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CALCULATION OF THE MINIMUM ENERGY VALUES OF THE THEORETICAL AND EXPERIMENTAL DATA BELONGING TO CANDIDATE SCIENCE TEACHERS ON THE SUBJECT OF PROCEDURAL KNOWLEDGE OF ELECTRICITY

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Abstract:
In this study, we calculate the minimum energy values of candidate science teachers' knowledge on the subject of electricity using 11 open-ended questions to measure their procedural knowledge. The goal is to enhance the teaching processes of candidate teachers by calculating the minimum amounts of energy that they consume, do not consume, and are expected to consume in the process of converting data into knowledge. It is important to know the energy that the people in the training process are spending or willing to spend, especially in getting information and measurement-evaluation. This energy will be calculated by information theories. In these calculations, energy equality of a biological unit will be used. The "bit" value in the energy calculations of the information theories will be determined by the VDOIHI statistical method. We find that candidate teachers' energy consumption is focused on success, and that they should consume more energy in independent variables to ensure the permanence of this success by converting knowledge into understanding. Efficiency is of primary importance in energy planning, and can be enhanced in problem solving techniques by developing methods in accordance with energy plans that prescribe the volume of energy to be consumed in independent variables.

Keywords: knowledge' energy, problem solving' energy, procedural knowledge, success' energy

1. Introduction

Information theories are based on the assumption that the more unexpected some event is (i.e., the higher the uncertainty), the more we will learn about that event after its occurrence (Bradshaw & Boose, 1988; Özenli, 1999, p. F1). The total amount of information embedded in the data learned from the event is measured through the

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Shannon entropy (Mostaghimi, 1997; Shannon & Weaver, 1949). In other words, the Shannon entropy enables us to measure the information content, or message entropy, of an event.

In systems similar to information theories, the Shannon entropy is an extension of the Gibbs/Boltzmann entropy (Dover, 2004; Zhao & Wu, 2011), which is expressed as $S = k \ln W$ (Mathai & Haubold, 2007; Niven, 2009). For information entropy measurements, the following formula is used: Boltzmann/Gibbs entropy $S_{BG}(P) = -k \sum_i p_i \log p_i$ (Masi, 2007), or simply $S = k \log W$ (Jaynes, 1965). In molecular machines, the minimum energy per bit is calculated as $E_{min} = k_B T \ln(2)$ (Schneider, 1991, 2010). However, Sanchez and Grau (2005) suggested that genetic information systems are essentially communication systems, just like other information systems; thus, the minimum energy needed for each bit can be calculated using the same formula, $E_{min} = k_B T \ln(2)$.

Knowledge can be defined in the same way as the bits in classical information theories. Although not necessarily including the details of information analyses, a similar, simple classification technique might be used (Guan & Bell, 1998). At the initial point of a system, data are related to information theories rather than to physics, and can be explained through the concept of information entropy (Jaynes, 1957a, 1957b, 1982). Similar to the definition of bits in information theories in cases with two possibilities (where the probability is 0.5), in this paper, we define knowledge and success for learning systems by dividing them into their smallest meaningful units (akp) and reducing them to cases with two possibilities of probability 0.5. Furthermore, we calculate the theoretical and experimental minimum energies of the "bit" values, already calculated in Yılmaz, 2017, for the procedural knowledge and success pertaining to the subject of electricity.

The energy that the students spend or spend during the education and training process is important. Knowing this energy ensures that education and training processes are planned correctly. It can also contribute to improving students' knowledge and achievement processes. Calculation of the energy they will spend in the process of knowledge and success in education can contribute to educating the students as healthier individuals. Because of these reasons, it is very important to calculate the energy to be spent on knowledge and success. On this paper, the energy of the knowledge, success, knowledge levels and success levels of electrical science teachers' candidates will be experimentally calculated.

2. Theory

The "entropy," or "information content," of technical and experimental data can be calculated in "akp" through the VDOİHİ (see e.g., Yılmaz, 2011; Yılmaz & Yalçın, 2011; Yılmaz, 2017) statistical method using the following formula, given in Yılmaz, 2017,

$$H(x) = -\sum_{i=1}^{M} \mathbf{P(i)} \log 2^{\mathbf{P(i)}} \quad (1)$$

$$H(x) = Pro(A).n \quad (2)$$

or in "bits" using the formula

$$H(x) = Pro(A).BGS \quad (3)$$

Multiplying the minimum energy per bit ($E_{min} = k_B T \ln(2)$), which is used for molecular machines or genetic information systems (Sanchez & Grau, 2005; Schneider, 1991, 2010), by the bit value, the energy value of data can be calculated as:

$$E_{min} = H(x).k_B T \ln(2) \quad (4)$$

3. Methodology

For this study, data were collected using the case study method. An assessment instrument consisting of 11 open-ended questions inquiring into the participants' procedural knowledge on the subject of electricity was used. In the data collection process, the participants (44 science teacher candidates in their first year of college) were asked to give answers to the open-ended questions using problem solving techniques after being instructed on the subjects. The VDOİHİ statistical method, based on the comparison of theoretical and experimental data (Yılmaz, 2011; Yılmaz & Yalçın, 2011), and related software were used to analyze the data. The study's theoretical data consisted of the akp of the correct responses to the problems, whereas the experimental data included the akp of the responses given by the participants.

Energy values were calculated using the "bit" values given in Tables 1 and 2 (see Yılmaz, 2017) in place of $H(x)$ in the expression for E_{min}. The $H(x)$ function in Yılmaz, 2017 and the minimum energy values were calculated separately using the following values calculated for the candidate teachers' knowledge and success levels: information specificity ($B^{E}_{B,b}$), information specificity status ($BD^{E}_{B,b}$), total information specificity ($TB^{E}_{B,b}$), information deficit ($E^{E}_{B,b}$), and desired information $akp_{B,b}$ ($OG^{E}_{B,b}$). Energies were also calculated in joules using $1.38 \times 10^{-23} J.K^{-1}$ for the Boltzmann constant (k_B) and 298.5K (for 25°C) for T in the E_{min} formula.

4. Results

Table 1 presents the minimum energy values that the teacher candidates were supposed to consume and did consume while solving the problems in the assessment instrument using problem solving techniques. These values were calculated by placing the bit values of the theoretical and experimental data given in Yılmaz, 2017 (Table 1) and the values of the Boltzmann constant, temperature, and constant ln(2) into the expression for E_{min}.

Table 1: Minimum Energy Values (Joules) Corresponding to the Bit Values of Knowledge

	Knowledge/ Variable	Given-Asked	Free-Body Diagram	Definition	Formulas	Operations	Variables of Average
Energy (Joul.bit) x10^{-23}	B_B^E	17.14	188.54	79.98	188.54	328.51	251.38
	BD_B^E	85.70	402,78	168.54	402.78	422.78	414.21
	TB_B^E	102.84	588.46	248.52	588.46	751.29	665.59
	E_B^E	3039.42	1125.50	4893.36	1125.50	4961.91	2762.33
	OG_B^E	3142.26	1713.96	5141.88	1713.96	5713.20	3427.92

The final row of Table 1 (OG_B^E) gives the theoretical minimum energies that the participants needed to consume to convert data into knowledge when solving the 11 procedural knowledge questions. E_B^E represents the experimental minimum energies that were not consumed in problem solving, whereas the other rows give the experimental values of the minimum energy consumed in problem solving. It is apparent that the candidate teachers did not consume sufficient energy when converting data into knowledge, as the values of TB_B^E and the averages of the independent variables (final column) were lower than the unconsumed minimum energy values (E_B^E). The values of E_B^E are the minimum amounts of energy needed to convert the data of this research into knowledge. To realize this conversion, these minimum energy amounts should be consumed in addition to the total energy consumed.

Table 2 presents the minimum energies that the participants were supposed to consume (but did not) to successfully solve the problems of the assessment instrument. These values were calculated by applying the bit values of the theoretical and experimental data given in Yılmaz, 2017 (Table 2) to the expression for E_{min}.

Table 2: Minimum Energy Values (Joules) Corresponding to the Bit Values of Success

	Variable	Energy
Energy (Joul.bit) x10^{-23}	B_b^E	1571.13
	BD_b^E	708.44
	TB_b^E	2279.57
	E_b^E	862.69
	OG_b^E	3142.26

The final row of Table 2 (OG_b^E) gives the minimum energy that must be consumed for theoretical success, whereas the other lines give the minimum energies consumed and unconsumed for successful problem solving. The candidate teachers were found to be success-oriented when solving problems, as indicated by the fact that the total amount of energy consumed for success (TB_b^E) was greater than the unconsumed minimum energy (E_b^E) in problem solving and the unconsumed energy was smaller than the total minimum energy consumed for knowledge. A smaller amount of energy was needed for success than for knowledge.

5. Discussion and suggestions

The results of this study show that the total minimum energy consumed for knowledge was less than the unconsumed minimum energy, and that the total minimum energy consumed for success was greater than the unconsumed minimum energy. These findings indicate that candidate teachers should consume more energy in understanding independent variables to ensure data are converted into knowledge. To convert data into knowledge, the energy needs of candidate teachers for teaching processes should be identified, and the efficient use of this energy should be planned. This can be achieved by developing methods that agree with the energy plans needed for independent variables in problem solving techniques. To successfully convert data into knowledge, it is not only necessary to develop teaching methods and techniques, but also to carry out studies to effectively support the energy needs of the biological infrastructure that would bring about this conversion. The theoretical and experimental infrastructures that would facilitate such studies have been presented in the three-part series constituting this paper. The theoretical and experimental assumptions made throughout this report can be approximated to real-life situations by gathering additional data from various fields of study.

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