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THE IMPACT OF DIGITAL DISINFORMATION ON QUALITY OF LIFE: A FUZZY MODEL ASSESSMENT

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Abstract. Quality of Life (QoL) is a multifaceted concept encompassing economic, social, environmental, psychological, and physical dimensions of an individual's life, including personal living conditions, happiness, well-being, and life satisfaction. As a vital criterion for sustainable development and active social policy in countries, QoL has been significantly influenced by the dynamic technological evolution of social media. However, the comprehensive impact of social media, including its role in disseminating disinformation – a major social and socio-economic concern – on QoL remains underexplored. This research aims to develop a novel fuzzy model to assess the level of disinformation on digital platforms and its correlation with the population's QoL. Employing a mathematical approach rooted in expert evaluation, this study leverages intellectual knowledge analysis and fuzzy set theory. Grounded in data from real respondents and knowledge-based models, this study pioneers an information model to evaluate inhabitants' QoL, incorporating factors such as financial concerns, perception of disinformation, and its influence on digital platforms. The fuzzy estimation model, verified with data from 3,036 respondents, quantitatively assesses citizens' QoL. An illustrative application of the model demonstrates its effectiveness. The findings are particularly valuable for policymakers, experts in economic and innovative development, aiding the creation of regulatory and monitoring mechanisms to foster sustainable economic growth and devise effective development strategies.

Keywords: quality of life, digital platforms, disinformation, wellbeing, fuzzy set, information security; intellectual knowledge analysis.

JEL Classification: I12, I18, C02, C51, C55.

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1. Introduction

Digital media platforms are the main source of information about current events in today's society. These platforms profit from their users' activities. Various methods, which are not always ethical, are used to increase the number of page views on digital platforms. One example of such unscrupulous behaviour is shocking news headlines containing disinformation. Many users read news headlines. They take them as objective reality. The low level of QoL of the inhabitants and their financial worries have a negative impact on the appropriate perception of the information surrounding them. Such people are more likely to notice current disinformation narratives on digital media platforms that make money from user activity. As a result, society's information security is directly threatened by fake headlines and outright disinformation.

The spread of fake news and disinformation is currently one of the most serious social and economic threats in many developed countries, closely related to rapid technological development and the introduction of advanced digital technologies, especially social media (Shu et al., 2020). Governments need to create adequate protective, regulatory and motivational mechanisms to influence the behaviour of the population in the desired direction (Dabbous et al., 2022; Katsirea, 2018). Research on disinformation is currently the subject of strong interest from different research teams, resulting in many studies and reports. However, the majority of the research is theoretical and subjective in nature (Weikmann & Lecheler, 2023; Humprecht et al., 2020), and no studies explicitly examine the impact of disinformation on QoL. This allowed us to define an important research gap. The present study offers technological solutions for the active management of threats to society's information security in the context of the perception of disinformation narratives, based on innovative methods of knowledge management regarding citizens' QoL.

The concept of QoL has been prevalent for several decades, but it is only in recent years that a more profound exploration and understanding of its influential determinants have emerged. Historically, QoL has predominantly been utilized to assess healthcare quality, contributing to the ongoing debate over its definition and measurement (Agborsangaya et al., 2013). Notably, in the 1990s, numerous conceptual studies focused on evaluating QoL within healthcare settings, influenced by the increase in life expectancy due to advancements in medical procedures (Fitzpatrick et al., 1992; Sprangers & Aaronson, 1992; Treurniet et al., 1997). Consequently, QoL evolved to serve as an additional indicator of morbidity and mortality and became instrumental in assessing the efficacy of health technologies.

The subsequent discourse centered on whether QoL is best understood through objective or subjective dimensions, or a synthesis of both (Santos et al., 2007). Subjective dimensions pertain to individual perceptions (Moons et al., 2006; Skevington & Böhnke, 2018), while objective dimensions are linked to tangible living conditions or physical functionality. These dimensions are seen as complementary in QoL research (Mirella et al., 2001; von Wirth et al., 2015). However, recent studies increasingly favor subjective dimensions (Oleś, 2016; Skevington & Böhnke, 2018), citing the "health disability paradox" (Albrecht & Devlieger, 1999), where individuals with disabilities often report a satisfactory QoL despite adverse living conditions. This observation has led many scholars to align QoL more closely with subjective well-being and life satisfaction (Veenhoven, 2015; Skevington & Böhnke, 2018). Moons et al. (2006) argue that conceptualizing QoL in terms of life satisfaction effectively addresses its conceptual complexities. Furthermore, numerous studies incorporate life satisfaction and economic factors as defining elements of QoL (Mikal et al., 2016; Eslami et al., 2019).

The primary aim of this research is to develop a fuzzy model for assessing the extent of disinformation spread on digital platforms, with a focus on the QoL of inhabitants in a certain region. Building upon this objective, our research hypothesis is formulated as follows: If respondents from the media space in a certain region report a high QoL, have negligible financial concerns, and perceive a very low level of disinformation, then it can be concluded that the spread of disinformation through digital platforms is correspondingly low in relation to the QoL of the citizens. This conclusion is based on the assessments derived from the developed fuzzy model.

2. An overview of existing research

QoL is a concept that encompasses the multiple dimensions of a person's personal circumstances, happiness, well-being, and life satisfaction (Chaaban et al., 2016). The development and maintenance of QoL is one of the main criteria of sustainable development (Fischer & Amekudzi, 2011) and part of the social policies of many countries (Prado-Lorenzo et al., 2012; Phillips, 2006). According to Costanza et al. (2008), QoL improves according to how well individuals are able to meet their needs and how they perceive these needs getting met. The research studies and their discussion platforms also provide a space for ongoing research into the impact of QoL on individual behaviour and its protective effects. People with negative perceptions of their physical health are more likely to believe health rumours, while people with more satisfied social relationships, such as women and the elderly, are more susceptible to health rumours, according to the results of the study by Wang et al. (2021). This confirms that people with different levels of QoL interact with health disinformation in different ways. The causal links between QoL and the positive and negative aspects of a person's life are also of interest. Research confirms the impact of higher QoL on a person's personal development, academic performance, and interpersonal trust (Edgerton et al., 2011). Simultaneously, QoL is considered a quantitative indicator of longevity and healthy life years (Wang et al., 2021).

Negative aspects of a person's life interact with low QoL. This is also demonstrated by studies confirming the association of low QoL with negative emotional states and behaviours, stress, as well as problematic internet use (Machimbarrena et al., 2019). A higher level of QoL is also associated with a lower level of dependence on addictive substances (Barros da Silva Lima et al., 2005). Disinformation can lead individuals or even groups to inappropriate and irrational behaviour in relation to their health. According to the results of the study, higher QoL is associated with lower psychological distress, while individuals with higher psychological distress are more likely to believe health rumours (Uscinski, 2018, Nyhan & Reifler, 2010). For this reason, Bramston et al. (2005) recommend the investigation of three determinants of QoL: individual level (stress), interaction level (social support) and community level (neighbourhood belonging). Social support was found to be the strongest predictor of life satisfaction in both the healthy and the mentally retarded groups.

The effects of globalisation, technological and social changes in society have stimulated the study of QoL concepts also from a geographical point of view. It has been shown that in addition to the study of the SDGs, there is also a need for the complementary study and assessment of QoL at the level of cities and urban neighbourhoods (Lotfi & Koohsari, 2009). However, this area of QoL, called Urban QoL (UQoL), does not possess uniform tools and indices for its measurement, while the preferred characteristics of an ideal model for a systematic, transparent, and objective assessment of UQoL have been sought for a long time (Mittal et al., 2020). In a review of 26 UQoL assessment tools, Mittal et al. (2020) found that although UQoL prefers qualitative value in people's lives, its assessment tools have a strong association with quantitative data collection.

2.1. QoL and social media

Recent studies clearly show increasing time spent on social networks and using different social media platforms among different population groups. Social media users are exposed to various stressful situations (Lim & Choi, 2017; Wolfers & Utz, 2022). This can lead to depressive states and mental illnesses (Guntuku et al., 2017). According to McCloskey et al. (2015), Facebook use leads to various emotional effects that make people more depressed. This is also supported by studies by Frost and Rickwood (2017) and Vahedi and Zannella (2021). Similarly, Primack et al. (2017) found that the length of time spent on social networks leads to higher levels of stress, increases feelings of depression and anxiety, and simultaneously decreases a person's subjective well-being. Not all age and social groups seem to share these aspects and causal relationships. On the other hand, there is evidence of positive aspects of social media use and positive effects on QoL (Weinstein, 2018). People who use social media have different motivations and experiences, and therefore social networks also have different effects on their QoL, according to the authors of the study by Oh and Syn (2015) and Campisi et al. (2015). Age is an important determinant, as older people can improve their QoL by using social media (Noguti et al., 2019), keeping in touch with friends or using it for dating (Campisi et al., 2015). Even serious mental illnesses, which are associated with feelings of loneliness, can be improved by using social media. This has a positive impact on their QoL (Yang, 2016). This suggests that the direction of the positive and negative effects of social media on QLs in different demographic and socioeconomic contexts cannot be generalised.

The complexity inherent in investigating the impact of social media on individual behaviour, and consequently, on QoL, is multifaceted. This complexity is further compounded by the paradoxical nature of social media's influence, as it can exert both positive and negative effects on an individual's behaviour and QoL. Haux and Lund (2018) underscore this "social media paradox", emphasizing the risks associated with the pressure for idealized self-presentation on these platforms. Such pressures can lead to frustration, anxiety, and stress, negatively impacting individuals' QoL through detrimental self-comparisons. Building on this, Cho et al. (2022b) examine the role of influencers in shaping the general well-being of users, thus influencing changes in their QoL. This raises critical questions about the specific social media activities that are perceived as pleasant or unpleasant by different demographic groups, and the underlying factors that may skew the perceived impact of social media use on individuals' feelings, behaviours, and ultimately, their QoL. Campisi et al. (2015) further highlight the necessity of investigating the interrelationships between social media use, QoL, the role of influencers, and conspicuous consumption. They advocate for the incorporation of qualitative methodologies alongside the more prevalent quantitative approaches. This mixed-methods approach could provide deeper insights into the various stressors emerging from social network interactions. Supporting this perspective, studies by Primack et al. (2017) and Dehghani and Zareei Mahmoodabadi (2018) have identified a correlation between excessive social media use and increased risks of depression and anxiety, particularly among young people. This is attributed to the compulsive behaviours associated with social media use, such as constant checking of updates, reactions, and likes. However, it is also noted that motivational processes can lead to positive outcomes from social media use, potentially enhancing QoL, especially among the elderly.

According to Primack et al. (2017), the use of social media not only leads to multitasking but also impacts cognitive mental health, resulting in lower subjective well-being and a consequent decrease in QoL. Misunderstandings and negative interactions on social networks can adversely affect mood across all age groups. Conversely, social support and direct interpersonal contact can alleviate depression and improve mood. The motivation behind social media use can significantly influence an individual's QoL. Radovic et al. (2017) note that for individuals with depression, social media can be detrimental if used for self-comparison, potentially deepening frustration and further diminishing QoL. Additionally, gender differences in social media use and their impact on QoL are notable. Anguzu et al. (2021) found that men derive more happiness from using social media than women, highlighting the subjective nature of social media's impact on QoL. Social media serves as a tool enabling individuals to engage with various platforms and co-create values. Haux and Lund (2018) emphasize the significant influence of influencers in shaping consumption patterns and attitudes among social network users. The portrayal of an often idealized and self-promotional lifestyle can lead to envy, frustration, dissatisfaction, stress, and similar negative emotions. The lack of control over social media content can substantially impact individuals' QoL by perpetuating a false perception of others living ostensibly superior lives.

2.2. Social networks and disinformation in a relation to QoL

Consumers are exposed to and disseminate vast amounts of information via the internet and social media. Online platforms, particularly social media, have emerged as prolific sources of both accurate and misleading information, thus becoming multipliers of disinformation (Bermes, 2021; Nguyen et al., 2021). The intensity of disinformation sharing on social media is notably higher than on other online platforms, highlighting its role in exacerbating this global issue (Kumar et al., 2023). Disinformation leads to significant disharmony and negative emotions among users (Lohani, 2021; Ahmad et al., 2022). Selected actors deliberately manipulate communication structures on social media to produce and disseminate disinformation, as observed by de Cock Buning (2018). This evolving landscape of disinformation production and dissemination, which is still not fully understood, complicates the study of its causality in relation to QoL. The corporate sector is increasingly concerned about the financial losses incurred due to disinformation about their products or services (Petratos, 2021). Righetto et al. (2021) highlight the growing collective imbecility and information dysfunction in postmodern societies, suggesting that combating these issues requires information literacy, encompassing lifelong learning. Beyond information literacy, there is a pressing need to establish a comprehensive system of media literacy accessible to all population groups. Educational institutions should emphasize education on the risks associated with social media use, the impacts of social comparison, and other ethical considerations that affect individuals' lives and QoL.

Institutions utilizing social media must seek ways to engage with consumers to better understand the relationship between consumers' QoL and social media, as well as the paradoxical effects of social media on QoL (Jeng & Lo, 2019). The perceived credibility of messages and the trust individuals place in specific information sources are crucial (Figl et al., 2019; Mayo, 2023), influenced by source characteristics, recipient characteristics, the message, the medium, and the context in which the message is received (Wathen & Burkell, 2002). This perceived credibility can also drive the spread of disinformation online. The consequences of health-related disinformation are particularly dire, with significant impacts on QoL and potential mortality risks. In addressing disinformation, Swire-Thompson and Lazer (2020) debate the effectiveness of personal versus online information access. Nguyen et al. (2021) argue that eHealth literacy can enhance health-related QoL, as those with higher eHealth literacy are more adept at locating reliable sources and evaluating online health information, thereby increasing their QoL. Khan and Idris (2019) identify income, education level, internet skills, and attitudes towards information verification as key factors in the ability to detect disinformation on social media. Martínez-Costa et al. (2023) find that people with higher education are more confident in their ability to identify disinformation, while younger individuals tend to distrust older people's capacity to discern false content.

The research studies reviewed yield several key insights:

- QoL concepts are integral to the sustainable development strategies and social policies of countries. However, their connection with social media and social networks, which exert significant positive and negative influences on them, remains underexplored.
- Investigations into the effects of social networks on QoL have been limited in scope, focusing only on specific aspects and defined population groups. This narrow focus fails to provide a comprehensive understanding of these effects across broader contexts.
- While both negative and positive impacts of QoL on selected populations have been identified, existing research highlights numerous limitations and underscores the need for more extensive exploration and elucidation of causal relationships.
- A notable gap exists in research concerning the influence of social media and disinformation on QoL changes across diverse populations, despite the rapid spread of disinformation through online media.
- Currently, there is an absence of tools linking QoL to disinformation narrative evaluation processes. This lack hinders the study of behavioral changes in populations across different geographical locations, leading to information systems and media literacy programs that do not adequately reflect the specific needs and information security status of various regions.
- Existing methodologies for measuring Urban Quality of Life (UQoL) also fail to account for the detrimental effects of social media. This oversight contributes to a disconnect in developed concepts, overlooking significant social risks such as the impact of disinformation on regions, society, and countries.

Our research study addresses these identified shortcomings, as evidenced by our defined research objectives, hypothesis, and methodological and analytical processes.

The study is organized as follows: part 3 delineates the formal problem statement and introduces the information models used for assessing both the QoL levels of citizens and the current disinformation narratives on digital platforms. This part also describes the fuzzy model developed for evaluating the levels of disinformation among citizens in relation to their QoL. Part 4 focuses on the experimental verification of the fuzzy model using real data, including examples of evaluations conducted on data subsets. Part 5 presents a comprehensive review of the study's findings, emphasizing the advantages of the fuzzy model while acknowledging its limitations. The study culminates in Part 6, where we outline future research directions and discuss preliminary scientific results.

3. Materials and methods

To fulfill the objectives of our study, we utilized data from the longitudinal study "CEDMO Trends: Czech Society in the Period of Change (1st Wave)". This data was collected through the CAWI (Computer-Assisted Web Interviewing) technique, executed by the professional agency Median. The data collection period spanned from 15 March 2023 to 27 March 2023. A total of 3,734 respondents were initially interviewed, yielding 3,036 valid responses. Respondents were invited to participate in the survey via email, with approximately one-third receiving at least one follow-up contact. The quota sampling was based on the population aged over 16 years, considering various socio-demographic categories such as gender, age, education level, region, size of dwelling, internet usage, and employment status. On average, respondents took 34.9 minutes to complete the questionnaire.

3.1. Formal formulation of the evaluation problem

In our study, we consider a region or country, denoted as R, to evaluate the extent of disinformation spread through digital platforms. When focusing on a single digital platform within this study, it will also be referred to as R. The study accounts for the QoL of the inhabitants and their psychological perspectives concerning financial worries. A key component of the knowledge management system in this research is the feedback from a set of respondents, $E=\{e_1;e_2;\ldots;e_m\}$, who participated in the survey. This feedback is gathered and analyzed using two primary information models: K_{QLC} – an information model for assessing the QoL of inhabitants, and K_{CDN}, an information model for evaluating current disinformation narratives on digital platforms. Additionally, the study considers the financial concern psychology of the respondents, denoted as F. The collected feedback is processed by M_{DP} – a fuzzy model for assessing the level of disinformation spread on digital platforms.

Formally, the study introduces a fuzzy model as an operator for assessing the level of disinformation spread on digital platforms. This model incorporates two key variables: the QoL of inhabitants and their financial concerns. The operator is designed to systematically evaluate how these factors influence the spread of disinformation.

$$\Xi\left(R,E,F,K_{QLC},K_{CDN},M_{DP}\right)\rightarrow\gamma\left(m_{QLC},m_{DP},m_{QID}\right). \tag{1}$$

X is an operator that, based on the input data R, E, F and their processing models K_{QLC}, K_{CDN}, M_{DP} derives the initial estimate of γ At the output of the fuzzy model is obtained: m_{QLC} – a quantitative assessment of the QoL of inhabitants, taking into account their financial concerns; m_{DP} – quantitative level of perception of disinformation on digital platforms in relation to m_{QLC}; m_{QID} – quantitative level of influence of disinformation by respondents. Reasoned decisions and policies of various levels are made by obtaining the initial estimate of γ.

In this research, which relies on expert data, we define the following key management subjects:

- Respondents: These are experts who have participated in our research survey or have provided feedback from web platforms. They contribute a set of input data, encompassing the following: statements about the QoL of inhabitants, statements regarding financial concerns, and perceptions of current disinformation narratives on digital platforms.

- Decision-Making Person (DM): This term encompasses all stakeholders involved in the research, ranging from non-governmental and public organizations to the highest levels of state governance. They are the primary users of the research findings.
- Systems Analyst: This individual is responsible for configuring all processes related to assessing the level of disinformation spread through digital platforms, using the developed models.

To aid in the understanding of the study's framework, a structural diagram is provided in Figure 1.

Figure 1 presents a structural diagram of the fuzzy model used for assessing the level of disinformation spread on digital platforms. At the model's entry point, we have a set of respondents, $E=\{e_1;e_2;\ldots;e_m\}$, who participated in a survey regarding the spread of disinformation narratives on digital platforms within region R. The feedback gathered is processed using information models K_{QLC}, K_{CDN}. Additionally, the model incorporates the psychology of respondents' financial concerns, denoted as F. This expert data, combined with information about the respondents' financial concerns (F), forms the database for our research task. Subsequently, this data is evaluated using the fuzzy model M_{DP}, designed to assess the level of disinformation spread on digital platforms. The knowledge gleaned and the decision-making levels settings for the M_{DP} model are stored in a knowledge base. As a result, the initial estimates $\gamma(m_{QLC}, m_{DP}, m_{QID})$ are generated, which inform the decisions of the DM. Should the results not meet the DM's satisfaction, a review process is initiated. This involves consulting the knowledge base to adjust the fuzzy model's parameters or to incorporate additional knowledge.

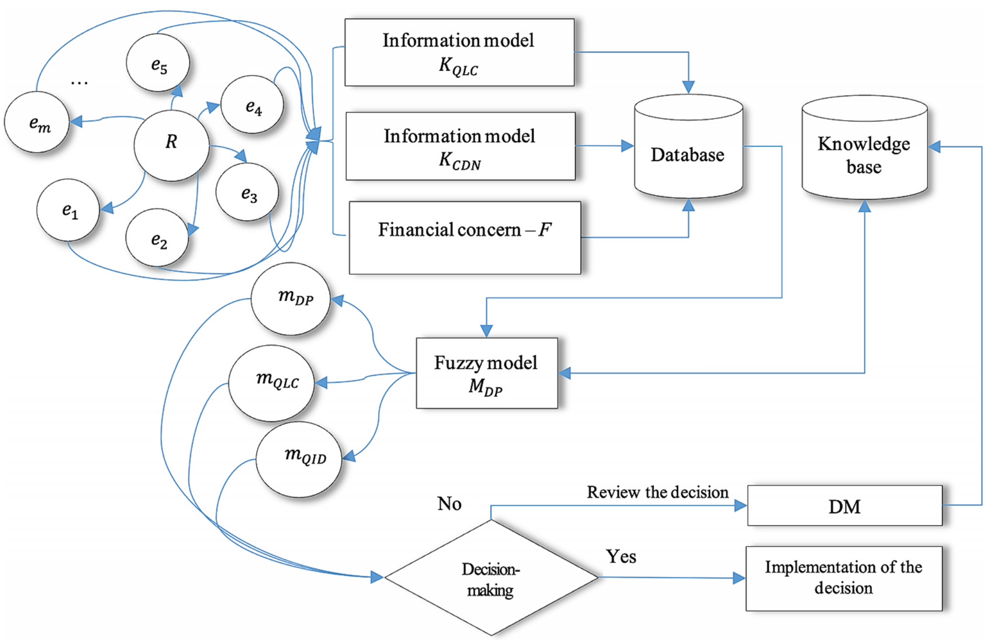

Figure 1. Structural diagram of the fuzzy evaluation model

3.2. Information model for assessing the QoL of inhabitants

The information model will assess the QoL of inhabitants according to various aspects. It consists of a set of evaluation criteria $K = \{K_1; K_2; \ldots; K_k\}$. These criteria consist of indicators representing a question to which the respondent must give a unified answer. The answer is chosen in the most acceptable way, or the first one that comes to mind.

The respondent's assessment of the level of QoL is a subjective and ambiguous task. Therefore, respondents are asked to give answers to questions about the level of quality of their own life in the form of linguistic variables from the term set $U_j = \{u_{j1}; u_{j2}; \ldots; u_{j5}\}$, $j = \overline{1,k}$. To effectively present the information model, the authors have defined specific criteria to ascertain respondents' evaluations of their QoL. These criteria, along with their respective answer options, are as follows:

K_1: QoL Evaluation
Question: "How do you rate the quality of your life?"
Answer Options:
U_1 = {Very bad; Bad; Neither bad nor good; Good; Very good}.

K_2: Health Satisfaction
Question: "How satisfied are you with your health?"
Answer Options:
U_2 = {Very dissatisfied; Dissatisfied; Neither satisfied nor dissatisfied; Satisfied; Very satisfied}.

K_3: Physical Pain Impact
Question: "To what extent do you feel that physical pain prevents you from doing what you need to do (in the past 4 weeks)?"

K_4: Treatment Necessity
Question: "How much treatment do you need to live a normal life?"

K_5: Life Enjoyment
Question: "How much do you like life?"

K_6: Life Meaningfulness
Question: "How meaningful do you think your life is?"

K_7: Concentration Ability
Question: "How well can you concentrate?"

K_8: Personal Safety
Question: "How safe do you feel in your everyday life?"

K_9: Environmental Health
Question: "How healthy is the physical environment in which you live?"

For criteria K_3 to K_9, the answer options are uniform and are determined from a term set, for instance, for K_3:

U_3 = {Not at all; A little bit; Medium; Very much; Maximum}.

To normalize and formalize the input data from these defined term-sets for evaluative purposes, the authors propose using the following membership functions:

$$\mu\left(K_1\right)=\begin{cases}0.2 & \text{if } u_{11}=\text{"Very bad"};\\ 0.4 & \text{if } u_{12}=\text{"Bad"};\\ 0.6 & \text{if } u_{13}=\text{"Neither bad nor good"};\\ 0.8 & \text{if } u_{14}=\text{"Good"};\\ 1 & \text{if } u_{15}=\text{"Very good"}.\end{cases} \quad (2)$$

$$\mu\left(K_2\right)=\begin{cases}0.2 & \text{if } u_{21}=\text{"Very dissatisfied"};\\ 0.4 & \text{if } u_{22}=\text{"Dissatisfied"};\\ 0.6 & \text{if } u_{23}=\text{"Neither satisfied nor dissatisfied"};\\ 0.8 & \text{if } u_{24}=\text{"Satisfied"};\\ 1 & \text{if } u_{25}=\text{"Very satisfied"}.\end{cases} \quad (3)$$

$$\mu\left(K_3\right)=\begin{cases}0.2 & \text{if } u_{31}=\text{"Not at all"};\\ 0.4 & \text{if } u_{32}=\text{"A little bit"};\\ 0.6 & \text{if } u_{33}=\text{"Medium"};\\ 0.8 & \text{if } u_{34}=\text{"Very much"};\\ 1 & \text{if } u_{35}=\text{"Maximum"}.\end{cases} \quad (4)$$

In addition to these criteria, residents' QoL is also influenced by psychological factors. The authors of the article set themselves the task of assessing the level of QoL through the prism of psychological factors in future research. Instead, one important factor is highlighted here – economic concerns. As you know, worrying about money affects the perception of the information space, as some worries lead to others, while the influence of disinformation increases. Such a factor is called criterion F, and the question is formulated as follows:

F. How much do you worry about money?

Answering options are offered here in the form of linguistic variables taken from the following set:

$f=\left\{f_1;f_2;\ldots;f_5\right\}$ = {Not at all; A little bit; Medium; Very much; Maximum}.

In order to normalize and formalize the responses to the money concern criterion, the following characteristic function is proposed:

$$\mu\left(F\right)=\begin{cases}\frac{1}{5} & \text{if } f_1=\text{"Not at all"};\\ \frac{3}{5} & \text{if } f_2=\text{"A little bit"};\\ 1 & \text{if } f_3=\text{"Medium"};\\ \frac{9}{5} & \text{if } f_4=\text{"Very much"};\\ \frac{11}{5} & \text{if } f_5=\text{"Maximum"}.\end{cases} \quad (5)$$

While experimenting with real data (Data from 3,036 residents, 2024), the levels of the characteristic function (5) were adjusted. The proposed criteria demonstrate the possibility of obtaining knowledge about the inhabitants' QoL. The set of questions itself is open and the model does not depend on their number. Therefore, other researchers can easily build their questions to assess the level of disinformation in their region.

3.3. Information model for the assessment of current disinformation narratives on digital platforms

An information model is proposed that can evaluate current disinformation narratives on digital platforms. A set of evaluation criteria $D=\{D_1;D_2;\ldots;D_d\}$ is also proposed. The proposed criteria represent a description of a situation or event that contains disinformation narratives. For each message that appears on digital platforms, the respondents analyse the situation and give a single answer that they consider to be the most acceptable. Obviously, the task of expert judgement is subjective and the data obtained are fuzzy.

The answers according to the criteria of the analysed situation are represented in the form of linguistic variables from the set of terms $H=\{h_1;h_2;\ldots;h_5\}$. The assessment of the level of disinformation in society must be deterministic, as well as linked to a specific region or country. Therefore, there are no standardised criteria for such a task. Depending on the period in which the level of disinformation is to be assessed, researchers must analyse the news and determine a set of their own criteria. A set of such criteria should consist of disinformation narratives (news) and descriptions of situations, which can be derived from the following question: To what extent do you consider the following news to be implausible or, on the contrary, to be credible? To present the information model, the authors defined examples of criteria for evaluating current disinformation narratives, which are given in the experimental part.

Such a set is open, so the developed model does not depend on their number.

The answer options are determined from the following set of terms:

H = {Entirely plausible; Rather plausible; Rather implausible; Completely implausible; I don't know/I can't judge}.

Similarly, linguistic variables need to be formalized to allow for data comparison, for example by the following membership function:

$$\mu\left(D_r\right)=\begin{cases}0.2 & \text{if } h_{r1}=\text{"Entirely plausible"};\\ 0.4 & \text{if } h_{r2}=\text{"Rather plausible"};\\ 0.8 & \text{if } h_{r3}=\text{"Rather implausible"};\\ 1 & \text{if } h_{r4}=\text{"Completely implausible"};\\ 0.3 & \text{if } h_{r5}=\text{"I don't know/I can't judge"}.\end{cases} \qquad r=\overline{1,d}. \tag{6}$$

3.4. Fuzzy model for assessing the level of disinformation spread on digital platforms

The fuzzy model is presented in two stages. The first stage is aimed at obtaining knowledge about the QoL of inhabitants. Here the data obtained from the respondents is formalized according to the information model K_{QLC}, the psychology of respondents' financial concern (F) is taken into account, and m_{QLC} is obtained – a quantitative assessment of the QoL of inhabitants. In the second stage, there is an assessment of current disinformation narratives on digital platforms, considering the level of QoL of inhabitants. Here, the data received from the respondents is formalized according to the K_{CDN} information model, to assess the perception of disinformation by individuals regarding their level of QoL. Here we get m_{DP}, the quantitative level of perception of disinformation on digital platforms.

The first stage of the fuzzy mode

Considering the psychology of respondents and their satisfaction with the level of QoL, data on the level of QoL of inhabitants is aggregated in the section regarding individual respondents $E=\{e_1;e_2;\ldots;e_m\}$. For this, the mathematical apparatus of the theory of fuzzy sets and intellectual analysis of knowledge is used. Such a formalization is proposed using a weighted sum:

$$\delta(e_i)=\frac{1}{k}\sum_{j=1}^{k}\mu(K_{ij}),\ i=\overline{1,m}. \tag{7}$$

where k is the number of evaluation criteria in the K_{QLC} information model, e_i is the i-th respondent.

For some region or country R, where a study is conducted to assess the level of disinformation spread on digital platforms, the group opinion of all respondents can be considered:

$$QLC(R)=\frac{1}{m}\sum_{i=1}^{m}\delta(e_i). \tag{8}$$

Thus, an aggregated normalized assessment $\left(QLC(R)\in[0;1]\right)$ is obtained in the studied region R, which determines the generalized level of satisfaction with the QoL of inhabitants, based on the information model of assessment criteria K_{QLC}.

The next step incorporates the psychology of respondents' financial concerns (F). The logic follows from the fact that the higher the financial concern, the worse the QoL. Accordingly, the following membership function is proposed:

$$m_{QLC}(e_i)=\begin{cases}0, & \delta(e_i)\le 0;\\ \left(\delta(e_i)\right)^{\mu(F)}, & 0<\delta(e_i)<1;\quad i=\overline{1,m}.\\ 1, & \delta(e_i)\ge 1.\end{cases} \tag{9}$$

where $\mu(F)$ is the threshold of financial concern of the respondents, the value of which changes depending on the answer options of the respondent e_i, expressed from the term set $f=\{f_1;f_2;\ldots;f_5\}$. Thus, $m_{QLC}(e_i)\in[0;1]$ is obtained – a quantitative assessment of the level of QoL of the respondent e_i.

The second stage of the fuzzy model

In the second stage of the model, the actual disinformation narratives on digital platforms are first evaluated according to the K_{CDN} information model.

Involving the options of respondents' answers to questions about disinformation narratives, data is aggregated according to evaluation criteria in the section of individual respondents $E=\{e_1;e_2;\ldots;e_m\}$. Based on the theory of fuzzy sets and intellectual analysis of knowledge, the following aggregation of data obtained according to Eq. (6) takes place:

$$m_{DP}\left(e_i\right)=\frac{1}{d}\sum_{r=1}^{d}\mu\left(D_r\right),\ i=\overline{1,m}. \tag{10}$$

where d is the number of disinformation narrative criteria in the K_{CDN} information model, e_i is the i-th respondent. As a result, a quantitative level of the perception of disinformation on digital platforms is obtained from the respondents.

For a given region or country R where the research is carried out, it is possible to consider the group opinion on the perception of disinformation by all respondents:

$$DP\left(R\right)=\frac{1}{m}\sum_{i=1}^{m}m_{DP}\left(e_i\right). \tag{11}$$

$DP\left(R\right)\in\left[0;1\right]$ is an aggregated normalized estimate of the perception of disinformation by inhabitants in the studied region R, based on the information model of the evaluation criteria K_{DP}.

Next, the received quantitative assessment m_{DP}, which characterizes the level of perception of disinformation by respondents on digital platforms, is delimited by the term-set of linguistic variables $L=\left\{l_1;l_2;l_3;l_4;l_5\right\}$ as follows:

$m_{DP}\in\left[0;0.5\right)$ – l_1: high level of perception of disinformation by inhabitants;

$m_{DP}\in\left[0.5;0.7\right)$ – l_2: the level of perception of disinformation by inhabitants is above average;

$m_{DP}\in\left[0.7;0.8\right)$ – l_3: average level of perception of disinformation by inhabitants;

$m_{DP}\in\left[0.8;0.9\right)$ – l_4: low level of perception of disinformation by inhabitants;

$m_{DP}\in\left[0.9;1\right]$ – l_5: very low level of perception of disinformation by inhabitants.

It should be noted that the verification of the delineation of quantitative levels was carried out in the process of conducting experiments on real data.

The influence of the level of QoL of the respondent $m_{QLC}\left(e_i\right)$ on the perception of disinformation on digital platforms L is calculated using the intelligent analysis of knowledge and membership functions of the “value is more” type. This is characterised by the following logical statement: if the respondent has a low assessment of his or her QoL, is constantly worried about finances and at the same time has a high perception of disinformation on digital platforms, then this determines the high impact of disinformation on him or her.

The given logical derivation can be formalized using an S-shaped membership function. Moreover, in the studied region R, the dependence x is expressed for all linguistic variables L:

$$m_{QID}\left(e_i\right)_1=\begin{cases}\frac{1}{5}\sqrt{\frac{m_{QLC}\left(e_i\right)}{2}}, & 0\le m_{QLC}\left(e_i\right)\le 0.5;\\ \frac{1}{5}\left(1-\sqrt{\frac{1-m_{QLC}\left(e_i\right)}{2}}\right), & 0.5<m_{QLC}\left(e_i\right)\le 1.\end{cases} \tag{12}$$

$$m_{QID}\left(e_i\right)_2=\begin{cases}\frac{1}{5}\left(\sqrt{\frac{m_{QLC}\left(e_i\right)}{2}}+1\right), & 0\le m_{QLC}\left(e_i\right)\le 0.5;\\ \frac{1}{5}\left(2-\sqrt{\frac{1-m_{QLC}\left(e_i\right)}{2}}\right), & 0.5< m_{QLC}\left(e_i\right)\le 1.\end{cases} \tag{13}$$

$$m_{QID}\left(e_i\right)_3=\begin{cases}\frac{1}{5}\left(\sqrt{\frac{m_{QLC}\left(e_i\right)}{2}}+2\right), & 0\le m_{QLC}\left(e_i\right)\le 0.5;\\ \frac{1}{5}\left(3-\sqrt{\frac{1-m_{QLC}\left(e_i\right)}{2}}\right), & 0.5< m_{QLC}\left(e_i\right)\le 1.\end{cases} \tag{14}$$

$$m_{QID}\left(e_i\right)_4=\begin{cases}\frac{1}{5}\left(\sqrt{\frac{m_{QLC}\left(e_i\right)}{2}}+3\right), & 0\le m_{QLC}\left(e_i\right)\le 0.5;\\ \frac{1}{5}\left(4-\sqrt{\frac{1-m_{QLC}\left(e_i\right)}{2}}\right), & 0.5< m_{QLC}\left(e_i\right)\le 1.\end{cases} \tag{15}$$

$$m_{QID}\left(e_i\right)_5=\begin{cases}\frac{1}{5}\left(\sqrt{\frac{m_{QLC}\left(e_i\right)}{2}}+4\right), & 0\le m_{QLC}\left(e_i\right)\le 0.5;\\ 1-\frac{1}{5}\sqrt{\frac{1-m_{QLC}\left(e_i\right)}{2}}, & 0.5< m_{QLC}\left(e_i\right)\le 1.\end{cases}, \quad i=\overline{1,m}. \tag{16}$$

The choice of Eqs (12)–(16), respectively, depends on the level of perception of disinformation by inhabitants on digital platforms $L=\{l_1;l_2;l_3;l_4;l_5\}$.

Of course, other membership functions of the "value is more" type can be used for this logical derivation, for example: harmonic S-spline, S-sigmoid membership function, and S-linear membership function. The choice of the type of membership functions is up to the system analyst when setting up the model, or the DM when using the model.

As a result, m_{QID} is obtained – the quantitative level of the influence of disinformation in the section by respondents e_i.

After that, the generalized level of disinformation spread on digital platforms is calculated – m_{QSD}. For this, in some region or country R where the research is conducted, it is necessary to consider the group opinion of the level of influence of disinformation by all respondents:

$$m_{QSD}\left(R\right)=\frac{1}{m}\sum_{i=1}^{m}m_{QID}\left(e_i\right). \tag{17}$$

$m_{QSD}\left(R\right)\in\left[0;1\right]$ is an aggregated normalized estimate of the perception of disinformation by inhabitants in the studied region R on digital platforms, featuring the level of QoL of inhabitants and their financial concern.

4. Results

During our study, a fuzzy model was rigorously tested using real data obtained from 3,036 inhabitants in 2024. By conducting a comprehensive questionnaire survey among these respondents, a robust dataset was formed, enabling an informed evaluation. The data collection process involved respondents from the Czech Republic in May 2023 and was part of an international, multidisciplinary project aimed at assessing the impact of disinformation on society. Statistical experts ensured that the dataset met the criteria for a representative statistical sample, paying particular attention to demographic criteria and encompassing all facets of the issues under study.

Leveraging this real dataset, a series of experiments were conducted to evaluate all parameters of the model. An illustration of the application of the developed fuzzy model on selected data is provided below to demonstrate its efficacy. The scenario involves examining the impact of disinformation in the Czech Internet media space on society. In this context, the initial estimates of γ are derived using the fuzzy estimation model M_{DP}, which informs subsequent decision-making by the DM.

Initially, feedback is gathered and analyzed based on the information models K_{QLC} and K_{CDN}.

Furthermore, the authors have formulated a set of evaluation criteria D, to be used in the information model for assessing current disinformation narratives on digital platforms.

D_1. The devastating earthquake at the beginning of February was not a natural phenomenon. It was the result of the use of the US secret weapon HAARP. The remote electromagnetic bombardment is intended to undermine the authority of Erdogan, who does not allow Sweden to join NATO.

D_2. The incredible coincidence of the results of the presidential elections in France, Slovakia and now the Czech Republic is a consequence of the indoctrination of education for the purpose of neo-liberal transformation.

D_3. Ukraine committed a war crime by using a nerve agent near Bakhmut. The weapon is manufactured by the Shaman Group of Ukraine and uses the banned substance "CK" cyanide.

D_4. The Nord Stream gas pipeline was destroyed by the Pentagon's remotely detonated explosives. The C4 charges were installed by US Navy divers as part of a NATO exercise.

D_5. With the inauguration of new President Peter Pavel, the Czech Republic is facing a mobilisation. After his election, President Peter Pavel made a video calling for troops and air support to be sent to Ukraine.

D_6. Hygienists in Olomouc have noticed an increase in tuberculosis linked to the training of Ukrainian military personnel in the Libava military district.

D_7. The police of the Czech Republic deliberately provoked aggression and violence in front of the building of the National Museum, where some of the demonstrators went after the Czech protest against poverty, which took place on Saturday 11 March 2023 in Wenceslas Square.

All input data are listed in the database (Data from 3,036 inhabitants, 2024). To illustrate the feedback received, fragments of respondents' answers to the questions are shown in Table 1.

Table 1. Fragment of respondents' input data

Information model	Criteria	Respondents			
		e_1	e_2	...	e_{3036}
K_{QLC} – for assessing the QoL of inhabitants	K_1	Neither bad nor good	Good	...	Bad
	K_2	Dissatisfied	Neither satisfied nor dissatisfied	...	Very dissatisfied
	K_3	Maximum	A little bit	...	Very much
	K_4	Maximum	A little bit	...	Medium
	K_5	Very much	Very much	...	Very much
	K_6	Maximum	Medium	...	Very much
	K_7	Medium	A little bit	...	Very much
	K_8	A little bit	Very much	...	Medium
	K_9	Medium	Very much	...	Very much
	F_1	Very much	A little bit	...	Maximum
K_{CDN} – for evaluating current disinformation narratives on digital platforms	D_1	Completely implausible	Completely implausible	...	Rather implausible
	D_2	Rather implausible	Rather implausible	...	Rather implausible
	D_3	Rather plausible	Rather plausible	...	Rather plausible
	D_4	Entirely plausible	Rather implausible	...	Rather implausible
	D_5	Rather implausible	Completely implausible	...	Rather implausible
	D_6	Rather implausible	Rather plausible	...	Rather plausible
	D_7	Entirely plausible	Rather implausible	...	Rather plausible

Next, the linguistic variables are formalised using the membership functions (2)–(6), Table 2.

Table 2. Fragment of the formalization of respondents' input data

Information model	Criteria	Respondents					
		e_1	e_2	...	e_{2023}	...	e_{3036}
K_{QLC} – for assessing the QoL of inhabitants	$\mu(K_1)$	0.6	0.8	...	0.8	...	0.4
	$\mu(K_2)$	0.4	0.6	...	0.8	...	0.2
	$\mu(K_3)$	1	0.4	...	0.4	...	0.8
	$\mu(K_4)$	1	0.4	...	0.4	...	0.6
	$\mu(K_5)$	0.8	0.8	...	1	...	0.8
	$\mu(K_6)$	1	0.6	...	1	...	0.8
	$\mu(K_7)$	0.6	0.4	...	0.8	...	0.8
	$\mu(K_8)$	0.4	0.8	...	0.8	...	0.6
	$\mu(K_9)$	0.6	0.8	...	0.8	...	0.8
	$\mu(F_1)$	1.8	0.6	...	0.6	...	2.2

End of Table 2

Information model	Criteria	Respondents					
		e_1	e_2	…	e_{2023}	…	e_{3036}
K_{CDN} – for evaluating current disinformation narratives on digital platforms	$\mu(D_1)$	1	1	…	1	…	0.8
	$\mu(D_2)$	0.8	0.8	…	1	…	0.8
	$\mu(D_3)$	0.4	0.4	…	0.8	…	0.4
	$\mu(D_4)$	0.2	0.8	…	0.8	…	0.8
	$\mu(D_5)$	0.8	1	…	1	…	0.8
	$\mu(D_6)$	0.8	0.4	…	0.8	…	0.4
	$\mu(D_7)$	0.2	0.8	…	0.8	…	0.4

Then, the first stage of the fuzzy model is considered.

On the basis of formalised data, data aggregation is performed at the level of inhabitants' QoL in terms of individual respondents according to Eq. (7). In the next step, the psychology of the respondents' financial concern (F) is added according to Eq. (9). In the second stage of the model, according to the K_{CDN} information model, the actual disinformation narratives on digital platforms are evaluated in accordance with the Eq. (10). Next, the obtained quantitative estimate $m_{DP}$is delimited by the set of linguistic variables L. Fragments of the computational results are presented in Table 3.

Table 3. Fragment of calculation results

Estimated scores	Respondents					
	e_1	e_2	…	e_{2023}	…	e_{3036}
$\delta(e_i)$	0.71	0.62	…	0.76	…	0.64
$m_{QLC}(e_i)$	0.541	0.725	…	0.845	…	0.38
$m_{DP}(e_i)$	0.533	0.644	…	0.756	…	0.578
L	l_2	l_2	…	l_3	…	l_2

Subsequently, the influence of the level of QoL of the respondent $m_{QLC}(e_i)$ on the perception of disinformation on digital platforms L is calculated using the S-shaped membership function, Eqs (12)–(16). The choice of Eqs (12)–(16) depends, respectively, on the value of $L=\{l_1;l_2;\ldots;l_5\}$:

$$m_{QID}\left(e_1\right)_2=\frac{1}{5}\left(2-\sqrt{\frac{1-0.541}{2}}\right)=0.304;\, m_{QID}\left(e_2\right)_2=\frac{1}{5}\left(2-\sqrt{\frac{1-0.752}{2}}\right)=0.33;\ldots;$$

$$m_{QID}\left(e_{2023}\right)_3=\frac{1}{5}\left(3-\sqrt{\frac{1-0.845}{2}}\right)=0.544;\ldots;\; m_{QID}\left(e_{3036}\right)_2=\frac{1}{5}\left(2-\sqrt{\frac{1-0.38}{2}}\right)=0.289.$$

In our study, the generalized level of disinformation spread on digital platforms was quantified by aggregating the group opinions of all respondents. This was calculated using Eq. (17): $m_{QSD}(R)$ = 0.511.

Furthermore, the generalized level of satisfaction with the QoL of the inhabitants in the studied region was computed based on the K_{QLC} information model evaluation criteria, as per Eq. (8): QLC(R) = 0.66. This suggests that 66% of respondents expressed satisfaction with their QoL. Additionally, we considered the collective opinion on the perception of disinformation among all respondents, as indicated by Eq. (11): DP(R) = 0.716. Notably, the residents' perception of disinformation diminishes as the DP(R) value approaches one, indicating a higher resistance to disinformation among the evaluated respondents. The results of the study, which involved data from 3,036 residents in 2024, corroborate the widely recognized fact that people across different socio-economic statuses are susceptible to disinformation. However, our research also uncovers new dynamics. Specifically, we found that a high level of financial anxiety, coupled with a low societal QoL, adversely affects the perception of information objectivity. This phenomenon, in turn, accelerates the dissemination of disinformation.

5. Discussion

In the theoretical section (Part 2) of our study, we explored the intricate relationships between social networks and QoL, as well as the conceptualization of QoL itself. The multidimensional aspects of QoL had generated a variety of causal relationships between social media usage and an individual's QoL, thereby creating a complex landscape that facilitated the reception of disinformation. The diverse motivational effects of using social networks, combined with the subjective perception of their impact, which varied by age and other socio-economic and demographic parameters, posed challenges in the early detection of potential risks associated with social network use and their adverse effects on QoL.

To address these complexities, we developed a fuzzy model to assess the level of disinformation spread on digital platforms in relation to the QoL of inhabitants. This involved establishing an information model for assessing residents' QoL, another for evaluating current disinformation narratives on digital platforms, and a fuzzy model for assessing the disinformation spread level. All parameters of the fuzzy model were meticulously verified, and an illustrative example was applied to data segments to determine the linguistic level of disinformation spread on digital platforms.

The value of our fuzzy model lay in its comprehensive approach: it had incorporated respondents' statements regarding their QoL and financial concerns; it had factored in respondents' perceptions of disinformation on digital platforms; and it utilized a fuzzy model for evaluating the level of disinformation spread, employing intellectual knowledge analysis tools. The result was a quantitative assessment of residents' QoL, taking into account their financial concerns, their perception of disinformation, and the influence of disinformation among respondents on digital platforms.

To formalize the data evaluation, we used a mathematical approach based on expert evaluation, rooted in intellectual knowledge analysis and fuzzy set theory. This model was tested against real-world data, ensuring its robustness. The application of this mathematical theory had allowed us to account for the subjectivity of respondents' opinions, to interlink the level of residents' QoL with their financial concerns and perception of disinformation, and to facilitate informed decision-making. The research, grounded in real respondent data and knowledge-based models, offered practical value for a range of stakeholders, including non-governmental and public organizations, as well as top-level governmental bodies.

Research exploring the impact of social media on individuals and their QoL is becoming increasingly vital due to the dynamic nature of social changes, influenced by economic, political, health, and social challenges. Current and anticipated global trends, underscored by the technological and innovative revolution, asymmetric development, and the growing clout of the financial sector and transnational corporations, are set to usher in radical shifts (Kellner, 2021). These shifts indicate a strong concentration of global economic power, paralleled by a deepening societal polarization, rising crime rates, militarization of countries, emergence of war conflicts, and heightened geopolitical risks (Leimgruber, 2020).

Such trends are poised to significantly affect the social sphere and individual lives, potentially leading social platforms to exert diverse pressures on society's negative processes, causing detrimental effects on individuals and communities. To adequately capture the impact of various social anomalies, it is essential to continue developing systems and conceptual frameworks for assessing different aspects of people's lives, including QoL. Previous studies have demonstrated that treating QoL as a standalone concept in distinct human life domains (health, economic, social) is insufficient (Moons et al., 2006; Martel & Dupuis, 2006).

Effective exploration of causalities and quantification of the relationships between known or identified QoL determinants require a comprehensive refinement of QoL concepts. This entails elucidating the influence and interdependence of each determinant, investigating the causal framework of its dimensions (economic, social, health, environmental), and uncovering connections with societal and global threats such as the proliferation of fake news and disinformation (Van Raemdonck & Meyer, 2022; Humprecht et al., 2020). Achieving this will enable defining new protective effects of QoL for individuals and the impact of QoL on individual behavior.

Consequently, the development of an integrated tool for measuring QoL in a complementary manner is necessary. Such a tool will aid in identifying policies and lifestyles that genuinely enhance individual QoL. In addition to providing crucial information for making informed personal choices to improve long-term QoL, well-informed policies will facilitate the creation of necessary opportunities (Costanza et al., 2008).

The strength of this study lies in its foundation on real respondent data and knowledge-based models. Hence, the research findings, grounded in initial evaluations, hold substantial practical value for a diverse range of stakeholders, including non-governmental and public organizations, as well as the highest echelons of public administration (Kim & Kim, 2012; Grasso & Canova, 2008).

The advantages of the fuzzy model are that: the model uses real data sets from respondents, which allows it to be correctly verified and ensures the adequacy of the obtained results; the set of criteria is open, and the model does not depend on their number, which allows other researchers to easily add their questions to assess the level of disinformation in their region; the fuzzy model allows you to gain knowledge from the individual opinions of respondents regarding the assessment of the level of QoL and their perception of current disinformation narratives on digital platforms, to collective knowledge.

The findings of our study underscore the necessity for systematic development and implementation of information and media literacy programs, tailored according to the demographic structure and social groups. Current approaches to information and media literacy, as highlighted in existing literature, often adopt aggregated forms or focus primarily on "critical" population groups within individual countries (Cho et al., 2022a; Stamps, 2021). However, it is evident that social media present a multitude of risks, some still unrecognized, that affect all segments of the population, including those with health limitations, intellectual disabilities, and those facing economic or social challenges (Borgström et al., 2019; Caton & Chapman, 2016). The detrimental effects of social media on these vulnerable groups can further diminish their QoL and potentially lead to deep crisis situations. The fuzzy model developed in this study is capable of actively reflecting these changes in population structures. It reflects on these changes in the population structures and capture not only the negative effects of social media on the QoL of the group, but also on the individual and hence, create optimal interventions at the level of the individual territorial areas.

A limitation of our study was the composition of the respondent sample for the research questionnaire. This aspect influenced the verification of the fuzzy model, particularly in distinguishing quantitative levels of disinformation perception by residents and the extent of disinformation spread through digital platforms. Additionally, the selection of one-dimensional membership functions and the construction of characteristic functions could potentially introduce ambiguities into the final results. Despite these limitations, they do not significantly undermine the reliability of the findings.

The hypothesis formulated for this scientific research is fully substantiated by the results obtained. The rationality of the obtained quantitative and linguistic conclusions proves the advantages of the developed model. The reliability of the research results is ensured by the justified use of mathematical apparatus.

6. Conclusions

The primary objective of this research was to devise a fuzzy model for evaluating the extent of disinformation spread on digital platforms, considering the QoL of residents. In achieving this goal, several significant scientific advancements were made: the development of an innovative information model for assessing residents' QoL; the creation of a novel model for evaluating current disinformation narratives on digital platforms; and the pioneering development of a fuzzy model for determining the level of disinformation spread on these platforms. This fuzzy estimation model was rigorously tested and verified using real data from 3,036 respondents. An illustrative example of the application of this fuzzy model on selected data sets was provided to demonstrate its practical effectiveness.

The developed fuzzy model holds substantial potential for policymakers, strategic development planners, and experts in sustainable development, as well as those specializing in conceptual processes and methodologies related to QoL and UQoL. Additionally, the study's findings are invaluable for a diverse array of experts, including social media specialists, by informing methodologies aimed at mitigating disinformation processes and bolstering information security. This research supports the development of monitoring and regulatory mechanisms and contributes to the construction of information and media literacy systems. It also aids in establishing benchmarking indicators for economically quantifying the impact of disinformation processes on society. These insights are vital for ensuring sustainable economic development and the formulation of effective political, economic, technological, and innovation strategies.

Looking ahead, the authors plan to develop innovative software to facilitate feedback collection from respondents and enable the practical application of this research for various decision-makers. Furthermore, addressing the challenge of accurately gauging the quantitative levels of disinformation perception among residents and its spread through digital platforms, the research will incorporate artificial intelligence technology and machine learning methods.

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Author contributions

BG: Formal analysis, Methodology, Data curation, Writing – original draft, Writing – review & editing, Visualization. VM: Conceptualization, Writing – review & editing, Visualization, Validation, Supervision. NH: Writing – original draft, Writing – review & editing, Visualization, Supervision. MM: Conceptualization, Methodology, Writing – original draft, Writing – review & editing, Supervision. VP: Formal analysis, Data curation, Methodology, Software, Validation. RG: Writing – original draft, Writing – review & editing, Supervision. MB: Writing – original draft, Writing – review & editing. BP: Data curation, Writing – original draft, Writing – review & editing. LS: Writing – original draft, Writing – review & editing.

Disclosure statement

Authors declare they have no conflict of interest.

Ethics

All subjects were informed about the study, and all provided informed consent. The study procedures were carried out in accordance with the Declaration of Helsinki and was approved by ethical committee of General University Hospital Prague (IORG0002175 – General University Hospital in Prague, IRB00002705 a Federalwide Assurance FWA00029052).

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