Diagnosing nursing students' errors in medication calculation

Designing a method based on the 4 Cs teaching model for analysing mathematical proficiency

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Not only is learning mathematics difficult, but so is teaching mathematics as well. This is an outstanding common observation which is shared among teachers in the first classes in primary schools and lecturers in professional higher education institutions. In a modern society, learning mathematics cannot (and it should not) be avoided by delegating mathematical reasoning to a small minority of especially talented people. On the contrary, mathematical conceptual thinking is now required everywhere, and it is not going to go away in a foreseeable future. Even though hand-held calculators have diminished the need for manual and mental computations, the advanced technology has tainted most traditional professions with novel and, one might say, non-trivial formal ways of working. Nowadays, more people meet formal concepts more often than ever before. Dealing with contemporary information technology is certainly one of the main culprits, but requirements of increased productivity make it impossible to return to old methods that must be deemed as inefficient and obsolete by today's standards.

Not only is learning mathematics difficult, but it has also become practically unavoidable in a modern society. Poor learning outcomes may sometimes have literally drastic consequences. Consider, e.g., a situation where a new-born baby dies as a result of receiving a medicine dose whose concentration was tenfold compared to what it should have been (Dekker, 2007). In such shocking cases, causes and reasons behind the events can sometimes be traced back to cognitive processes of professionals that were just carrying out their everyday work. One has to ask some inconvenient questions: How was it possible that the decimal separator got in a wrong place, how come the result was so crudely wrong, and none of this was discovered until it was too late? Is there something that can be done to prevent such accidents from happening again?

Among a multitude of other reasons, the explanations may be related to professionals' deficient or even lacking understanding of mathematical concepts such as conversion of measurement units or critical thinking in terms of classes of magnitudes. Or, perhaps, the intellectual understanding was, in fact, sufficient but it was not applied or applicable in the particular situation for some reasons unknown. To err is human, and the structure of an error may well be as complicated as human thinking itself.

In this article, we take first steps in approaching the anatomy of human error in elementary mathematical computations. Our point-of-view derives from earlier experiences in using e-learning systems for teaching mathematics. More precisely, we are seeking for a theoretical background and practical ways to analyse mathematical proficiency. The general objective of this work is to reduce errors in professional medication calculation, and thus to improve patient safety in hospitals.

We report preliminary results on developing and validating a statistically sound method for categorising nursing students' mathematical errors, based on the phases of the 4 Cs teaching model proposed by Johnson and Johnson (2002) for medication calculation. In this study, the categorisation work is carried out manually to validate the proposed 4 Cs model as a robust error categorisation principle. In a long term, the error analysis will eventually be carried out automatically by an artificially intelligent software agent that is to be built up from large response databases. The STACK learning environment is a suitable choice for creating such e-learning materials for various mathematical contexts (Sangwin, 2013; Rasila, Harjula & Zenger, 2007). Our previous studies show that using STACK alone has an impact on learning outcomes (Rasila, Havola, Majander & Malinen, 2010). Utilised together with an analysis method such as the 4 Cs based error categorisation principle, it has the potential of enhancing the students' entire learning curve.

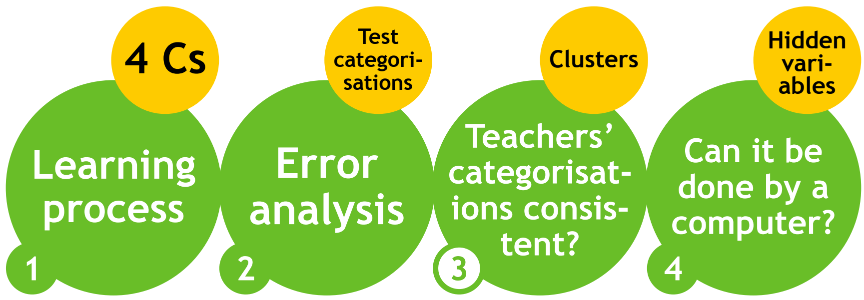

Figure 1. Scheme for designing an error classification system. Learning process described with the 4 Cs learning model is investigated by means of error analysis. The focus of this article is in answering the question regarding categorisation consistency, using clustering as the approach. The ultimate goal is to automate this analysis within an e-learning environment in order to find hidden variables in the data, reflecting students' learning and behaviour.

The outline of this article is as follows (Figure 1): We first review the relevant background in nurse education and practise as it appears in Finland. The 4 Cs teaching model is briefly introduced, and its applications as an error categorisation principle is defined. The validity of the proposed error categorisation is then formulated as research problems to which preliminary answers are given in this article. Materials and methods of the study are described, including the k-means clustering approach that is used to evaluate the amount of consensus between different test subjects that assess the same students' error material according to the proposed 4 Cs categorisation principle. Our results indicate that the k-means clustering typically leads to a robust consensus cluster that is a simple majority within test subjects. This is an encouraging argument for the validity of the 4 Cs categorisation principle. We conclude the article by a discussion whether some modifications should be made to the classification principle, and we present some aspects on how to produce similar assessment automatically using large data within a computer-aided learning environment.

Background

In most health care professions, the required mathematical skills are not advanced. Nurses do not deal with derivatives or integral calculus but, instead, the mathematical methods used in pharmaceutical medication calculation belong to the field of basic arithmetic. Naturally, the operations also require logical reasoning, deduction, and critical thinking: skills that are all learned in primary school. According to Huhtala (2000), young people enrolling for health care degree programmes are often not mathematically oriented. They are sometimes rather confused when confronted with the strict requirements in the repeated tests and exams.

Pharmacotherapy has developed considerably during the last decades. There are more pharmaceuticals, some of them are more potent than their predecessors, and the field of pharmaceuticals has extended to include also biopharmaceuticals in addition to chemical substances. This development poses new demands on nurses and on other healthcare professionals (Ministry of Social Affairs and Health, 2009), too. At the same time, nursing education, among other sectors of education, is facing decreasing mathematics skills among their students (Røykenes & Larsen, 2010; Wright, 2006).

Consequences of the medication errors within health care are a serious problem both nationally and internationally (Grandell-Niemi, Hupli, Leino-Kilpi & Puukka, 2003; Grandell-Niemi, Hupli, Puukka & Leino-Kilpi, 2006; McMullan, Jones & Lea, 2009; Pasternak, 2006). The problem is so prominent that it has also been noticed among the broad audience (Rantanen, 2013). It has been estimated that 700–1700 persons die in Finland each year due to medical errors, compared to the annual number of about 250 road-traffic fatalities (Official Statistics of Finland, 2013). A very common medical error occurs in pharmaceutical treatments: the medicine given to the patient is either incorrectly dosed or not even the substance intended for the patient.

In preventing pharmaceutical errors, the training of nursing students plays a key role. Unfortunately, there are shortcomings in both teaching dosage calculations as well as the skills of nursing students and working nurses alike. A recent Finnish study showed that few nurses or nursing students were able to complete flawlessly the MCS-exam that measures the basic skills needed to calculate medication doses (Grandell-Niemi et al, 2006).

The 4 Cs teaching model as pedagogical approach

Both national and international studies report low level of proficiency in medication calculation among both nursing students and registered nurses (Grandell-Niemi et al, 2003; McMullan et al, 2009; Sheriff, Wallis & Burston, 2011; Wright, 2006). Teaching and learning medication calculation is known to be a complex phenomenon (Johnson & Johnson, 2002). It is a big challenge for nurse educators to facilitate learning and to create learning strategies that result in a mastered level of medication calculation.

There are several pedagogical approaches for facing the challenges of teaching nursing mathematics. Johnson and Johnson (2002) have created a learning strategy theoretically based on nursing research, theory in social learning, and literature about critical thinking. The teaching model is called the 4 Cs. The acronym comes from the four steps into which the medication calculation is structured: *Compute, Convert, Conceptualise*, and *Critically evaluate*, as illustrated in Figure 2.

In the first phase *Compute*, student performs basic arithmetic calculations. The difficulties in this phase relate to consistent errors showing that the basic understanding and skills are not on a satisfactory level. The second phase *Convert* involves the skills needed in various conversions between different scales and units. These skills require not only correct computations but also ability to use correct conversion factors. Students should be able to use the correct mathematical method to solve the problem in the third phase *Conceptualise*. At this stage, students should also be able to determine what kind of information is needed for solving the problem, and what is the appropriate unit and precision for the outcome. During the final stage *Critically evaluate*, the student should analyse and assess the problem solving process and evaluate the answer.

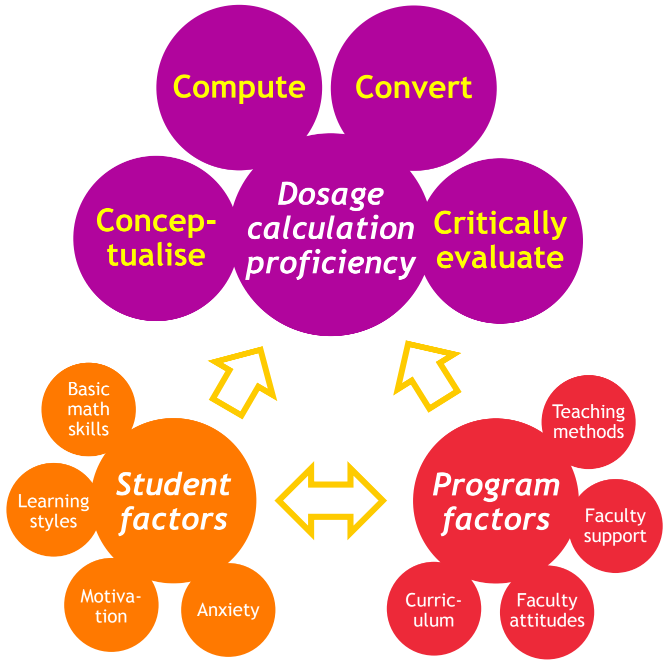

Figure 2. The 4 Cs teaching model (Johnson & Johnson, 2002). Student and program factors interact creating basis for dosage calculation proficiency. The four Cs give structure to the learning curve.

Three of the four Cs, *Calculate, Convert,* and *Conceptualise*, are used as the error categorisation principle in this article. The classification system was rendered exhaustive by adding the class *Uncategorisable* which gives the classifiers the possibility of waive any of the actual classes. The fourth C, i.e., *Critically evaluate*, was excluded from the classification system since the focus in this study is in primary errors: what was the first reason for the erroneous answer. If the student fails to evaluate the outcome critically, some other sort of error must have already occurred.

Research problems

The traditional computer-aided mathematics assessment systems such as STACK provide a framework for programming decision logic to classify the students' solutions, to give appropriate feedback based on the classification, and finally to grade the solution. Identifying a mathematical problem within such an automatic assessment system requires not only skills in computer programming but also understanding the typical errors students make. Obtaining such an understanding is far from a trivial matter, and the development of high quality e-learning materials takes often many iterations. Indeed, it may be quite difficult for the material developer to match the ingenuity of the students in coming up with surprising error variants that challenge the assessment logic originally proposed by the developer.

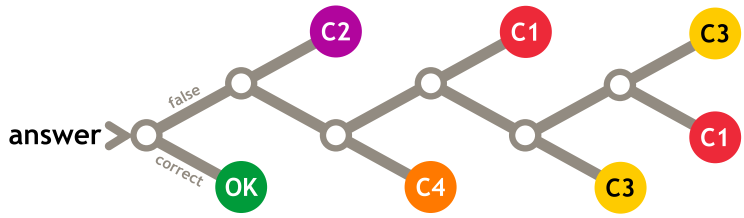

Figure 3. An idealised example of a STACK response tree. Student's answer is first compared to the correct answer. If a false answer occurs, it will be compared further to pinpoint the particular type of error. The results are used for producing relevant interactive feedback to the student. The taxonomy of the false answers can be correlated with, e.g., the 4 Cs based error categorisation.

In practical use, the automatic assessment system produces a vast amount of data containing student responses to the provided calculation problems. The assessment logic of a typical, automatically assessable mathematics exercise does not try to classify, e.g., the cognitive or emotional state of the student during problem solving. The assessment logic simply runs a series of cleverly designed tests, based on symbolic manipulations, on a student's response to place it into a pre-defined exercise-dependent error category as defined by the assessment logic as shown in Figure 3. It is, however, to be expected that student response data contains relevant information also regarding the student her/himself that can be extracted from the automatic classifier output by means of, e.g., statistical analysis and data mining. The manual processing is excluded because the data sets are too large.

In this article, we are interested in looking at the error classification problem from a human point of view. Instead of automatically classifying student responses according to strictly defined error categories, we want to classify a set of nursing students' mathematics solutions (that all contain errors) manually according to a pedagogical framework known as 4 Cs, as described below. Prior to implementing the 4 Cs model (or any other comparable model) as an artificially intelligent agent that is able to operate on very large data sets, it is necessary to validate the categorisation principle itself. If experienced human classifiers are not able to reach a reasonable consensus about the student errors according to 4 Cs model, then there is little hope that an automatic process could do any better. The purpose of this article is to give preliminary results indicating that the 4 Cs model, indeed, does give grounds for reasonable consensus between human classifiers. Thus, the 4 Cs model may be regarded a suitable classification principle for further developments.

More precisely, we give preliminary answers to the following problems:

1. Can the classification based on the 4 Cs teaching model be used for analysing the nursing students' errors?
2. Does the 4 Cs classification principle work as is or does it require modification?
3. How to deal with intersectional classes; i.e., when an error appears not to be uniquely classifiable?

We conclude the paper by discussing how the classification process could be automated within a learning environment such as STACK.

Materials and methods

The primary material of this study was obtained from the returned exam papers of the initial tests in medication calculation for two cohorts of first year nursing students (N = 88) at Arcada. Both exams had ten dosage calculation problems, and it covered the contents of the whole course in medication calculation for nursing students. Out of these exam papers, all erroneous answers to any of the exam questions were picked out, resulting in a set of hand-written unsuccessful attempts (n = 90). This set is the primary material of the current study.

The primary material was given to teachers (henceforth, classifiers, whose number is m = 9) of which two are within their profession teaching courses in medication calculation and the other classifiers are either engaged in teaching mathematics or educating nursing students. The classifiers performed their subjective categorisation by applying the classification system. The main goal was to classify the primary errors. Since an erroneous answer often contains many errors, the classifiers were also given a possibility of proposing secondary classifications for the following errors. Such errors are called secondary.

All the classifiers, including the teacher that marked the initial tests, are engaged in education. Their ages ranged from 34 years to the age of retirement. There were one male and eight female classifiers. Seven classifiers have a background in nursing – their first education is Registered Nurse. All of them are engaged in educating health care professionals. One of these classifiers with a nursing background is teaching on a vocational level while six are lecturers or senior lecturers at a University of Applied Sciences. The senior lecturers have completed the required Master's level studies as well as subject studies in education.

Seven classifiers are in their teaching tightly connected to the practical setting where medication is administered. Two classifiers are teaching medication calculation courses. Two of the nine classifiers have their background in mathematics and chemistry. One of them has no connection to nursing education while the other classifier has been engaged in teaching basic math for nursing students as well as having remedial sessions with them.

The classifiers were introduced to their task both personally and in writing. Furthermore, they were all provided with the article about the 4 Cs model written by Johnson and Johnson (2002). Only two of the classifiers (in fact, classifiers number 4 and 5 that are also authors of this article) had previous knowledge of the 4 Cs model. All classifiers did their work independently at their own pace and in an environment of their choice. It took the classifiers between 2 and 8 hours to carry out the work, and they reported the results using a pre-defined Excel worksheet that was provided to them (panel 1 in Figure 4).

Figure 4. Production and analysis of the secondary material. Classifiers evaluated each error by entering the category into the Excel sheet (panel 1). These classifications were coded to numbers 1–4, where numbers 1–3 represent the classes *Compute, Convert, and Conceptualise*. Number 4 represents the choice Uncategorisable (2). The numeric data were analysed using the MATLAB k-means algorithm (3).

The error categorisations by the classifiers are the secondary material of this study, and statistical analysis was carried out on this data. So as to the preliminary results reported here, the main tool is the k-means clustering algorithm as realised in the MATLAB 8.1.0.604 (R2013a) function *kmeans* with Euclidean distance as metrics. The algorithm is able to group the classifiers ($m = 9$) into a given number (say, k) of subclasses where k can be chosen between the trivial values $k = 1$ and $k = m$. We used $k = \text{floor}(m/2) + 1$, i.e., rounded below to the nearest integer; for $m = 9$ we have $k = 5$. This is the largest number of classes that makes it possible to have one of the classes as a simple majority (in which case all the other classes must consist of single elements). It should be observed that the function *kmeans* is an iterative algorithm whose initial conditions are chosen randomly by MATLAB. Hence, the clustering may somewhat vary between different runs of the clustering code, and some of the classifiers may or may not get into the consensus cluster depending on the run.

The grouping by k-means is based on the similarity or dissimilarity measured by the Euclidian distance of the students' error classifications as produced by the classifiers. The details can be found in the wide literature of the k-means clustering algorithm, of which we mention the classical works Steinhaus (1957), MacQueen (1967), and Lloyd (1982), and the survey article of Bock (2008). All clustering experiments were carried out taking into account the full set of attempts ($n = 90$). To ensure robustness of the results, the same experiments were carried out by rejecting 5 % ($n = 85$) and 10 % ($n = 81$) of the solution attempt data at random.

Results

One of the first observations is that the data produced by human classifiers is far from being random. There is a fair amount of correlation between the classification results of different classifiers, and we will give a full statistical analysis with a larger data set in a forthcoming article. For now, we restrict the analysis only to preliminary classification experiments.

The results of the k-means classification experiments show a strong tendency to a consensus cluster that forms a simple majority as well (Figure 5). This is a robust result in a sense that it is not significantly affected by random exclusions of 5 % or even 10 % of the data. Indeed, using 500 random selections which leave out 5 % of the data from the full set and computing 100 times the k-means clustering for each selection, we have estimated the following probabilities for the classifiers to belong to the consensus cluster: 0.74, 0.94, 0.02, 1.00, 0.95, 1.00, 0.02, 0.01, and 0.02 (given in the order of enumeration of classifiers). Using 500 random exclusions of 10 % of the data, the similarly estimated probabilities are 0.71, 0.90, 0.01, 0.96, 0.94, 0.96, 0.02, 0.01, and 0.02. The probabilities are illustrated in Figure 6.

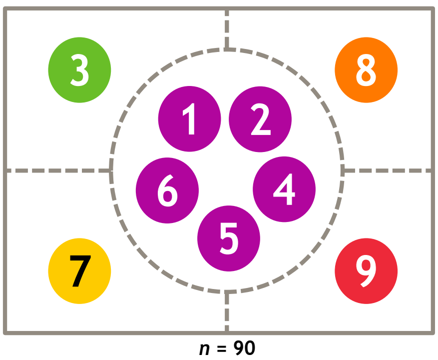

Figure 5. K-means analysis of the secondary data to five clusters ($k = 5$). Consensus cluster of five classifiers forms. No opposition clusters appear, and other classifiers end up as separate clusters each. Note: these figures are simplified into two dimensions and are not in scale. Distances between evaluators are not real. Actual image should have 9 dimensions.

Probabilities show that the larger fraction of the primary data is taken into account, the more probable the original consensus cluster members stay in the cluster. It is also indicated that classifier number 1 is the most likely to leave the consensus cluster.

It is another observation (albeit, with no statistical justification at this point) that the two most experienced mathematics teachers among the classifiers (in fact, subjects number 4 and 5 that are also authors of this article) belong with very high probability in the consensus cluster even if parts of the primary data are excluded as explained above. The number of errors that the classifiers deemed as *Uncategorisable* are 4, 7, 21, 0, 8, 2, 0, 17, 14 (given in order of enumeration of classifiers). We conclude that the classifiers in the consensus cluster tend to deem relatively few errors as *Uncategorisable*.

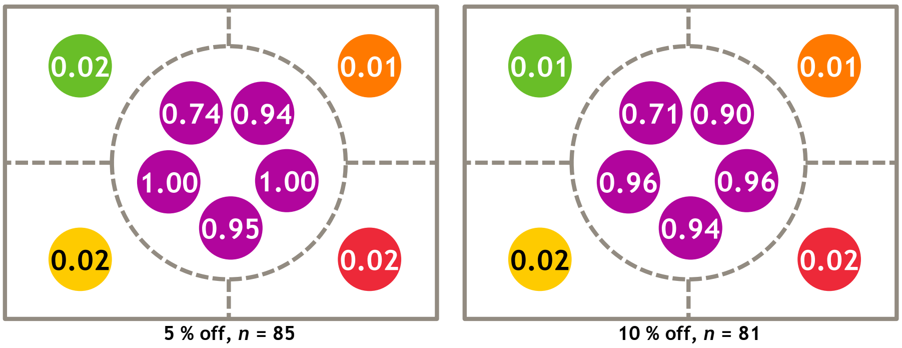

Figure 6. Testing the robustness. The probabilities for classifiers belonging to the consensus cluster after exclusion of 5 % and 10 % of the complete data. Probabilities are gathered using 500 random selections and computing 100 times k-means clustering for each selection.

Discussion

The 4 Cs model (with the removal of *Critically evaluate*) appears to be a valid error categorisation principle for the mathematics exam response data from first year nursing students. This observation is supported by the fact that the k-means consensus cluster with simple majority typically arises among the classifiers of student error materials. However, the experiments and data proposed in this article are preliminary, and many observations as well as reservations are in order.

As explained above, the classifiers were given the opportunity of proposing a secondary classification of the student error but this data was not used in clustering experiments. This raises the question of intersectional classes: some student errors may quite reasonably be classified into more than one of the 4 Cs categories, and labelling one of the classifications as secondary may be subjective guesswork at best. To add intersectional classes as new, separate classes to 4 Cs model does not appear to be an inviting alternative: it is one of the merits of the 4 Cs model that the low number of classes prevents the derived categorisation principle from becoming overly difficult to understand and use.

The uncategorisable part of the data is interesting, and we expect to find rich statistical structure in it in future studies with a significantly larger classifier number m. Keeping Occam's razor in mind, we should be prepared to add a new class to the error classification principle only if there is strong evidence for the need of it. For example, following cases were found ambiguous for used error principle: 1) student has performed correctly with the right answer written on the paper but has failed to pick the right piece of data for the final answer; 2) student has performed again perfectly but has stopped writing the answer without any visible reason; and 3) the answer makes no sense at all, and there is nothing on the answer paper which relates to the given problem.

It remains to comment on the potential confounding factors related to the experimental design: The primary material was real exam answer papers, and it included original markings by the examiner. All exam answers were hand-written. However, students' anonymity was considered in the primary material, and the name or other personal information was not explicitly present.

Conclusions

We propose a scientific framework for understanding the implications of student error classifications using the four Cs of the 4 Cs teaching model as a categorisation principle. Data on students' errors in medication calculation exams are a good starting point to conceptualise their learning processes. In addition to written exams, such primary data can be collected from responses to exercises and even from databases of e-learning systems such as STACK. Further development of e-learning environments into more "human-like" direction requires understanding of typical error profiles.

This study was focused on finding consensus where it is, rather than analysing those parts of the data where no consensus can be found. More research is required with a larger data set to evaluate the statistical structure in those errors that were less consistently classified by classifiers. Lack of consensus may indicate a need for adding new classes to the categorisation principle. The final design of the categorisation principle will have to take into account the intersectional classes in some way. Information about these can be obtained from the secondary errors, but this was not investigated in this study.

Automated classification of responses in STACK requires assignments to be constructed in such way that the answers can be evaluated by human classifiers as well. Classification data from STACK is not necessary easily readable. Hence, the data must be converted to a representation in which both computerised and human classifications can be studied in a same statistical framework. STACK exercises have their classification logic, but it may have to be modified if the resulting student solutions are to be used for 4 Cs type of error categorisation. Data from many traditional STACK exercises may not be suitable for a meaningful error categorisation of the type proposed in this article.

The fourth C, *Critically evaluate*, was not part of the categorisation principle. This category can be quite demanding for a human classifier since it requires knowledge regarding the dosage of the medicines in question. However, implementing this class to the STACK classifier is expected to be easy because hazardous dosages are well-known and easy to introduce into STACK decision logic.

In the 4 Cs model, Perceived Self-Efficacy (PSE) is an important concept related to Albert Bandura's Social Learning Theory (Johnson & Johnson, 2002). PSE includes the student's self-belief and ability to learn and to successfully perform and accomplish a task. Moreover, PSE is connected to motivation to learn and to ask for advice. A motivated student is willing to work in order to achieve competence. PSE increases when the student experiences success. Hodge (2002) found that there was a significant positive relationship between nursing students' ability to perform medication calculation and mathematics self-efficacy and computer-assisted instruction. There are also other indications that computer aided mathematics teaching is motivating for the students as it is now (Majander & Rasila, 2011). Combining such teaching methods with automated analysis of the students' progress and feedback can help in creating an even more motivating learning environment.

All students are different in their mathematics skills, learning styles, and motivation, and they all benefit from innovative and motivating teaching and learning methods made possible by ICT. Teaching should acknowledge the individual differences among students in comprehending a given problem and developing a solution for it. The methods should support each student in identifying their individual ways of setting up and solving mathematical problems in the context of their profession. One approach is to use e-learning environments such as Sigma and STACK that are under brisk development at the moment (Leikas, Granberg, Ståhl, Kurko, Antikainen, Airaksinen & Pohjanoksa-Mäntylä, 2012; Sangwin, 2013).

In this study, the primary data set consisted of traditional exam papers, providing a data set that was not extensive. As e-learning environments are developed, they will provide the opportunity to collect extensive log data describing the users' choices and responses which open up for educational data mining and learning analytics. This, however, requires that the users are well-informed that data regarding their use of the environment will be logged and used for analysis and research purposes. The issue regarding informed consent needs to be carefully considered. For the purpose of this study, the Ethical Board at Arcada University of Applied Sciences has approved the analysis of the errors in (anonymous) medication calculation tests.

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