Modelling the process of forming the intelligent systems design quality*

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Abstract

The relevance of the issue of modelling the processes of forming the intelligent systems design quality is driven by the rapid development of information technology, the increasing complexity of digital products and the growing demands for user experience. In modern conditions, the effective functioning of intelligent systems directly depends on the quality of their design, which is not only an aesthetic or functional element, but also a complex characteristic that includes ergonomics, accessibility, inclusiveness, cognitive clarity and adaptability to user needs. This necessitates a formalised approach to structuring knowledge in this area and a systematic assessment of the factors that affect the quality of design of such systems.
The study uses an ontological approach that provides a structured representation of knowledge about the subject area, formalises the relationships between key concepts and supports decision-making processes in the design of intelligent systems. An ontological class graph has been developed to reflect the model of the design quality formation process. This graph enables the integration of a set of multi-level influence factors into a unified, coordinated system.
The functional sets of factors that determine the quality of design of intelligent systems are identified. The key ones include: ergonomic and cognitive aspects of user interaction with the system, principles of accessibility and inclusiveness, as well as quality indicators of information architecture and visual design. The relationships between these factors are formalised using the predicate logic, which made it possible to implement their multi-level ranking in accordance with the priority of influence on the quality of the final product.
On the basis of the obtained data, using the methodology of structural analysis, a multilevel model of the priority influence of these factors on the process of forming the quality of design of intelligent systems is built. The model takes into account the hierarchical structure of functional blocks, which allows flexible adaptation to specific development requirements and provides a holistic view of the factors that shape the quality of design solutions in the context of intelligent technologies.

Keywords

intelligent system, design quality, ontological class graph, factors of system design quality, predicate logic, ranking of factors, methodology of structural analysis, multilevel model

1. Introduction

With digital technologies rapidly advancing and computing systems expanding their capabilities, intelligent solutions play a key role in transforming the way people interact with the digital environment. The use of artificial intelligence, machine learning, and adaptive algorithms significantly changes not only the functional content of software solutions but also the principles of building their interface structure [1, 2]. That is why the quality of design of intelligent systems is becoming not a

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secondary concern, but a matter systemic importance, as it affects the overall efficiency of use, security, ethics, user confidence in the system and the level of its integration into real processes [3–5].

In this context, the process of forming design quality cannot be considered as a set of empirical decisions or subjective design preferences, as modelling plays an important role, i.e. building a conceptually and formally sound system that takes into account a wide range of interrelated factors, including cognitive, technological, social and psychological parameters [6]. Such a model should describe the structural and dynamic dependencies between the design quality assessment criteria and the characteristics of an intelligent system, providing an opportunity for objective analysis, comparison, and improvement of design solutions [7-9].

The formation of the design quality of intelligent systems is based on the integration of three key sets of factors, each of which represents a separate aspect of the interaction between the user and the intelligent environment [10]. The first set includes factors of ergonomics and cognitive principles that determine the physiological, psychophysical, and intellectual usability. These factors include the optimal placement of controls, reducing the burden on eyesight and attention, and the interface's compliance with natural mechanisms of perception and information processing [11]. Particular attention is paid to the cognitive load, which should remain at an acceptable level to ensure quick mastery of the system, reduce the risk of erroneous actions and support the user in the decision-making process. In addition, this group of factors takes into account the use of users' mental models, logic of thinking, expectations, and behavioural patterns, which allows for a high level of intuitive understanding of the interface [12, 13].

The second set includes accessibility and inclusivity factors that determine the ability of a system to be equally suitable for the widest range of users, regardless of their physical, sensory, cognitive, or social characteristics [14]. Accessibility involves the implementation of technical and design solutions that provide equal access to the system's functionality for people with visual, hearing, motor or other disabilities. In this context, compatibility with assistive technologies, the use of contrasting colour schemes, scalability of fonts, the availability of alternative text for visual elements, and flexibility in the way information is presented are important. Inclusiveness, in turn, focuses on the cultural, age, linguistic and social diversity of the audience [15, 16]. It ensures that the needs of vulnerable groups, including the elderly, children, or those with limited digital experience, are taken into account. In this way, an inclusive approach to the design of intelligent systems creates the preconditions for ethical, open and humanistic digital interaction.

The third set of factors relates to the quality of information architecture and visual design, which determine the structural organisation, navigation logic, and aesthetic appeal of the interface. Information architecture includes the principles of data organisation, content placement, categorisation of functions, and development of a logical hierarchy of navigation paths [17]. It should ensure quick and accurate orientation of the user in the system, reduce the time spent searching for the necessary information and avoid cognitive confusion. Visual design, in its turn, determines the graphic style, colour palette, typography, spatial organisation of the interface, as well as the consistency of graphic elements among themselves. Its goal is to create an aesthetically balanced, emotionally appealing, and functionally appropriate environment that supports and enhances the user experience. Visual hierarchy, consistency of fonts and colours, rhythm of interface elements, and consideration of cultural and contextual features of the target audience are important in this regard.

There is a growing need for design approaches that not only provide functionality but also allow the user to maintain control, feel predictable and safe system actions [18]. In this regard, the task is to develop a model that will take into account these factors as variables in the process of quality formation, allowing to apply a systematic analytical approach to the evaluation and improvement of design.

In view of the above, the relevance of our study is determined by the need to formalise a complex process that encompasses human interaction with intelligent technologies through an interface shell. The development of a model of the design quality process opens up opportunities to increase the manageability of design decisions, reduce the risk of errors, improve user experience, and increase the overall efficiency of intelligent systems in applied areas.

The main contributions of the authors in this study are as follows:

- an ontological model of classes was developed, which serves as a conceptual framework for systematising the factors that determine design quality. This model provides a consistent representation of multilevel information and creates the prerequisites for its integration into a single cognitive-oriented structure suitable for further analysis and modelling.
- the conceptual allocation of functional clusters of factors influencing the quality of design, as well as the formalisation of their interrelationships through the use of predicate logic tools, which provided the possibility of a clear logical interpretation of the interaction between the elements of the model.
- a multi-level model of priority influence has been formed, which represents the hierarchical organisation of functional components of the design of intelligent systems and reflects the degree of their importance in shaping the overall quality of user interaction with the system.

2. Literature review

The current scientific literature on the study of the principles of forming the quality of digital interface design describes various methodological approaches.

Study [19] examines the impact of emotional design of user interfaces on cognitive processes, motivation, and learning effectiveness in the digital environment. The main advantage is the empirical confirmation of the link between emotionally oriented design and improved learning outcomes. We have taken into account the rationale of this work regarding some factors that evoke positive emotions, which can increase user engagement and the level of learning. Among the shortcomings, it is worth noting the limited generalisation of the findings due to the specifics of the sample and the experimental environment.

In [20], a systematic review of the literature on the use of heuristic evaluation to improve the usability of digital products was conducted. It is noted that usability is influenced by three competing factors, namely design principles, user engagement, and evaluator perception. However, there is no extended model of priority criteria and detailed justification. Instead, [21] presents a comprehensive methodology for evaluating user interface and user experience. The study combines heuristic evaluation, cognitive analysis with a think-aloud protocol, and UX surveys to identify usability problems and improve learning efficiency. Among the advantages is the integration of several methods for deeper analysis. However, the limitation is that it is limited to assessing the design of a cyberlearning environment. It should be noted that most studies deal with a small number of design factors or are aimed at evaluating specific environments.

It is rightly noted in [22] that stages or individual procedures of technological processes require consideration of certain factors (criteria, requirements, parameters) to ensure quality implementation. These factors differ in type, purpose, methods of application, peculiarities of influence on the process, etc. However, the study of factors influencing the quality of the analysed process is a necessary initial stage of predictive quality assessment. In [23], a method for determining the priority of factors based on mathematical modelling of hierarchies is proposed. This method allows determining the dominance of factors by constructing a matrix of pairwise comparisons and the required number of iteration tables. Paper [24] also uses the analytic hierarchy process for a reasonable choice of the optimal algorithm for the process under study, taking into account a set of key criteria. The main advantage is the simplicity of mathematical modelling. However, this approach is based on a discrete representation of interdependencies and does not take into account the degree of intensity of the impact, which can lead to the loss of some of the relevant information in multifactorial systems. That is why in our study we chose a ranking method that allows us to set weighting coefficients for different types of relationships. In [25], the authors determined the optimal method for implementing the process using the principle of multi-objective optimisation. The main limitation is the insufficient number of analysed factors, which reduces the complexity of the findings. This approach is partially justified by the Pareto rule, which focuses on the most influential variables but does not allow for a full reflection of the entire structure of interdependencies in complex systems. Instead, we used expert evaluation to form a set of factors and identified three main blocks that affect the quality of intelligent systems design.

The main advantages of our approach, compared to the other analysed ones, are a clear presentation of the sets of factors influencing the formation of the intelligent systems design quality and prioritisation of factors based on the ranking method, which allows taking into account the weight values of the links between them. The results of the study can be integrated into practical design evaluation and management tools based on ontological and logical-analytical approaches, providing a more systematic, evidence-based and predictable environment for the development and improvement of intelligent digital systems.

3. Material and methods

3.1. Developing an ontology

A computer ontology is a description of a subject area using a hierarchical structure of concepts in the form of a finite set. The fundamental principles of ontology development are clarity, validity, extensibility, minimum level of coding, and minimum ontological involvement [26, 27]. In view of the above, let us formulate the following statements that reflect the requirements for the development of ontological models:

Statement 1. An ontology should provide an adequate and accurate reflection of reality, based on formally defined concepts and terms, the semantic interpretation of which is unambiguous and generally accepted.

Statement 2: The designation of concepts in the ontology should comply with semiotic standards and be formalised on the basis of agreed definitions recorded in scientific journals such as glossaries and dictionaries.

Statement 3: The structure of the ontology should be consistent, developed using axiomatic foundations and formal rules to ensure consistency of statements and their relationships.

Statement 4. An ontology should be developed taking into account the principle of extensibility, which implies the possibility of dynamic addition of new concepts and statements without loss of integrity and consistency.

Statement 5. A formalised ontology model should not depend on specific representation formats, software environments or technologies.

Statement 6. The construction of an ontology should be based on minimal ontological assumptions, avoiding unnecessary detail and limiting itself to only those concepts that are critically necessary for the performance of the tasks.

Statement 7. All definitions in the ontology should be formally verified to ensure the reliability and validity of the model.

Statement 8. The ontology should support integration with other formalised knowledge systems through the standardised interoperability protocols to ensure effective interaction.

Statement 9. An ontological model should be oriented towards universality and reusability.

An ontological representation provides a structured description of a subject area using concepts, their properties and relationships.

According to Figure 1, the initial stage of ontology development involves the research and systematisation of knowledge related to assessing the quality of intelligent systems design. Based on the data obtained, the basic concepts and principles of the ontology are formed. A list of problems that can be solved with the help of an ontological approach is also outlined. The next step is to formulate the main functions and tasks of the ontology to develop design rules and constraints. For example, requirements for hierarchical structure or relationships between elements. At the same time, the implementation of clear rules and constraints ensures the consistency, unambiguity, and functionality of the ontological model. For effective project implementation, it is important to choose an information system for graphical representation of ontological models. The availability of built-in consistency checking algorithms and compatibility with modern standards such as OWL (Web Ontology Language) and RDF (Resource Description Framework) are crucial when choosing a system. In this study, the creation, editing, visualisation, and verification of the ontological model was carried out using Protégé, a free and open-source platform developed by a team from Stanford University [27,28].

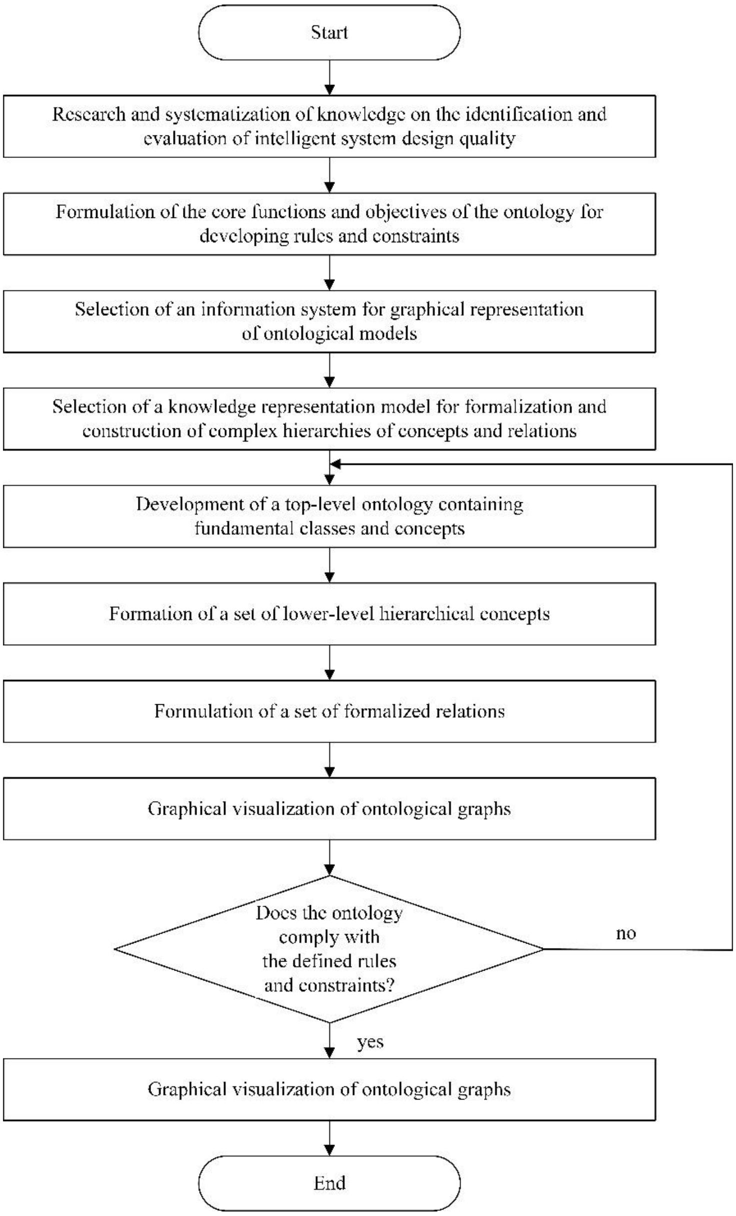

Figure 1: Flowchart of the ontology development algorithm.

The graphical display of ontological graphs greatly facilitates the perception of complex ontological models. Visualisation allows you to quickly identify key elements, relationships, and potential conflicts of the ontology.

3.2. Ranking of factors

The multi-factor ranking method [29, 30] enables the ordering of factors based on their values within the structure of cause-and-effect relationships. The methodological foundation is the construction of hierarchical models that represent interdependencies among sets of factors affecting the quality of intelligent system design. This approach makes it possible to determine the weights of relationships between factors.

The relationships between elements are classified as influences and dependencies, which in turn may be either direct or indirect. Differentiating the types of relationships allows for a more precise description of factor interactions and avoids reductionist assumptions regarding linearity or independence of model components. This classification serves as the basis for building a tree-like structure that simulates real-world design conditions for intelligent systems, particularly in shaping the quality of the final product [22].

The quality of intelligent system design involves a significant number of factors $G=\{g_1,g_2,...,g_n\}$ and is formed based on three components $G=\{E;D;I\}$, where: E — ergonomics and cognitive principles of interaction, D — accessibility and inclusiveness, I — information architecture and visual design. Let us conventionally denote the factors of a specific component as $X=\{x_1,x_2,...,x_n\}$. By a qualitative result, we shall understand a function that formalizes the cumulative contribution of a set of influencing factors to the improvement of the quality of the studied process. Let us denote this result as $F(x_m)$, where k corresponds to a specific process. Therefore, the following expression, which represents the quality function of this component, holds true:

$$F(x_m)=\bigcup_{j=1}^{n}\omega(x_{jm}),\quad (m=1,2,3), \tag{1}$$

where: $F(x_m)$ — the integral quality function of the process with index m; $\omega(E_{jm})$ — the coefficient representing the additional quality contributed by factor j within process m; n — the total number of factors relevant to the given process.

Thus, the statement regarding the existence of a set of factors influencing the quality of the process can be presented in a formalized form:

$$(\exists g)(\forall x)C(x_m);\quad g\in G;\quad x\in X. \tag{2}$$

In the context of multifactor analysis of a technological process, the degree of importance of each factor is determined by its rank, which formally corresponds to the value of its weight coefficient. The rank serves as a numerical indicator that allows the set of factors to be ordered according to their level of influence on the target function.

Let a set of weight coefficients be given $W=\{w_{1_m},w_{2_m},...,w_{n_m}\}$ under the condition $G(w)=max\{w_{1_m},w_{2_m},...,w_{n_m}\}$, then:

$$(\exists g)(\forall w)G(w);\ g\in G;\ w\in W. \tag{3}$$

It should be noted that there is at least one factor that dominates in terms of weight value. The factor with the highest weight is considered a priority and has a decisive influence. Absolute equivalence of factors is unlikely, as each is characterized by its own intensity of influence, determined by its structural role and interactions with other elements.

The construction of graph-based models relies on the existence of causal or functional relationships between the factors of the studied process. The identification of such connections at the initial stage is carried out using expert evaluation, which enables the formation of a preliminary graph structure that reflects the hierarchy of individual factor influences. The initial ranking is determined by identifying the prevailing connections between the graph nodes that represent the corresponding factors. In this way, a multi-level model is formed, within which priorities are established based on the intensity of one factor's dominance over another.

If the condition $B(w)=w_j>w_{j+1}$ is satisfied for $(j=1,2,...n-1)$, then the following expression can be formulated:

$$(\forall w)B(w);\quad w\in W. \tag{4}$$

Given the above, it is advisable to apply a structural analysis methodology using graph-based representations to develop a model of the prioritized influence of factors on the quality of intelligent system design. This approach requires the preliminary identification of a set of relevant factors and the determination of the nature of the interrelationships among them. The initial informational structure is built based on expert evaluation, where the connections between system elements represent a hierarchical organization of influences.

Quantitative ranking of influences requires the introduction of formal parameters, particularly weight coefficients, which reflect the significance of each type of connection. To formalize both direct and indirect influences between factors, an indexing system is introduced, allowing dependencies to be classified by their order. Let us assume that h_{ij} — is the number of connections of the i-th type for the j-th factor where $j = 1,...,n$, then w_i will represent the weight value of the i-th type of connection. That is, each type of interaction corresponds to a specific index: for direct influences $i = 1$, for indirect influences $i = 2$, for direct dependencies $i = 3$, and for indirect dependencies $i = 4$. The order of dependency correlates with the distance of influence within the graph structure: first-order indicates a direct influence, while second-order refers to an indirect influence through an intermediate factor. This aligns with the logic of systems analysis, where the strength of interaction decreases with increasing distance in the graph.

It is reasonable to assume that influence weights will be positive, while all dependencies will have negative values. Moreover, indirect connections carry less weight than the direct ones. Therefore, the following conditions hold true: $w_1 > 0$, $w_2 = w_1 / 2$, $w_3 < 0$, $w_4 = w_3 / 2$. Next weight coefficients will be used: $w_1 = 10$, $w_2 = 5$, $w_3 = -10$, $w_4 = -5$.

The ranks of the factors X_{ij} are calculated as a weighted sum of all types of influences, normalized by the corresponding coefficients:

$$X_{ij} = \sum_{i=1}^{4} \sum_{j=1}^{n} h_{ij} w_i , \tag{5}$$

where n — the ordinal number of the factor.

Given that $w_3 < 0$ and $w_4 < 0$ next will be obtained $R_{3j} < 0$ and $R_{4j} < 0$.

To ensure the correct construction of the model based on weight characteristics, it is necessary to normalize the corresponding values to a unified coordinate system. This eliminates distortions caused by the uneven impact of different types of connections. In terms of graphical interpretation, this corresponds to the procedure of vertically shifting a histogram that represents the set of interactions.

The shift is implemented by introducing a compensatory component that accounts for the boundary values of the matrices of direct and reverse influences. The calculation is performed according to the following relation:

$$\Delta_j = max\left|X_{3j}\right| + max\left|X_{4j}\right|, \left(j = 1,2,...,n\right). \tag{6}$$

Further calculations are carried out using an aggregated function that combines influence coefficients, weight values, and corresponding adjustments:

$$X_{Fj} = \sum_{i=1}^{4} \sum_{j=1}^{n} \left(h_{ij} w_i + \Delta_j\right). \tag{7}$$

Formula (7) provides a generalization of the quantitative parameters and establishes an analytical foundation for developing the factor prioritization model.

4. Experiment, results and discussion

The quality of intelligent system design is shaped by three sets of factors: $E=\{E_1,E_2,E_3,E_4,E_5,E_6\}$ — a set of factors related to ergonomics and cognitive principles of interaction, $D=\{D_1,D_2,D_3,D_4,D_5\}$ — a set of factors related to accessibility and inclusivity, and $D=\{I_1,I_2,I_3,I_4,I_5\}$ — a set of factors associated with the quality of information architecture and visual design. Given the above, the developed ontological model of intelligent system design quality is presented as an ontological class graph (Fig. 2).

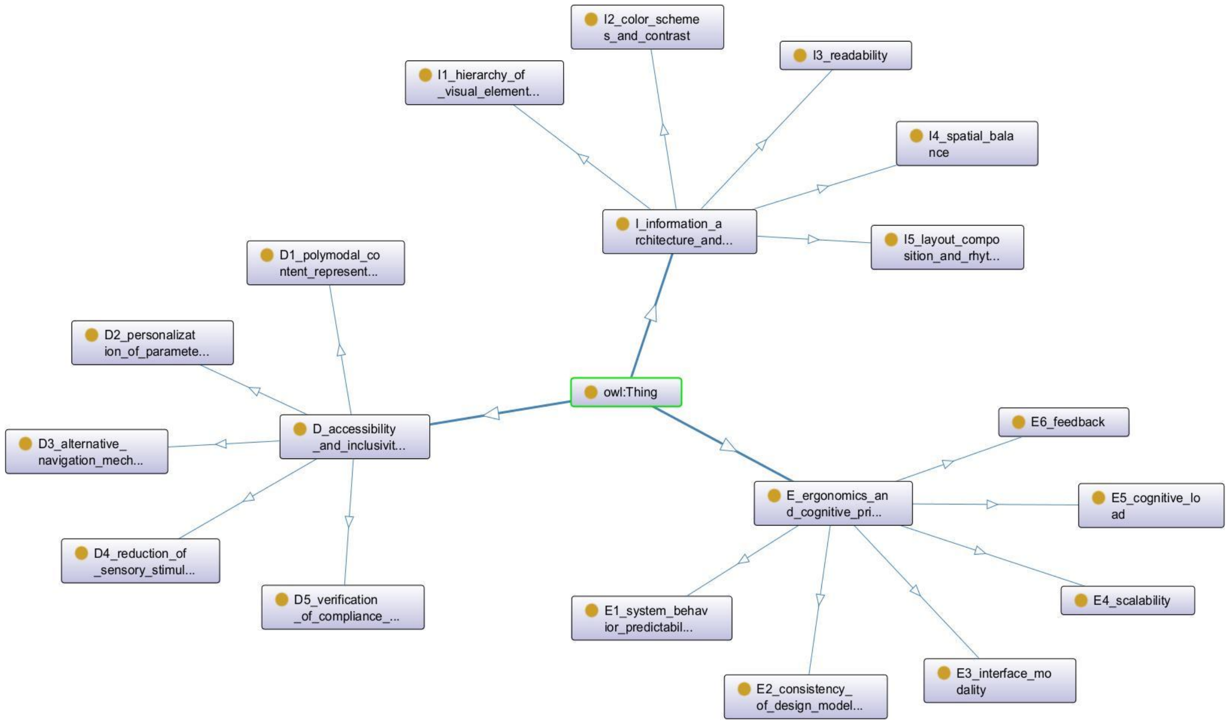

Figure 2: Ontological class graph of the ontology of intelligent system design quality.

For ease of further analysis, the sets of factors influencing the quality of intelligent system design (ontology classes) are presented in Table 1.

Table 1
Factors of intelligent system design quality

Ergonomics and cognitive principles of interaction (E)	Accessibility and inclusivity (D)	Information architecture and visual design (I)
System behaviour predictability (E_1)	Polymodal content representation (D_1)	Hierarchy of visual elements (I_1)
Consistency of design models (E_2)	Personalization of parameters (D_2)	Colour schemes and contrast (I_2)
Interface modality (E_3)	Alternative navigation mechanisms (D_3)	Readability (I_3)
Scalability (E_4)	Reduction of sensory stimuli (D_4)	Spatial balance (I_4)
Cognitive load (E_5)	Verification of compliance with accessibility standards (D_5)	Layout composition and rhythm (I_5)
Feedback (E_6)		

The description of relationships between factors is most appropriately carried out using predicate logic. This approach enables precise representation of the relations between entities that form the knowledge structure. The foundation of this description lies in the use of logical structures, particularly the universal $\forall$ and existential $\exists$, quantifiers, logical conjunction «and» $\wedge$ and implication «if» $\leftarrow$. Connections between factors (terms) are defined through predicates—logical functions that take one or more terms as arguments. This allows for the representation of both simple and complex relationships between concepts within a single formal system.

Description of ergonomics and cognitive interaction principles factors: ($\forall$ E_i) [$\exists$ (E_1, predictability of system behavior) $\leftarrow$ optimizes (E_1, E_5) $\wedge$ is determined by (E_1, E_2) $\wedge$ is modified by (E_1, E_3) $\wedge$ is optimized by (E_1, E_6)]; ($\forall$ E_i) [$\exists$ (E_2, consistency of design models) $\leftarrow$ defines (E_2, E_1) $\wedge$ influences (E_2, E_4) $\wedge$ optimizes (E_2, E_5)]; ($\forall$ E_i) [$\exists$ (E_3, interface modality) $\leftarrow$ modifies (E_3, E_1) $\wedge$ influences (E_3, E_5)]; ($\forall$ E_i) [$\exists$ (E_4, scalability) $\leftarrow$ modifies (E_4, E_6) $\wedge$ depends on (E_4, E_2)]; ($\forall$ E_i) [$\exists$ (E_5, cognitive load) $\leftarrow$ is optimized by (E_5, E_1) $\wedge$ is optimized by (E_5, E_2) $\wedge$ depends on (E_5, E_3) $\wedge$ is optimized by (E_5, E_6)]; ($\forall$ E_i) [$\exists$ (E_6, feedback) $\leftarrow$ optimizes (E_6, E_1) $\wedge$ optimizes (E_6, E_5) $\wedge$ is modified by (E_6, E_4)].

The developed hierarchical models of direct and indirect influences of factors (Fig. 3), as well as direct and mediated dependencies between factors (Fig. 4), are presented using the example of ergonomics and cognitive principles of interface interaction. Analogous hierarchical structures have been constructed for the factors of accessibility and inclusivity, as well as for those pertaining to information architecture and visual design.

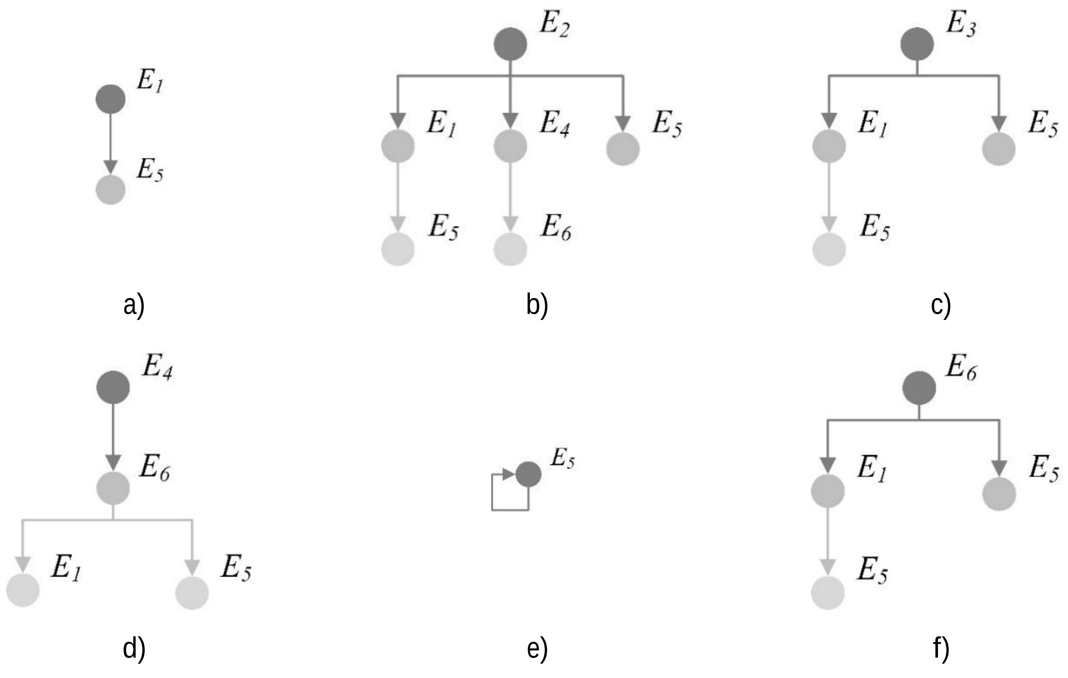

Figure 3: Hierarchical models of the influences of factors related to ergonomics and cognitive interaction principles: a) — predictability of system behaviour; b) — consistency of design models; c) — interface modality; d) — scalability; e) — cognitive load; f) — feedback.

Factors of accessibility and inclusivity: ($\forall$ D_i) [$\exists$ (D_1, polymodal content representation) $\leftarrow$ defines (D_1, D_2) $\wedge$ initiates (D_1, D_3) $\wedge$ is initiated by (D_1, D_5)]; ($\forall$ D_i) [$\exists$ (D_2, personalization of parameters) $\leftarrow$ optimizes (D_2, D_4) $\wedge$ is determined by (D_2, D_1) $\wedge$ is determined by (D_2, D_5)]; ($\forall$ D_i) [$\exists$ (D_3, alternative navigation mechanisms) $\leftarrow$ supports (D_3, D_4) $\wedge$ is initiated by (D_3, D_1) $\wedge$ is initiated by (D_3, D_5)]; ($\forall$ D_i) [$\exists$ (D_4, reduction of sensory stimuli) $\leftarrow$ is optimized (D_4, D_2) $\wedge$ is supported by (D_4, D_3) $\wedge$ is optimized (D_4, D_5)]; ($\forall$ D_i) [$\exists$ (D_5 , verification of compliance with accessibility standards) $\leftarrow$ initiates (D_5, D_1) $\wedge$ defines (D_5, D_2) $\wedge$ initiates (D_5, D_3) $\wedge$ optimizes (D_5, D_4)].

Factors of information architecture and visual design quality: ($\forall$ I_i) [$\exists$ (I_1 , hierarchy of visual elements) $\leftarrow$ defines (I_1, I_3) $\wedge$ supports (I_1, I_4) $\wedge$ is initiated by (I_1, I_2) $\wedge$ is initiated by (I_1, I_5)]; ($\forall$ I_i) [$\exists$ (I_2 , colour scheme and contrast)) $\leftarrow$ initiates (I_2, I_1) $\wedge$ is determined by (I_2, I_3) $\wedge$ is determined by (I_2, I_5)]; ($\forall$ I_i) [$\exists$ (I_3 , readability) $\leftarrow$ is determined by (I_3, I_1) $\wedge$ is determined by (I_3, I_2) $\wedge$ is optimized (I_3, I_4) $\wedge$ is optimized (I_3, I_5)]; ($\forall$ I_i) [$\exists$ (I_4 , spatial balance) $\leftarrow$ optimizes (I_4, I_3) $\wedge$ is supported by (I_4, I_1) $\wedge$ is determined by (I_4, I_5)]; ($\forall$ I_i) [$\exists$ (I_5 , layout composition and rhythm) $\leftarrow$ initiates (I_5, I_1) $\wedge$ defines (I_5, I_2) $\wedge$ optimizes (I_5, I_3) $\wedge$ defines (I_5, I_4)].

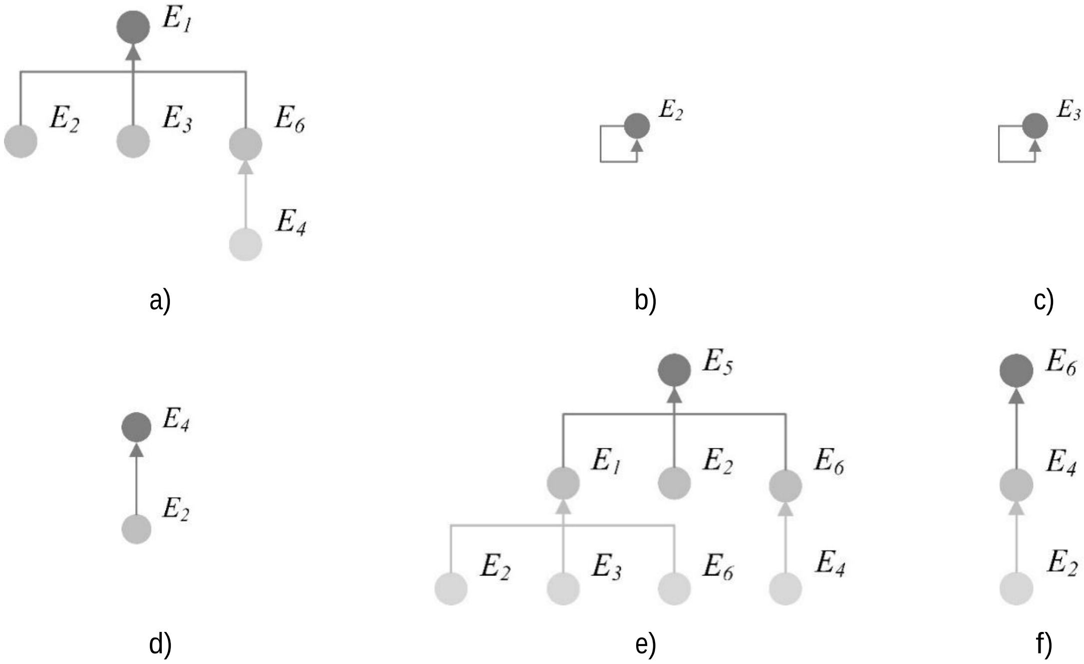

Figure 4: Hierarchical models of the dependencies between factors related to ergonomics and cognitive interaction principles: a) — predictability of system behavior; b) — consistency of design models; c) — interface modality; d) — scalability; e) — cognitive load; f) — feedback.

The obtained results concerning the ranks and priorities of factors related to ergonomics and cognitive interaction principles — based on expressions (6), (7), and taking into account the assigned weight values for first- and second-order influences and dependencies — are presented in tabular form (Table 2).

Table 2
Ranks of factors related to ergonomics and cognitive principles of interaction

j	h_{1j}	h_{2j}	h_{3j}	h_{4j}	E_{1j}	E_{2j}	E_{3j}	E_{4j}	E_{Fj}	Factor rank	Priority level
1	1	1	3	1	10	5	-30	-5	30	2	4
2	3	2	0	0	30	10	0	0	90	5	1
3	2	1	0	0	20	5	0	0	75	4	2
4	1	2	1	0	10	10	-10	0	60	3	3
5	0	0	3	4	0	0	-30	-20	0	1	5
6	2	1	1	1	20	5	-10	-5	60	3	3

The ranking results for the factors of accessibility and inclusivity are presented in Table 3, while those for the factors of information architecture and visual design are shown in Table 4.

Table 3
Ranks of accessibility and inclusivity factors of intelligent systems

j	h_{1j}	h_{2j}	h_{3j}	h_{4j}	D_{1j}	D_{2j}	D_{3j}	D_{4j}	D_{Fj}	Factor rank	Priority level
1	2	2	1	0	20	10	-10	0	70	3	2
2	1	0	2	1	10	0	-20	-5	35	2	3
3	1	0	2	1	10	0	-20	-5	35	2	3
4	0	0	3	4	0	0	-30	-20	0	1	4
5	4	4	0	0	40	20	0	0	110	4	1

Table 4
Ranks of information architecture and visual design factors

j	h_{1j}	h_{2j}	h_{3j}	h_{4j}	I_{1j}	I_{2j}	I_{3j}	I_{4j}	I_{Fj}	Factor rank	Priority level
1	2	1	2	1	20	5	-20	-5	65	3	3
2	2	2	1	0	20	10	-10	0	85	4	2
3	0	0	4	5	0	0	-40	-25	0	1	5
4	1	0	2	2	10	0	-20	-10	45	2	4
5	4	5	0	0	40	25	0	0	130	5	1

Based on the data presented in Table 2 through Table 4, a model for constructing the quality of intelligent system design has been developed (Fig. 5). This model comprises three main blocks containing factors arranged according to their priority levels.

The main factor influencing the ergonomics and cognitive principles of interaction with the interface is the consistency of design models, which received the highest weight (90 units). This factor ensures consistency in the behaviour of interface elements, which reduces the number of errors and speeds up user learning. Interface modularity allows you to adapt the interaction environment to the context of the task, reducing information overload, and is the second highest priority. Scalability and feedback were rated equally, as they are equally important for supporting the dynamics of cortical scenarios. Predictability of the system's behaviour has a lower priority, as its absence is partially compensated by other principles, in particular, consistency. The lowest priority belongs to the cognitive load factor. However, a score of 0 does not mean that it has no impact on the process under study, but rather that it has the lowest weight among the other factors analysed.

The second block of the model, which visualizes the influencing factors on accessibility and inclusivity, consists of four levels. The most dominant among them is the factor of verifying compliance with accessibility standards.

This result is logically grounded from a technological perspective, as this factor ensures the basic compatibility of interfaces with regulatory requirements and guarantees legal compliance. Polymodal content representation provides access to information through multiple sensory channels, enhancing the universality of perception. The factors of parameter personalization and alternative navigation mechanisms hold medium priority—each scoring 35 units. The reduction of sensory stimuli received the lowest weight in the model, as this factor has a narrow specialization and a comparatively lesser impact on the overall level of accessibility than fundamental criteria such as technical compatibility and multimodal information presentation.

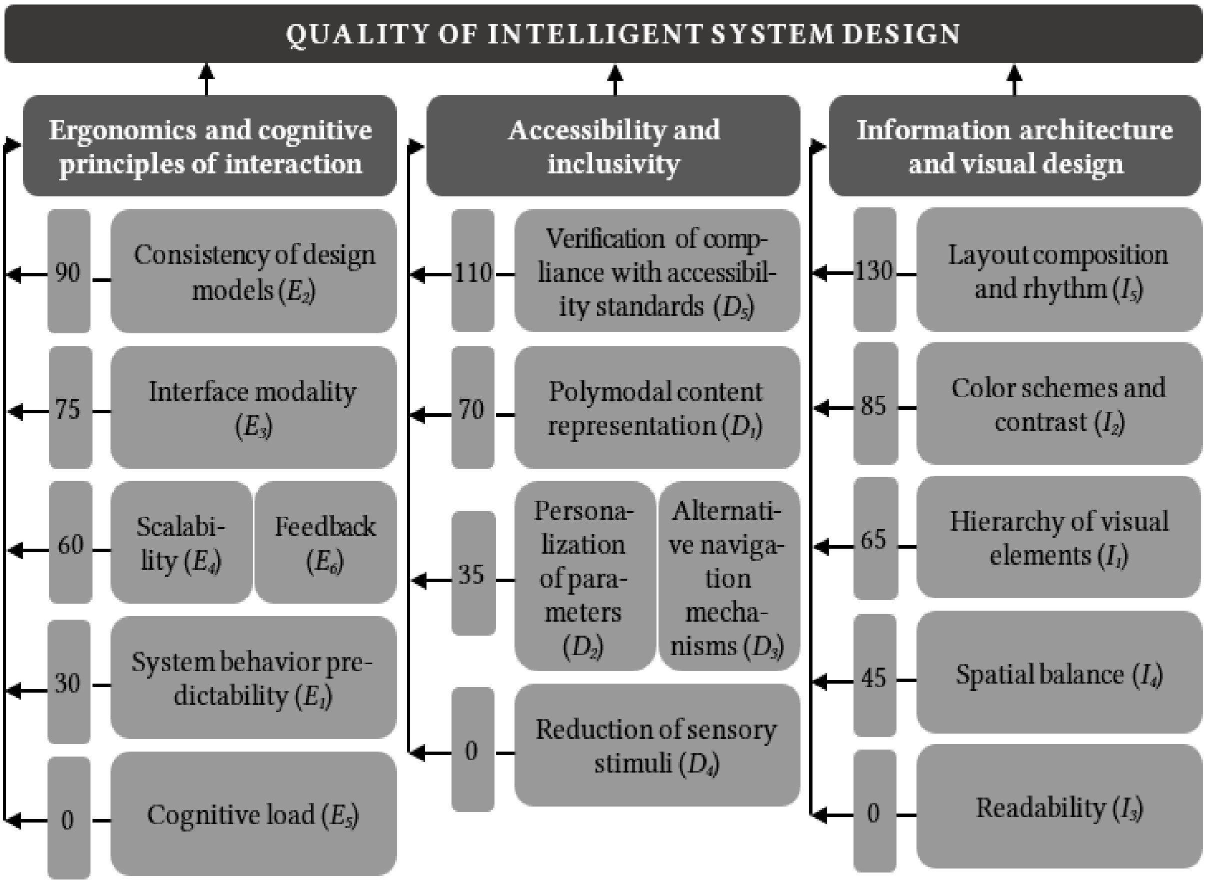

Figure 5: Model for constructing the quality of intelligent system design.

The highest-priority factor influencing the quality of information architecture and visual design is the layout composition and rhythm. This factor determines the overall coherence and consistency of the visual environment, supports logical content navigation, and minimizes visual noise, thereby improving content perception efficiency.

The colour scheme and contrast factor rank second with a score of 85 units, as it directly affects the visual accessibility of elements. The least dominant factor is readability, as it largely depends on other factors.

Thus, a scientifically grounded approach to modelling the process of forming the design quality of intelligent systems is presented. It is based on domain-specific ontological modelling, formal representation of inter-factor relationships through predicate logic, and the use of ranking methods to determine factor prioritization.

The developed model of prioritized factor influence on design quality can have significant practical applications across various fields of digital engineering, where user interaction quality and adaptability are critical. It can be used to create effective interfaces in complex digital systems—from mobile applications to industrial SCADA solutions. Additionally, it holds potential for application in personalized learning environments, particularly on e-learning platforms, to adapt the learning environment design to users' cognitive characteristics.

The model may also serve as a foundation for defining standards, criteria, and assessment procedures for design quality during certification or internal quality control in IT companies and startups. It should be noted that the list of factors is not exhaustive. The main limitation of this study lies in the fixed set of factors in the developed model. When adding new factors, the proposed methodology requires recalculating the weight values.

Future research prospects include optimizing the model to avoid equal prioritization of factors and applying machine learning and fuzzy logic methods to develop a design evaluation system.

5. Conclusions

The study carried out a comprehensive modelling of the processes of forming the quality of design of intelligent systems, which is extremely relevant in view of modern technological challenges. The analysis shows that the design of intelligent systems should be considered not only as a set of visual or structural solutions, but also as a complex, multi-level system of user interaction with the digital environment, based on ergonomic, cognitive, inclusive, architectural and informational factors. Understanding these aspects in the context of a systems approach is critical to creating effective, convenient, and functionally complete solutions.

The introduction of the ontological approach allowed us to formalise knowledge about the subject area, establish clear relationships between key factors and build a holistic model that supports design decision-making.

The developed ontological class graph served as the foundation for further structuring the factors influencing design quality, enabling the integration of multi-level data into a unified logical system. This not only increases the transparency of design processes, but also contributes to the standardisation of approaches to evaluating its effectiveness.

A significant achievement of the study was the identification of functional sets of influence factors and the implementation of their logical relationships using predicate logic. This approach allowed for a multi-level ranking of factors by the degree of their impact on the quality of the final product, which is extremely useful both in the development of new systems and in the audit and improvement of existing ones. The ordering of factors by priority of influence contributes to making informed decisions on the allocation of resources in the design process.

On the basis of the structural analysis, a multi-level model of priority influence of factors is built, reflecting the hierarchy of functional blocks of the design of intelligent systems. This model is a universal basis for flexible customisation of design processes in accordance with the specifics of an application area, system type or target audience. This approach forms a platform for further automation of design quality assessment and implementation of intelligent UX/UI solutions.

In general, the results of the study indicate the feasibility and effectiveness of using formalised ontological models in the process of designing intelligent systems. They demonstrate that high-quality user interaction with intelligent digital environments can be achieved only through systematic knowledge integration, factor prioritization, and logical relationship structuring.

In the future, it is promising to expand the proposed model by including adaptive mechanisms for self-updating based on user feedback, as well as introducing machine learning elements for automated prediction of the impact of individual factors on the overall quality of design. In addition, it is advisable to create tools for visualising and dynamically managing ontological structures in the process of developing complex intelligent systems.

The approaches proposed in this study can be effectively applied in the areas where it is critical to ensure high quality user interaction with intelligent digital systems. This applies to the development of interfaces for complex software products, decision support systems, adaptive learning platforms, as well as digital services in the fields of healthcare, finance, transport, and others. The ontological model allows you to structure knowledge about the factors that affect the quality of design and supports sound design based on system analysis. This enables the formal evaluation of the design, its adaptation to the specific characteristics of the target audience, and its improvement based on logically justified priorities. The results can be integrated into the practice of auditing, standardisation and automated quality management of digital solutions.

Declaration on Generative AI

The authors have not employed any Generative AI tools.

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