Evaluation of the quality of compositional design of information systems using fuzzy logic*

Alona Kudriashova[1,*,†], Iryna Pikh[1,†], Vsevolod Senkivskyy[1,†], Yurii Slipetskyi[1,†] and Volodymyr Bernatsek[1,†]

[1] *Lviv Polytechnic National University, Stepan Bandera Str., 12, Lviv, 79013, Ukraine*

Abstract

Multidirectional information systems occupy a prominent place in modern human life. The relevance of this research topic is determined by the rapid development of digital technologies, the growing role of information systems in various spheres of social activity, and the increasing user demands for the quality of compositional design. Therefore, the evaluation of the quality of compositional design of information systems based on the theory of fuzzy sets is a relevant scientific task addressed in this study.A model for forming the quality of compositional design of information systems has been developed, which includes three partial indicators — ergonomics and cognitive interaction principles, accessibility and inclusivity, and information architecture and visual design — along with the corresponding sets of linguistic variables that influence the quality of these partial indicators. Term sets and universal sets of values have been identified for all linguistic variables.Based on the comparison of the significance of the terms, membership functions were formed, and fuzzy sets were obtained. Their values were substituted into fuzzy logical equations developed from the constructed knowledge matrices. In other words, fuzzification and defuzzification of fuzzy data were carried out.The proposed methodology makes it possible to determine the integral indicator of the quality of compositional design of any information system by selecting the input parameters from the universal sets of values. This enables objective, theoretically grounded decisions to be made regarding the approval or necessary improvement of information system prototypes.

Keywords

compositional design, design, information system, quality evaluation, quality formation model, fuzzy logic, fuzzy set [1]

1. Introduction

With the development of a human-centered approach in the design of information systems, increasing attention is paid not only to functional completeness and technical reliability but also to the quality of compositional design of user interfaces [1–3]. This indicator is determined by the consistency of visual elements, rational use of space, balance of color schemes and typography, as well as the logical arrangement of functional components [4, 5]. Compositional solutions influence user convenience, task completion speed, and the overall impression of the system [6]. The rapid advancement of technology has led to the emergence of new tools for designing and testing interfaces [7]. On the one hand, this provides designers with greater opportunities to create original and adaptive solutions. On the other hand, it raises the issue of objective quality assessment, which becomes complicated due to the presence of subjective perception factors [8, 9].

Hence, there arises the need to integrate methods capable of combining quantitative and qualitative indicators, taking into account expert judgments and fuzzy criteria. One of the effective approaches to solving multi-criteria analysis problems that considers both quantitative and qualitative indicators is the use of fuzzy logic methods [10–12]. These methods enable the

* *AdvAIT-2025: 2nd International Workshop on Advanced Applied Information Technologies: AI & DSS, December 05, 2025, Khmelnytskyi, Ukraine, Zilina, Slovakia*

[1*] Corresponding author.
[†] These authors contributed equally.
alona.v.kudriashova@lpnu.ua (A. Kudriashova); iryna.v.pikh@lpnu.ua (I. Pikh); vsevolod.m.senkivskyi@lpnu.ua (V. Senkivskyy); yurii.b.slipetskyi@lpnu.ua (Yu. Slipetskyi); volodymyr.v.bernatsek@lpnu.ua (V. Bernatsek)
0000-0002-0496-1381 (A. Kudriashova); 0000-0002-9909-8444 (I. Pikh); 0000-0002-4510-540X (V. Senkivskyy); 0009-0003-6931-6767 (Yu. Slipetskyi); 0000-0001-8955-1762 (V. Bernatsek)

integration of expert judgments with objective measurements, formalize vague concepts, and obtain a comprehensive assessment close to real user perception.

Fuzzy logic is a branch of mathematical modeling that allows working with imprecise and ambiguous data. It is applied to describe situations where traditional binary logic fails. In real-world processes, evaluations are often expressed verbally, and such assessments are difficult to represent as exact numbers. Fuzzy logic makes it possible to translate them into mathematical form [13, 14].

Fuzzy logic is based on the concept of fuzzy sets. The membership of an element in a set is described not by a rigid boundary but by a gradual transition from belonging to not belonging. This approach reflects real processes where classification is not always distinct. The membership function takes values from zero to one: zero indicates complete non-membership, one indicates full membership, and intermediate values describe various degrees of correspondence of an element to a concept. This property makes fuzzy sets suitable for describing complex technological systems where factors often have a qualitative nature [15, 16].

Fuzzification transforms crisp values into fuzzy ones. Each value of an input variable obtains a membership function, allowing the description of factors that lack precise numerical expression. Examples include verbal assessments such as "low level," "medium level," and "high level." A linguistic variable is considered an abstraction that formalizes concepts expressed in natural language. Its values are described by words or phrases that represent certain qualitative characteristics of an object or process. Such variables are effectively applied to model situations where traditional numerical parameters cannot adequately reflect the actual state of affairs due to complexity, multifactoriality, or uncertainty [17].

Introducing membership functions enables the representation of subjective expert assessments as well-defined numerical dependencies. Thus, each descriptive term used to denote a specific property or process state is associated with a mathematical function that determines the degree of membership of any variable value to the corresponding fuzzy set [16, 18]. The reverse procedure, called defuzzification, converts the fuzzy representation into a specific number. The defuzzified value is used in practical decision-making [18].

In view of the above, evaluating the quality of compositional design of information systems based on fuzzy set theory is a relevant scientific task, which is the focus of this research.

2. Literature review

The issue of evaluating the quality of compositional design of information systems has become the focus of numerous studies conducted within an interdisciplinary framework that integrates results from software engineering, cognitive science, ergonomics, design theory, and information technology. Modern research covers a wide range of topics, including user experience and interface interaction studies [19], the implementation of accessibility and inclusivity principles [20], adaptive and responsive design [21], personalization of system parameters [22], and automation of IT project design [23–25].

In [19], an evaluation of the design of a system interface prototype was conducted. The study was based on a focus group survey and usability testing. The authors used verbal feedback and research notes to analyze and improve the developed prototype. The main advantage of the study lies in the use of the UEQ scale as an effective and reliable tool for measuring user experience. The disadvantage of the applied method is the subjectivity of analysis and the complexity of processing responses. Moreover, only 15 participants took part in the evaluation, with an uneven gender distribution. This is explained by the significant time, human, and financial resources required. In contrast, we propose assessing the interface quality based on the selection of descriptive characteristics (terms) of quality parameters (linguistic variables). The proposed approach is a robust and theoretically grounded addition to such studies.

The work [20] focuses on exploring the potential of improving the digital accessibility of information systems for people with disabilities. Based on the analysis of expert responses in the field of digital accessibility, a comprehensive framework was proposed that outlines a multifaceted approach combining advanced technologies, design principles, universal access strategies, social and economic inclusion policies, and corresponding standards for developing an accessible Metaverse. However, the study does not identify the key factors that could be used to evaluate the level of accessibility and inclusivity of existing information systems. We propose considering accessibility and inclusivity as a partial quality indicator of the compositional design of information systems, with a specific list of influencing factors.

In [21], the authors discuss design aspects that ensure interface adaptability across different devices and maintain a consistent user experience. Three main groups of consistency factors among interface series are identified: overall design, adaptive design, and individual design factors. A hierarchy of design factors for multi-terminal interfaces was developed. However, the research focuses only on the interface design of main pages for smartphones, tablets, and desktop computers. To improve the comprehensiveness of such studies, the proposed methodologies should also be applied to other intelligent terminals (e.g., smartwatches, smart TVs) and interfaces.

The study [22] examines the personalization of parameters in information systems, using e-commerce platforms as an example. A framework was developed combining three conceptual components to deliver user-relevant content based on behavioral patterns. These components include user and behavioral knowledge, awareness of users' current interests, and situational understanding with intent prediction. Considering the importance and relevance of this topic, our research identifies parameter personalization as one of the key factors of accessibility and inclusivity in information systems.

A considerable number of studies are also devoted to the automation of interface creation. In particular, [23] addresses the automatic transformation of templates and use-case scenarios into ready-made information system prototypes. In [24], a method for automatic generation of mobile application GUI code based on UML models was proposed. In [25], an automated GUI code generator was developed, combining deep learning and image processing techniques.

However, insufficient attention has been given to the comprehensive evaluation of the quality of compositional design of information systems, which is the main objective of this study. To achieve this goal, three partial quality indicators of compositional design were identified: ergonomics and cognitive interaction principles, accessibility and inclusivity, and information architecture and visual design. The quality assessment of the studied process is based on the application of fuzzy logic methods and tools, which allow the inclusion of linguistic quality parameters that lack precise numerical values.

3. Material and methods

To determine the predicted indicator of the quality of the compositional design of information systems, let us introduce a universal set S, which encompasses all values within the studied domain. A fuzzy subset N is defined by the membership function $\mu_N(s)$ [16, 18]:

$$N=\{(\mu_N(s),s),s\in S\}. \tag{1}$$

The function $\mu_N(s)$ determines the degree of membership of each element, where $(0\leqslant\mu_N(s)\leqslant 1), N\in S$. For a discrete and finite scale, the expression takes the form [15, 18]:

$$N=(\mu_N(s_1)/s_1,\mu_N(s_2)/s_2,\dots,\mu_N(s_n)/s_n)=\sum_{i=1}^{n}\mu_N(s_i)/s_i, \tag{2}$$

where the symbol "/" denotes the correspondence between an element and its membership-function value (not the division operation). Membership functions act as identifiers in fuzzy form [18].

Linguistic variables are defined by words or phrases of natural language. The set of such values constitutes a term set, and its individual elements are terms. Each term corresponds to a specific membership function, determined on the basis of expert data or statistical observations [26].

The implementation of the compositional design process of information systems can be described by the function:

$$\Psi = F(x_1, x_2, \dots, x_n), \tag{3}$$

where m — amount of factors.

The input factors may have either quantitative or qualitative nature. If the values are expressed numerically, an interval of possible values can be assigned for each variable. This approach makes it possible to consider boundary conditions and existing real-world constraints. The lower limit represents the minimum permissible value of the parameter, and the upper limit represents the maximum allowable value. Such representation is convenient for further modeling, as it provides a clear definition of the domain of admissible values [27].

According to expression (3), the compositional design of information systems is described by a set of input variables x_i and one output variable Ψ. For quantitative variables, the interval specification can be written as:

$$|\underline{x}_i, \overline{x}_i|, i = |\underline{\Psi}, \overline{\Psi}|. \tag{4}$$

If the input variables are not numerical, they are described by a set of admissible qualitative assessments. Importantly, this representation allows the combination of different data types within a single model. These may include values of linguistic variable terms or conditional units determined by expert judgment. In this case, the formalization takes the form [13, 18]:

$$P = \{p^{(1)}, p^{(2)}, \dots, p^{(j)}\}, \tag{5}$$

where $p^{(k)}, k = \overline{1, j}$ — denotes the collection of values that can be expressed numerically or linguistically; j — is the index indicating their number.

The output variable Ψ can also be represented as a set of conditional units. This is especially useful when the result is expressed not as a single numerical value but as a combination of qualitative characteristics, each having its own degree of significance or membership [16]:

$$\Psi = \{\varphi^{(1)}, \varphi^{(2)}, \dots, \varphi^{(g)}\}. \tag{6}$$

The relationships between input and output variables are established through a knowledge base, which contains a collection of rules reflecting dependencies within the studied process. The knowledge base is represented in the form of a matrix, which links combinations of input factors with evaluations of the output variable. These relationships are formulated as "if — and — then" rules. Subsequently, the knowledge matrix is used to construct fuzzy logical equations that combine the membership functions of input data with those of the results [13, 18].

Possible resulting operations for two membership functions are defined as follows [16]:

$$\mu_1 \vee \mu_2 = max\,(\mu_1, \mu_2) = \begin{cases} \mu_1, \text{if } \mu_1 \geq \mu_2, \\ \mu_2, \text{if } \mu_1 < \mu_2. \end{cases} \tag{7}$$

$$\mu_1 \wedge \mu_2 = min(\mu_1, \mu_2) = \begin{cases} \mu_1, \text{if } \mu_1 \leq \mu_2, \\ \mu_2, \text{if } \mu_1 > \mu_2. \end{cases} \tag{8}$$

The maximum operation describes the union of fuzzy sets, while the minimum operation represents their intersection. For more complex problems, other operators can be applied that more flexibly account for data properties [13, 15, 17].

For the mathematical description of Ψ_e, a universal fuzzy set P is introduced $P=\{p_1, p_2, \dots, p_n\}$, which contains a system of linguistic variables $r_\varphi(d_i)$ and the corresponding rank values within the interval $p_i(i=1,\dots,n)$. Then, the formalized expression for the top-level term takes the form:

$$\Psi_F=\{\frac{\mu_\varphi(p_1)}{p_1}, \frac{\mu_\varphi(p_2)}{p_2}, \dots, \frac{\mu_\varphi(p_n)}{p_n}\}, \tag{9}$$

where $\mu_\varphi(p_i)$ – is the degree to which the element $p_i \in P$ belongs to the set Ψ_F at a given level $\Psi_F \subset P$.

The representation of membership degrees can be written as:

$$\frac{\mu_1}{r_1}=\frac{\mu_2}{r_2}=\dots\frac{\mu_n}{r_n}, \tag{10}$$

where $\mu_i=\mu_\varphi(p_i)$; $r_i=r_\varphi(p_i)$ for $i=1,\dots,n$ under the condition $\sum_{i=1}^{n}\mu_i=1$.

To compute the numerical values of membership functions, the following relationships are used:

$$\left.\begin{array}{l}
\mu_1=\left(1+\frac{r_2}{r_1}+\frac{r_3}{r_1}+\dots+\frac{r_n}{r_1}\right)^{-1}; \\
\mu_2=\left(\frac{r_1}{r_2}+1+\frac{r_3}{r_2}+\dots+\frac{r_n}{r_2}\right)^{-1}; \\
\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots \\
\mu_n=\left(\frac{r_1}{r_n}+\frac{r_2}{r_n}+\frac{r_3}{r_n}+\dots+1\right)^{-1}.
\end{array}\right\} \tag{11}$$

Assume that the range of possible values of each linguistic variable is conditionally divided into two parts. This division is sufficient to introduce three control points, which allow a graphical interpretation of qualitative linguistic terms. The positions of points (p_1, p_2, p_3) define the conditional boundaries of the variable's value interval within the given set. Based on the relative ranks of these terms, a square reciprocal symmetric matrix $W=w_{ij}$, which satisfies the condition $w_{ij}=r_i/r_j$, if $i,j=1,2,3$ [18].

If the factor ranks are not predetermined, a pairwise comparison matrix is used. Its elements are established according to the relative importance scale of the objects [28]. For each linguistic term, the ratio of its significance relative to another term is determined. The corresponding element of the matrix is placed in the position (i,j):

$$W=\begin{bmatrix} 1 & \frac{r_2}{r_1} & \frac{r_3}{r_1} \\ \frac{r_1}{r_2} & 1 & \frac{r_3}{r_2} \\ \frac{r_1}{r_3} & \frac{r_2}{r_3} & 1 \end{bmatrix}. \tag{12}$$

Taking into account the theoretical foundations presented above, the research problem can be formulated as the task of finding the maximum value of the function that characterizes the quality of the compositional design of information systems:

$$\left.\begin{array}{c} G_F=F(e_n,d_n,i_n)\rightarrow max\,, n=\overline{1,4}\,; \\ e_n>0\,, d_n>0\,, i_n>0\,; \\ \mu_q(p_i)\rightarrow max\,, p_i\in P\,, G_F\subset P\,, i=\overline{1,3}\,. \end{array}\right\} \tag{13}$$

where the goal is to achieve the maximum value of the function, indicating the highest possible level of design quality of the information system.

To transition from the qualitative description of the compositional design process to its quantitative evaluation, the centroid (center of gravity) method is used. This approach provides a balanced integral indicator by weighting all terms of the fuzzy set. The analytical expression of the computational procedure is given by [18]:

$$G=\frac{\sum_{i=1}^{m}\left[G+\frac{(i-1)*G-\overline{G}}{m-1}\right]\times\mu_i(G)}{\sum_{i=1}^{m}\mu_i(G)}, \tag{14}$$

where $\underline{G}$ and $\underline{G}$ — denote the lower and upper bounds of the quality index range; m — the number of fuzzy terms;; $\mu_i(G)$ — the membership function value of the i-th term at the given level of the input variable.

It should be noted that the weights are represented by the membership function values, and the coordinates of the center of gravity are determined by discretizing the interval $[\underline{G},\overline{G}]$ into m equally spaced points.

Thus, the evaluation of the quality of the compositional design of information systems begins with defining the terms and universal set. Next, a hierarchy of variables is formed, where the highest level determines the predicted quality indicator. For each variable, a membership function is established, and its values are normalized and matched with the corresponding elements of the universal set. A knowledge base is then created to describe interrelations in the form of conditional ("if – then") rules. At the final stage, fuzzy equations are constructed, which allow obtaining a fuzzy forecast. Afterward, defuzzification is performed, yielding a specific numerical value that can be used for quality assessment and management.

4. Experiment, results and discussion

The model of compositional design quality of information systems can be viewed as a representation of the relationship between a set of influencing factors and the integrated predicted quality indicator [18, 29, 30]. Each factor is a linguistic variable, reflecting the fundamental features of ergonomics and cognitive interaction principles, accessibility and inclusivity, and information architecture and visual design. The quality indicator of compositional design is expressed as a combination of partial indicators belonging to individual linguistic variables, each with its own functional role in the model's structure.

The functional representation of the compositional design process can be written as:

$$G = \{E; D; I\}, \tag{15}$$

where argument E corresponds to the quality of ergonomics and cognitive interaction principles, argument D — to accessibility and inclusivity, I— to information architecture and visual design.

When forming the integral quality indicators of compositional design, only Pareto-optimal factors should be considered [14]. Thus, the quality indicator of ergonomics and cognitive interaction principles is expressed as:

$$E = F_E(e_1, e_2, e_3, e_4), \tag{16}$$

where: e_1 — consistency of design models, e_2 — interface modality, e_3 — scalability, e_4 — feedback.

The quality of accessibility and inclusivity formation, based on Pareto-optimal factors, is defined as:

$$D = F_D(d_1, d_2, d_3, d_4), \tag{17}$$

where: d_1 — verification of compliance with accessibility standards, d_2 — polymodal content representation, d_3 — parameter personalization, d_4 — alternative navigation mechanisms.

The quality indicator of information architecture and visual design is expressed as:

$$I = F_I(i_1, i_2, i_3, i_4), \tag{18}$$

where: i_1 — composition and rhythm of layout, i_2 — color scheme and contrast, i_3 — hierarchy of visual elements, i_4 — spatial balance.

Table 1
Description of Linguistic Variables

Variable	Variable name	Range	Terms
e_1	Consistency of design models	(1−3) c. u.	chaotic, partially consistent, holistic
e_2	Interface modality	(1−5) modes	single-modal, multimodal, cross-modal
e_3	Scalability	(1−3) c. u.	limited, moderate, high
e_4	Feedback	(1−3) c. u.	slow, medium, fast
d_1	Verification of accessibility standards	(1−3) c. u.	low, partial, full
d_2	Polymodal content representation	(1−5) formats	single-channel, multichannel, cross-channel
d_3	Parameter personalization	(1−3) c. u.	minimal, extended, full
d_4	Alternative navigation mechanisms	(1−3) mechanisms	limited, extended, full
i_1	Composition and layout rhythm	(1−3) c. u.	disharmonious, moderate, harmonious
i_2	Color and contrast	(1−3) c. u.	low, medium, high
i_3	Visual hierarchy	(1−3) c. u.	unclear, moderate, clear
i_4	Spatial balance	(1−3) c. u.	overloaded, moderate, balanced

For further analysis, each linguistic variable is associated with a universal term set and a set of linguistic terms. Table 1 describes all variables, which include both quantitative and qualitative parameters. Each parameter has a defined value range ensuring the correct construction of membership functions.

The number of interface modes is defined within the range 1–5. A single mode corresponds to the simplest configuration with minimal functionality. Three modes provide combined interaction methods (text, audio, visual). Five modes represent the upper limit where further additions do not improve effectiveness.

The number of content representation formats ranges from 1 to 5. One format indicates a single channel (e.g., text only). Three formats (text, image, video) create multimedia diversity typical for modern products. Five formats achieve maximum variety without overloading the interface.

The number of alternative navigation mechanisms is also within 1–5. One mechanism offers basic navigation; two provide user-choice flexibility; three are optimal for usability without complexity. More mechanisms add little practical value and complicate maintenance.

The obtained values were used to build the model of compositional design quality formation (Fig. 1).

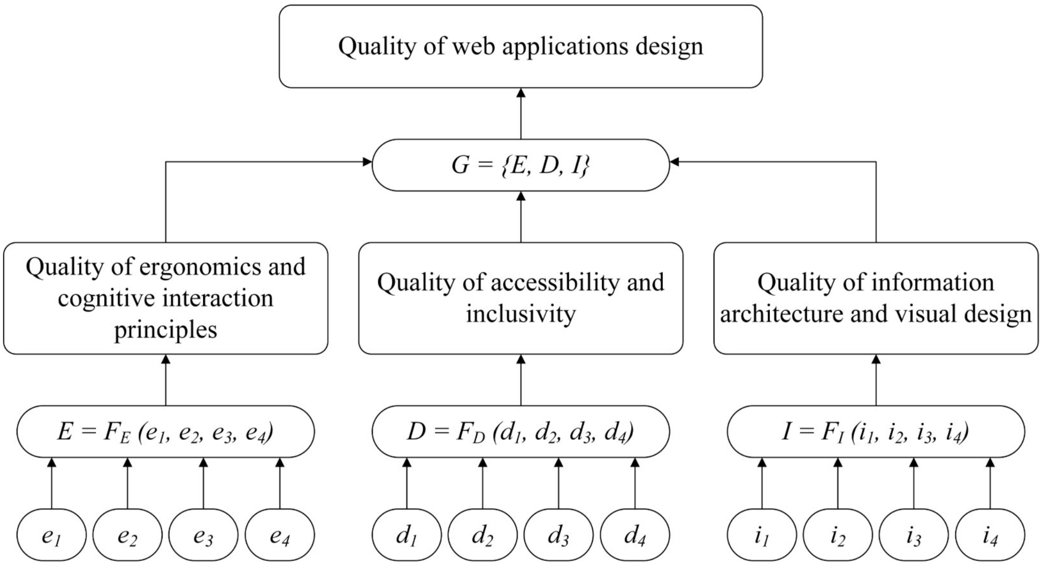

Figure 1: Model of compositional design quality formation for information systems.

The predicted quality indicator is formed gradually. At the first level, partial indicators are determined for variable groups. Then, results are aggregated upward, forming an overall evaluation. This approach ensures a realistic reflection of dependencies between parameters and final outcomes.

To synthesize fuzzy sets representing linguistic terms of compositional design variables, matrices were constructed. For example, for the variable "consistency of design models," a matrix W was created based on the value set (1–3 c. u.), defining discrete levels with clear interpretative meaning. The term set represents the degree of sequence and coherence of graphical elements and styles across system pages.

Membership function values were calculated for each term by finding the eigenvectors of matrices followed by normalization. For the terms "chaotic," "partially consistent," and "holistic," the values were computed and normalized relative to unity using the normalization coefficient:

$$W_{chaotic}(e_1)=\begin{bmatrix} 1 & \frac{4}{9} & \frac{1}{9} \\ \frac{9}{4} & 1 & \frac{1}{4} \\ 9 & 4 & 1 \end{bmatrix}. W_{partially\,consistent}(e_1)=\begin{bmatrix} 1 & 7 & 1 \\ \frac{1}{7} & 1 & \frac{1}{7} \\ 1 & 7 & 1 \end{bmatrix}. W_{integral}(e_1)=\begin{bmatrix} 1 & 3 & 9 \\ \frac{1}{3} & 1 & \frac{9}{3} \\ \frac{1}{9} & \frac{4}{9} & 1 \end{bmatrix}.$$

The corresponding membership-function values were computed for each term by finding the eigenvectors of the matrices and then normalizing them. For the terms “chaotic,” “partially consistent,” and “holistic,” the values were obtained accordingly:

$$\mu_{chaotic}(p_1)=0{,}081;\mu_{chaotic}(p_2)=0{,}183;\mu_{chaotic}(p_3)=0{,}734.$$
$$\mu_{partially\ consistent}(p_1)=0{,}466;\mu_{partially\ consistent}(p_2)=0{,}066;\mu_{partially\ consistent}(p_3)=0{,}466.$$
$$\mu_{integral}(p_1)=0{,}692;\mu_{integral}(p_2)=0{,}23;\mu_{integral}(p_3)=0{,}076.$$

Next, the membership values are normalized to unity using a normalization coefficient defined as [18]:

$$k_e=\frac{1}{max\ \mu_e(p_i)},(i=1,2,3), \tag{19}$$

where: e — terms; p_i — elements of the universal set; $\mu_e(p_i)$ — denotes the membership-function values at those points.

Then the obtained membership values are scaled by the normalization coefficient so that the maximum membership for each term equals one [18].

$$\mu_{e_n}(p_i)=k_e\times\mu_e(p_i), \tag{20}$$

As a result, the normalized values for the terms “chaotic,” “partially consistent,” and “holistic” of the variable “consistency of design models” are obtained:

$$\mu_{chaotic_n}(p_1)=0{,}11;\mu_{chaotic_n}(p_2)=0{,}249;\mu_{chaotic_n}(p_3)=1.$$
$$\mu_{partially\ consistent_n}(p_1)=1;\mu_{partially\ consistent_n}(p_2)=0{,}142;\mu_{partially\ consistent_n}(p_3)=1.$$
$$\mu_{integral_n}(p_1)=1;\mu_{integral_n}(p_2)=0{,}332;\mu_{integral_n}(p_3)=0{,}11.$$

The fuzzy sets for the variable “consistency of design models” are then written using relation (9) as:

$$\Psi_{chaotic}=\left\{\frac{0{,}11}{1};\frac{0{,}249}{2};\frac{1}{3}\right\}\text{ c. u.};\Psi_{partially\ consistent}=\left\{\frac{1}{1};\frac{0{,}142}{2};\frac{1}{3}\right\}\text{ c. u.};$$
$$\Psi_{integral}=\left\{\frac{1}{1};\frac{0{,}332}{2};\frac{0{,}11}{3}\right\}\text{ c. u.}$$

Analogous steps were performed for the other linguistic variables of compositional design of information systems.

A knowledge base was formed to capture the relationships between combinations of linguistic terms of individual variables and the integrated quality indicator. This reproduces the algorithm for achieving the target quality level under a specific implementation scenario.

The quality indicator of the compositional design of information systems G includes the terms “low,” “medium,” and “high.”

For the variables E — “quality of ergonomics and cognitive interaction principles formation,” D — “quality of accessibility and inclusivity formation,” and I — “quality of information architecture and visual design,” a similar three-level gradation principle of terms is applied.

Considering expression (11) and the model of forming the quality of compositional design of information systems presented in Figure 1, the fuzzy knowledge bases for the highest level of quality and partial indicators have the following form:

$$\begin{gathered} \text{IF } E = \langle \mathit{low}, \mathit{medium}, \mathit{high} \rangle \\ \text{AND } D = \langle \mathit{low}, \mathit{medium}, \mathit{high} \rangle \\ \text{AND } I = \langle \mathit{low}, \mathit{medium}, \mathit{high} \rangle, \\ \text{THEN } G = \langle \mathit{low}, \mathit{medium}, \mathit{high} \rangle. \end{gathered} \tag{21}$$

$$\begin{gathered} \text{IF } e_1 = \langle \mathit{chaotic}, \mathit{partially\ consistent}, \mathit{integral} \rangle \\ \text{AND } e_2 = \langle \mathit{unimodal}, \mathit{multimodal}, \mathit{multimodal} \rangle \\ \text{AND } e_3 = \langle \mathit{limited}, \mathit{moderate}, \mathit{high} \rangle \\ \text{AND } e_4 = \langle \mathit{slow}, \mathit{medium}, \mathit{fast} \rangle, \\ \text{THEN } E = \langle \mathit{low}, \mathit{medium}, \mathit{high} \rangle. \end{gathered} \tag{22}$$

$$\begin{gathered} \text{IF } d_1 = \langle \mathit{low}, \mathit{partial}, \mathit{full} \rangle \\ \text{AND } d_2 = \langle \mathit{single-channel}, \mathit{multichannel}, \mathit{multi-channel} \rangle \\ \text{AND } d_3 = \langle \mathit{minimal}, \mathit{extended}, \mathit{full} \rangle \\ \text{AND } d_4 = \langle \mathit{limited}, \mathit{extended}, \mathit{full} \rangle, \\ \text{THEN } D = \langle \mathit{low}, \mathit{medium}, \mathit{high} \rangle. \end{gathered} \tag{23}$$

$$\begin{gathered} \text{IF } i_1 = \langle \mathit{disharmonious}, \mathit{moderate}, \mathit{harmonious} \rangle \\ \text{AND } i_2 = \langle \mathit{low}, \mathit{medium}, \mathit{high} \rangle \\ \text{AND } i_3 = \langle \mathit{fuzzy}, \mathit{moderate}, \mathit{clear} \rangle \\ \text{AND } i_4 = \langle \mathit{overloaded}, \mathit{moderate}, \mathit{balanced} \rangle, \\ \text{THEN } I = \langle \mathit{low}, \mathit{medium}, \mathit{high} \rangle. \end{gathered} \tag{24}$$

Based on the conditions formed in expressions (21)–(24), the knowledge matrices presented in Tables 2–5 are constructed. These matrices represent a formalized set of rules that establish the relationships between the sets of input and output linguistic variables.

Table 2
Knowledge Matrix for Overall Compositional Design Quality

Quality of ergonomics and cognitive interaction principles E	Quality of accessibility and inclusivity D	Quality of information architecture and visual design I	Overall quality of compositional design of information systems G
low	low	low	low
low	medium	low	
medium	medium	medium	medium
medium	medium	high	
high	high	medium	high
high	high	high	

A knowledge matrix was formed based on the identified patterns of interaction between the factors that determine the quality of ergonomics and cognitive interaction principles formation (Table 3). The developed knowledge matrix for the linguistic variable D — "quality of accessibility and inclusivity formation" and its partial indicators is also presented in tabular form (Table 4).

Table 3
Knowledge Matrix for Ergonomics and Cognitive Interaction

Consistency of design models (e_1)	Interface modality (e_2)	Scalability (e_3)	Feedback (e_4)	Quality of ergonomics and cognitive interaction principles (E)
chaotic	unimodal	limited	slow	low
partially consistent	unimodal	limited	slow	
partially consistent	multimodal	moderate	medium	medium
partially consistent	multimodal	moderate	medium	
holistic	multimodal	high	fast	high
holistic	multimodal	high	fast	

Table 4
Knowledge Matrix for the Quality of Accessibility and Inclusivity Formation

Verification of compliance with accessibility standards (d_1)	Polymodal content representation (d_2)	Personalization of parameters (d_3)	Alternative navigation mechanisms (d_4)	Quality of accessibility and inclusiveness formation (D)
low	single-channel	minimal	limited	low
low	single-channel	extended	limited	
partial	multichannel	extended	extended	medium
partial	multichannel	extended	extended	
full	multichannel	extended	full	high
full	multichannel	full	full	

The construction of the next knowledge matrix is carried out by combining the most probable values of the input variables and determining, for each combination, the corresponding level of the linguistic variable I (Table 5).

Table 5
Knowledge Matrix for the Quality of Information Architecture and Visual Design

Composition and rhythm of the layout (i_1)	Color scheme and contrast (i_2)	Hierarchy of visual elements (i_3)	Spatial balance (i_4)	Quality of information architecture and visual design (I)
disharmonious	low	fuzzy	overloaded	low
disharmonious	low	moderate	overloaded	
moderate	medium	moderate	moderate	medium
harmonious	medium	moderate	moderate	
moderate	high	clear	balanced	high
harmonious	high	clear	balanced	

According to Table 2, fuzzy logical equations were developed for the linguistic variable G — "quality of compositional design of information systems" — for the terms "low," "medium," and "high".

$$\begin{gathered}\mu_{low}(G)=\mu_{low}(E)\wedge\mu_{low}(D)\wedge\mu_{low}(I)\vee\mu_{low}(E)\wedge\mu_{medium}(D)\wedge\mu_{low}(I),\\ \mu_{medium}(G)=\mu_{medium}(E)\wedge\mu_{medium}(D)\wedge\mu_{medium}(I)\vee\\ \vee\mu_{medium}(E)\wedge\mu_{medium}(D)\wedge\mu_{high}(I),\\ \mu_{high}(G)=\mu_{high}(E)\wedge\mu_{high}(D)\wedge\mu_{medium}(I)\vee\mu_{high}(E)\wedge\mu_{high}(D)\wedge\mu_{high}(I).\end{gathered}\tag{25}$$

Based on the knowledge matrices for the partial indicators of the quality of the compositional design of information systems presented in Tables 3–5, fuzzy logical equations have also been formulated:

$$\begin{gathered}\mu_{low}(E)=\mu_{chaotic}(e_1)\wedge\mu_{unimodal}(e_2)\wedge\mu_{limited}(e_3)\wedge\\ \wedge\mu_{slow}(e_4)\vee\mu_{partially\,consistent}(e_1)\wedge\mu_{unimodal}(e_2)\wedge\mu_{limited}(e_3)\wedge\mu_{slow}(e_4),\\ \mu_{medium}(E)=\mu_{partially\,consistent}(e_1)\wedge\mu_{multimodal}(e_2)\wedge\mu_{moderate}(e_3)\wedge\\ \wedge\mu_{medium}(e_4)\vee\mu_{partially\,consistent}(e_1)\wedge\mu_{multimodal}(e_2)\wedge\mu_{moderate}(e_3)\wedge\mu_{medium}(e_4),\\ \mu_{high}(E)=\mu_{integral}(e_1)\wedge\mu_{multimodal}(e_2)\wedge\mu_{high}(e_3)\wedge\\ \wedge\mu_{fast}(e_4)\vee\mu_{integral}(e_1)\wedge\mu_{multimodal}(e_2)\wedge\mu_{high}(e_3)\wedge\mu_{fast}(e_4).\end{gathered}\tag{26}$$

$$\begin{gathered}\mu_{low}(D)=\mu_{low}(d_1)\wedge\mu_{single-channel}(d_2)\wedge\mu_{minimal}(d_3)\wedge\\ \wedge\mu_{limited}(d_4)\vee\mu_{low}(d_1)\wedge\mu_{single-channel}(d_2)\wedge\mu_{extended}(d_3)\wedge\mu_{limited}(d_4),\\ \mu_{medium}(D)=\mu_{partial}(d_1)\wedge\mu_{multichannel}(d_2)\wedge\mu_{extended}(d_3)\wedge\\ \wedge\mu_{extended}(d_4)\vee\mu_{\partial}(d_1)\wedge\mu_{multichannel}(d_2)\wedge\mu_{extended}(d_3)\wedge\mu_{extended}(d_4),\\ \mu_{(high)}(D)=\mu_{(complete)}(d_1)\wedge\mu_{(multichannel)}(d_2)\wedge\mu_{(extended)}(d_3)\wedge\\ \wedge\mu_{(complete)}(d_4)\vee\mu_{(complete)}(d_1)\wedge\mu_{(multichannel)}(d_2)\wedge\mu_{(complete)}(d_3)\wedge\mu_{(complete)}(d_4).\end{gathered}\tag{27}$$

$$\begin{gathered}\mu_{low}(I)=\mu_{disharmonious}(i_1)\wedge\mu_{low}(i_2)\wedge\mu_{fuzzy}(i_3)\wedge\\ \wedge\mu_{overloaded}(i_4)\vee\mu_{disharmonious}(i_1)\wedge\mu_{low}(i_2)\wedge\mu_{moderate}(i_3)\wedge\mu_{overloaded}(i_4),\\ \mu_{medium}(I)=\mu_{moderate}(i_1)\wedge\mu_{medium}(i_2)\wedge\mu_{moderate}(i_3)\wedge\\ \wedge\mu_{moderate}(i_4)\vee\mu_{harmonious}(i_1)\wedge\mu_{medium}(i_2)\wedge\mu_{moderate}(i_3)\wedge\mu_{moderate}(i_4),\\ \mu_{high}(I)=\mu_{moderate}(i_1)\wedge\mu_{high}(i_2)\wedge\mu_{clear}(i_3)\wedge\\ \wedge\mu_{balanced}(i_4)\vee\mu_{harmonious}(i_1)\wedge\mu_{high}(i_2)\wedge\mu_{clear}(i_3)\wedge\mu_{balanced}(i_4).\end{gathered}\tag{28}$$

For defuzzification, the values of the membership functions were substituted into the fuzzy logical equations (26)–(28). For the experiment, the mean values of the universal data sets were used. The obtained results for the partial indicators of the quality of the compositional design of information systems were then substituted into the fuzzy logical equations (25).

$$\begin{gathered}\mu_{low}(G)=0{,}166\wedge0{,}249\wedge0{,}199\vee0{,}166\wedge0{,}123\wedge0{,}199=0{,}166;\\ \mu_{medium}(G)=0{,}142\wedge0{,}123\wedge0{,}123\vee0{,}142\wedge0{,}123\wedge0{,}249=0{,}123;\\ \mu_{high}(G)=0{,}249\wedge0{,}249\wedge0{,}123\vee0{,}249\wedge0{,}249\wedge0{,}249=0{,}249.\end{gathered}$$

Under the given conditions, m = 3, which corresponds to three levels of qualitative evaluation — low, medium, and high. For these terms, the membership function values are denoted as $\mu_1(G)=\mu_{low}(G)$, $\mu_2(G)=\mu_{medium}(G)$, $\mu_3(G)=\mu_{hig}(G)$. The range of the variable G is defined as: $\underline{G}=1\%, \overline{G}=100\%$. The choice of this interval is determined by the expediency of interpreting the quality indicator values in relative units. The defuzzification procedure involves substituting into formula (14) three representative points corresponding to the intervals 1 %, 50 %, and 100 %, to align the center of gravity with the main quality levels [18]. The obtained values $\mu_1(G)=0{,}166$, $\mu_2(G)=0{,}123$, $\mu_3(G)=0{,}249$ reflect the degree of membership of the process to each term under the selected input parameters.

$$G_{predicted} = \frac{1 \cdot 0{,}166 + 50 \cdot 0{,}123 + 100 \cdot 0{,}249}{0{,}166 + 0{,}123 + 0{,}249} = 58{,}022\,\%.$$

When selecting other parameters, the indicator will change according to similarly performed calculations.

Thus, the study proposes a scientifically grounded approach to evaluating the quality of compositional design of information systems, based on the application of fuzzy set theory, the use of linguistic variables, and the formalization of their interrelations in the form of fuzzy logical equations. The proposed quality formation model, presented in Fig. 1, enables the integration of both quantitative and qualitative parameters that reflect ergonomics and cognitive principles of interaction, accessibility and inclusivity, as well as information architecture and visual design. This makes it possible to form an objective integral quality indicator and eliminate limitations related to excessive subjectivity of expert assessments.

The obtained results have practical significance for the design of information system prototypes focused on a human-centered approach. They can be applied in the development of interfaces for web services, mobile applications, e-commerce systems, educational platforms, as well as specialized industrial and corporate information environments where requirements for usability, accessibility, and design integrity are critical. The proposed quality assessment methodology allows optimization of decision-making processes regarding project approval or improvement, increases interface testing efficiency, and reduces costs associated with repeated design iterations.

It should be noted that the proposed methodology has certain limitations related to the fixed list of factors included in the model. When expanding the set of parameters, it becomes necessary to recalculate membership functions and update the knowledge base, which may complicate the practical application of the model. In addition, the accuracy of results depends on the quality of expert evaluations used at the stage of determining the significance of terms.

Future research perspectives involve improving mechanisms for automatic generation of weighting coefficients using machine learning methods, as well as employing fuzzy-neural logic approaches for adaptive model updating when system usage conditions change.

5. Conclusions

1. The key factors influencing the quality of compositional design have been identified and systematized into three fundamental categories: ergonomics and cognitive principles of interaction, accessibility and inclusivity, and information architecture and visual design. The formalization of these factors as linguistic variables and term sets made it possible to represent the multidimensional nature of the interface design process and to account for real user interaction conditions within information systems.
2. A model for forming the quality of compositional design of information systems has been developed, based on the application of fuzzy logic methods, which allows objective consideration of heterogeneous parameters. The model integrates 12 linguistic variables and provides their formalization in the form of membership functions. This made it possible to combine quantitative indicators with qualitative expert evaluations, which is fundamentally important for objective assessment of digital product design.
3. The advantages of applying fuzzy logic in the design of information systems have been substantiated, as it enables the formalization of vague and ambiguous criteria inherent to the design field. Membership functions were identified, and normalization of values for all terms was performed. For example, for the variable “consistency of design models,” normalized membership function values were obtained within the range of 0,11–1,00, ensuring coherence between qualitative and quantitative assessments. A system of knowledge matrices and logical equations has been constructed to reproduce the patterns of interconnections between groups of variables and the final integral quality indicator. A

formalized knowledge base has been created, encompassing possible interface formation scenarios and allowing for variable evaluation.

4. Fuzzification and defuzzification of data were carried out, making it possible to obtain accurate numerical results of quality assessment. In particular, for the average values of universal data sets, the integral quality indicator was 58,022 %. This confirms the adequacy of the proposed methodology and its ability to reproduce real expert evaluations in numerical form. Moreover, the proposed approach not only allows assessment of the current quality level but also identifies directions for further improvement of compositional design, which enhances the practical value of the results.

Declaration on Generative AI

The authors have not employed any Generative AI tools.

References

[1] P. Sulikowski, M. Kucznerowicz, I. Bąk, A. Romanowski, T. Zdziebko, Online store aesthetics impact efficacy of product recommendations and highlighting, Sensors 22(23) (2022) 9186. doi:10.3390/s22239186.

[2] A. Giannakoulopoulos, M. Pergantis, A. Lamprogeorgos. User experience, functionality and aesthetics evaluation in an academic multi-site web ecosystem, Future Internet 16(3) (2024) 92. doi:10.3390/fi16030092.

[3] G. Li, L. Wang, J. Hu, Integration with visual perception — research on the usability of a data visualization interface layout in zero-carbon parks based on eye-tracking technology, Sustainability 15(14) (2023) 11102. doi:10.3390/su151411102.

[4] R. Zhang, O-S. Son, A measurement model for visual complexity in HCI: Focusing on visual elements in mobile GUI design, Electronics 14(5) (2025) 942. doi:10.3390/electronics14050942.

[5] N. Zhang, J. Zhang, S. Jiang, W. Ge, The effects of layout order on interface complexity: An eye-tracking study for dashboard design, Sensors 24(18) (2024) 5966. doi:10.3390/s24185966.

[6] J. Galindo-Losada, C. Ayala-Tipan, M. Santórum, M. Carrión-Toro, P. Acosta-Vargas, WYDISWYG: A method to design user interfaces combining design principles and quality factors, Electronics 12(13) (2023) 2772. doi:10.3390/electronics12132772.

[7] M. Whaiduzzaman, A. Sakib, N. J. Khan, S. Chaki, L. Shahrier, S. Ghosh, M. S. Rahman, M. J. N. Mahi, A. Barros, C. Fidge et al., Concept to reality: An integrated approach to testing software user interfaces, Applied Sciences 13(21) (2023) 11997. doi:10.3390/app132111997.

[8] M.-X. Chen, H. Hu, R. Yao, L. Qiu, D..Li, A survey on the design of virtual reality interaction interfaces, Sensors 24(19) (2024) 6204. doi:10.3390/s24196204.

[9] Q. Li, B. Zheng, T. Wu, Y. Li, P. Hao, A method for evaluating user interface satisfaction using facial recognition technology and a PSO-BP Neural Network, Applied Sciences 14(13) (2024) 5649. doi:10.3390/app14135649.

[10] V. Senkivskyy, S. Babichev, I. Pikh, A. Kudriashova, N. Senkivska, I. Kalynii, Forecasting the reader's demand level based on factors of interest in the book, in Proceedings of the CIT-Risk'2021: 2nd International Workshop on Computational & Information Technologies for Risk-Informed Systems, Kherson, Ukraine, 16–17 September (2021) 176–191. URL: https://ceur-ws.org/Vol-3101/Paper12.pdf.

[11] S. Scott, W. Orlikowski, The digital undertow: How the corollary effects of digital transformation affect industry standards, Information Systems Research 33(1) (2022) 311–336. doi:10.1287/isre.2021.1056.

[12] F. N. Kumala, A. Ghufron, P. P. Astuti, M. Crismonika, M. N. Hudha, C. I. R. Nita, MDLC model for developing multimedia e-learning on energy concept for primary school students, Journal of Physics: Conference Series 1869(1) (2021) 012068. doi:10.1088/1742-6596/1869/1/012068.

[13] K. Kabassi, C. Karydis, A. Botonis, AHP, Fuzzy SAW, and Fuzzy WPM for the evaluation of cultural websites, Multimodal Technologies and Interaction 4(1) (2020) 5. doi:10.3390/mti4010005.
[14] I. Pikh, V. Senkivskyy, A. Kudriashova, N. Senkivska, Prognostic assessment of COVID-19 vaccination levels, Lecture Notes in Data Engineering, Computational Intelligence, and Decision Making (2022) 246–265. doi:10.1007/978-3-031-16203-9_15.
[15] J. Deng, Y. Deng, Information volume of fuzzy membership function, International Journal of Computers Communications & Control 16(1) (2021) 1–14. doi:10.15837/ijccc.2021.1.4106.
[16] V. Repeta, Y. Kukura, V. Kukura, Analysis of the relationship of quality factors in the solventless lamination process, Journal of Print and Media Technology Research 7(1) (2023) 27–34. URL: https://jpmtr.net/index.php/journal/article/view/79.
[17] Y. Li, L. Zhu, Failure modes analysis related to user experience in interactive system design through a fuzzy failure mode and effect analysis-based hybrid approach, Applied Sciences 15(6) (2025) 2954. doi:10.3390/app15062954.
[18] B. Durnyak, I. Hileta, I. Pikh, A. Kudriashova, Y. Petiak, Designing a fuzzy controller for prediction of tactile product quality, in: Proceedings of the 1st International Workshop on Digital Content & Smart Multimedia (DCSMart 2019) (2019) 70–81. URL: https://ceur-ws.org/Vol-2533/paper7.pdf.
[19] D. Zhu, D. Wang, R. Huang, Y. Jing, L. Qiao, W. Liu, User interface (UI) design and user experience questionnaire (UEQ) evaluation of a to-do list mobile application to support day-to-day life of older adults, Healthcare 10(10) (2022) 2068. doi:10.3390/healthcare10102068.
[20] A. Othman, K. Chemnad, A. E. Hassanien, A. Tlili, C. Y. Zhang, D. Al-Thani, F. Altınay, H. Chalghoumi, H. S. Al-Khalifa, M. Obeid et al., Accessible metaverse: A theoretical framework for accessibility and inclusion in the metaverse, Multimodal Technologies and Interaction 8(3) (2024) 21. doi:10.3390/mti8030021.
[21] W. Li, Y. Zhou, S. Luo, Y. Dong, Design factors to improve the consistency and sustainable user experience of responsive interface design, Sustainability 14(15) (2022) 9131. doi:10.3390/su14159131.
[22] O. Oguntola, S. Simske, Context-aware personalization: A systems engineering framework, Information 14(11) (2023) 608. doi:10.3390/info14110608.
[23] G. Paolone, M. Marinelli, R. Paesani, P. Di. Felice. Automatic code generation of MVC web applications, Computers 9(3) (2020) 56. doi:10.3390/computers9030056.
[24] H. Zafar, S. Ur Rehman Khan, A. Mashkoor, H. U. Nisa, MOBICAT: a model-driven engineering approach for automatic GUI code generation for Android applications, Frontiers in Computer Science 6 (2024) 1397805. doi:10.3389/fcomp.2024.1397805.
[25] B. Cai, J. Luo, Z. Feng, A novel code generator for graphical user interfaces, Scientific Reports 13(1) (2023) 20329. doi:10.1038/s41598-023-46500-6.
[26] M. A. Ali, S. Mekhilef, N. Yusoff, B. Abd Razak, Laser simulator logic: A novel inference system for highly overlapping of linguistic variable in membership functions, Journal of King Saud University-Computer and Information Sciences 34(10) 2022 8019–8040.
[27] H. Talhaoui, T. Ameid, O. Aissa, A. Kessal, Wavelet packet and fuzzy logic theory for automatic fault detection in induction motor, Soft Computing 26(21) (2022) 11935–11949. doi:10.1007/s00500-022-07028-5.
[28] Y. Lin, F. Jin, D. Wang, S. Wang, X. Liu, Dual-task network for road extraction from high-resolution remote sensing images, IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing 16 (2023) 66–78. doi:10.1109/JSTARS.2023.3289217.
[29] V. Senkivskyi, A. Kudriashova, I. Pikh, I. Hileta, O. Lytovchenko, Models of postpress processes designing, in: Proceedings of the 1st International Workshop on Digital Content & Smart Multimedia (DCSMart 2019) (2019) 259–270. URL: https://ceur-ws.org/Vol-2533/paper24.pdf.
[30] T. Hovorushchenko, I. Zabelina, K. Rei, O. Hovorushchenko, Method of creating an information system for monitoring infectious patients, Computer Systems and Information Technologies 3 (2023) 59–64. doi:10.31891/csit-2023-3-7.