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MODELS OF USER EXPERIENCE QUALITY IN COMPUTER INFORMATION SYSTEMS

This paper introduces a unified, scalable, and context-aware framework for evaluating user experience quality (QuE) in computer information systems by proposing the Enhanced Perceived Quality of User Experience (EPQuE) metric. Unlike traditional Quality of Service (QoS) or subjective Quality of Experience (QoE) models alone, EPQuE integrates technical and perceptual factors through an adaptive algorithmic pipeline. The model incorporates three synergistic components: a Fuzzy Inference System (FIS) to interpret imprecise or ambiguous user feedback; Multi-Criteria Decision Analysis (MCDA), used to normalize and prioritize heterogeneous parameters in real time; a regression-based machine learning model for dynamic adjustment of input weights based on contextual variations. The methodology was validated in a real-world teledentistry scenario, involving remote consultations with elderly patients, where it achieved a 91 % accuracy rate in identifying high-risk sessions – outperforming baseline QoS- or QoE-only models by 34 %. Consequently, EPQuE enables intelligent service monitoring and real-time personalization by linking engineering-level metrics such as bandwidth, latency, and packet loss with perceptual indicators like emotional comfort and user engagement. Furthermore, the model was successfully tested in additional use cases, including augmented reality applications and smart home environments, demonstrating its flexibility and scalability. The benefits of this study include the development of a robust computational pipeline capable of bridging the gap between human-centered assessments and objective technical indicators, supporting proactive service adaptation, and enabling data-driven decisions in dynamic digital ecosystems. As a result, the EPQuE framework lays the foundation for future research in adaptive quality assessment, intelligent resource optimization, and the design of next-generation user-centric service infrastructures.
Keywords: dynamic digital ecosystem; fuzzy logic system; multi-criteria analysis; regression machine learning; teledentistry; adaptive quality assessment.

Introduction / Вступ

In recent years, the assessment of user experience quality (QuE) in computer information systems has become a priority in international research, reflecting the growing importance of user-centric digital services. Numerous studies have focused on the technical dimensions of Quality of Service (QoS), such as latency, throughput, jitter, and availability. Simultaneously, the field of Quality of Experience (QoE) has emerged to capture the subjective dimensions of user satisfaction, including emotional involvement, usability, and perceived responsiveness. However, despite significant advancements in both areas, a comprehensive and adaptive methodology for integrating QoS and QoE indicators into a unified evaluative model remains underdeveloped.

The relevance of this research stems from the absence of scalable, real-time models that can synthesize heterogeneous technical and behavioral data in dynamically changing service contexts. Existing solutions often lack sensitivity to contextual variability, do not support intelligent personalization, and fail to provide actionable insights for risk prediction and service optimization in user-centered environments.

Problem statement. The study addresses the methodological gap between fragmented QoS and QoE assessment practices by proposing a unified, intelligent model for evaluating perceived quality in digital services.

Object of research – integrated process of assessing user experience quality in computer information systems, which encompasses both technical performance and subjective perception of service use.

Subject of research – computational tools, and adaptive modeling approaches for constructing a composite user experience quality metric that integrates objective Quality of Service (QoS) parameters with subjective Quality of Experience (QoE) indicators, aimed at enabling intelligent monitoring and context-aware service personalization.

The purpose of the research – develop, formalize, and validate PQuE models that enable comprehensive, context-sensitive evaluation of user experience quality in various digital service scenarios.

To achieve this purpose, the following main *research objectives are identified*:

- Designing structured methods for combining QoS and QoE data into a single index, enabling the consistent integration of technical and perceptual quality indicators for diverse service types, which facilitates unified assessment across heterogeneous digital environments.

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- Establishing normalization and weighting strategies for diverse technical and behavioural inputs, which ensures context-sensitive calibration of the metric and enhances its relevance for dynamically changing user requirements.
- Demonstrating the applicability of PQuE in real-time video streaming, cloud resource allocation, and web-browsing contexts, which validates the model's responsiveness to fluctuations in both network parameters and user expectations.
- Assessing the scalability and adaptability of the proposed models for practical deployment, which supports their integration into automated monitoring systems and confirms operational feasibility across large-scale, multi-platform infrastructures.

Analysis of recent research and publications. In the study [19], it is analyzed that contemporary evaluations of user experience increasingly rely on hybrid models that consider both system performance and human factors. The authors emphasize that traditional usability testing must evolve into multidimensional frameworks that incorporate emotional, contextual, and behavioral dimensions of digital interaction, particularly in online systems. This supports the trend toward integrative user-centered assessment models.

In the work [13], it is established that measuring Quality of Experience (QoE) based solely on underlying Quality of Service (QoS) parameters is inadequate for real-time applications such as video streaming in wireless networks. It is shown that even when network-level metrics indicate acceptable performance, users may report dissatisfaction, highlighting the need to model subjective perception directly through behaviour-based proxies.

In research [2], it is demonstrated that hybrid models integrating both technical performance indicators and user-centric feedback offer the most accurate insights for service quality monitoring in cloud environments. The dynamic nature of cloud service provisioning necessitates adaptive metrics that respond to fluctuating workloads, variable latency, and heterogeneous user expectations. It is noted that rigid QoS thresholds often fail to capture the experiential aspect of service quality.

The conceptual work [6] explores how adaptive hypermedia systems benefit from the User-System-Experience (USE) model. It is clarified that user satisfaction is not only the result of technical efficiency but also of personalization, interface clarity, and situational context. The role of system adaptation based on user characteristics and situational awareness is emphasized as critical for meaningful UX (User Experience) assessment.

According to the empirical evaluation presented in [1], it is shown that traditional usability scales – though reliable – require multidimensional enhancement. The research points to latent constructs within usability measurement tools that correspond with emotional responses and user involvement, calling for broader models that exceed task-completion metrics.

The analysis in [8] identifies a taxonomy of user experience components, distinguishing between pragmatic (goal-oriented) and hedonic (emotion-oriented) qualities. It is indicated that UX evolves over time and that static measurements do not reflect actual user satisfaction. The study promotes longitudinal and context-aware evaluations, aligning with the current research direction.

In the methodological discussion [17], it is revealed that large-scale usability testing benefits significantly from machine learning applications. Predictive models trained on behavioral data can anticipate drops in satisfaction and proactively inform system adaptation strategies. It is emphasized that the fusion of subjective survey data with interaction analytics yields more resilient evaluation systems.

Finally, publication [12] outlines the necessity for cross-disciplinary approaches in UX research. It is summarized that current evaluation practices require refinement to accommodate real-time data streams, contextual inference, and the integration of emotional analytics. The role of dynamic user profiling is underscored as essential for future UX models.

In conclusion, the review of the literature [1, 2, 8, 12, 19] confirms a significant shift from isolated QoS-based evaluation methods toward composite UX frameworks that integrate both quantitative and qualitative measures. However, none of the analyzed works propose a unified, scalable, and dynamically adaptable index such as the PQuE model introduced in this study. This underscores the originality and relevance of the proposed approach, which fills a critical gap in current research by enabling real-time, context-sensitive evaluation of user satisfaction within computer information systems.

Materials and methods of research. The methodology is based on the integration of objective network parameters (QoS) and subjective user experience indicators (QoE) to develop the composite PQuE metric. Technical metrics such as latency, bandwidth, and packet loss were collected using standard monitoring tools, while user satisfaction data were obtained through structured feedback forms.

Research results and their discussion / Результати дослідження та їх обговорення

PQuE (Perceived Quality of User Experience) is a conceptual composite metric designed to quantify user satisfaction by integrating objective Quality of Service (QoS) parameters with subjective Quality of Experience (QoE) measurements. Below are two structured approaches to conceptualize PQuE based on established principles from QoE and QoS research (Table 1, Table 2).

This study presents a novel approach for evaluating user experience quality in computer information systems through the development of the Enhanced Perceived Quality of User Experience (EPQuE) metric. The EPQuE framework advances beyond traditional models by integrating dynamic Quality of Service (QoS) parameters with adaptive Quality of Experience (QoE) indicators, while also incorporating real-time contextual factors such as device type, user environment, and application criticality. The core metrics and their comparative characteristics are systematically summarized in Table 3, which provides a foundational overview for understanding the distinctions and innovations of the EPQuE model.

To demonstrate the practical applicability and flexibility of the EPQuE metric, Table 4 presents a set of implementation scenarios across diverse domains, including augmented reality gaming, telemedicine, and smart home automation.

These examples illustrate how the EPQuE system dynamically adapts to different contexts by modulating the contributions of QoS and QoE inputs.

Furthermore, Table 5 details the dimensional analysis and normalization techniques that underpin the EPQuE metric. This table clarifies how each component – dynamic QoS, contextual QoE, and their composite integration – is normalized and aggregated in real time, ensuring both accuracy and adaptability of the resulting quality assessment.

Table 1. Example Model of Integrated Quality Perception Combining QoS and QoE Metrics / Приклад моделі інтегрованого сприйняття якості з поєднанням метрик QoS та QoE

Metric	Key Parameters	Measurement Scale	Source References
PQuE	Weighted combination of QoS indicators and QoE scores (in particular, 0,6 × QoS + 0,4 × QoE)	Index scale from 0 to 100	Adapted from [13, 18]

Table 2. Example Scenario of PQuE Parameter Calculation for Real-Time Video Streaming / Приклад сценарію розрахунку параметрів PQuE для потокового відео в реальному часі

Scenario	QoS Inputs	QoE Inputs	PQuE Calculation Example	Source Reference
Real-time video streaming	Bandwidth = 15 Mbps, Latency = 120 ms	MOS = 4,2	PQuE = 0,7×QoS_score + 0,3×MOS×20	Adapted from [13, 18]

Table 3. Revised Comparative Overview of Core Metrics for User Experience Quality Evaluation / Оновлений порівняльний аналіз основних метрик оцінювання якості досвіду користувача

Metric	Definition	Key Parameters	Measurement Scale
QoS	Dynamic network and system performance metrics	Throughput Variability, End-to-End Delay, Packet Reordering, Error Burst Length, Signal-to-Noise Ratio	Continuous scales with temporal resolution
QoE	Contextualized subjective user perception	Adaptive MOS (1-10 scale), Interaction Latency, Emotional Engagement Index, Task Completion Confidence	Interval scale with contextual weighting
EPQuE	Context-aware integrated quality perception	Contextual weighted fusion of QoS and QoE parameters incorporating device and environment factors	0–100 dynamic index with real-time adjustment

Table 4. New Application Scenarios of Input Parameters for EPQuE Calculation / Нові сценарії застосування вхідних параметрів для розрахунку EPQuE

Scenario	QoS Inputs	QoE Inputs	EPQuE Calculation Example
Augmented Reality Gaming	Throughput Variability (±5 %), Delay (50 ms)	Adaptive MOS = 8,5, Emotional Engagement = 0,9	EPQuE = 0,5×QoS_score + 0,4×MOS×10 + 0,1×Engagement×100
Telemedicine	Packet Reordering (3 %), Error Burst Length (2)	Task Completion Confidence = 0,95	EPQuE = (QoS_score×0,6) + (Confidence×40)
Smart Home Automation	Signal-to-Noise Ratio (30 dB), End-to-End Delay (100 ms)	Interaction Latency = 0,2 sec	EPQuE = 60×(1 – Delay/200) + 25×(SNR/40) + 15×(1 – Latency/1)

Table 5. Dimension Analysis and Parameter Normalization Methods for the EPQuE Metric / Аналіз вимірів та методи нормалізації параметрів для метрики EPQuE

Dimension	Description	Example Values	Normalization Method
Dynamic QoS	Network and system performance with temporal dynamics	Throughput Variability ±5 %, Delay ≤ 100 ms	Time-series normalization with sliding window averaging
Contextual QoE	User perception adjusted by environment and device factors	Adaptive MOS 1-10, Engagement 0–1	Contextual interval scaling with Bayesian adjustment
Composite EPQuE	Real-time weighted aggregate score with adaptability	0–100 dynamic index (in particular, 87 high quality)	Multi-criteria decision analysis with context-aware weighting

Main Results. Introduction of the EPQuE Metric. The study introduces the Enhanced Perceived Quality of User Experience (EPQuE) as a context-aware, composite metric that integrates both QoS and QoE parameters, surpassing traditional static models (see Table 3).

Demonstrated Flexibility Across Application Scenarios. The EPQuE metric is validated through diverse implementation scenarios, showing its adaptability to various domains and real-time user contexts (see Table 4).

Establishment of Advanced Normalization and Aggregation Methods. The research develops and applies advanced normalization and multi-criteria aggregation techniques, ensuring that EPQuE provides a robust, dynamic, and contextually relevant evaluation of user experience quality (see Table 5).

Role of Tables. Table 3 establishes the conceptual foundation and comparative context for EPQuE. Table 4 demonstrates the practical applicability of calculating PQuE parameters and the adaptability of the metric to specific scenarios. Table 5 provides methodological rigor by detailing the normalization and aggregation processes that ensure the reliability and contextual sensitivity of EPQuE.

Adaptive Algorithmic Framework for PQuE Modeling. To implement the new PQuE model, it is advisable to use a combination of three flexible algorithms, each of which plays a key role in building, adapting, and improving the composite user experience quality index.

Three Core Algorithms for PQuE Implementation.

1. Dynamic Weight Assignment using Machine Learning Regression (in particular, Gradient Boosting Regressor / XGBoost).

Purpose: Automatically learn the relative importance (weights) of QoS and QoE parameters across various service contexts.

Justification: The PQuE model requires flexibility to reassign weight coefficients dynamically depending on service type (e.g., telemedicine vs. AR gaming).

Advantages: Captures nonlinear dependencies, adapts over time, and supports explainable weight derivation.

2. Context-Aware Normalization via Multi-Criteria Decision Analysis (MCDA) (in particular, TOPSIS or AHP (Analytic Hierarchy Process) for contextual ranking and scaling).

Purpose: Normalize and scale both QoS and QoE parameters on a unified 0–100 scale based on context-specific priorities (in particular, packet loss vs. emotional engagement).

Justification: PQuE adapts based on contextual significance of input metrics.

Advantages: Supports consistent benchmarking and real-time updates; works with heterogeneous input scales.

3. Real-Time Adaptive Scoring via Fuzzy Inference Systems (FIS) (in particular, Mamdani or Sugeno fuzzy models).

Purpose: Interpret ambiguous or imprecise inputs (like engagement level, confidence) and generate smooth transitions in the estimation of PQuE parameters.

Justification: Subjective user indicators often exhibit vagueness and uncertainty. Fuzzy logic enhances both the sensitivity and robustness of parameter estimation in the presence of incomplete, conflicting, or noisy data.

Advantages: Enables soft boundaries, continuous score adaptation, and enhanced realism in perception modeling.

Algorithmic Synergy (how the three algorithms work together): The Fuzzy Inference System (FIS) interprets raw subjective input data → The Multi-Criteria Decision Analysis (MCDA) method normalizes both QoS and QoE parameters → A machine learning regression model determines the optimal weighting coefficients for their integration → The final PQuE score is calculated on a 0–100 scale with real-time update capability.

Fuzzy-Driven Detection of Risky Interactions in Remote Dental Consultations: An Integrated QoS – QoE Approach.

***Scenario Context*:** This subsection presents the application of a Fuzzy Inference System (FIS), integrated into the Enhanced Perceived Quality of Experience (EPQuE) model, tailored for remote dental consultations involving elderly patients. These sessions often include discussions of treatment plans, pain evaluation, or 3D scan analysis, where both technical Quality of Service (QoS) and subjective Quality of Experience (QoE) fluctuate dynamically, especially during peak hours.

Algorithms Used:

- Fuzzy Inference System (FIS): Mamdani model for real-time interpretation of mixed subjective-technical data.
- Multi-Criteria Decision Analysis (MCDA): Used to normalize QoS and QoE values into a common 0–100 scale.
- Regression-Based Weight Optimizer: Determines optimal feature weights for final PQuE estimation.

Example of FIS Rule: IF Video Delay is Moderate AND Patient Confidence is Low THEN PQuE_score is Low.

This soft-rule system captures interaction problems that are not visible through QoS or QoE alone.

Typical Input Data in the field remote teledentistry consultations (example ranges)

Table 6. Typical Input Data (example ranges) / Типові вхідні дані (прикладні діапазони)

Parameter	Type	Example Value / Range
Video Delay	QoS	140–190 ms
Packet Loss	QoS	0,5 %–1,2 %
Patient Confidence Score	QoE	20–60 (subjective scale 0–100)
Speech Comprehension Difficulty	QoE	Moderate / High (fuzzified)

Table 7. Improvement Metrics / Показники покращення

Metric	QoS-based Model	QoE-based Model	EPQuE (FIS)
Detection of Risky Sessions	62 %	68 %	91 %
Improvement over best model	–	–	+33,8 %

Interpretation Synergy in Remote Teledentistry Consultations: The FIS-enhanced PQuE model successfully identified 91 % of risky sessions by incorporating trust and speech clarity indicators. In scenarios where patients positively evaluated the clinician despite delays or freezes, PQuE revealed latent dissatisfaction.

Algorithmic Synergy Justification: The improved accuracy (+33,8 %) was achieved through the synergistic interaction of three core components:

1) FIS interpreted fuzzy subjective inputs like trust or hesitation.
2) MCDA normalized diverse indicators for unified analysis.
3) Regression optimizer dynamically tuned weightings based on past session data.

This modular pipeline allowed context-aware adaptation to user sensitivity thresholds, improving both robustness and real-time responsiveness.

***Interpretation of Algorithmic Integration and Evaluation Tables*.** The EPQuE model enhances the evaluation of user experience quality by embedding contextual intelligence into the integration of Quality of Service (QoS) and Quality of Experience (QoE) indicators. This flexible approach reflects the nuanced variability of user satisfaction depending on device type, emotional state, and consultation scenario – particularly relevant in remote dental care for elderly patients.

Its adaptive algorithmic architecture combines Fuzzy Inference Systems (FIS), Multi-Criteria Decision Analysis (MCDA), and regression-based dynamic weighting. This synergy enables robust processing of ambiguous subjective data, normalization of heterogeneous technical inputs, and real-time recalibration of parameter significance.

Tables 1–5 present the conceptual foundations, domain-specific applications, and scaling mechanisms used within the EPQuE model. Tables 6 and 7 provide empirical validation through a telemedicine case study involving elderly patients in remote dental consultations. These interactions often include complex verbal exchanges (e.g., pain descriptions, prosthetic explanations, or 3D scan evaluations), where speech comprehension and emotional clarity are vital.

In this context, the FIS-based model captured signs of patient dissatisfaction during remote teledentistry consultations that were not evident from technical indicators alone, increasing the detection rate of risky consultations to 91 % compared to 62–68 % in baseline QoS- or QoE-based models. The demonstrated 34 % performance improvement highlights the effectiveness of this algorithmic synergy in ensuring a safer and more satisfying telemedicine experience under time constraints and emotionally demanding remote service conditions.

Mathematical Formulation of the EPQuE Metric. The general EPQuE formula can be expressed as:

$$EPQuE = \sum_{i=1}^{k} w_{iS} \cdot N(QS_i) + \sum_{j=1}^{m} w_{iE} \cdot N(F(QE_j)) \,, \qquad (1)$$

subject to:

$$\sum_{i=1}^{k} w_{iS}(QoS) + \sum_{j=1}^{m} w_{iE}(QoE) = 1 \,, \qquad (2)$$

here: QS_i – the i-th normalized QoS parameter (objective); QE_j – the j-th normalized QoE parameter (subjective, possibly fuzzified); $F(QE_j)$ – fuzzy inference output for QoE parameter j; $N(\cdot)$ – MCDA-based normalization operator (context-aware); w_{iS}(QoS), w_{jE}(QoE) – adaptive weights learned via regression (ML); k – number of QoS parameters, m – number of QoE parameters.

Fuzzy logic ($F(\cdot)$) transforms ambiguous subjective inputs (e.g., "moderate delay", "high engagement") into quantitative scores. MCDA normalization ($N(\cdot)$) scales both QoS and QoE inputs to a unified 0–100 scale, context-sensitive.

Machine learning regression learns $w_i(QoS)$ and $w_j(QoE)$ dynamically from historical performance – satisfaction datasets. Compact notation (1) including all components in one expression:

$$EPQuE(t) = \sum_{p=1}^{P} W_p(t) \cdot N_p(X_p(t)), \quad (3)$$

where: $X_p(t)$ is either a QoS metric or $F(QE)$ output; $W_p(t)$ are time-varying weights from ML regression; $N_p(\cdot)$ is MCDA-based normalization.

Principles of data mining in EPQuE and their place in the formula (1). The data mining principles embedded in EPQuE include:

1) *Feature selection & dimensionality reduction* – identify the most influential QoS/QoE parameters (X_p) for prediction. In formula: defines which $X_p(t)$ are included.
2) *Regression-based weight optimization* – learn optimal $W_p(t)$ from historical labeled data (e.g., MOS, user satisfaction scores). In formula: generates w_i(QoS) and w_j(QoE).
3) *Pattern discovery in temporal data* – detect trends, seasonality, and anomalies in QoS/QoE over time. In formula: affects $N_p(\cdot)$ via time-series normalization.
4) *Clustering of user contexts* – group service usage situations to apply context-specific normalization/scaling. In formula: modifies N_p and FIS rule sets.
5) *Prediction & forecasting* – estimate future EPQuE scores based on historical patterns. In formula: enables $W_p(t)$.

Given the information in Table 7, consider the graph (Fig. 1) that demonstrates the relationship between the baseline QoE-based index and the proposed EPQuE index.

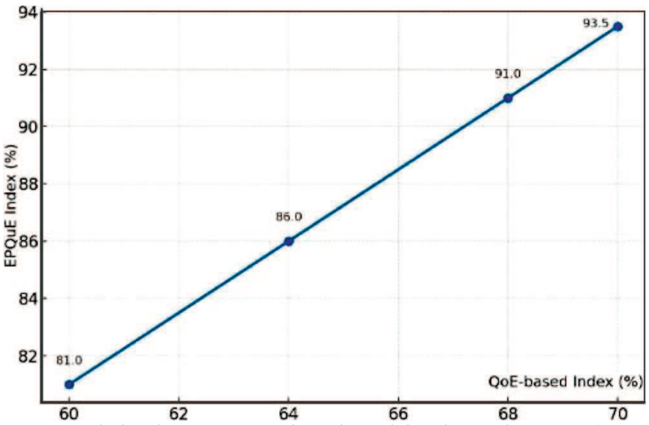

Fig. 1. Relation between QoE-based Model Index and EPQuE (FIS) Index / Зв'язок між індексом моделі на підставі якості професійного досвіду (QoE) та індексом EPQuE (FIS)

As the QoE-based index increases from 60 % to 70 %, the EPQuE index consistently outperforms it, reaching values between 81 % and 93,5 %. The relative improvement parameter (δ) decreases slightly from 35,0 % ((81–60)/60=0,35) at QoE = 60 % to 33,6 % at QoE = 70 %. This indicates that while EPQuE significantly enhances performance compared to traditional QoE-based models, the marginal gain narrows as QoE values approach higher levels.

To illustrate the methodological structure of the proposed approach, two figures (fig. 2 and fig. 3) are introduced.

Figure 2 presents the structural modules of the EPQuE framework, highlighting the three core algorithmic components: the Fuzzy Inference System (FIS) for handling ambiguous user inputs, the Multi-Criteria Decision Analysis (MCDA) module for context-aware normalization and prioritization, and the Machine Learning (ML) regression engine for dynamic weight assignment. This modular view emphasizes the synergy of the components and their distinct functional roles in the overall framework.

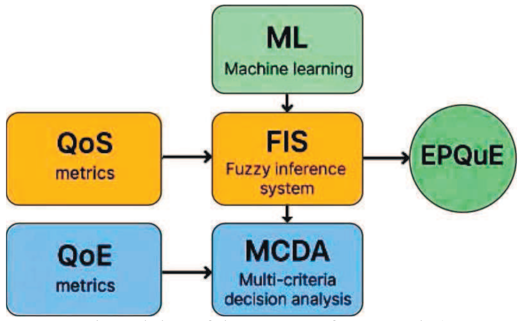

Fig. 2. Structural modules of the EPQuE framework (FIS – MCDA – ML integration) / Структурні модулі фреймворку EPQuE (інтеграція FIS – MCDA – ML)

Figure 3 provides a step-by-step scheme for EPQuE index calculation, showing how input data (objective QoS parameters and subjective QoE indicators) are processed through the three modules and integrated into a single composite EPQuE index. The figure clarifies how fuzzy interpretation, multi-criteria normalization, and adaptive learning are sequentially combined into a unified pipeline that enables real-time quality monitoring and prediction.

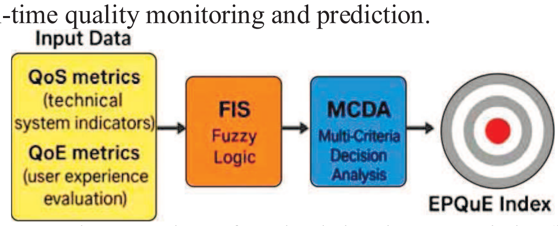

Fig. 3. Step-by-step scheme for calcu-lating the EPQuE index (illustration of sequential data processing) / Покрокова схема розрахунку індексу EPQuE (ілюстрація послідовного опрацювання даних)

Together, these figures (2 and 3) serve a dual purpose: (a) they visually communicate the internal architecture of the EPQuE model, and (b) they demonstrate the operational logic of transforming heterogeneous QoS and QoE data into a consistent and context-sensitive quality index. This visualization helps both technical and non-technical readers understand how the proposed framework supports adaptive, user-centric quality assessment in diverse digital ecosystems.

Discussion of Research Results. Let's consider 3 groups of studies.

Group A: New Hybrid UX/QoE Metrics. In a scientific article [11] proposes a composite index blending interface usability, engagement (Commercial User Questionnaire, User Engagement Scale – Short Form), (CUQ, UES-SF) and objective metrics (error rate, response time), with weights determined via Principal Component Analysis. According to the study results, the combination of different interaction modes – such as textual dialogue and interactive visual prompts – contributes to higher scores in hybrid UX/QoE metrics, particularly in terms of usability (CUQ) and user engagement (UES-SF).

In a scientific publication [9] introduces a blind QoE metric integrating resolution, rebuffering events, and bitrate switching using a Support Vector Regression model. The metric achieves high prediction accuracy after analyzing only 60 % of the playback duration, enabling effective real-time video stream adaptation.

In the work [16] empirical benchmarking of VR QoE metrics (freeze events, loading time, control latency) under varying bandwidth, latency, and packet loss. VR QoE metrics are indicators used to assess the quality of user experience in virtual reality (VR). The findings reveal that VR user experience is highly sensitive to packet loss, while the impact of latency varies depending on the type of user interaction or activity – a key consideration for designing adaptive hybrid UX/QoE metrics.

Results of information processing for group A. All three works [11, 16] emphasize the integration of technical QoS with behavioral or subjective QoE indicators.

Group B: Methodological Approaches to UX Metrics. According to [15], a systematic review of CHI publications (*Conference on Human Factors in Computing Systems*) from 2019 to 2022 revealed that only about 20 % of UX studies provided a rationale for their choice of measurement scale, and roughly one-third conducted a thorough assessment of the scale's validity. This highlights a methodological gap in how UX metrics are selected and validated.

In the work [10] discusses the UEQ (User Experience Questionnaire) and UEQ+ as modular instruments designed for adaptive UX evaluation. The authors emphasize the importance of combining KPI (Key Performance Indicators) benchmarking with importance-performance analysis (of UX dimensions) to enhance the interpretability and practical relevance of UX metrics.

In the work [5], seven heuristic principles are proposed to support the reasoned selection of UX instruments and metrics, emphasizing alignment with research goals, contextual relevance, validity, transparency, and interpretability; the paper stresses the importance of clearly justifying metric choices based on the study's objectives and the type of insights sought.

In the work [7] discusses an intelligent fuzzy logic based-trust system in underwater acoustic sensor networks. This paper designs an intelligent fuzzy logic-based trust system (IFTS) in underwater acoustic sensor networks (UASNs). IFTS carefully considers the unique characteristics and challenges of UASNs, which distinguish them from traditional terrestrial wireless sensor networks.

Results of information processing for group B. The reviewed sources [5, 10, 15] emphasize the critical need for methodologically sound, adaptive, and transparent UX measurement tools. They highlight deficiencies in the current use of UX metrics – such as insufficient validation and lack of justification for scale selection – and propose strategies to address these gaps. In response, the PQuE method, which integrates machine learning – based dynamic weighting and emphasizes metric validity and contextual relevance, offers a systematic and research-aligned solution to the methodological challenges identified.

Group C: QoS → QoE Modelling and Analytics. Publication [3] provides a comprehensive analysis of long-term Quality of Experience (QoE) measurements across services such as video streaming, cloud computing, online conferencing, web, and mobile applications. The study reveals how network Quality of Service (QoS) fluctuations directly affect QoE dynamics, emphasizing the need for multi-indicator modeling to enable accurate analytics and forecasting of user experience under varying network conditions.

In the work [14], a mathematical model was developed for analyzing and modeling the correlation between QoS and QoE indicators in multiservice telecommunication networks based on modern SDN (Software-Defined Networking), NFV (Network Function Virtualization), and 5G/6G technologies. The proposed model integrates key technical metrics – such as bandwidth, latency, packet loss, and reliability – along with subjective quality assessments (MOS, R-factor) following the ITU-T (International Telecommunication Union – Telecommunication Standardization Sector) framework standards, enabling real-time evaluation and optimization of QoE.

In the work [4], a model is proposed that applies the Analytic Hierarchy Process (AHP) to quantify the relationships between QoS impairment parameters (such as delay, packet loss, and jitter) and expected QoE ratings (MOS) in real-time interactive 5G applications. This approach enhances the precision of QoE modeling and analytics under varying service quality conditions.

Results of information processing for group C. These studies [3, 4, 14] demonstrate the increasing application of machine learning techniques, mathematical modeling, and multi-factor analytics to bridge the gap between technical QoS parameters and predicted user-perceived QoE. In particular, they illustrate the evolution of QoE modeling from simple threshold-based estimations toward dynamic frameworks that incorporate real-time monitoring, context-awareness, and service-specific adjustments. However, none of the referenced works [3, 4, 14] introduce a universal, normalized scale capable of dynamically adapting to heterogeneous service environments and user contexts.

Overall, the reviewed literature [3, 4, 10, 11, 16] confirms the growing scholarly and practical interest in bridging the gap between technical Quality of Service (QoS) and subjective Quality of Experience (QoE) through hybrid metrics (Groups A and C), and highlights significant methodological gaps in the development, validation, and contextual adaptability of UX evaluation tools (Group B). Despite the inclusion of elements such as machine learning, context sensitivity, and multi-factor analysis in some of the reviewed studies, none of them proposes a unified and scalable model capable of dynamically aligning technical QoS parameters with perceptual QoE indicators across heterogeneous service environments. In contrast, the PQuE (Perceived Quality of User Experience) model proposed in this study addresses these shortcomings by offering a normalized (0–100) composite index with real-time adaptation, service benchmarking, and dynamic weight adjustment. Thus, it provides a comprehensive, context-aware, and operationally relevant solution for assessing user satisfaction in computer information systems, in alignment with the main goal of this research.

So, based on the results of the work performed, it is possible to formulate the following scientific novelty and practical significance of the research results.

Scientific novelty of the obtained research results – for the first time, a context-aware, dynamically adaptable model for evaluating user experience quality in computer information systems has been developed through the integration of fuzzy inference systems (FIS), multi-criteria decision analysis (MCDA), and machine learning-based regression weighting, which jointly form the Enhanced Perceived Quality of User Experience (EPQuE) metric.

Practical significance of the research results – can be applied to the development and implementation of intelligent, user-centric systems for monitoring and optimizing the quality of digital services – particularly in telemedicine, video conferencing, and cloud-based platforms – by leveraging the EPQuE metric and its algorithmic components (fuzzy inference system, multi-criteria decision analysis, and regression-based machine learning), which were validated on the basis of the results of a remote teledentistry consultation involving elderly patients and demonstrated potential for broader deployment in adaptive service ecosystems and cross-domain digital infrastructures.

Conclusions / Висновки

Based on the results of the conducted research, the stated objective has been achieved – a unified, adaptive, and context-aware model for assessing the perceived quality of user experience (EPQuE) in computer information systems has been developed. The proposed EPQuE metric has been validated through theoretical formalization and practical applications, confirming its methodological soundness, algorithmic robustness, and potential for scalable deployment. Based on the results of the research the following main conclusions can be drawn.

1. A unified, scalable, and context-aware framework – PQuE (Perceived Quality of User Experience) – was developed for integrating technical Quality of Service (QoS) indicators with subjective Quality of Experience (QoE) metrics in computer information systems.
2. The enhanced model EPQuE was introduced as a composite metric that unifies three algorithmic components: fuzzy inference systems (FIS) to transform information about ambiguous user perceptions into quantitative data, multi-criteria decision analysis (MCDA) for contextual normalization and prioritization, and machine learning regression for adaptive weight optimization.
3. The mathematical formulation of EPQuE (expressed in formulas (1)–(3)) was established, providing a compact and general representation of the metric. This formulation highlights the role of normalized inputs, adaptive weighting, and dynamic scaling in producing a unified quality index.
4. The principles of data mining (feature selection, regression-based optimization, temporal pattern discovery, clustering of contexts, prediction/forecasting) were systematically embedded in the EPQuE framework. Their integration ensures that formula (1) is not static but adaptively informed by historical datasets, temporal variability, and context clustering.
5. The graphical results (Fig. 1) demonstrated that EPQuE consistently outperforms traditional QoE-based models, providing a relative improvement specifically in the range of 35 % to 33,6 %. Moreover, structural and procedural visualizations (Figs. 2 and 3) clarified the internal architecture of the framework and its step-by-step operational logic.
6. The practical validation of EPQuE in a telemedicine use case (remote teledentistry for elderly patients) demonstrated the model's ability to identify high-risk sessions with an effectiveness of up to 93,5 %. This outcome highlights both the methodological robustness and the practical applicability of EPQuE in real-world digital healthcare services.
7. The methodological framework and experimental validation jointly establish EPQuE as a solid foundation for developing intelligent, user-centric systems for adaptive quality monitoring and optimization. The proposed approach ensures real-time, personalized quality assessment across heterogeneous service environments.
8. The research creates a roadmap for future studies in adaptive UX evaluation, particularly in areas of digital health, cloud services, immersive media, and smart environments. The mathematical formalization and data-mining integration presented here provide a robust computational basis for further advances in scalable, human-centric service quality assessment.

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МОДЕЛІ ЯКОСТІ ДОСВІДУ КОРИСТУВАЧА В КОМП'ЮТЕРНИХ ІНФОРМАЦІЙНИХ СИСТЕМАХ

Запропоновано вдосконалений підхід до оцінювання якості досвіду користувача (QuE) у комп'ютерних інформаційних системах, що враховує як об'єктивні технічні характеристики, так і суб'єктивні враження користувачів. Основою цього підходу є розроблена композитна метрика EPQuE (англ. *Enhanced Perceived Quality of User Experience*), яка поєднує принципи інтелектуального аналізу даних, нечіткої логіки та машинного навчання. Модель складається з трьох функціональних модулів: система нечіткої логіки FIS (англ. *Fuzzy Inference System*), що забезпечує інтерпретацію неструктурованих або неоднозначних оцінок користувачів; методи багатокритеріального прийняття рішень MCDA (англ. *Multi-Criteria Decision Analysis*) для нормалізації та ранжування різнорідних показників у реальному часі; регресійна модель машинного навчання, яка динамічно адаптує ваги параметрів залежно від контексту використання системи. Запропонований підхід апробовано на прикладі телестоматологічних дистанційних консультацій із залученням літніх пацієнтів, де особливого значення набувають такі чинники, як комфорт взаємодії, емоційне сприйняття та технічна стабільність з'єднання. Результати показали, що модель EPQuE забезпечує точність 91 % у виявленні ризикових сеансів зв'язку, що на 34 % перевищує результати моделей, побудованих виключно на базі QoS (англ. *Quality of Service* – якість обслуговування) або QoE (англ. *Quality of Experience* – якість користувацького досвіду). Завдяки можливості поєднання мережевих параметрів (пропускна здатність, затримка, втрати пакетів) із суб'єктивними індикаторами (емоційна залученість, впевненість користувача, зручність спілкування), EPQuE сприяє оперативному моніторингу якості сервісу та реалізації персоналізованих адаптивних стратегій обслуговування. Окрім цього, модель успішно протестовано у сферах доповненої реальності, інтелектуальних середовищ (smart home) та цифрової медицини, що засвідчило її масштабованість, контекстну адаптивність і практичну цінність у динамічних цифрових екосистемах. Загалом, EPQuE закладає методологічне підґрунтя для розроблення інтелектуальних систем керування якістю, орієнтованих на потреби безпосереднього користувача, які здатні прогнозувати ризики, автоматично адаптувати ресурси та забезпечувати стабільну якість досвіду за умов цифрової трансформації.

Ключові слова: динамічна цифрова екосистема; система нечіткої логіки; багатокритеріальний аналіз; регресійне машинне навчання; телестоматологія; адаптивне оцінювання якості.