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METHOD FOR RANKING THE RELIABILITY FACTORS OF TEXT MESSAGES

In recent years, the problem of information reliability has become a subject of increased scientific interest, which led to the formation of an interdisciplinary approach that combines methodologies of computer science, psychology, sociology and media education. Within the framework of the modern scientific paradigm, a comprehensive study of various aspects of this subject is carried out: from natural language processing and analysis of fake news to the study of the mechanisms of disinformation spread in social networks, the features of functioning of scientific and political communication, as well as manifestations of information confrontation.

Despite the existing scientific achievements, the proposed study presents the initial phase of developing a new concept that involves the use of factor analysis to solve problems related to assessing the reliability of information messages. The main idea is in transition from an a posteriori to an a priori approach, which allows for a predictive assessment of the data reliability even before their potential appearance in the information space. Within the framework of the proposed model, a set of factors is identified that influence the reliability level of text messages. To arrange the specified factors according to their significance degree, a ranking method is used in combination with semantic modelling based on the language of predicates, which provides a linguistic interpretation of the relationships between the elements of the system. Taking into account the expert determination of weight coefficients for the types of relationships in the semantic network, preliminary weight priorities for each factor are established. Based on the mathematical formalism of the algorithm for calculating the weight of predicates, a generalized description of weight sets for relationships of the "influence" and "dependency" types is constructed. This allows forming a system of integrated weight preferences that determine the factor priority levels in terms of their influence on the reliability of information messages. As a result, a multilevel model of factor influence is constructed taking into account the additional action of predicates that reflect semantic relationships in the information space.

Keywords: reliability of text messages, factor, semantic network, predicate language, ranking method, multilevel model.

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МЕТОД РАНЖУВАННЯ ФАКТОРІВ ДОСТОВІРНОСТІ ТЕКСТОВИХ ПОВІДОМЛЕНЬ

Упродовж останніх років проблема достовірності інформації стала предметом посиленого наукового інтересу, що зумовило формування міждисциплінарного підходу, який поєднує методології комп'ютерних наук, психології, соціології та медіаосвіти. У межах сучасної наукової парадигми здійснюється комплексне вивчення різноманітних аспектів цієї тематики: від обробки природної мови та аналізу фейкових новин до дослідження механізмів поширення дезінформації в соціальних мережах, особливостей функціонування наукової та політичної комунікації, а також проявів інформаційного протиборства.

Попри наявний науковий доробок, у запропонованому дослідженні представлено початкову фазу розробки нової концепції, яка передбачає використання факторного аналізу для вирішення завдань, пов'язаних з оцінюванням достовірності інформаційних повідомлень. Основна ідея полягає у переході від апостеріорного до апріорного підходу, що дозволяє здійснювати прогнозну оцінку правдивості даних ще до їх потенційної появи в інформаційному просторі. У межах запропонованої моделі виокремлено сукупність факторів, які чинять вплив на рівень достовірності текстових повідомлень. Для впорядкування зазначених факторів за ступенем їхньої значущості використано метод ранжування у поєднанні з семантичним моделюванням на основі мови предикатів, що забезпечує лінгвістичну інтерпретацію взаємозв'язків між елементами системи. З урахуванням експертного визначення вагових коефіцієнтів для типів зв'язків у семантичній мережі встановлено попередні вагові пріоритети кожного з факторів. На основі математичного формалізму алгоритму обчислення вагомості предикатів здійснено побудову узагальненого опису множин вагомості для зв'язків типу «вплив» і «залежність». Це дозволило сформувати систему інтегрованих вагових переваг, які визначають рівні пріоритетності факторів щодо їхнього впливу на достовірність інформаційних повідомлень. У результаті було побудовано багаторівневу модель факторного впливу з урахуванням додаткової дії предикатів, що відображають семантичні зв'язки в інформаційному просторі.

Ключові слова: достовірність текстових повідомлень, фактор, семантична мережа, мова предикатів, метод ранжування, багаторівнева модель.

Introduction

Assessing the reliability of text information messages is a critically important problem in the conditions of a modern information society. The rapid development of digital technologies, the mass distribution of the Internet and social media, as well as the growth of the generated information volume necessitate the development of efficient means for determining the veracity, reliability and quality of the received data.

In recent years, the topic of information reliability has attracted the attention of a wide range of researchers who apply an interdisciplinary approach, combining the achievements of computer science, psychology, sociology and media education. In the area of modern scientific approaches, various aspects of the problem are studied, in particular, the natural language processing and the analysis of fake news, the spread of disinformation in social networks, the features of scientific and political communication, as well as information wars.

Within the modern research framework, algorithmic and analytical approaches are actively being developed aimed at identifying signs of manipulative influence, analysing sources of information dissemination and determining its reliability degree [1, 2]. The involvement of the latest data processing technologies, in particular machine learning and artificial intelligence tools, significantly increases the efficiency of assessing information flows, helping to minimize the negative impact of destructive content on social processes, as reflected in the work [3]. The intensive development of artificial intelligence technologies, machine learning methods, linguistic analysis and neural network architectures ensures increased efficiency in processing text and multimedia data [4, 5]. The efficiency of the application of artificial intelligence and machine learning methods in the cybersecurity field with an emphasis on their ability to detect threats and anomalies is reflected in the work [6]. The study [7] highlights the use of multimodal methods for recognizing fake news based on semantic information, while drawing the attention to the loss of relevant surface-level data due to the focus exclusively on deep content features. The work [8] presents a taxonomy of models, machine learning and deep learning functions used to detect fake news based on content analysis. Despite the achievements in the automation of identifying false information, no effective solutions have been proposed to improve the accuracy of classification or adapt to new formats of manipulative influence. The authors of this publication [9] analyse the use of neural networks in the tasks of detecting fake messages. The efficiency of the considered approaches is assessed based on a comparative analysis of strategies, methods for assessing errors and accuracy of results on different data samples.

The goal of these studies is to provide scientists with guidelines for selecting relevant criteria and optimal methods for solving applied problems of intellectual analysis of manipulative content [10]. A detailed review of methods for detecting and generating deepfakes is carried out, current challenges for detection systems are highlighted, and potential ways to overcome them using deep learning are outlined. At the same time, the results of empirical testing of the efficiency of the proposed solutions in real conditions remain unpublished. The study [11] focuses on analysing the problem of radicalization of large language models, identifying semantic vulnerabilities and shortcomings in the learning process based on human feedback. The main attention is paid to theoretical aspects, while practical recommendations for the implementation of protection mechanisms are absent. The publication [12] considers the problem of manipulative influence by artificial intelligence systems. Criteria for assessing the level of manipulation are proposed, and the emphasis is placed on the need to create transparent decision-making systems capable of counteracting external influence. However, the study does not provide clear quantitative metrics and efficient methods for assessing this level.

Despite the existence of significant scientific achievements in the relevant area, the article describes the initial phase of a new concept, the essence of which is to apply factor analysis to solve the problem of assessing the reliability of information messages. It is proposed, in contrast to the known approaches to a posteriori assessment of news, to apply a strategy of a priori, predictive establishment of the data veracity even before their probable appearance in the media space. Within the framework of the specified approach, a set of factors affecting the data reliability is taken into account, the mechanism of formation, assessment and consideration of linguistic relationships between the identified factors, reflected in the graph semantic network, is revealed, on the basis of which a multilevel graphical model of the priority influence of factors on the reliability of text information messages is developed using the ranking method [13].

Ranking of Reliability Factors of Text Messages

The basis for applying the ranking method to develop a multilevel graphical model of factors influencing the reliability of text messages is considered to be a semantic network – a formalized means of displaying relationships between factors and indicators of the reliability of news data content (Fig. 1). In this case, the set of specified criteria has the following formalized representation:

$$X = \{x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8\}, \tag{1}$$

where x_1 is professionalism of the author, x_2 is objectivity of the author, x_3 is informativeness of the message context, x_4 is a source of information, x_5 is fact checking, x_6 is multiple publication (verification through the search for multiple publication), x_7 is refutation and criticism, x_8 is social trust.

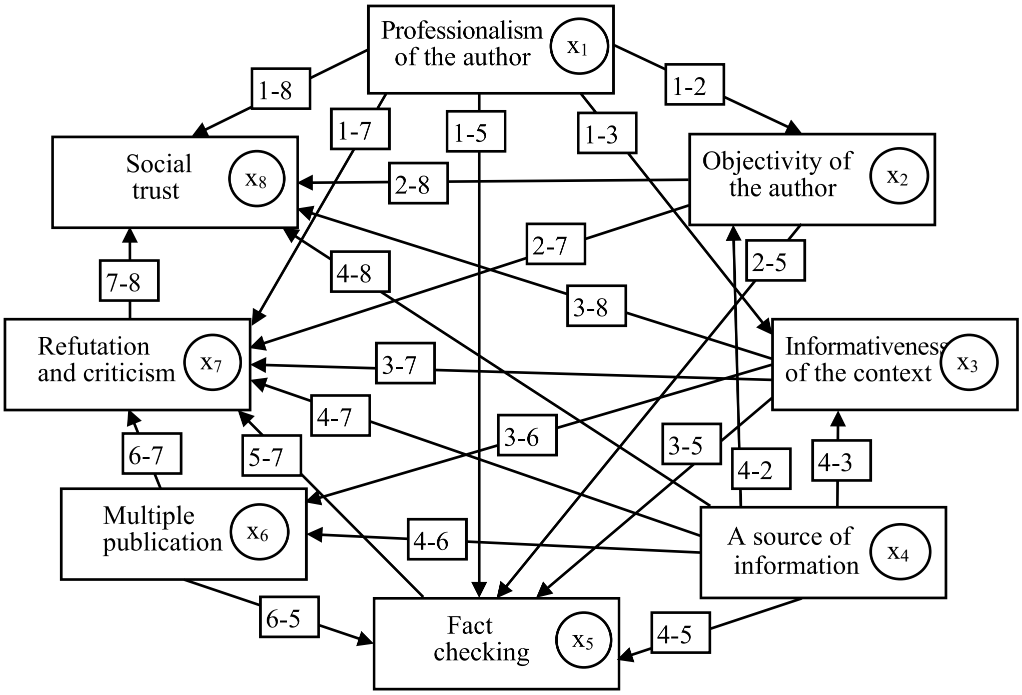

Fig. 1. Semantic network of reliability factors of text messages

The prerequisite for obtaining the specified levels (ranks) of the reliability factors of text messages is the calculation of the numerical weight priorities of the specified factors without regard to the presence of predicates that determine the linguistic type of relationships between the factors. To synthesize a multilevel graphic model of the priority influence of the selected criteria, a shortened version of the mathematical interpretation of the ranking method will be presented [14-16].

Suppose z_{ij} is the number of influences or dependencies for the i -th type of relationship and j -th factor ($j = 1,...,n$); w_i is the weight of the i -th type of relationship. Suppose $i = 1$ determines the influence of the source factor on the receiver factor, $i = 2$ is the dependency of the factor on the factor. In addition, for influences, the weights will be positive, i.e. $w_1 > 0$, for dependencies will be negative, i.e. $w_2 < 0$. The final weight values of the influence of factors on the reliability of test data, taking into account the types of relationships, will be denoted by the variable S_{ij} , the value of which is obtained from the expression:

$$S_{ij} = \sum_{i=1}^{2} \sum_{j=1}^{n} z_{ij} w_i \quad , \tag{2}$$

where n is a conditional factor number [16].

Since, according to the stated prerequisites $S_{2j} < 0$, the values obtained in the calculations are corrected by the value $\Delta_j = \max\left|S_{2j}\right|, \; \left(j = 1, 2, ..., n\right)$, after which the formula (2) will take the following form:

$$S_{Fj} = \sum_{i=1}^{2} \sum_{j=1}^{n} \left(z_{ij} w_i + \max\left|S_{2j}\right| \right) \quad , \tag{3}$$

where S_{Fj} is the final value of the numerical degree of a factor influence on the process.

Experiments

Quantitative indicators of influences and dependencies between factors are presented in Table 1.

Table 1

Quantitative indicators of relationships between factors

Factor name	Designation	Number of influences	Number of dependencies
Professionalism of the author	X1	5	0
Objectivity of the author	X2	3	2
Informativeness of the context	X3	3	2
Source of information	X4	6	0
Fact checking	X5	1	5
Multiple publication	X6	2	2
Refutation and criticism	X7	1	6
Social trust	X8	0	5

Let one assume the following values for the weights of both types of relationships: $w_1 = 10$, $w_2 = -10$ conditional units. The calculation results are presented in Table 2.

Table 2

Calculated data of preliminary ranking of factors

j	z_{1j}	z_{2j}	S_{1j}	S_{2j}	S_{Fj}	Levels
1	5	0	50	0	110	2
2	3	2	30	-20	70	3
3	3	2	30	-20	70	3
4	6	0	60	0	120	1
5	1	5	10	-50	20	5
6	2	2	20	-20	60	4
7	1	6	10	-60	10	6
8	0	5	0	-50	10	6

Let one pay attention to the peculiarity of calculating the value S_{Fj} in Table 2. The value $\Delta_j = \max\left|S_{2j}\right| = 60$ causes an increase in the real values of the variable S_{Fj} by 60 conditional units to obtain positive values when setting the preliminary numerical priorities of the factors.

The next step will concern the mathematical interpretation of the algorithm for determining the weight of predicates [14], which will ensure the establishment of the final levels and the corresponding weight values of the priority of factors. Let one introduce the indicator of the influence of the predicate in the form of a weight coefficient k_{ip}, which will determine the strengthening or weakening of the relationships between the factors for the i-th type of relationship and the p-th predicate. Let one recall that $i = 1$ identifies the influence of one factor on another, $i = 2$ is a dependency. The predicate number is denoted by the variable l.

Let one specify the values of the weight coefficients of the predicates in a table.

Table 3

Weight coefficients of semantic network predicates

l	Predicates of influence	k_{1p_l}	Predicates of dependency	k_{2p_l}
1	determines	5	is determined	5
2	forms	5	is formed	5
3	conditions	4	is conditioned	4
4	becomes the basis	5	is based	5
5	foresees	3	is predicted	3
6	takes into account	3	is considered	3
7	acts	4	receives	4

In addition to the quantitative information in Table 3, the following initial data will be additionally used: the number and type of predicates for each of the factors, reflected in the semantic network in Fig. 1; the linguistic essence of the predicates, reproduced in the specified table. Thus, one has a sufficiently complete initial database for the formation of a certain set for each of the factors, the elements of which correspond to the weight coefficients of the predicates. The numerical values of the elements of these sets will provide the calculation of the weight identification of the predicates and the final weight priorities of the factors. The sets of the weight coefficients of the predicates are denoted by WIJ, where I determines the type of relationship, J determines the conditional factor number. For the type of relationship "influence", the generalized description of the sets of the weight of the predicates for the factors of the semantic network takes the following form:

$$x_1 \subset W11 = \left\{k_{1,p_2}; k_{1,p_3}; k_{1,p_5}; k_{1,p_7}; k_{1,p_8}\right\};\ x_2 \subset W12 = \left\{k_{1,p_5}; k_{1,p_7}; k_{1,p_8}\right\};$$
$$x_3 \subset W13 = \left\{k_{1,p_5}; k_{1,p_6}; k_{1,p_7}; k_{1,p_8}\right\};\ x_4 \subset W14 = \left\{k_{1,p_2}; k_{1,p_3}; k_{1,p_5}; k_{1,p_6}; k_{1,p_7}; k_{1,p_8}\right\};$$
$$x_5 \subset W15 = \left\{k_{1,p_7}\right\};\ x_6 \subset W16 = \left\{k_{1,p_5}; k_{1,p_7}\right\};\ x_7 \subset W17 = \left\{k_{1,p_8}\right\};\ x_8 \subset W18 = \left\{0\right\} \quad (4)$$

According to the values of the weight coefficients from Table 3, one obtains:

$$x_1 \subset W11 = \{4;5;3;3;5\};\ x_2 \subset M12 = \{5;4;4\};\ x_3 \subset W13 = \{5;3;5\};$$
$$x_4 \subset W14 = \{4;4;3;5;5;5\};\ x_5 \subset W15 = \{4\};\ x_6 \subset W16 = \{3;5\};$$
$$x_7 \subset W17 = \{5\};\ x_8 \subset W18 = \{0\}. \quad (5)$$

For the type of relationship "dependency", the expressions are omitted similarly to (4) and immediately the sets are written (6), using the description of the semantic network and the numerical weights of the predicates. In this case, for WIJ one has: $I = 2$; $J = 1,...,8$.

$$x_1 \subset W21 = \{0\};\ x_2 \subset W22 = \{4;4\};\ x_3 \subset W23 = \{5;4\};$$
$$x_4 \subset W24 = \{0\};\ x_5 \subset W25 = \{3;5;5;3;3\};\ x_6 \subset W26 = \{3;3\}; \tag{6}$$
$$x_7 \subset W27 = \{3;4;4;5;4;5\};\ x_8 \subset W28 = \{5;4;5;5;5\}.$$

For the convenience of using sets (5) and (6), the average values are calculated for each of the factors taking into account all the components of the sets. They express the generalized coefficients of strengthening or weakening of the factor action in pairwise interaction with each other and ensure their integral influence on the reliability of text data. The corresponding calculations are performed taking into account the numerical values given by sets (5) and (6).

Finally, the calculation is performed according to the formula, the logic of which is described above.

$$d_{ij} = \sum_{r=1}^{z_{ij}} \left(Wij_r / z_{ij} \right), \quad \text{for } i = 1,2;\ j = 1,2,...,8, \tag{7}$$

where: Wij_r are elements of sets (5) and (6); z_{ij} is a number of elements in sets.

The weight values of the factors P_{ij} are obtained after multiplying the weight priorities S_{ij} in Table 3 by the coefficients d_{ij}. Since for the types of relationships "dependency" $P_{2j} < 0$, one proceeds (as above) as follows. The obtained numerical results are shifted by the value $\max\left|P_{2j}\right|,\ \left(j = 1,2,...,8\right)$.

Finally, an expression is obtained for calculating the weight priorities of factors:

$$P_{Fj} = INT\left(\sum_{i=1}^{2} \sum_{j=1}^{8} \left(d_{ij} S_{ij} + \max\left|P_{2j}\right| \right) \right). \quad (8$$

The weight priorities of the factors, performed according to the formula (8) using the data of Table 2 and the influence of predicates, provide the next iteration of the factor ranking process, presented in Table 4.

Table 4

Ranking of reliability factors of text data taking into account semantic network predicates

j	d_{1j}	d_{2j}	S_{1j}	P_{1j}	S_{2j}	P_{2j}	P_{Fj}	Rank	Priority level
1	4.2	0	50	210	0	0	450	7	2
2	2.6	4	30	78	-20	-46	272	5	4
3	4.3	4.5	30	129	-20	-90	279	6	3
4	4.3	0	60	258	0	0	498	8	1
5	4	3.8	10	40	-50	-190	90	3	6
6	2	3	20	40	-20	-60	260	4	5
7	5	4.2	10	50	-60	-252	38	2	7
8	0	4.8	0	0	-50	-240	0	1	8

The final multilevel factor model is presented in Fig. 2.

The model is obtained as a result of the next iteration of the process of assessing the effect of a set of factors on the reliability indicator of text messages, taking into account the influence of semantic network predicates. The previous stages of determining the importance levels of factors are implemented on the basis of the semantic network and the method of hierarchy analysis, which is based on the reachability matrix. The final result is obtained on the basis of the ranking method, which takes into account the number of types of relationships between factors and their conditional weight values. The listed means significantly depend on the expert (subjective) assessment of the numerical parameters used, therefore they cannot be considered decisive steps for making an adequate decision regarding the final weight priorities of factors in the process of assessing the reliability indicator of text information messages. In view of the above, the future stage of the study will consist in optimizing the weight values of factors using the pairwise comparison method.

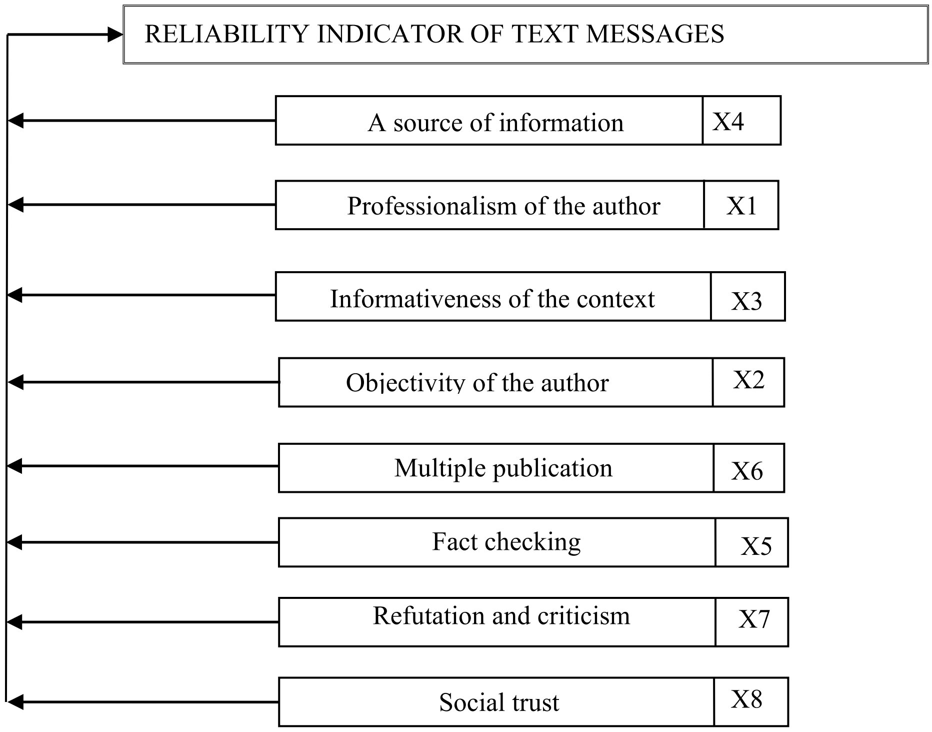

Fig. 2. Multilevel model of reliability factors of text messages taking into account the influence of semantic network predicates

Conclusions

The conducted research confirms the growth of scientific interest in the problem of information reliability, which contributed to the formation of an interdisciplinary approach that combines the methodological principles of computer science, social disciplines and media education. Within the framework of the proposed concept, the feasibility of moving from an a posteriori to an a priori approach in assessing the reliability of text messages is substantiated. This approach allows predicting the reliability level of information even before its appearance in the information space, which has practical value for countering disinformation and manipulative content.

The developed model is based on the identification of key factors that affect the reliability level of messages and their ordering by significance degree. For this purpose, the ranking method is used in combination with semantic modelling based on the language of predicates, which makes it possible to linguistically interpret the relationships between the elements of the system. The involvement of expert assessment in determining the weight coefficients for the types of relationships in the semantic network allows the formation of a preliminary system of weight preferences.

Based on the constructed mathematical apparatus, the formalization of weight sets for relationships of the type "influence" and "dependency" is carried out, which makes it possible to form a generalized system of integrated priorities of factors. As a result, a multilevel model of factor influence is constructed taking into account the semantic structure of the information space, which can be used as the basis for future tools for automated assessment of the reliability of information messages.

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