THE ROLE OF THINKER CONSCIOUSNESS IN MEASUREMENT ACCURACY: AN INFORMATIONAL APPROACH

Boris Menin

Abstract: *This article contends that understanding measurement accuracy requires considering the thinker's consciousness in the process. In contrast to modern statistical methods, which analyze sources of uncertainty related to variables and measurements, this study proposes an approach that also accounts for the thinker's role in storing, transmitting, processing, and utilizing information to formulate the model. By incorporating the finite amount of information in the model, the study proposes a method for estimating the limit of measurement accuracy and provides examples of its application in experimental physics and technological processes.*

Keywords: *Amount of Information; Finite Information Quantity; International System of Units; Modeling; Physical Constant; Speed of Sound*

ITHEA Keywords: *H.1 MODELS AND PRINCIPLES; I.6 SIMULATION AND MODELING*

DOI: *https://doi.org/10.54521/ijita29-03-p01*

Introduction

The remarkable progress in modern science and technology, from space exploration to the study of subatomic particles, would not have been possible without the development of measurement theory, sophisticated methods for processing experimental data, and powerful computers. To achieve even greater accuracy in scientific and technical calculations, researchers often rely on models that reflect their philosophical views, intuition, and experience. However, while scientists tend to focus on calculating known uncertainties when processing experimental data, they may overlook the importance of understanding the underlying uncertainties that arise during modeling, prior to conducting experiments.

Applying the concepts and mathematical apparatus of information theory can help us comprehend the physical reasons behind the uncertainties that surround observed physical objects [1]. One of the primary factors contributing to uncertainty during the model formulation stage (defining the qualitative-quantitative set of variables and functional relationships between them) is the amount of information contained within the model, a concept commonly used in physics and engineering fields to describe the complexity of theoretical models that explain physical phenomena.

In the article by Jaynes [2], the application of information theory to statistical mechanics and thermodynamics is explored, suggesting that entropy in thermodynamics can be understood as a measure of the amount of missing information about a system.

Kapur's book [3] discusses the use of maximum entropy models to extract the maximum amount of information from limited data and provides an overview of the role of information in physics.

Gell-Mann and Lloyd [4] argue that information is a fundamental aspect of the universe and explores the relationship between information and physical systems from an information theory perspective.

Allaire et al.'s article [5] proposes an information-theoretic metric for quantifying the complexity of engineering systems. The authors demonstrate the usefulness of their metric by applying it to a variety of engineering systems, including an aircraft wing, a gas turbine engine, and an electric power grid. They show that their metric can capture the key features of each system's complexity, including the number of components, the degree of interaction between components, and the level of redundancy built into the system.

Deffner and Jarzynski [6] present an information-theoretical approach to thermodynamics, characterizing the amount of information contained in the state of the system and obtaining a generalization of Kelvin-Planck, Clausius, and Carnot's provisions on the second law of thermodynamics for situations related to information processing. It is suggested that this approach can provide insight into the thermodynamic behavior of complex systems.

Fang and Ouellette's article [7] presents a novel approach for measuring the information content contained in fluid flow data. The proposed method employs information theory, a branch of mathematics that deals with the quantification and transmission of information, to analyze the patterns and structures present in fluid flow data. Authors suggest that the proposed approach has the potential to advance our understanding of fluid flow dynamics, providing crucial insights for addressing pressing engineering and biological challenges.

The examples represent just a small sample of the many works that have explored the concept of "the amount of information contained in the model" within the field of physics and technology.

This concept is derived from the necessity for researchers to use a system of units with a certain level of complexity. By using this idea, it is possible to calculate the value of the threshold discrepancy between the model and the observed object [8-10].

Physical and Mathematical Foundations of the Information Method

Every experiment or measurement is preceded by the researcher's decision to construct a model. Therefore, it is impossible to calculate the minimum achievable measurement accuracy without considering the modeling stage. In other words, *the accuracy limit for describing physical objects is not determined by the material measuring instrument employed, but by the design of the model* *constructed in accordance with the individual preferences, philosophical and theoretical positions, and will of the researchers.* Furthermore, this limit of accuracy far surpasses the limit imposed by quantum mechanics on measurement precision.

To calculate the limit of object reproduction accuracy, researchers can conceptualize the model as a "communication channel" between the observed phenomenon and the thinker. In doing so, they must select significant variables while disregarding potential connections between them, leading to the oversight of hidden effects. The selected variables are typically derived from a system of units, such as the International System of Units (SI).

According to [11], each variable is comprised of a scalar time parameter, a universal constant, an one-dimensional position or momentum component, and a dimensionless number that take real values from the set R. Additionally, each variable contains a "piece of information" [12] that is bounded from above and defined as a "finite information variable" or FIQ by Del Santo and Gisin [11]. The number of dimensionless FIQs in the SI system can be calculated as μ_{SI} = 38265 [13]. These concepts and formulas are applicable to models using different systems of units [14] and containing any FIQ, both dimensional and dimensionless [15].

The process of modeling physical phenomena involves representing the analyzed phenomenon as a communication channel [9,16]. However, because this model is subject to noise and various distortions introduced by the thinker, uncertainty is present even during the formulation stage, preceding computer calculations and experiments.

An important remark follows regarding the modeling process. To accurately capture the essence of this process, it is preferable to use the term "thinker" instead of the more commonly used term " observer". This choice of terminology emphasizes that during the act of modeling, the phenomenon being studied is not influenced by external factors, and that reality exists independently of the individual conducting the study. By using the term "thinker," we can better convey the idea that the modeling process involves a careful and deliberate consideration of the underlying principles governing the phenomenon, without the imposition of external biases, distortions, or perturbations.

The process of model coding involves mapping the original set of FIQs from the SI system to the model structure, using a specific mapping process designed to minimize the threshold for mismatches between the model and the object being studied. To accomplish this, the researcher selects the FIQs from the SI, which contains seven base quantities [17]: length (L), mass (M), time (T), thermodynamic temperature (Θ), electric current (I), luminous intensity (J), and quantity of substances (F). The selected base quantities and derived variables determine the group of phenomena (GoP) inherent in the model. A GoP refers to a set of natural phenomena or technological processes characterized by a qualitative and quantitative group of variables that reflect certain properties of the observed reality [18].

For instance, in experiments involving Faraday's law, reduced variables with dimensions, such as length (L), mass (M), time (T), and electric current (I), which belong to the GoP_{SI} ≡ LMTI, are typically used. Due to limited financial resources, time, computing power, and philosophical preferences, the researcher selects a very small number of variables in the model compared to the μ_{SI}, which was equal to 38.265 [8]. Consequently, by calculating the amount of information in both the model and SI, the comparative uncertainty of the model, ε, can be determined [9].

$$\varepsilon = \Delta_{\Sigma} / S = [(z' - \beta')/\mu_{SI} + (z'' - \beta'')/(z' - \beta')] \quad (1)$$

where Δ_{Σ} is the a priori general uncertainty of the model due to the choice of GoP and the number of FIQs considered, S is the observation interval of the main studied FIQ, z' is the number of FIQs in the selected GoP, β' is the number of base values in the selected GoP, z'' is the number of FIQs, recorded in the model, and β'' is the number of independent values recorded in the model. ε is an important element of information theory [19], although almost no attention has been paid to it in modern scientific and technical literature.

To determine the optimal number of FIQs for a specific GoP, it is necessary to calculate the derivative of ε with respect to z' - β' and set it equal to zero:

$$\left(z''-\beta''\right)=\left(z'-\beta'\right)^{2}/\mu_{SI} \tag{2}$$

By using equations (1) and (2), one can determine the characteristics of any model that impose certain requirements for the transmission of information from the observed phenomenon to the thinker and the number of variables needed in the model to achieve the optimal value of ε_{opt} specific to each GoP. ε_{opt} can be considered as the capacity of the communication channel (model) and is an important concept in the modeling process that has not been extensively covered in existing scientific literature. It can be used to describe the characteristics of the model that reproduces the studied process, as well as the preferred method for measuring certain objective functions, such as physical constants.

Table 1 presents the optimal values of ε_{opt} and the corresponding recommended amount of FIQs for each GoP, which were obtained using (1) and (2) [14].

The data in Table 1 reveal the boundaries that can be reached for source compression, which involves replacing the μ_{SI} of the object with the representation parameter $W(GoP_{SI})$ necessary to ensure minimal distortion (threshold mismatch) D (ε_{opt}) that can theoretically be achieved by reproducing the observed object. In this case, the bandwidth of the communication channel is determined as a function of *the a priori total amount of information obtained when formulating a model of a physical phenomenon*:

$$W(D)=\max_{\gamma_{CoP}\in Z_D}\Delta A(\mu_{СИ};\gamma_{CoP}) \tag{3}$$

where W(D) is the reproduction (or source distortion) parameter and Z_D is the set of all possible optimal FIQ variables corresponding to GoPs. The GoP corresponds to a distortion ε equal to D(ε_{opt}) when the source (object) is transformed into a model. Δ*A* is the a priori total amount of information in units of entropy obtained when formulating a physical phenomenon model.

Table 1. Comparative uncertainties and the optimal number of dimensionless criteria

GoP_{SI}	Comparative uncertainty, ε_{opt}	Number of FIQs attributable to GoP_{SI}, $\gamma_{GoP} = z'-\beta'$	Optimal FIQs number inherent in the model, $\gamma_{mod} = z''-\beta''$
LMT	0.0048	91	≈ 0.2 < 1
LMTF	0.0146	279	≈ 2
LMTI	0.0245	468	≈ 6
LMTθ	0.0442	846	≈ 19
LMTIF	0.0738	1412	≌ 52
LMTθF	0.1331	2546	≈ 169
LMTθI	0.2220	4247	≈ 471
LMTθFI	0.6665	12 751	≈ 4,249

The distortion resulting from compressing the source can be attributed to the researcher's preferences. The researcher selects a specific GoP based on his philosophical beliefs, which determines the number of FIQs included in the model. The difference between the number of selected FIQs and the optimal number of FIQs inherent in the model (γ_{mod}) is shown in Table 1. For example, let γ_1 and γ_2 be the number of FIQs in the first and second models, respectively, if the models refer to the same GoP, and $\gamma_1 < \gamma_{GoP} < \gamma_2$ and $|\gamma_1 – \gamma_{GoP}| < |\gamma_{GoP} – \gamma_2|$. By applying (1), we obtain the following equation:

$$|\varepsilon_1 - \varepsilon_{opt}| = |2 \cdot (\gamma_1 - \gamma_{CoP}) / \mu_{CИ}|, |\varepsilon_2 - \varepsilon_{opt}| = |2 \cdot (\gamma_2 - \gamma_{CoP}) / \mu_{CИ}|, \quad (4)$$

$$|\varepsilon_1 - \varepsilon_{opt}| / |\varepsilon_2 - \varepsilon_{opt}| = |\gamma_1 - \gamma_{CoP}| / |\gamma_2 - \gamma_{CoP}| < 1, \quad (5)$$

where ε_1 and ε_2 are the comparative uncertainties of the first and second model, respectively.

Although models with a large number of variables are generally preferred, this conclusion may not hold within the proposed approach. This is because the researcher can quickly determine a lower value when comparing $|\varepsilon_1 - \varepsilon_{opt}|$ with $|\varepsilon_{opt} - \varepsilon_2|$. Specifically, ε_1 uses a larger number of dimensionless criteria, which may be closer to the optimal γ_{GoP} and the optimal comparative uncertainty ε_{opt}. Therefore, a more informative model would utilize γ_1, which is closer to γ_{GoP}. Consequently, the informational approach enables the identification of the most suitable method for calculating the preferred model for the object under study.

The informational approach involves several key features during the modeling process. Firstly, researchers, guided by their own understanding of the observed phenomenon's physical nature (which is an arbitrary act), strive to create a model that closely represents the object in a reasonable amount of time and with limited financial costs. As a result, GoP_{SI} models with a small number of base quantities, such as LMT, LMTθ, and LMTI, are commonly used.

Models related to LMTθI or LMTθF are used much less frequently. This is largely due to the limited computing power of computers, the ease of establishing mathematical relationships between selected variables, and the lower complexity of calculating the variable under study's value and its measurement uncertainty using existing statistical methods.

Secondly, the use of a GoP with a limited number of base quantities and a low value of γ_{mod} (< 2), such as GoP_{SI} ≡ LM, GoP_{SI} ≡ LMT, and GoP_{SI} ≡ LMTF (refer to Table 1), may not achieve the required value of ε_{opt} in theory or practice. Conversely, the use of GoPs with many base quantities and high γ_{mod} values (>169, refer to Table 1) is hindered by the increased difficulty in calculating the model uncertainty due to the limited computing power of modern computers. This topic is discussed in detail in the chapter "Application examples of the information method".

Thirdly, it is evident that the researcher's worldview leads to the initial and inevitable uncertainty of the model ε. It is not possible to calculate ε using statistical methods that rely on weighted factors or consistency criteria to process experimental data or computer calculations for a model that has already been constructed and implemented in the field. This fundamental difference highlights the disparity between the use of information as a physical substance and measurement theory [20].

Application examples of the information method

An analysis of scientific and technical works was conducted by *comparing the achieved comparative uncertainty of the model* ε_{mod} *with the theoretically substantiated* ε_{opt}, as shown in Table 1. When the uncertainties are close ($\varepsilon_{mod}/\varepsilon_{opt} \to 1$), it confirms the validity and usefulness of using either model to describe the process under study. On the other hand, a significant difference between these uncertainties ($\varepsilon_{mod}/\varepsilon_{opt}$<<1) indicates a high risk of applying a particular model.

This approach enables the use of concepts related to transmission, accumulation, and transformation of information in both theoretical research and applied problems.

The mass of information accumulated on the planet

There are two opposing perspectives regarding the nature of information. The first perspective asserts that information has no mass [12]. The second perspective, known as Landauer's principle, suggests that information is inherently physical [21]. For instance, [22] calculates the total mass of information (M_{info}) in kilograms that has been accumulated on the planet over n years, considering the annual growth rate (f %) of digital content creation on Earth:

$$M_{info}(n) = N_b \cdot k_b \cdot T \cdot \ln 2 \cdot ((f+1)^{n+1} - 1)/(f \cdot c^2) \approx 4.7 \cdot 10^{-16} \quad (6)$$

where N_b is the current annual rate of digital bit production on Earth, N_b = 7.3 1021 bits, T = 300 K is the temperature at which information is stored, f = 0.01, n = 1 year [22], $k_b = 1.3805 \cdot 10^{-23}$ m²·kg/(s²·K) - Boltzmann constant [23], ln2 = 0.6931, c = $2.99792458 \cdot 10^8$ m/s is the speed of light [23].

The accuracy of a calculated value for a physical variable is often assessed using relative uncertainty [24]. According to [15], the relative uncertainty (r_M) when calculating M_{info} (6) is found to be very small, approximately 4.2×10^{-6}. This suggests that Eq. (6) could be practically applicable. To further investigate the plausibility of the presented results, comparative uncertainty was used.

In [14], the authors used a model with $GoP_{SI} \equiv LMT\theta$ ($\gamma_{LMT\theta}$ = z'-β' = 846, Table 1) and γ_1 = z''-β'' = 1, based on the π-theorem [25].

$$\varepsilon_M = (846/38,265 + 1/846) \approx 0.0233 \quad (7)$$

The ratio of ε_M to ε_{opt} is found to be approximately 0.53 << 1 (where ε_{opt} = 0.0442 and GoP_{SI} ≡ LMTθ, Table 1). This is because the mechanical-thermal model used in [25] only considers one criterion (γ_1 = z"-β" = 1), instead of the recommended γ_{mod} = z"-β" = 19 (Table 1). As a result, the original model presented in [22] is overly simplified and requires further development to account for potential hidden influencing variables. Consequently, any predictive calculations within the framework of the FIQ-based method, which are deemed to have a clear physical content by the authors due to their philosophical ideas, should be accompanied by appropriate explanations of the possible limits of their applicability [26].

Measurement accuracy of physical constants

The approval of a new version of the International System of Units [17] stands as one of the important scientific achievements of the 21st century. This progress was made possible using of advanced experimental stands, as well as statistical methods for processing experimental data. The data for measuring physical constants were analyzed in accordance with the recommendations of the Committee on Data for Science and Technology (CODATA), using methods such as Bayesian linear regression and the method of least squares (LSA). However, it should be noted that the LSA approach can sometimes yield inadequate results [27], as the initial experimental values are often "corrected" to check the consistency of the results. Moreover, conflicting results may increase uncertainty, as noted by Pavese [28]. Additionally, statistical expert bias driven by personal beliefs or preferences [29] and the presence of subjective judgment [30] cannot be ignored.

The CODATA methodology was used to analyze the results of experiments based on models formulated by scientists, which overlooks the systematic effect resulting from the comparative uncertainty associated with the choice of GoP and the number of variables considered in the model. Therefore, this study proposes to analyze the data on measuring some physical constants using the FIQ-based method, which does not rely on tools such as consistency, asymptotic normality, or weighted estimates or coefficients.

An analysis of the results of measuring physical constants using various methods is presented in [9,10,14,15,31]. The data covers studies conducted by research centers from 2000-2019. Table 2 presents the results of applying measurement methods to obtain specific values of the experimental and optimal relative uncertainty, ε_{exp} and ε_{opt}, respectively.

The analysis of the results of measurements of physical constants using various methods from 2000-2019 revealed the following observations:

- A decrease in the ratio $\varepsilon_{exp}/\varepsilon_{opt}$ occurs when transitioning from models with a low number of base quantities (LMT) to models with a larger number of base quantities, such as LMTθ, LMTI, LMTθF, and LMTθI.

- All ratios of $\varepsilon_{exp}/\varepsilon_{opt}$ are greater than 1, which confirms the FIQ-based method's [18] fundamental proposition that any model's accuracy limit is determined by ε_{opt}.

- The use of BDL, BAO, and mechanical methods for measuring the Hubble constant and gravitational constant are not promising.

- In measuring the Boltzmann constant, k_b, researchers using DCGT achieved outstanding results compared to AGT ($\varepsilon_{exp}/\varepsilon_{opt} \approx 3.6$) and DBT ($\varepsilon_{exp}/\varepsilon_{opt} \approx 3.7$) at small values of $\varepsilon_{exp}/\varepsilon_{opt} \approx 2.3$.

Table 2. Summarized data for $\varepsilon_M / \varepsilon_{opt}$.

Ratio $\varepsilon_{exp} / \varepsilon_{opt}$	Physical Constant	Measurement method	GoP
2.3	Boltzmann constant, k_b	DCGT[1]	*LMTθI*

3.6	Boltzmann constant, k_b	AGT[2]	*LMTθF*
3.7	Boltzmann constant, k_b	DBT[3]	*LMTθF*
7.9	Gravitational constant, *G*	Electro-mechanical methods	*LMTI*
100	Gravitational constant, *G*	Mechanical methods	*LMT*
4.1	Hubble constant, H_0	CMB[4]	*LMTθ*
104	Hubble constant, H_0	BAO[5]	*LMT*
710	Hubble constant, H_0	BDL[6]	*LMT*
15.9	Planck constant, *h*	KB[7]	*LMTI*
32.6	Planck constant, *h*	XRCD[8]	*LMTθF*

[1]DCGT—dielectric constant gas thermometer,

[2]AGT—acoustic gas thermometer,

[3]DBT—Doppler broadening thermometer,

[4]CMB—cosmic microwave background,

[5]BAO— baryonic acoustic oscillations,

[6]BDL—brightness of distance ladder,

[7]KB — Kibble balance,

[8]XRCD—X-ray crystal density.

- Electromechanical methods provide a higher degree of confidence in measuring the gravitational constant, resulting in greater measurement accuracy (εexp/εopt ≈ 2.3) than mechanical methods (εexp/εopt ≈ 100).

- The BAO method (GoP_{SI} ≡ LMT) and BDL method (GoP_{SI} ≡ LMT) result in significantly higher ratios ($\varepsilon_{exp}/\varepsilon_{opt}$ ≈ 100 and $\varepsilon_{exp}/\varepsilon_{opt}$ ≈ 710, respectively) when measuring H_0 compared to $\varepsilon_{exp}/\varepsilon_{opt}$ ≈ 4.1 achieved using CMB. This suggests the possibility of missing hidden variables and indicates that considering all possible sources of uncertainty does not guarantee obtaining the true value of H_0 using the BAO method. The CMB method is theoretically substantiated, and the most reliable experimental data is achievable using this method.

- Of the two methods used to measure Planck's constant (KB, XRCD), the KB method ($\varepsilon_{exp}/\varepsilon_{opt}$ ≈ 15.9) is the more promising option for achieving higher accuracy in determining the value of *h*.

The results presented in this study provide strong support for the reliability of the FIQ-based method in identifying the preferred structure of the physical constant measurement method model. By utilizing comparative uncertainty as a criterion, the FIQ-based method has demonstrated its effectiveness as a reliable tool for this purpose, as demonstrated by the theoretically formulated and proven Equation 3.

It is important to note that the informational method approach differs fundamentally from the personalist Bayesian approach when it comes to evaluating the results of measurements of physical constants. While the Bayesian approach focuses on analyzing experimental data obtained after the model has been formulated, the informational method prioritizes the selection of the optimal model structure.

To achieve this, the FIQ-based method evaluates the comparative uncertainty of each candidate model structure, thereby enabling the identification of the most suitable model’s structure for the given data. In contrast, the Bayesian approach involves assembling an installation, testing the test bench, and implementing a series of measurements while simultaneously calculating all emerging uncertainties identified. Scientists consider both methods to be effective, but they differ in their approach and priorities.

While the CODATA method for processing experimental data on the measurement of physical constants has many advantages and is widely used, it is important to acknowledge some of the disadvantages of the Bayesian approach it relies on. These include:

- Limited experimental data: The CODATA method relies heavily on experimental data, and if there are only a limited number of high-quality measurements available, the resulting values for physical constants may be less precise or accurate. This can be particularly problematic for less well-studied physical constants or for those that are difficult to measure.

- Potential for bias: The CODATA method involves combining data from different experiments, each of which may have its own sources of bias or error. If these sources of bias are not properly accounted for, they may introduce additional bias into the result.

- Uncertainty estimation: Estimating the uncertainty associated with the measurements is an important part of the CODATA method. However, it can be challenging to accurately determine the uncertainty, particularly if there are multiple sources of error or if the uncertainty is non-uniform across the range of measurements.

- Dependence on assumptions: The CODATA method also relies on several assumptions, such as assuming that the underlying distribution of measurements is Gaussian or that the measurement errors are uncorrelated. These assumptions may not always be held in practice and can affect the accuracy of the result.

- Limited applicability: the CODATA method is primarily designed for processing experimental data on physical constants. It may not be as useful for other types of data or in situations where there are significant systematic errors or unknown sources of bias.

Application of the FIQ-based method for the analysis of measurements of the speed of sound

To analyze the results of measuring the speed of sound, three studies were selected, each with its own unique method of measurement, medium of sound propagation, and number of variables considered in the model. In [32], hydrogen chloride in the liquid and dense vapor phases was used as the medium. In [33], experiments were conducted on binary mixtures (N_2 + H_2), while in [34], a group of scientists used 36 elementary solids, including semiconductors and metals with high binding energies, as the propagation medium.

Each of the three studies presented novel and accurate experimental data, showing good agreement between theoretical calculations and experimental results, or with the available experimental literature data. In [33], three thermodynamic models were proposed based on the Helmholtz energy and their effectiveness was tested by comparing the experimental data on the speed of sound and acoustic virial coefficients with the results predicted by the reference thermodynamic models. In [34], the authors proved the existence of an upper limit on the speed of sound in condensed phases, which depends on the combination of two physical constants: the fine structure constant α and the ratio of the mass of an electron to the mass of a proton. According to the authors of [32], the proposed equation of state is applicable to the entire liquid region, making an important contribution to the accurate modeling of the thermal properties of hydrogen chloride.

However, none of the studies have compared the achieved relative uncertainty of the experiment with the difference between the theoretical predictions and the experimental data, which raises doubts about the legitimacy of using the formulated models. The application of these models in describing the propagation of sound in various media carries a significant risk. Moreover, in the case of relative uncertainty, the question of which model to prefer remains unanswered. To address this issue, we employed the FIQ-based method to determine the preference for the physical meanings of the compared models.

Table 3 presents the compressed data for the measurement of the speed of sound. After a careful analysis of the information provided in the articles, we have formulated the following comments:

Table 3. Comparison of research results

Variable/ Reference	Chosen GoP_{SI} of the model	Number of FIQs inherent in GoP_{SI}, γ_{GoP} = z'-β'	Optimal number of FIQs inherent in a model, γ_{modi} = z''-β'', i ☐ 1, 2, 3	The achieved experimental comparative uncertainty of the model, ε_i	The comparative uncertainty of the model, theoretically justified for the selected GoP, ε_{opti}	Ratio of $\varepsilon_i/\varepsilon_{opti}$
[32]	LMTθ	846	$\gamma_{mod1} \approx 19$	$\varepsilon_1 = 0.0233$	ε_{opt1} = 0.0442	≈ 0.53
[33]	LMTθ	846	$\gamma_{mod1} \approx 19$	$\varepsilon_2 = 0.0305$	ε_{opt2} = 0.0442	≈ 0.69
[34]	LMTIF	1412	$\gamma_{mod1} \approx 52$	$\varepsilon_3 = 0.0596$	ε_{opt3} = 0.0738	≈ 0.8

The researchers involved in the study of sound propagation may have their own philosophical biases that influence their choice of variables when modeling the process. However, it is important to note that the number of selected variables may be limited, potentially resulting in the omission of important, and underlying connections. This highlights the importance of considering a broader range of variables and potential interactions between them to model the complex process of sound propagation more accurately in different environments.

The ratios obtained from the experiments ($\varepsilon_1/\varepsilon_{opt1}$=0.53 < $\varepsilon_2/\varepsilon_{opt2}$=0.69 < $\varepsilon_3/\varepsilon_{opt3}$=0.8) provide evidence that the model proposed in [34] is the preferred choice. This is because the number of dimensionless variables considered in the [34] model is much closer to the recommended one. This is supported by the values of the ratio $\gamma_i \backslash \gamma_{opti}$:

$\gamma_1 \backslash \gamma_{mod1}$ = 1\19 = 0.05 [32] < $\gamma_2 \backslash \gamma_{mod2}$ = 4\19 = 0.21 [33] < $\gamma_3 \backslash \gamma_{opt3}$ = 18\52 = 0.35 [34].

While acknowledging the scientific progress achieved in previous studies [32] and [33], the informational approach highlights the importance of considering many variables in a model. In the case of sound velocity, the model presented in [34] is preferred due to its inclusion of a greater number of variables. This approach deepens our understanding of the true nature of the phenomenon and opens up new avenues for research, revealing hidden connections and expanding our knowledge.

Discussion

This article presents a new approach to the problem of achievable measurement accuracy. Instead of focusing on technical improvements to statistical methods, computers, and experimental equipment, this approach considers the modeling process that precedes the experiment. It recognizes that model uncertainty, which is influenced by the consciousness of the thinker, introduces a new element that limits measurement accuracy.

The ε-equation represents a deep connection between the accuracy of measurement and the consciousness (will) of the thinker. While this equation may be difficult to understand, it highlights the importance of the model formulation stage in the measurement process. This approach shows that the existence of an additional limit on measurement accuracy is not mysterious; it is simply a consequence of the finite amount of information contained in the model used to understand the object under study.

By acknowledging the role of consciousness in the modeling process, this approach overcomes the difficulties of determining the causes of the initial "blurring" of the object under study and sets a possible limit on measurement accuracy. While this concept may be challenging to accept, it provides a clear and logical explanation for the limitations of measurement accuracy beyond the Heisenberg uncertainty principle.

The concept of ε represents an intrinsic conceptual uncertainty in any physical or mathematical model, independent of the measurement process. This uncertainty depends on the number of base and derived variables and the chosen GoP, which are determined by the thinker's will. It is important to note that ε is not a result of the measurement, but rather an inherent property of the model. While the overall uncertainty of the model's objective function is much larger than ε due to additional uncertainties arising from the structure of the model and processing of experimental data, ε provides a fundamental limit to the achievable accuracy of the measurement.

This proposal presents a new approach to assessing the achievable accuracy of measurements with a clear physical basis. While the implications of this approach for biological systems have not been fully discussed, we deliberately did not explore the application of the FIQ-based method to genetic processes, as variables from the system of units are not used in this area of research. Nonetheless, the use of information theory to represent the modeling of physical phenomena or technological processes is highly relevant and important in scientific and technical research. This informational approach provides a valuable tool for understanding the limitations and possibilities of modeling physical systems.

Our study has demonstrated the applicability of the information approach in selecting the optimal structure of the model for studying the behavior of a physically observable object. We have applied this method to calculate the speed of sound, measure physical constants, and investigate the potential mass of information on Earth. By adopting this paradigm, scientific research can go beyond the mere description of "how" a measurement is prepared and move towards constructing an optimal model from the thinker's perspective. Our findings provide a valuable framework for scientific research that can help researchers choose the best structure of the model for their studies.

Conclusions

The information method is not a direct solution for building an accurate model of an observed object. Instead, it provides researchers with a tool in the form of comparative uncertainty to construct a model that minimizes mismatches with the phenomenon or process under study.

The research presented the trade-off between model complexity and accuracy, as measured by the amount of information. It also explains why finding the optimal structure for a model that accurately describes a physical object can be challenging and ultimately depends on the subjective decisions of the researcher.

The informational approach can be useful in avoiding overly simplistic or complex assumptions, as real-world phenomena are often more complex than the models used to represent them. By striving for greater accuracy through more complex models, researchers can use the informational approach to better understand the world around them.

The informational approach also emphasizes the role of the intellect, will, consciousness, intuition, and life experience of the researcher as integral components of the reality being studied. This highlights the importance of considering the subjective experience of the researcher in modeling physical objects and processes.

The FIQ-based method is a promising approach that has the potential to improve our understanding of physical systems. It is based on the mathematical framework of information theory and provides a clear definition of comparative uncertainty, which can help us identify the most reliable structure for a model and interpret experimental results in a balanced manner. The method takes into account the finite amount of information available in the system of units and the model, as well as the subjective decisions of the researcher.

When building a model to represent a process, it's important to acknowledge that only a finite amount of information is available to accurately describe its state. This information is inherently uncertain, and this uncertainty cannot be avoided. This principle of finiteness, as described by [35], is not a result of mathematical or physical limitations, but rather a fundamental aspect of the model building process. Therefore, it's crucial to consider the limitations of the available information and the resulting uncertainty when using models to make predictions or draw conclusions.

Finally, while the FIQ-based method shows great potential, there is still much work to be done to fully develop and refine this approach. However, continued research into this method has the potential to deepen our understanding of physics and technology, and to provide new insights into the behavior of complex physical systems.

Bibliografy

[1] Grecis, F. On the meaning of measurement uncertainty. Measurement, Vol. 133, 2018, pp. 41-46. https://sci-hub.tw/10.1016/j.measurement.2018.09.073

[2] Jaynes, E.T. Information theory and statistical mechanics. Revs. Modern Physics, vol. 27, No. 289, 1955, pp. 620-630. https://bayes.wustl.edu/etj/articles/theory.1.pdf

[3] Kapur, J.N. Maximum-Entropy Models in Science and Engineering. Wiley eastern Limited, New Delhi, India, 1993. https://books.google.co.il/books?id=LuNIAp3QorUC&printsec=frontcover&vq=%22Maximum+Entropy+and+Bayesian+Methods%22&source=gbs_citations_module_r&cad=3#v=onepage&q=%22Maximum%20Entropy%20and%20Bayesian%20Methods%22&f=false

[4] Gell-Mann, M., Lloyd, S. (1996). Information measures, effective complexity and complete information. Difficulty, Vol. 2, N. 1, 1996, pp. 44–52. https://sci-hub.hkvisa.net/10.1002/(sici)1099-0526(199609/10)2:1%3C44::aid-cplx10%3E3.0.co;2-x

[5] Allaire, D., He, Q., Deyst, J., Willcox, K. An Information-Theoretic Metric of System Complexity With Application to Engineering System Design. J. Mech. Des., Vol. 134, No. 10, 100906, 2012. Pp. 1-10. https://doi.org/10.1115/1.4007587

[6] Deffner, S., Jarzynski, K. Information Processing and the Second Law of Thermodynamics: An Inclusive Hamiltonian Approach, 2013, pp. 1-14. https://arxiv.org/pdf/1308.5001.pdf

[7] Fang, L., Ouellette, N.T. (2021) Assessing the information content of complex flows. Phys. Rev. E, Vol. 103, 023301, 2021, pp. 1-7. https://link.aps.org/accepted/10.1103/PhysRevE.103.023301

[8] Menin B. 2017 Information Measure Approach for Calculating Model Uncertainty of Physical Phenomena. Amer. J Comput. Appl. Math.,

Vol. 7, No. 1, 2017, pp. 11–24. https://goo.gl/m3ukQi

[9] Menin, B. Construction of a model as an information channel between the physical phenomenon and thinker. J. Assoc. inf. sci. Technol., Vol. 72, No. 9, 2021, pp. 1198-1210. doi: 10.1002/asi.24473.p.

[10] Menin, B. Can Information Theory Help to Formulate an Optimal Model of a Physical Phenomenon? Journal of Applied Mathematics and Physics, Vol. 10, No. 10, 2022, pp. 2940-2950. https://www.scirp.org/pdf/jamp_2022101214331576.pdf

[11] Del Santo, F., Gisin, N. Physics without determinism: Alternative interpretations of classical physics. Phys. Rev. A, Gen. Phys., Vol. 100, No. 6, 2019, pp.1-9. doi: 10.1103/PhysRevA.100.062107.

[12] Burgin, M. Information theory: a multifaceted model of information. Entropy, Vol. 5, No. 2, 2003, pp. 146–160. https://sci-hub.tw/10.3390/e5020146

[13] Menin, B. Simplest Method for Calculating the Lowest Achievable Uncertainty of Model at Measurements of Fundamental Physical Constants. Journal of Applied Mathematics and Physics, Vol. 5, No. 11, 2017, pp. 2162-2171. https://goo.gl/qNyUC8

[14] Menin, B. *h*, *k*, N_A: Evaluating the Relative Uncertainty of Measurement. Am. J. Comp. Appl. Math., Vol. 8, No. 5, 2018, pp. 93–102.

http://article.sapub.org/10.5923.j.ajcam.20180805.02.html

[15] Menin, B. Hubble Constant Tension in Terms of Information Approach. Phys. Sci. Int. J., Vol. 23, No. 4, 2019, pp. 1-15. https://doi.org/10.9734/psij/2019/v23i430165

[16] Menin, B. Unleashing the Power of Information Theory: Enhancing Accuracy in Modeling Physical Phenomena. Journal of Applied Mathematics and Physics, Vol. 11, No. 3, 2023, pp. 760-779. Doi: 10.4236/jamp.2023.113051.

[17] Newell, D.B., Tiesinga, E. The International System of Units (SI). NIST Special Publication. Gaithersburg, MD, USA, Tech. Rep. 330, 2019, pp. 1–138. https://doi.org/10.6028/NIST.SP.330-2019

[18] Sedov, L.I. Similarity and Dimensional Methods in Mechanic. USA: CRC Press, Florida, 1993.

[19] Brillouin, L. Science and Information Theory. New York, NY, USA: Academic Press, 1953.

[20] Menin, B. Applying Measurement Theory and Information-based Measure in Modeling Physical Phenomena and Technological Processes. Eur. J. Eng. Res. Sci., Vol. 3, No. 1, 2018, pp. 28-34. https://ej-eng.org/index.php/ejeng/article/view/594

[21] Landauer, R. Information is Physical. Phys. Today, Vol. 44, No. 5,

1991, pp. 23-29. https://sci-hub.se/10.1063/1.881299

[22] Vopson, M.M. The information catastrophe. AIP Adv., Vol. 10, 2020, pp. 1-5. https://sci-hub.se/10.1063/5.0019941

[23] Mohr, P.J., Newell, D.B., Taylor, B.N., Tiesinga, E. Data and analysis for the CODATA 2017 special fundamental constants adjustment. Metrologia, Vol. 55, 2018, pp. 125–146. https://iopscience.iop.org/article/10.1088/1681-7575/aa99bc/pdf

[24] Khruschov, V.V. 2021 On possible ways for future redefinition of the SI time unit, 2021, pp. 1-10. https://arxiv.org/ftp/arxiv/papers/2102/2102.05863.pdf

[25] Yarin, L. The Pi-Theorem. Berlin, Germany: Springer-Verlag, 2012. https://goo.gl/dtNq3D

[26] Menin, B. High accuracy when measuring physical constants: from the perspective of the information-theoretic approach. J. Appl. Math. Phys., Vol. 8, No. 5, 2020, pp. 861–867. DOI: 10.4236/jamp.2020.85067

[27] Wübbeler, G., Bodnar, O., Elster, C. 2017 Robust Bayesian Linear Regression with Application to an Analysis of the CODATA Values for the Planck Constant. Metrologia, Vol. 55, 2017, pp. 20-28. https://sci-hub.hkvisa.net/10.1088/1681-7575/aa98aa

[28] Pavese, F. The New SI and the CODATA Recommended Values of

the Fundamental Constants 2017 Compared with 2014, with a Comment to Possolo et al. Metrologia, Vol. 55, 2018, pp. 1-11. https://arxiv.org/ftp/arxiv/papers/1512/1512.03668.pdf

[29] Dodson, D. Quantum Physics and the Nature of Reality (QPNR) Survey: 2011. 2013. https://newatlas.com/confusion-basic-nature-quantum-mechanics/26216/

[30] Henrion, M., Fischhoff, B. 1986 Assessing Uncertainty in Physical Constants. Am. J. Phys., Vol. 54, 1986, pp. 791-798. https://sci-hub.se/10.1119/1.14447

[31] Menin, B. Simplicity of Physical Laws: Informational-Theoretical Limits. IEEE Access, Vol. 10, 2022, pp. 56711-56719. https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=9780195

[32] Thol, M., Dubberke, F.H., Baumhögger, E., Span, R., Vrabec, J. Speed of Sound Measurements and a Fundamental Equation of State for Hydrogen Chloride. J. Chem. Eng. data., Vol. 63, No. 7, 2018, pp. 2533–2547. https://doi.org/10.1021/acs.jced.7b01031

[33] Segovia, J.J., Lozano-Martin, D., Tuma, D., Moreau, A., Carmen Martín, M., Vega-Maza, D. Speed of sound data and acoustic virial coefficients of two binary (N2 + H2) mixtures at temperatures between (260 and 350) K and at pressures between (0.5 and 20) MPa.

The Journal of Chemical Thermodynamics, Vol. 171, 2022, pp. 1-13.

https://doi.org/10.1016/j.jct.2022.106791

[34] Trachenko, K. et al. 2020 Speed of sound from fundamental physical constants. Sci. Adv., Vol. 6, No. 41, 2020, pp. 1-6.

https://advances.sciencemag.org/content/advances/6/41/eabc8662.full.pdf

[35] Sternlieb, A. The principle of finiteness – a guideline for physical laws. J. Phys.: Conf. Ser., Vol. 437, 012010, 2013, pp. 1-12.

https://iopscience.iop.org/article/10.1088/1742-6596/437/1/012010/pdf

Authors' Information

Boris Menin – Mechanical & Refrigeration Expert, Beer-Sheva 8464209 Israel; e-mail: meninbm@gmail.com

Major Fields of Scientific Research: Modeling physical phenomena, Applying information theory for the model structure, Pumpable ice technology