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MECHANISM OF DYNAMIC ADAPTATION OF SIMULATOR PARAMETERS FOR IMPLEMENTING INDIVIDUAL-AND-TEAM STRATEGIES IN AIR TRAFFIC CONTROLLER TRAINING

The paper presents mechanism for dynamic adaptation of simulator content aimed at implementing individual-and-team strategies in air traffic controller (ATCO) training within a competency-based learning paradigm. The relevance of the study is determined by the transition of ATCO training to ICAO- and EASA-based competency models, as well as by the need to improve simulator efficiency under increasing traffic complexity, staffing constraints, and stringent flight safety requirements. The purpose of the paper is to design mechanisms for dynamic control of simulator parameters that adapt the scenario to the individual-and-team state of trainees. The research combines systems analysis, competency-based training and assessment principles, Bayesian Knowledge Tracing for estimating the probability of mastering specific skills, and interpretable machine-learning models for explaining the team result. A cyclic six-module architecture of an adaptive simulator is proposed. It includes behaviour monitoring, diagnostics of risk and good-practice indicators, prediction of skill acquisition, dynamic scenario adaptation, explainable assessment, and post-session reporting. The study formalizes the session state vector, workload index, skill-deficit index, and the rule of wave-like complexity variation based on the logic "increase – peak – recovery". It is shown that adaptation should be not only quantitative but also targeted: depending on the dominant deficit, the system selects a focused event from a library of scenario interventions without driving the team beyond the productive training zone. Gradient boosting models combined with SHAP analysis are proposed to explain team assessment and to identify individual, negative, positive, and compensatory contributions of team members. The practical value of the results lies in creating a foundation for a new generation of simulator systems capable of maintaining trainees in a productive workload zone in real time, generating a post-training report for instructor, and increasing the precision of corrective pedagogical influence.

Key words: *air traffic controller, simulator training, adaptive learning, team competence, explainable artificial intelligence, BlueSky.*

Пальоний А. С., Зєнов Д. О. Механізм динамічної адаптації параметрів тренажерного середовища для реалізації індивідуально-командних стратегій підготовки авіадиспетчерів

У статті подано механізм динамічної адаптації контенту тренажерного середовища для реалізації індивідуально-командних стратегій підготовки авіадиспетчерів у логіці компетентнісно орієнтованого навчання. Актуальність дослідження зумовлена переходом системи підготовки авіадиспетчерів до компетентнісних моделей ICAO та EASA, а також потребою підвищення ефективності тренажерної підготовки в умовах зростання складності повітряного руху, кадрових обмежень і високих вимог до безпеки польотів. Метою статті є розроблення механізмів динамічного керування параметрами тренажерного середовища, які забезпечують адаптацію сценарію до поточного індивідуально-командного стану курсантів. У роботі використано системний аналіз, навчання та оцінювання на основі компетенцій, байєсівське відстеження знань для оцінювання ймовірності засвоєння окремих навичок, а також інтерпретовані моделі машинного навчання для пояснення командного результату. Запропоновано циклічну шестимодульну архітектуру адаптивного тренажера, що включає моніторинг поведінки, діагностику індикаторів ризику та позитивної практики, прогнозування засвоєння навичок, динамічну адаптацію сценарію, пояснювану оцінку та післятренажерну звітність. Формалізовано вектор поточного стану сесії, індекс навантаження, індекс

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дефіциту навички та правило хвильової зміни складності за логікою «нарощування – пік – відновлення». Показано, що адаптація має бути не лише кількісною, а й адресною: залежно від домінувального дефіциту система обирає подію з бібліотеки сценарних інтервенцій, не виводячи команду за межі навчального напруження. Для пояснення командної оцінки запропоновано використання моделей градієнтного бустингу з SHAP-аналізом, що дає змогу визначати індивідуальні, негативні, позитивні та компенсаційні внески членів команди. Практичне значення результатів полягає у створенні основи для тренажерних систем нового покоління, здатних у реальному часі підтримувати курсантів у зоні продуктивного навантаження, формувати прозорий післятренажерний звіт для інструктора та підвищувати адресність коригувального впливу.

Ключові слова: *авіадиспетчер, тренажерна підготовка, адаптивне навчання, командна компетентність, пояснюваний штучний інтелект, BlueSky.*

Formulation of the problem. A contemporary trend in the training of air traffic controllers (ATCOs) is the paradigm shift from practicing isolated procedures to developing measurable competencies within a real-world operational context, while the international regulatory framework explicitly requires the implementation of competency-based training and assessment (CBTA) for air traffic services (ATS) personnel [1, 2]. The revised Aviation Rules of Ukraine regarding ATCO licenses and certificates implement the provisions of Regulation (EU) 2015/340 and reinforce the need for formalized, evidence-based, and reproducible procedures for assessing and maintaining competency [3].

However, this problem is not exclusively educational in nature. By the end of 2024, delays within the Air Traffic Management (ATM) system in Europe reached their worst levels in a decade, with the *capacity and staffing* factor remaining a primary source of network instability [4, 5]. Under these conditions, the quality of ATCO simulator training has a particularly profound impact on the ATM system's capability to maintain safe, regular, economical, and environmentally sustainable air traffic by ensuring the operational resilience of the ATS system.

The majority of current simulator solutions either reproduce rigidly predefined scenarios or employ crude adjustments in complexity. Such an approach fails to account for the fact that an ATCO may experience either cognitive underload or overload, and that a team can partially mitigate the deficiencies of an individual specialist. Consequently, static adaptation loses its pedagogical precision: it cannot differentiate whether it is necessary to increase overall traffic intensity, generate a specific problematic event, or transition to a micro-step increment in workload. Therefore, there is a highly relevant need to develop a mechanism that integrates continuous assessment of team competency, predictive modeling of individual skill acquisition, and real-time scenario management.

Analysis of recent research and publications. The methodological foundation of modern ATCO training is shaped by ICAO and EASA documents, wherein competency is defined as the integration of knowledge, skills, and observable behaviors that must be assessed in the context of real or near-real operational conditions [1, 2, 6]. In European practice, a crucial supplementary framework is Team Resource Management (TRM), which focuses on team interaction and the collective utilization of information, technical equipment, and human resources to ensure safe and efficient ATS [7].

Two primary research streams can be distinguished within the international literature. The first involves formalized competency assessment models. Y. Hu et al. constructed a model for assessing the basic competencies of entry-level ATCOs based on ICAO Doc 10056, while J. Duan et al. developed a quantitative model for evaluating controller competency in a multi-position operational mode. M. Antoško et al. proposed a neuro-fuzzy technology for assessing the practical knowledge of student ATCOs in multi-tasking scenarios [8–10]. The advantage of these studies lies in their high degree of formalization; however, they predominantly conclude at the assessment stage and rarely progress to the adaptive management of simulator scenarios in real time.

The second stream encompasses research on workload, stress, fatigue, and the limits of an ATCO's productive performance. In contemporary literature, workload is increasingly conceptualized as a multidimensional state that can be evaluated using behavioral, temporal, operational, and physiological indicators. Academic studies focused on workload assessment in the ATC environment demonstrate the efficacy of combining expert, process-based, and empirical metrics; a distinct line of research is advancing the use of wearable sensors, electrophysiological, and multimodal data to detect stress and fatigue during simulator or near-operational activities [11, 12].

One of the key avenues of scientific inquiry directly related to the subject of our research involves team cognition – primarily shared mental models, team situational awareness, implicit coordination, and compensatory behavior within the controller crew. For instance, studies by M. Mathieu et al. demonstrated that a team's shared mental models and task characteristics interact and significantly influence the collective efficacy of controllers. Papers analyzing teamwork phenotypes in control towers and measuring the accuracy of team situational awareness in simulated environments further prove that the same final team performance can be achieved through different pathways – either via stable coordination or through the compensatory actions of individual members [13, 14].

In our previous studies, certain aspects of these approaches were adapted into a system of indicators for ATCO team competency and a hybrid model for its automated assessment [15]. Moreover, to track learning dynamics, interpretable machine learning models can be applied, facilitating the transition from «black-box» assessment to transparent post-simulation debriefing. Systematic reviews of Bayesian Knowledge Tracing (BKT)

indicate that this class of models remains one of the most suitable for the step-by-step estimation of the probability of acquiring a specific skill based on a sequence of observable actions. More recent research, even outside the aviation industry, confirms that BKT can function effectively as the core of an adaptive system when combined with human-like reasoning mechanisms or the intelligent selection of pedagogical interventions [16, 17]. Within the domain of explainable AI (XAI), studies in ATM and research on SHAP analysis, alongside work on human-centric explainability, demonstrate that the mere presence of an accurate prediction is insufficient: the instructor and the ATCO must receive a comprehensible explanation as to why the team lost or gained points, which specific factors were negative, which were compensatory, and which were proactively positive [18, 19].

Thus, contemporary scientific literature and regulatory documents already provide competency frameworks, objective data collection methods, and interpretable models for assessing ATCO team competency. However, there is an almost complete absence of solutions that integrate these components into a unified "monitoring – prediction – targeted adaptation – explanation" cycle. It is precisely this gap that defines the subject of our scientific research.

The purpose of the article is to develop mechanisms for the dynamic control of simulator environment parameters, facilitating the implementation of combined individual and team-based training strategies for ATCOs.

Presenting main material. Conceptually, a cyclical six-module architecture for an adaptive simulator is proposed, wherein monitoring results are directly translated into control actions applied to the scenario. The architecture includes: a behavior monitoring module, a diagnostic module for risk and good practice indicators, a predictive module for skill acquisition assessment, a dynamic scenario adaptation module, an explainable evaluation module, a post-simulation reporting module (Fig. 1). The open-source BlueSky simulator, which supports scenario management, text-based scenarios, and Python extensions, is utilized as the foundational implementation environment [20].

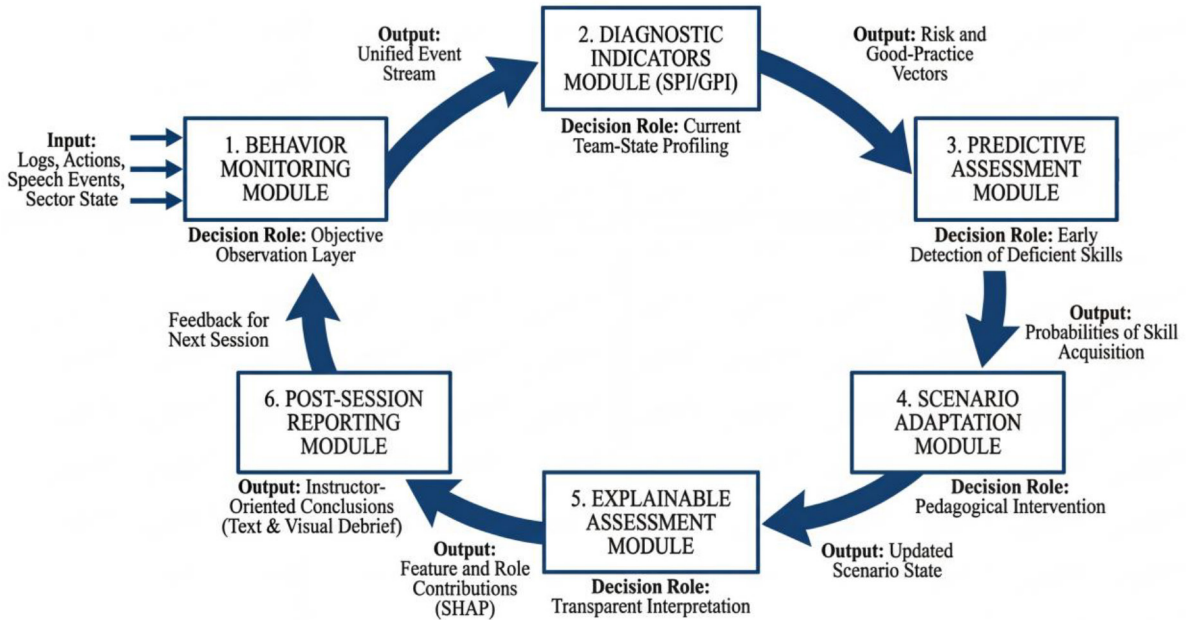

Fig. 1. Cyclical six-module architecture of an adaptive ATC simulator

In the proposed system, the dynamic adaptation module is not reduced to simply increasing or decreasing the exercise complexity. Its function consists of selecting a scenario state wherein the ATCO team is maintained within a zone of productive cognitive tension: without premature simplification, which preserves weaknesses, and without excessive complication, which shifts the performance into a state of disorganization.

Formally, the adaptive loop is described by the generalized state vector of the training session:

$$s(t) = (L(t), S(t), p(t), R(t), G(t)), \tag{1}$$

where $L(t)$ is the current level of scenario workload; S(t) is the stress (overload) state index; $p(t) = \{p_1(t), \ldots, p_K(t)\}$ is the vector of skill acquisition probabilities ($p_k(t)$ is the probability that the k-th skill is formed at time t); $R(t)$ is the vector of risk indicators; $G(t)$ is the vector of good practice indicators.

Within the framework of the proposed system, the current state vector of the training session is represented as:

$$s(t) = (x^{ind}(t), x^{team}(t), x^{sit}(t), R(t), G(t)), \tag{2}$$

where $x^{ind}(t)$ denotes the individual actions of specific trainees; $x^{team}(t)$ represents the team interaction characteristics; $x^{sit}(t)$ signifies the situational parameters of the air traffic environment.

Such a structure allows for the integration of log data, team response delays, conflict density, role distribution, and manifestations of proactive behavior into a unified description of the current state.

For each monitored skill k, a variable $p_k(t)$, is introduced, which is interpreted as the current probability of its acquisition. The updating of this value is executed using a simplified Bayesian tracking scheme:

$$p_k(t+\Delta t) = p_k(t) + \lambda_k y_k(t)(1-p_k(t)) - \mu_k(1-y_k(t))p_k(t), \tag{3}$$

where $p_k(t+\Delta t)$ is the updated probability of acquiring the k-th skill; $y_k(t)$ is the result of local observation; λ_k is the learning increment coefficient; μ_k is the penalty coefficient for persistent erroneous actions.

This model enables tracking not only the final outcome of the exercise but also the trajectory towards the stable mastery of a specific skill.

To prevent subjective mode switching, an aggregated operational workload index is primarily introduced:

$$W(t) = \beta_1 n_{ac}(t) + \beta_2 n_{conf}(t) + \beta_3 d_{resp}(t) + \beta_4 n_{coord}(t), \tag{4}$$

where $n_{ac}(t)$ is the number of aircraft in the sector; $n_{conf}(t)$ is the number of predicted or actual conflicts; $d_{resp}(t)$ is the average delay of critical responses; $n_{coord}(t)$ is the intensity of coordination acts; β_i are weight coefficients.

Thus, the index $W(t)$ reflects not only the geometric complexity of the air traffic but also the communication and coordination workload, which is of paramount importance for team training.

Based on $W(t)$ and the stress index $S(t)$ the current training zone is determined:

$$Z(t) = \begin{cases} Z_{relax}, & W(t) < \theta_1 \wedge S(t) < \sigma_1, \\ Z_{opt}, & \theta_1 \le W(t) \le \theta_2 \wedge S(t) \le \sigma_2, \\ Z_{over}, & W(t) > \theta_2 \vee S(t) > \sigma_2. \end{cases} \tag{5}$$

where Z_{relax} is the underload or "relaxation" zone"; Z_{opt} is the target optimal learning zone; Z_{over} is the overload zone; θ_1, θ_2 – are the lower and upper thresholds of scenario workload; σ_1, σ_2 are the thresholds of the stress index.

Next, a local skill deficit index is determined for each skill k:

$$D_k(t) = \omega_1(1-p_k(t)) + \omega_2 \bar{R}_k(t) - \omega_3 \bar{G}_k(t), \tag{6}$$

where $p_k(t)$ is the current probability of acquiring the k-th skill; $\bar{R}_k(t)$ is the aggregated risk contribution of those indicators specifically associated with skill k; $\bar{G}_k(t)$ is the aggregated positive contribution of the corresponding good practice indicators; ω1, ω2, ω3 are the weight coefficients representing the importance of the three components.

The probability of acquisition must be tracked separately for each skill. The higher $D_k(t)$ is, the more likely it is that the system should generate an event specifically targeting skill k. The proposed solution cannot rely solely on errors, because positive team behavior sometimes compensates for individual deficits and must not be ignored.

After determining the training zone and local deficits, the control action regarding the scenario complexity level is calculated:

$$L(t+\Delta t) = \Pi_{[L_{\min}, L_{\max}]}(L(t) + \delta_Z + \mu \max_k D_k(t) - \nu S(t)), \tag{7}$$

where $L(t+\Delta t)$ is the new level of scenario workload; $\Pi_{[L_{\min}, L_{\max}]}$ is the bounding operator within the permissible range; δ_Z is the base change depending on the zone $Z(t)$: $\delta_Z > 0$ in zone Z, $\delta_Z \approx 0$ in zone Z_{opt} and $\delta_Z < 0$ in zone Z; μ is the reaction coefficient to the largest identified skill deficit; ν is the workload suppression coefficient in response to rising stress.

Thus, the "wave" mechanism emerges not as an arbitrary sinusoid, but as a sequence of controlled phases: the system increases the intensity, maintains it at an educationally beneficial peak, and then partially releases the complexity if overload begins to accumulate. It is precisely this principle – not a linear escalation, but the alternation of phases – that constitutes the core operational principle of the «wave generator».

However, adjusting $L(t)$ alone is insufficient: the system must also select the ***type of complication***. To this end, a set of permissible events $E = \{e_1, \ldots, e_M\}$, is introduced, where each event possesses its own profile of didactic impact $d_e = (d_{e1}, \ldots, d_{eK})$. Then, the selection of the targeted event is defined as:

$$e^*(t) = \arg\max_{e \in E} \sum_{k=1}^{K} D_k(t) d_{ek} \quad \text{subject to} \quad \Delta W_e \le \Delta W_{\max}, \quad S_e \le \Delta S_{\max}, \tag{8}$$

where d_{ek} is the measure of the extent to which event e trains skill k; ΔW_e is the expected workload increment resulting from the event's introduction; ΔS_e is the expected stress index increment; $\Delta W_{\max}$ і $\Delta S_{\max}$ are the permissible increment limits.

This implies that the system does not select the "most difficult" event, but rather the one that most effectively addresses the identified deficit while simultaneously preventing the team from being pushed beyond the safe operational threshold.

Depending on the maximum value of $D_k(t)$ the adaptation module selects an event from the library of scenario interventions. If a coordination deficit predominates, the system generates an additional external or intra-sector coordination requirement; if resource management is lacking, it introduces a partial loss of informational support or a brief time constraint; if shared situational awareness deteriorates, it triggers an event requiring plan synchronization between the executive controller and the planning controller. Consequently, the adaptation assumes a targeted rather than a generalized character.

The dynamic scenario adaptation algorithm is presented in Fig. 2.

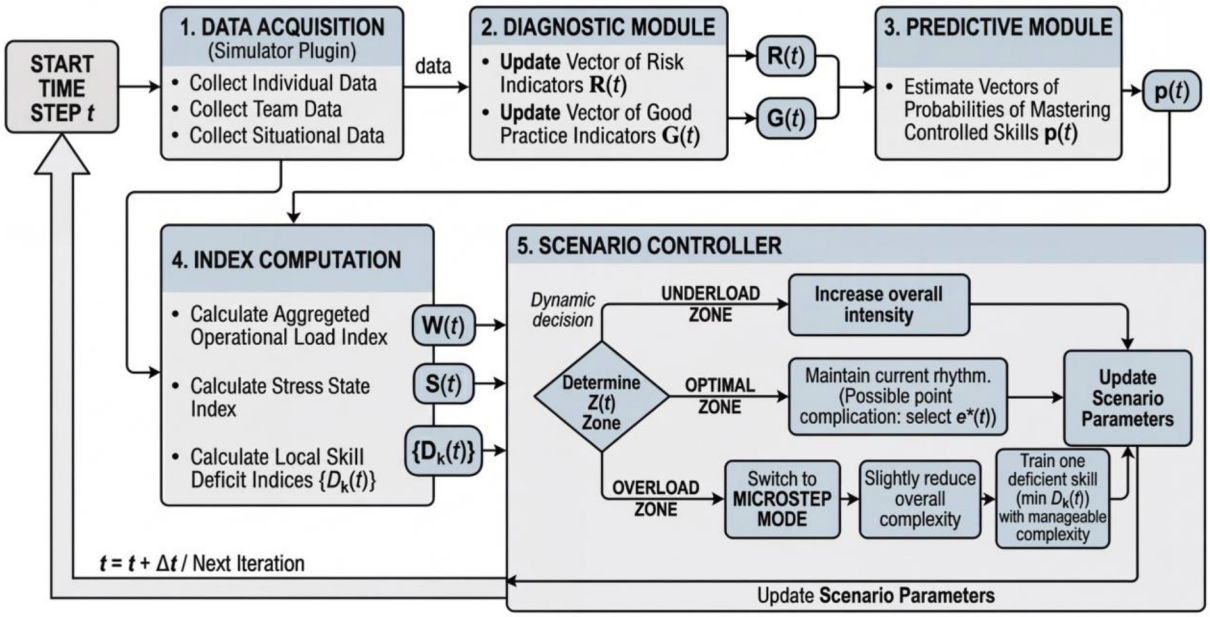

Fig. 2. Dynamic scenario adaptation algorithm model

At each time step, the simulator plugin collects individual, team, and situational data; diagnostic module updates $R(t)$ and $G(t)$; the predictive module updates $p(t)$; subsequently $W(t)$, $S(t)$, the zone $Z(t)$ and the deficits $D_k(t)$ are calculated; thereafter, the regulator adjusts the overall workload level $L(t + \Delta t)$ and, if necessary, selects the targeted event $e^*(t)$. If the team is in the underload zone, the intensity is increased; if they are in the optimal zone, the current rhythm is maintained with possible pinpoint complications; if overload is detected, the system transitions to a micro-step mode, wherein the overall complexity is slightly reduced, but the single most deficient skill continues to be trained through limited, controlled complication.

For the integral team assessment, the use of a gradient boosting model is proposed, and for its interpretation, SHAP (SHapley Additive exPlanations) analysis is utilized. The final prediction is decomposed into a base component and the sum of the contributions of individual features:

$$\hat{y} = \phi_0 + \sum_{f=1}^{F} \phi_f, \tag{9}$$

where $\hat{y}$ is the predicted final score of the team; ϕ_0 is the basic average value of the model; ϕ_f is the contribution of feature f; F is the total number of features.

The application of this approach makes it possible to explain exactly why the team received a specific result, detailing which indicators decreased it and which increased it.

For an ATCO team, not only feature-based but also role-based interpretation is crucial. Therefore, it is appropriate to define the individual contribution of participant "*a*" as the sum of their own SHAP contributions and a portion of the pairwise interactions:

$$\Delta_a = \sum_{f \in F_a} \phi_f + \frac{1}{2} \sum_{b \neq a} \sum_{f \in F_a} \sum_{g \in F_b} \Phi_{fg}, \tag{10}$$

where Δ_a is the contribution of participant "*a*" to the team result; F_a is the set of features characterizing their actions; Φ_{fg} represents the interaction between two features.

Due to this, the model can detect compensatory effects, where a high positive contribution from one participant partially neutralizes the risk manifestations of another.

Because the direct interpretation of multidimensional SHAP tensors Δ_a and Φ_{fg} can be excessively complex for the instructor's cognitive perception during a time-constrained debriefing, the explanatory module is supplemented

with a Natural Language Explanations (NLE) generation subsystem. The calculated metrics of individual contributions and compensatory effects are passed as structured context to a local language model. The model automatically translates the numerical values into a coherent pedagogical narrative, forming a conclusion. For example: "The controllers working as a pair ensured flight safety during peak workload thanks to the proactive coordination of the planning controller (compensatory contribution +14 %), which completely mitigated the temporary loss of situational awareness by the executive controller in the trajectory intersection zone (penalty –9 %)".

The proposed mechanism is implemented using a hybrid «simulator plugin – external Python engine» architecture. The plugin is responsible for collecting events and logs, and applying scenario modification commands, while the external engine performs indicator calculations, skill acquisition assessment, workload wave management, and explanation generation. Such an architecture combines modularity, reproducibility, and experimental flexibility, and aligns with the EASA regulatory logic regarding the transparency and controllability of machine learning models in critical aviation applications [21].

Conclusions. Within the scope of this study, a mechanism for the dynamic adaptation of simulator environment content was developed to implement combined individual and team-based training strategies for ATCOs. The proposed solution is structured as a closed "monitoring – diagnosis – prediction – adaptation – explanation – reporting" loop, which transitions assessment from a passive monitoring function to an active pedagogical management function. Throughout the research, the input data space was formalized, a model for assessing the probability of individual skill acquisition was proposed, an algorithm for wave-based workload adaptation was constructed, and a framework for the explainable evaluation of team performance was defined.

The scientific novelty lies in the integration of three loops that are predominantly treated separately in existing literature: team competency assessment, skill acquisition tracking, and training scenario management. The practical significance of this work consists in establishing a foundation for next-generation simulator systems capable of maintaining trainees within a zone of productive cognitive tension in real time. For the instructor, this implies the ability to receive a substantiated post-simulation report indicating which factors decreased or increased the final score, who provided compensatory actions, and what type of subsequent training intervention is most appropriate.

Prospects for future research are associated with the following: creating a system prototype based on the BlueSky simulator; conducting empirical validation of the adaptation rules across series of scenarios of varying complexity; expanding the input data space through ASR/NLP (Automatic Speech Recognition / Natural Language Processing) analysis of ATC communication; combining the rule-based wave generator with recurrent predictive models, provided that transparency and controllability are strictly preserved. Additionally, the skill deficit thresholds, the parameters of wave-based workload variation, and the criteria for safe scenario intensification require further calibration. Furthermore, a transition from using an exclusively static event library to the application of procedural generative synthesis (specifically, involving a specialized Large Language Model acting as a pseudo-pilot) is planned, aiming to significantly increase the diversity and operational unpredictability of scenario interventions.

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