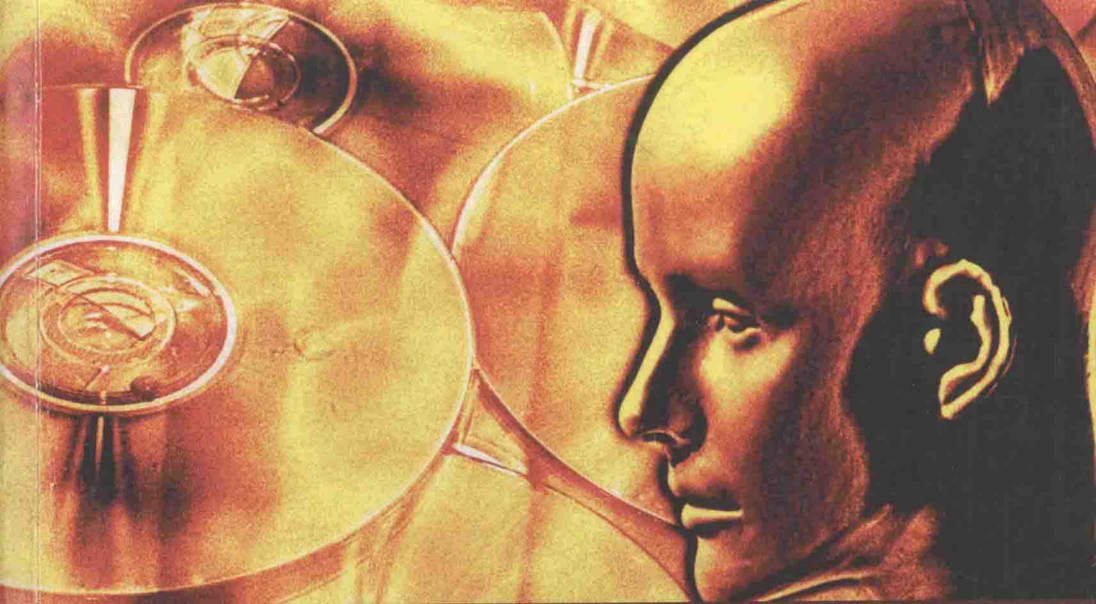

V. C. I Ulinwa

Machine Intelligence Quotient

A Multiple Perspective Analysis of Intelligent Artificial Systems Including Educational Technology

VDM
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CHAPTER 1: INTRODUCTION TO THE STUDY

Scientists by nature want to measure every concept and thing. Measurement in science has a long tradition, even though the degrees to which things are measured differentiate a well-developed science such as physics from some of the less-well-developed sciences such as psychology or sociology (Abreu, 1993). The meter was properly defined in 1889, whereas measuring temperature was more complicated until Fahrenheit in 1714 and Celsius in 1742 introduced the measurement intervals for temperature, which graduate from one point to another (Lind & Vairavan, 1989). Similarly, Rene Descartes implicitly introduced the notion of measuring machine intelligence in 1637 by articulating some ideas for disproving machine intelligence before Alan Turing proposed a formal measure of machine intelligence in 1950 (Wolfram, 2002). Among other types of measurement is fuzzy logic, which extends classical logic by permitting linguistic variables to take values on intervals between zero and one (Zadeh, 1972, 1973, 1978).

From 1904 to present, intelligence quotient (IQ)—a cognitive statistical correlation of answers to test questions—has been used to define, measure, interpret, and rank human intelligence. Several versions of the test have been developed to strengthen and validate IQ as a concept. Early attempts to measure intelligence quantified reasoning abilities about simple objects such as faces or coins before the questions were arranged to reflect mental age levels. Prior to the general intelligence factor *g*, no general factor of intelligence had been used; instead at least five subsets that include neurosis, extraversion, conscientiousness, agreeableness, and openness were used in different parts of the tests. Despite the popularity of the tests, culture, language, and access to technology are not measured. Speech recognition, vision, and hearing are also not measured.

The search for a means to measure intelligence began when the French Ministry of Education required Alfred Binet to design a test for identifying students with learning problems. Binet was influenced by Paul Broca's study on a correlation between intelligence and brain size. Realizing that brain size was not statistically significant with a data sample (Binet originally proposed to use Broca's criteria for an intelligence study) Binet developed a set of questions that served as the basis for modern IQ test (Dewdney, 1997). In 1910, H. H. Goddard introduced the test to the United States to screen feeble-minded boys and girls for Vinland Training School in New Jersey. Goddard firmly believed in the theory of inheritance and that a single letter *g* could represent intelligence despite Binet's caution against such a statistical or interpretation error (Dewdney).

Using factor analysis, Charles Spearman showed some significant correlation among certain IQ results. The statistical procedure indicated how uniform a large number of correlations are. Based on the statistical assumption, Spearman inferred that a single general intelligence factor *g* should represent intelligence. Also, Arthur R. Jensen of the University of California at Berkeley and John B. Carroll of the University of North Carolina at Chapel Hill believed Spearman's general intelligence factor is a reliable measure. Thus *g* became a working definition and measure of human intelligence (Dewdney, 1997; Gottfredson, 1998). Moreover, as Dewdney noted, the Stanford-Binet written test by Lewis Terman of Stanford University is a derivative of Binet's test.

Some researchers and philosophers, believing there are some possibilities that some machines are intelligent or more intelligent than humans, want a measure of machine intelligence. For them a device should be intelligent and have a mind if and only if it passes a test (Penrose, 1990, 1994). The main idea of these researchers and philosophers is that any mental activity including human thinking and conscious intentionality can be algorithmically carried out and measured in a well-defined manner. An algorithm is a calculation procedure of a computing device. Thus, whenever the algorithm is performed, the device would experience feelings and also have consciousness. It becomes a mind (Penrose, 1990, 1994). For example, after noticing their heuristic problem-solving device is an adaptive system, Simon and Newell (Kurzweil, 1999) proclaimed,

> There are now in the world machines that think, that learn and that create. Moreover, their ability to do these things is going to increase rapidly until—in a visible future—the range of problems that they can handle will be co-extensive with the range to which the human mind has been applied. (p. 69)

Thus developers and scientists of similar computing devices could contend their devices also think, are genuinely intelligent, and in some cases feel pain and happiness and pride (Penrose, 1990). In a famous work on computing machinery and intelligence, Alan M. Turing set a standard for determining if a given artificial device is intelligent (Arbib, 1965; Balkenius, 1994, 1995; Boden, 1990; Mershin, Nanopoulos, & Efthimios, 2000). A machine is considered intelligent if for any reason an examiner could not reliably identify it from other Turing test takers. Penrose (1990) expressed the view that a Turing test is unreliable because the interviewer could ask some complex arithmetic questions that only the computing device could answer correctly and quickly. In such a case the interrogator could easily identify the machine unless its developers intentionally programmed it to be stupid sometimes. Grounded on the same necessity for a machine intelligence quotient (MIQ) measure, although from a different computing assumption, Zadeh noted the principal reason for a MIQ includes the ability to reason, experiential learning, and unintervened decision making (Zadeh, 1972, 1973). Zadeh also posited high MIQ systems are the results of computational hybrid systems.

Problem Statement

Measuring machine intelligence is a daunting task that faces those who are concerned with the intelligence of computational systems. Current literature supports the notion that machine intelligence is defined and acceptable within the domain of systems developers and should be as given to the end users (Bien, Bang, Kim, & Han, 2002; Falqueto, Lima, Borges, & Barreto, 2000; Finkelstein, 2000; Gatherer, 2002; Messina, Meystel, & Reeker, 2001). Therefore, reliability or the measure of consistency among the experts must correlate to establish the acceptance of the MIQ. This measurement approach introduces concern regarding the merit of experts' consensus.

It seems then that the lack of peers' consensus affects the measure of machine intelligence (Konar, 2000). Wolfram (2002) urged for a simple scientific description of a phenomenon such as MIQ to determine if a universal theory can be found so developers of ineffective computing devices would not contend their devices think and are genuinely intelligent. It is important that a study be conducted to report the existing MIQ measuring methods. An attempt is made to use a multiple perspective inquiring system that includes technical, organization, and personal perspectives to analyze and classify current literature on measures of machine intelligence. The perspectives were also used for elucidating a new measurement for MIQ based on the criteria uncovered from the literature. These properties would be necessary for generalizing a measure for excluding artificial systems that lack such criteria. The study, therefore, sought to provide a widely acceptable definition that measures and classifies machine intelligence. Understanding MIQ would help technology evaluators and policy makers in assaying and understanding the relevance of machines that claim intelligence.

Purpose of the Study

The study analyzed and synthesized factors and methodologies useful for determining and measuring the intelligence of artificial systems. Levels of MIQ complexity are reported according to the perspectives. Also, a measurement guideline is carefully outlined to ensure measurement criteria from computing constituents are consistent with MIQ standards. The guideline stems from the imperative to determine a comprehensive and standard method for measuring computational intelligence. Moreover, contemporary methods for measuring machine intelligence are abstract, are technical-specific, and lack rigor by excluding the personal, technical, or organizational perspective. Excluding any of the perspectives, if such is the case, leads to an incomplete theory, definition, measure, and classification of machine intelligence.

Theoretical Framework

In spite that Kantians encouraged a broad view and placed equal emphasis or value on both data and theory (that new knowledge is a derivative of existing knowledge), this study pragmatically grounds on three major theories by emphasizing the Singerian theoretic science. The science chooses and creates knowledge solution from various sources. The first one, the foreground or methodology, used the Singerian method (the multiple perspective analysis (TOP)) to study the phenomenon: MIQ. The second, a body of theories of machine intelligence measurement, emphasized the various theoretic approaches of measuring machine intelligence. The third theory brought to bear the fuzzy (possibilistic) set tools: linguistic complex fuzzy set and a linguistic Choquet fuzzy integral, as a linguistic mathematical framework to classify, analyze, and synthesize the measures from which a new MIQ calculus was developed. These theories are explained in chapter two, three, four, and Appendix B.

Assumptions

The study is based on the following assumptions. First, machine intelligence researchers, designers, and consumers have a common desire for an accurate meaning, classification, and measure of machine intelligence. Second, the method and purpose of the study are applicable and generalizable to all intelligent artificial systems (IASs). Third, the sources chosen from reputable experts are good representations of measures of MIQ.

Research Questions

1. What are the commonalities and differences among the current measurement theories of machine intelligence?

2. How should the current diverse measures be synthesized and MIQ realized using the multiple perspective inquiring system by Linstone (1984)?

Nature of the Study

At the center of every academic discipline is a set of research instruments necessary for conducting a sound scientific inquiry. By the nature of the phenomenon, this study is a qualitative case study. Multiple perspective inquiring analysis developed by Linstone (1984) is used. Precisely, the methodologies set forth by Lowell (1995) to deduce types of uncertainty, by Zeiber (1996) to study decision making, by Sapp (1987) to study electricity demand, and by Tarr (1990) to investigate new technology integration within a business are employed.

Moreover, the questions imposed by this study are within the scope of ones R. K. Yin (1984) suggested that are suitable for a case study research. In addition, Tellis (1997) used case study method to investigate information technology. Due to the level of secrecy that exists in the technology industry (Bien et al., 1999; Hall, 1989), it was envisioned that it would be difficult if not impossible to obtain any sample computer codes. Therefore, secondary sources eliminated statistical biases common in interview and quantitative research. Furthermore, multiple perspective analysis is suitable for discovering any underlying technology, organization, and personal perspective solutions to the research questions. The study used a case study method to examine and document relevant secondary data on measures of machine intelligence and utilized the multiple perspective inquiring system to examine, organize, classify, and report the research.

Significance of the Study

The study is within the context for educational technologists and those who are concerned with and affected by understanding, measuring, and improving machine intelligence. Because artificial systems' behaviors inevitably cause the technology sector to adapt to new environments, the systems affect societal acquisition of new knowledge about and ways humans interact with the systems. For example, the availability of e-mail and the Internet affects modern societal communication methods. Although computational intelligence or understanding how to measure machine intelligence might seem to be in the fields of computer science and electronic engineering, both fields are affected by interdisciplinary assumptions from other disciplines such as psychology and neuroscience (Pallmann, 1999; Principe, Euliano, & Lefebvre, 1999; Wooldridge & Jennings, 1995). For this reason, understanding MIQ would help technology evaluators and policy makers in assaying the relevance of machines that claim intelligence.

Social Change

The impacts of machine intelligence and its MIQ are profound possibilities that must not be ignored by any society. The widespread use of computing is challenging some of the very core principles of social thinking, which includes information property, concepts of community,