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An approach for assessing uncertainty associated with electronic tutoring performance in engineering academic environment

Masengo ILUNGA
Department of Civil Engineering
University of South Africa
Pretoria, South Africa

Kemlall RAMDASS
Department of Industrial Engineering
University of South Africa
Pretoria, South Africa

ABSTRACT

Two variables (planning and organisation of e-tutorials, and knowledge of the subject matter, before and during covid-19) are preliminarily considered to assess e-tutoring in an engineering department of the University of South Africa. A Monte Carlo simulation has been performed on the two variables respectively, by making comparison of e-tutoring performance before and during covid-19. The results illustrated a probabilistic performance based on trials as opposed to a deterministic approach. Academic departments may make informed decisions for e-tutor programme based on a range of possibilities related to the variables under investigation.

Keywords: Online tutoring, simulation, uncertainty, higher education, performance

1. INTRODUCTION

Institutions of higher learning around the globe and mostly in South Africa make provision of tutoring programme to assist students in their learning activities. This can happen in a face-to-face mode, hence tutoring can be strictly used, whereas electronic (e-) tutoring is used for learning mediated via electronic means, usually computer systems. This last avenue is the focus of distance education institutions. E-tutoring was introduced in 2013 to increase learner support, passrate and throughput at the University of South Africa (UNISA). The e-tutor programme activities include online teaching and learning activities to assist students. The e-tutor is meant to be a subject matter expert to facilitate teaching and learning. A well experienced e-tutor, who provides a more in-depth support on pedagogical aspects of the learning experience regarding scientific topics tends to work with the teacher [1]. The interaction between e-tutor and students on a group site is housed in a learning management system (LMS). The group site uses discussion fora or other communication tools available [2]. In a distance education setting, some of observations associated with e-tutoring cover three important aspects that are central to the success of e-tutoring among others, i.e. engagement of both learners and e-tutor, the practical and meaningful context of material for teaching and learning presented online [3]. Effective learning is one of the main tasks pursued by the e-tutor during interaction with learners [4]; [5]. Maré and Mutezo [4] showed some positive impact on the students' performance by engaging effectively on e-tutor sites, in a case study at UNISA. It is common for UNISA to conduct an e-tutor evaluation periodically to ensure students have benefited from the process. Usually, surveys are organised where students score e-tutors based on specific criteria/variables. In a recent survey conducted at UNISA, in a specific department, the survey outcome showed that the % of different perception levels on e-tutoring performance were found [6], in a deterministic way, while in actual sense, they should be approached in a probabilistic way since the perceptions on e-tutoring are subjective, not always very accurate. Hence perceptions are associated with some degree of uncertainty as far as e-tutor performance is concerned. Different variables used, were associated with perceptions. However, two of them, namely planning and organisation of e-tutorials, and knowledge of the subject matter, were considered in this study to conduct a Monte Carlo (MC) simulation. From its elegant way of handling random processes (displaying uncertainty), MC has found a wide scope of applications since most natural or real processes are not deterministic. Since students' perceptions are associated with uncertainty, this paper takes an opportunity to explore MC to assess the uncertainty displayed in the evaluation criteria process of e-tutoring.

In the following, the suffixes "approach", "technique", "method" and "simulation" to Monte Carlo will be used interchangeably.

2. OVERVIEW OF MONTE CARLO METHOD

The use of Monte Carlo (MC) has been witnessed in diverse fields. This technique derives its essence from the use of probability and random sampling to find solutions to a variety of problems, that are underlined by random processes. Computations involved in the MC simulation enable individuals to find a wide range of solutions that take into consideration of the risk aspects. A probability/frequency distribution may be approximated from the observations of the statistical behaviour of a random process. Hence the technique goes beyond the deterministic solution as an outcome of a given problem. Usually, sets of random numbers are generated from the initial observations to compute the results repetitively, in way to get a range of possible solutions. Generally, two types of problems related to randomness and certainty are solved by the Monte Carlo technique, which requires the deterministic problem for the establishment of a probability model [7]. Qiang (2018) [8] summarised in a very simple manner the steps involved in the MC method, i.e. domain definition of possible inputs from which the statistical probability distribution is derived; through random sampling, generate possible inputs from the probability distribution over the domain and finally simulations are conducted using parameters derived from the inputs.

Applications of MC have been documented for instance in finances [7], health related fields [9], [10]; social sciences [11], biochemistry [12], water resources [13], environmental epidemiology [14]. However, the literature on Monte Carlo simulation in evaluating e-tutoring process is almost inexistent. Hence this paper subscribes to the MC application of this process.

3. DATA AND METHODS

Data availability

Data were extracted from the evaluation of e-tutor programme in an engineering department, UNISA [6]. The data are related to two variables under investigation, i.e. planning and organisation of e-tutorials, and knowledge of the subject matter, as summarised in Table 1, below. Variables are evaluated using scale levels from extremely satisfied to extremely dissatisfied. The number of participants corresponding to the data in the Table were 66.

Table 1: Students' perceptions of e-tutor programme performance

	Extremely satisfied	satisfied	Neutral	Dissatisfied	Extremely dissatisfied
Before covid-19					
Planning and organisation of e-tutorials	5.6 (4)	44.4 (29)	27.8 (18)	11.1 (8)	11.1 (7)
Knowledge subject matter	11.1 (7)	50 (33)	16.7 (12)	16.7 (11)	5.6 (3)
During Covid-19					
Planning and organisation of e-tutorials	11.1 (7)	38.9 (26)	5.6 (4)	27.9 (18)	16.7 (11)
Knowledge subject matter	5.6 (4)	44.4 (29)	22.2 (15)	16.69 (11)	11.11 (7)

Methods

As elegantly expressed by Qiang (2018), [8] the MC technique was carried out as follows:

- For a given variable, a frequency distribution is established
- Cumulative frequency distribution is derived.
- Range of random numbers is defined based on the problem
- Random numbers are generated.
- Simulation is carried out repeatedly after a certain number of runs, based on the initial distribution.

4. RESULTS AND DISCUSSION

The results are shown in Table 2, 3, before Covid-19 and Tables 4 and 5 during covid-19. These values were obtained after 10 runs of simulations, to have negligible variations of the values of each scale level. The number of random numbers generated was 500 to reach fairly these variations. These tables showed that there is a range of values for each scale level as opposed to the deterministic observed frequency from measured perceptions. Since perceptions are subjective, the range of values for each scale level translated the uncertainty associated with the specific level. Hence, one would say that the scale level would vary within a certain range rather being equated to only one. The larger the range, the higher the uncertainty around the scale level. This gives the probabilistic nature of perception.

E-tutoring evaluation performance before Covid-19

From Table 2, it was found out that students who were satisfied and neutral about e-tutoring performance before covid-19, were associated with more uncertainty as opposed to extremely satisfied and extremely dissatisfied. This was deduced from the range values of uncertainty around 0.06 as far as planning and organisation of e-tutorials is concerned. Table 2 demonstrated that the range of values for extremely satisfied and extremely dissatisfied and dissatisfied had the same value. The range translates the risk association with responses from students in the evaluation process.

Table 2: Planning and organisation of e-tutorials before Covid-19

	Min	Max	Average	Frequency	Range
Extremely Satisfied	0.032	0.07	0.051	0.06	0.038
Satisfied	0.42	0.48	0.45	0.44	0.06
Neutral	0.23	0.294	0.262	0.29	0.064
Dissatisfied	0.104	0.14	0.122	0.11	0.036
Extremely dissatisfied	0.096	0.134	0.115	0.11	0.038

Table 3. Knowledge subject matter before covid-19

	Min	Max	Frequency	Average	Range
Extremely Satisfied	0.078	0.126	0.11	0.102	0.048
Satisfied	0.458	0.528	0.5	0.493	0.07
Neutral	0.148	0.21	0.167	0.179	0.062
Dissatisfied	0.122	0.19	0.167	0.156	0.068
Extremely dissatisfied	0.042	0.066	0.056	0.054	0.024

From Table 3, it was found out that students who were satisfied about e-tutoring performance before covid-19, were associated with more uncertainty as opposed to extremely dissatisfied, which was associated with the least possibilities for knowledge subject matter.

E-tutoring evaluation performance during Covid-19

Table 4 showed that during covid-19, satisfied level was still associated with more uncertainty as opposed to extremely satisfied.

Table 5 showed that before covid-19, satisfied level was still associated with more uncertainty as opposed to extremely dissatisfied.

Table 4: Planning and organisation of e-tutorials during Covid-19

	Min	Max	Frequency	Average	Range
Extremely Satisfied	0.048	0.08	0.06	0.064	0.032
Satisfied	0.398	0.472	0.44	0.435	0.074
Neutral	0.252	0.308	0.29	0.28	0.056
Dissatisfied	0.092	0.138	0.11	0.115	0.046
Extremely dissatisfied	0.098	0.14	0.11	0.119	0.042

Table 5: Knowledge subject matter before covid-19

	Min	Max	Frequency	Average	Range
Extremely Satisfied	0.042	0.08	4	0.061	0.038
Satisfied	0.396	0.488	29	0.442	0.092
Neutral	0.188	0.228	15	0.208	0.04
Dissatisfied	0.15	0.208	11	0.179	0.058
Extrely dissatisfied	0.096	0.12	7	0.108	0.024

Uncertainty comparison before and during Covid-19

Comparing planning and organisation of e-tutorials before and during Covid-19 (see Table 2 and 4), the highest uncertainty was related to neutral, followed by satisfied before Covid-19, whereas the opposite occurred during Covid-19. Satisfied displayed the wider range of risk during Covid-19 than before Covid-19. For this variable, extremely satisfied was recorded to have smaller uncertainty range during than before Covid-19.
Comparing subject matter expert before and during Covid-19 (see Table 3 and 5), the highest uncertainty was related to satisfied, followed by dissatisfied before Covid-19, whereas during Covid-19, still satisfied level displayed the wider range of risk than before Covid-19. For this variable, extremely dissatisfied was recorded to have smaller uncertainty range during than before Covid-19.

From the foregoing, decision makers in academic department could understand the risk range associated with each variable at different scale levels and could take necessary measures to concentrate on critical areas of e-tutoring.

5. CONCLUSIONS

In this paper, the versatility of Monte Carlo technique has been demonstrated to account for uncertain perceptions in the evaluating e-tutor programme of an engineering department, at the University of South Africa. The results revealed that an envelope around the initial frequency values of each variable should be taken into consideration during the evaluation process. The risk analysis or uncertainty level associated with each scale level was determined. Hence, Monte Carlo technique has been confirmed to deal with both deterministic and random processes. During covid-19, highest uncertainty around satisfied level was recorded for both planning and organisation of e-tutorials, and knowledge subject matter. This methodology can be extended to more academic departments at the institution and beyond. Further research should be extended to the e-tutor programme evaluation after Covid-19.

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