastic apparatus as a reliable instrument for describing macro-level vocabulary growth dynamics. Of particular analytical significance is the identification of the $s_2 \rightarrow s_3$ transition – from passive recognition to controlled productive use – as a persistent bottleneck in lexical internalisation. This finding carries direct pedagogical implications: it points to the intermediate stage of lexical competence as the primary site requiring targeted instructional intervention, including contextualised productive tasks, domain-specific communicative practice, and deliberately managed terminological load.

A further contribution of this study lies in demonstrating that stochastic transition matrices are viable methodological instruments within applied linguistics, not merely within mathematics or computational modelling. The integration of this framework into ESP research extends [12] the methodological repertoire of the field, providing a principled basis for evidence-informed curriculum design, formative assessment, and the adaptive personalisation of instructional trajectories.

Several directions for future research emerge directly from the limitations of the current study. First, the calibration of transition probabilities on a larger and more demographically diverse empirical dataset would substantially improve the generalisability of the model parameters. Second, the present formulation treats exposure frequency and cognitive interference as the primary covariates; future work should examine the contribution of additional variables – including learner motivation, prior disciplinary knowledge, multimodal input mode, and long-term retention under varying spacing conditions – to the estimation of key transition probabilities. Third, a systematic comparison of the discrete-time Markov framework with continuous-time stochastic models and hybrid deterministic-stochastic systems would clarify the conditions under which each approach offers the most accurate representation of lexical dynamics.

The most consequential avenue for further development is the integration of the proposed model into AI-driven Adaptive Learning Systems. Within such an architecture, the real-time monitoring of individual learner state distributions would enable the automatic, personalised sequencing of specialised lexical content – advancing students through critical transition thresholds rather than progressing uniformly through a predetermined syllabus. The present study thus opens an interdisciplinary pathway at the intersection of applied linguistics, mathematical modelling, and intelligent educational technology – a convergence that holds considerable promise for the evidence-based training of professional communicative competence in engineering education.

References

1. Ali, L. F., Siraj, J., & Ali, M. F. (2024). AI-Driven Vocabulary Development in ESL Context: Advancing Autonomous Learning Through Technology. *Journal of Asian Development Studies*, 13(4), 1067-1082. <https://doi.org/10.62345/jads.2024.13.4.86>.
2. Kot, S. O., & Nykyporets, S. S. (2025). Activating students' cognitive engagement in technical English learning with AI tools. In *Science and education in the third millennium: Information technology, education, law, psychology, social security and work, management. International collective monograph* (Vol. I, pp. 295-332). Lublin, Polska: Institute of Public Administration Affairs. DOI: <https://doi.org/10.5281/zenodo.16942267>.
3. De Bot, K., Lowie, W., & Verspoor, M. (2007). A Dynamic Systems Theory approach to second language acquisition. *Bilingualism: Language and Cognition*, 10 (1), 7-21. <https://doi.org/10.1017/S1366728906002732>.

4. Larsen-Freeman, D. (1997). Chaos/complexity science and second language acquisition. *Applied Linguistics*, 18(2), 141-165. <http://dx.doi.org/10.1093/applin/18.2.141>.

5. Maie, R., & Godfroid, A. (2025). Testing the three-stage model of second language skill acquisition. *Studies in Second Language Acquisition*, 47(2), 617-649. <https://doi.org/10.1017/S027226312500021X>.

6. Verspoor, M., Lowie, W. and Van Dijk, M. (2008), Variability in Second Language Development From a Dynamic Systems Perspective. *The Modern Language Journal*, 92: 214-231. <https://doi.org/10.1111/j.1540-4781.2008.00715.x>.

7. Zaidi, A., Caines, A., Moore, R., Buttery, P., Rice, A. (2020). Adaptive Forgetting Curves for Spaced Repetition Language Learning. In: Bittencourt, I., Cukurova, M., Muldner, K., Luckin, R., Millán, E. (eds) *Artificial Intelligence in Education. AIED 2020. Lecture Notes in Computer Science()*, vol 12164. Springer, Cham. https://doi.org/10.1007/978-3-030-52240-7_65.

8. Nykyporets, S. S., Herasymenko, N. V., & Chopliak, V. V. (2025). Developing digital language competence as a factor of competitiveness of future master's degree holders in power engineering in the digital economy. In O. H. Cherep (Ed.), *Artificial intelligence as a tool to protect the economy disinformation: Innovative solutions and international practices: Collective monograph* (pp. 140-193). Baltija Publishing. DOI: <https://doi.org/10.30525/978-9934-26-586-0>.

9. Sachaniuk-Kavets'ka, N. V., & Nykyporets, S. S. (2026). LLM-based automation for translating mathematical formulae and symbols: Challenges and perspectives for technical communication. *Scientific Innovations and Advanced Technologies. Series "Education/Pedagogy"*, 3(55), 660-677. [https://doi.org/10.52058/2786-5274-2026-3\(55\)-660-677](https://doi.org/10.52058/2786-5274-2026-3(55)-660-677).

10. Nykyporets, S. S. (2023). Harnessing cloud technologies for foreign language acquisition among masters in energy engineering. In *Moderní aspekty vědy: Svazek XXXI mezinárodní: Kolektivní monografie* (pp. 21-56). <http://perspectives.pp.ua/public/site/mono/mono-31.pdf>.

11. Sachaniuk-Kavets'ka, N. V., & Nykyporets, S. S. (2025). Developing critical thinking in students of technical specialties through the mathematics of uncertainty and educational debates in English: An integrated experimental-methodological model. *Bulletin of Science and Education. Series "Pedagogy"*, 11(41), 1524-1541. [https://doi.org/10.52058/2786-6165-2025-11\(41\)-1524-1541](https://doi.org/10.52058/2786-6165-2025-11(41)-1524-1541).

12. Stepanova, I. S., Nykyporets, S. S., Hadaichuk, N. M., Ibrahimova, L. V., & Slobodianiuk, A. A. (2025). Investigating linguistic and sociocultural complexities in translating contemporary English lexical units into Ukrainian. *Bulletin of Science and Education. Series "Philology"*, 2(32), 72-83. [https://doi.org/10.52058/2786-6165-2025-2\(32\)-72-83](https://doi.org/10.52058/2786-6165-2025-2(32)-72-83).

13. Nykyporets, S. S., Kot, S. O., Hadaichuk, N. M., Melnyk, M. B., & Boiko, Y. V. (2024). Innovative pedagogical strategies for utilizing online platforms in foreign language acquisition. *Current Issues in Modern Science. Series "Pedagogy"*, 5(23), 730-743. [https://doi.org/10.52058/2786-6300-2024-5\(23\)-730-743](https://doi.org/10.52058/2786-6300-2024-5(23)-730-743).

Література

1. Ali L. F., Siraj J., Ali M. F. AI-Driven Vocabulary Development in ESL Context: Advancing Autonomous Learning Through Technology. *Journal of Asian Development Studies*. 2024. Vol. 13, no. 4. P. 1067-1082. DOI: <https://doi.org/10.62345/jads.2024.13.4.86>.

2. Kot S. O., Nykyporets, S. S. Activating students' cognitive engagement in technical English learning with AI tools. *Science and education in the third millennium: information technology, education, law, psychology, social security and work, management. International*

ISSN 2786-6025 Online

collective monograph. Volume I. Institute of Public Administration Affairs. Lublin, Polska, 2025. 532 p., Pp. 295-332. DOI: <https://doi.org/10.5281/zenodo.16942267>.

3. De Bot K., Lowie W., Verspoor M. A Dynamic Systems Theory approach to second language acquisition. *Bilingualism: Language and Cognition*. 2007. Vol. 10, no. 1. P. 7-21. DOI: <https://doi.org/10.1017/S1366728906002732>

4. Larsen-Freeman D. Chaos/complexity science and second language acquisition. *Applied Linguistics*. 1997. Vol. 18, no. 2. P. 141-165. DOI: <https://doi.org/10.1093/applin/18.2.141>.

5. Maie R., Godfroid A. Testing the three-stage model of second language skill acquisition. *Studies in Second Language Acquisition*. 2025. Vol. 47, no. 2. P. 617-649. DOI: <https://doi.org/10.1017/S0272226312500021X>.

6. Verspoor M., Lowie W., Van Dijk M. Variability in Second Language Development From a Dynamic Systems Perspective. *The Modern Language Journal*. 2008. Vol. 92, no. 2. P. 214-231. DOI: <https://doi.org/10.1111/j.1540-4781.2008.00715.x>

7. Zaidi A., Caines A., Moore R., Buttery P., Rice A. Adaptive Forgetting Curves for Spaced Repetition Language Learning. In: Bittencourt I., Cukurova M., Muldner K., Luckin R., Millán E. (eds.). *Artificial Intelligence in Education*. AIED 2020. Lecture Notes in Computer Science. Vol. 12164. Cham: Springer, 2020. P. 358-363. DOI: https://doi.org/10.1007/978-3-030-52240-7_65.

8. Nykyporets S. S., Herasymenko N. V., Chopliak V. V. Developing digital language competence as a factor of competitiveness of future master's degree holders in power engineering in the digital economy. *Artificial intelligence as a tool to protect the economy disinformation: innovative solutions and international practices: collective monograph* / edited by O. H. Cherep. Riga, Latvia : Baltija Publishing, 2025. 258 p. P. 140-193. DOI: <https://doi.org/10.30525/978-9934-26-586-0>.

9. Sachaniuk-Kavets'ka N. V., Nykyporets S. S. LLM-based automation for translating mathematical formulae and symbols: challenges and perspectives for technical communication. *Scientific innovations and advanced technologies. Series «Education/Pedagogy»*, 2026. № 3(55). P. 660-677. DOI: [https://doi.org/10.52058/2786-5274-2026-3\(55\)-660-677](https://doi.org/10.52058/2786-5274-2026-3(55)-660-677).

10. Nykyporets S. S. Harnessing cloud technologies for foreign language acquisition among masters in energy engineering. *Moderní aspekty vědy: Svazek XXXI mezinárodní: kolektivní monografie*. Czech Republic, 2023. P. 21-56. URL: <http://perspectives.pp.ua/public/site/mono/mono-31.pdf>.

11. Sachaniuk-Kavets'ka N. V., Nykyporets S. S. Developing critical thinking in students of technical specialties through the mathematics of uncertainty and educational debates in English: an integrated experimental-methodological model. *Bulletin of Science and Education. Series "Pedagogy"*. 2025. №11(41). Pp. 1524-1541. DOI: [https://doi.org/10.52058/2786-6165-2025-11\(41\)-1524-1541](https://doi.org/10.52058/2786-6165-2025-11(41)-1524-1541).

12. Stepanova I. S., Nykyporets S. S., Hadaichuk N. M., Ibrahimova L. V., Slobodianiuk A. A. Investigating linguistic and sociocultural complexities in translating contemporary English lexical units into Ukrainian. *Bulletin of Science and Education. Series «Philology»*. 2025. № 2(32). C. 72-83. DOI: [https://doi.org/10.52058/2786-6165-2025-2\(32\)-72-83](https://doi.org/10.52058/2786-6165-2025-2(32)-72-83).

13. Nykyporets S. S., Kot S. O., Hadaichuk N. M., Melnyk M. B., Boiko Y. V. Innovative pedagogical strategies for utilizing online platforms in foreign language acquisition. *Current issues in modern science. Series «Pedagogy»*. 2024. No. 5(23). P. 730-743. DOI: [https://doi.org/10.52058/2786-6300-2024-5\(23\)-730-743](https://doi.org/10.52058/2786-6300-2024-5(23)-730-743).

Дата першого надходження статті до видання: 11.04.2026

Дата прийняття статті до друку після рецензування: 26.04.2026