THE INFLUENCE OF TECHNOLOGY ON WHAT VOCATIONAL STUDENTS NEED TO LEARN ABOUT STATISTICS: THE CASE OF LAB TECHNICIANS

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The presence of advanced technology in the workplace influences what employees need to know. This paper focuses on the question of what student lab technicians in vocational education need to learn about statistics in the presence of technology. Through interviews with lab apprentices, apprentice supervisors and teachers, a questionnaire administered to apprentices, and workplace observations we have identified what statistical knowledge is taught and required. The knowledge required turned out to diverge across labs and be highly influenced by the degree to which work is mediated by technology. For example, calibration and validation of measurement instruments is based on linear regression, but is often automated. Many computations are carried out on Excel sheets, but not all schools dedicate enough instruction time on spreadsheets. At least 30% of the apprentices (N=300) felt insufficiently prepared in terms of mathematics or statistics.

INTRODUCTION

The competences required in the workplace have changed over the past decades due to increasing use of information technology (Felstead et al., 2007). This has also affected the statistical knowledge required, because that has increasingly become mediated by technology (Hoyles et al., 2007). Laboratory work involves many calculations, which are often carried out by dedicated software. Common in industry, but also in health services and safety institutes, laboratories are statistically rich, hence interesting places to study the influence of advanced technology on the statistical knowledge required by employees; hence the paper's focus on lab technicians.

A first exploration of this influence is puzzling. On the one hand, automation generally takes away computation from employees, which suggests that advanced calculations can be carried out by intermediate-level employees with the help of user-friendly software. In their case study of a pathology lab, Hoyles et al. (2002) indeed observed that "all the work of the laboratory is highly computerised and automated" (p. 62). One of the interviewees noted "that we do not do much maths in haematology, because the analysers [machines] do so much work for us" (p. 64). On the other hand, the advent of process improvement techniques, mostly statistically based, has caused that more and more employees, even at lower levels, are faced with handling data (Hoyles et al., 2010). This implies that many employees with vocational or little general education need some insight into data, variability, distribution, centre, spread, data trending et cetera (Hoyles et al., 2002). Many even need to draw inferences from samples, for example about production processes (Bakker et al., 2008).

This faces vocational education with the question of how to prepare future employees. In their review of competence-based vocational education, Van den Berg and De Bruijn (2009) noted that most research in vocational education in the Netherlands, Germany, and Switzerland (countries with long vocational traditions) focuses on how-questions (with regard to teaching, supervision, assessment, learning environments, etc.). Only a small minority address the question of *what* students actually need to learn. The importance of the what-question, however, is growing in a changing environment, as discussed above, hence the research question addressed in this paper: *What do student lab technicians in vocational education need to learn about statistics given the computerisation trend?*

BACKGROUND

About 40% of Dutch senior secondary students (16-17) attend general education or pre-university tracks; the remaining 60% enrol in senior secondary vocational education (MBO). MBO used to have attainment targets for each MBO occupation (including hair dresser, baker, electrician, lab technician). For mathematics and statistics in many technical programmes this was

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a list of about fifty topics, and attainment targets that were less relevant for the occupation were ignored by mathematics teachers. Thus such general subjects were generally considered separate from the occupation. With the introduction in the Netherlands of competence-based vocational education, qualification files for 241 occupations were formulated in terms of what starting employees should be able to do. In the file for lab technicians, references to the statistical knowledge required were scarce and broadly phrased (e.g., “basic knowledge of mathematics”; “care for quality”), with the effect that such knowledge was taught and assessed less than about ten years ago. Teachers often had a hard time to convince their managers that students needed some disciplinary knowledge such as statistics in order to develop the competences in the qualification files. In most cases, the number of teaching hours for such subjects decreased considerably.

Within this historical development the what-question has become urgent, even though it is often considered unanswerable by established research methods (for a discussion of this issue see Van den Heuvel-Panhuizen, 2005). We therefore address descriptive and evaluative questions that form the basis for answering the main normative question:

1. What do student lab technicians learn about statistics in various schools?
2. How has laboratory work changed over the past decades according to experienced lab technicians and teachers?
3. What statistical knowledge do apprentices at MBO level need at work?
4. How well do apprentices feel prepared for the computational part of their work?

METHODS

An answer to question 1 was sought by interviewing teachers at four different vocational laboratory schools (MBO, which is below Bachelor level) and studying their course materials. We also observed several lessons to get a sense of how course materials were used. For an answer to questions 2, 3 and 4, we conducted interviews with six supervisors of apprentices in a variety of labs (in total 6:40 hrs), two managers (1:50 hrs), nine apprentices in the workplace (4:20 hrs), two apprentices who presented their work at school (2:16 hrs) five teachers at four different schools (14:25 hrs). In addition, we undertook four workplace tours in different labs (2:10 hrs), spent a day of observation and interviewing in one lab, and collected several prototypical artefacts that represented how statistical knowledge was mediated (e.g., Standard Operating Procedures including calculations, graphs, data etc.). The interviews were transcribed verbatim and coded for statistical knowledge required during apprenticeships and general issues relevant to our questions (e.g., trends, influence of technology and transition from school to work).

Due to the large variability in findings from the interviews, we decided to administer a questionnaire to apprentices of ten laboratory schools to get a better image of how representative particular findings were. The questionnaire focused on the following questions:

1. Which calculations [not necessarily statistical] have you performed over the last weeks, for what purpose, and with which tools did you perform them?
2. What (other) mathematical and statistical knowledge did you need?
3. How well do you feel that school has prepared you in terms of mathematics and statistics?

We received 300 usable forms from nine schools. The national population of MBO lab students is 3,500 (16 schools); they spend about a third of their time as apprentices, hence we assume to have information from about 30% of the apprentice population. When filling in the questionnaires, most students were about halfway through their apprenticeship. To get a better image of what statistical knowledge they needed at the end of their final nine months’ apprenticeship in the fourth year, a teacher and the first author also studied 27 final reports by apprentices on their research carried out in the workplace.

RESULTS

1. What do students learn about statistics at school?

The topics addressed in the course materials are summarised in Table 1. There was considerable consistency across schools, partly because the same resource book was used

(Raadschelders & den Rooyen, 2005) in addition to the teachers' own materials. Several schools used project materials provided by one organisation (SCB) that aims to develop high quality projects in which all competences required can be developed. Alongside these projects, general subject teachers address the general knowledge required in each project.

Table 1. Statistical topics addressed in the course materials

Descriptive statistics	• Arithmetic mean, SD, outlier, range, coefficient of variation, variance • Correlation, Linear regression for calibration • Histogram, scatter plot • Frequency distribution, normal distribution
Inferential statistics	• t-test, F-test, Dixon's test for outliers • confidence intervals
Quality control	• Youden plot: a graphical data analysis technique for carrying out an interlab comparison • SPC (Shewhart or Levey-Jennings) and Westgard rules

There were differences in when statistics was taught and for how long. In one school, statistics was taught during the one-day-at-school or block-release days during apprenticeships in the third and fourth year. In others, it was taught mainly in the first and second year. Topics such as the Dixon's test for outliers or the normal distribution were often introduced in one lesson. We observed one lesson in which students learned to make Shewhart control charts in Excel. One observation at another school was that significance tests were quickly introduced with their formulae and manually practised with three exercises. Given that these topics are not part of the general education curriculum and that vocational students typically find mathematics and statistics harder to learn than students from general education, we wonder how well these topics are understood, but also whether they learn the right things about these tests.

2. How has laboratory work changed?

The changes over the past fifteen years differed per type of lab. The most "old-fashioned" lab we visited was a veterinary lab in which calculations were still mainly done manually or with calculators. As the supervisor said, "I'm computing all day long," but very few calculations went beyond means and standard deviations. As a contrasting case we mention a quality control lab in which all procedures were standardized by means of SOPs (Standard Operating Procedures). The supervisor repeatedly said that the work of lab technicians at MBO level had become "like baking apple pie" and that this was common for regulated and accredited test labs. In line with Good Manufacturing Practices (GMP) all steps are prescribed and the acceptable range of possible outcomes is predetermined. All analyses are double-checked by employees with higher levels of education and there is hardly any room for judgement of results by MBO lab technicians. Their task has become to monitor computer outcomes and report anomalies to their supervisors. This seemed common for all laboratories that were highly regulated, either by GMP or health and safety rules (such as in hospitals). The drive to make the work error-free, one manager commented, has led to a situation where the younger generation often no longer knows what happens behind the screens. The paradoxical situation is that this does not lead to problems–those have been ruled out by the system–but we did hear concerns about this situation; many lab technicians found it important for apprentices to understand what they were doing and we have evidence from observations in one lab that blindly following procedures can lead to waste of materials and time.

The most apparent trend, the focus of this paper, is that of computerisation. A typical consequence is that calibrating machines was in some cases done by means of pressing "calibrate" in a control panel with the result that MBO lab technicians did not encounter calibration graphs or the statistics behind them. In the old days, regression lines were made and correlation calculated.

3. Which statistical knowledge do apprentices need at work?

From the interviews and questionnaire we summarise the statistical topics encountered in laboratories. Because of the small number of labs visited, we only make a distinction between rare, common and pervasive to give a sense of their frequency. ‘BA’ refers to examples carried out by a lab technician at BA level (higher professional education). A comparison of Tables 1 and 2 indicates a large amount of overlap and we indeed had the impression that teachers stayed in touch with workplaces–sometimes through their students–to see if they still taught the right topics. However, the question remains what these students need to understand about more complex statistics if it is carried out by a computer system. The fact that we saw t-tests being used in a lab does not necessarily mean that an MBO lab technician should understand the formula or be able to perform one by hand, or even with a software package.

Table 2. Topics encountered in different laboratories. BA refers to Bachelor level

Descriptive statistics	• Collecting and reporting data (pervasive) • Arithmetic mean, standard deviation (pervasive, often automated) • Relative standard deviation, coefficient of variance (common) • Weighted mean when some measurements are more reliable than others and geometric mean in logarithmic scales (BA) • Scatter plot, histogram, line chart (pervasive) • Youden plot (rare) • Correlation and linear regression for calibration, validation of instruments (pervasive, but often automated)
Inferential statistics	• Interpreting confidence intervals (pervasive) • Interpreting results of significant tests (common) • Using tests for outliers: Grubbs, Dixon’s Q (common) • Carrying out with software: t-test, F-test, Fisher, analysis of variance, multivariate data analysis (BA)
Quality control	• Statistical process control; Westgard rules for trends; difference between common-cause and special-cause variation (common) • Design of experiment (BA – rare)
General	• “Number sense”: a feel for which numbers are correct, outliers (pervasive) • Statistics in Excel (pervasive), mostly using standard worksheets • Understanding to some extent choices and what software is doing (common)

We highlight a few general issues. First, we frequently heard about the need for “number sense”, by which supervisors typically meant a feel for which numbers are correct and which are outliers. This is not just based on statistical insight (e.g., SD cannot be bigger than the range), but also on contextual knowledge (e.g., typical concentrations of particular substances).

Secondly, computations are not always taken away from employees. In some labs (according to the questionnaire results about 14%), *all* calculations were automated in Excel sheets or dedicated computer software (such as LIMS: Laboratory Information Management System). In most others, a mix of computational tools (calculator, Excel, software) was used. The general image from the interviews was that calculations had become easier over the years because of software and automated machines, but what lab technicians need to know has not become less, only different; for example fluency in Excel has become more important. Not surprisingly, a new book for the laboratory sector focuses on doing statistics with Excel (Klaessens, 2009).

Thirdly, with computations outsourced to software, it becomes important to know something about the software and what it is doing. A simple example might illustrate this. When using Excel to compute a SD, one is faced with a choice between several types of STDEV: which one should be used? To realise there is a difference between the SD of a population and a smaller sample, one needs to know something about statistics as well as the Excel conventions.

4. How well do apprentices feel prepared?

The questionnaire results indicated that 45.7% of our sample felt well prepared by school, but 27.0% thought they were not well prepared. 16.3% wrote they had not used any mathematics or statistics at all over the past weeks or had learned more than necessary. 3.3% noted insufficient preparation for specific topics and 7.7% gave no answer or an answer we could classify. Some students felt competent in terms of the statistics, but not the mathematics needed; some students from other schools reported the reverse. We speculate this can be explained by when statistics is taught. The former group learned their statistics in their third and fourth year and mathematics in the first and second year (in one case their teacher had been ill). A few also complained that they had forgotten much of what they had learned in the first year by the time they did their apprenticeship. Some mentioned that they had not learned to use Excel spreadsheets at school, although these were often used in workplaces. This points to the importance of developing technology-mediated statistical knowledge (acknowledged in most schools). By and large our impression is that laboratory schools prepare students well, considering the limited amount of instruction time, but 30.3% (27+3.3) feeling not well prepared is worrying. Not surprisingly, all teachers complained that their hours for these disciplines had diminished due to longer apprenticeships and the tendency to work competence-based–a trend that several teachers considered to be a matter of economising on costs. In practice this meant more time on projects and learning on demand, and less on general subjects such as languages and mathematics.

CONCLUSION AND DISCUSSION

The answers to the four questions form the basis of a tentative answer to the main question of what student lab technicians need to learn about statistics given the trend of computerisation. If we only look at the topics taught in schools and encountered in laboratories, there seems to be a good match. However, the trend of computerisation might require a different approach to these topics. For example, knowing how a SD is computed seems to have become less important, at least at this vocational level, but knowing how to use Excel and dedicated laboratory software has become more important. This is not necessarily easier, for several reasons. First, because computations are black-boxed (Williams & Wake, 2007) it can be hard to detect what has gone wrong if the outcome is odd. Secondly, software often offers many choices as the STDEV example illustrated and might do things automatically that the user is not aware of (e.g., removing an outlier from a computation). Students therefore need to learn more about the software packages themselves. Thirdly, we see a need for learning about the use of statistics as a consumer rather than a producer: Is it OK that a t-test was used? Is the outcome reasonable? If the range of the data set is 10, is it reasonable that the SD is 1.8? In fact, there is a similarity with the calculator discussion in general education, in which estimation has become more important so that pupils can check the outcomes (Ruthven, 2006).

With 30.3% feeling underprepared and about 70% of the MBO lab technicians deciding to move on to a BA degree or certificates in higher professional education, where a higher level of abstraction is expected, it seems wise to spend more time on mathematics and statistics in laboratory schools. Moreover, this 30.3% might well be flattered: as the interviews indicated, supervisors generally adapted workplace tasks to the level of their particular apprentices. Difficult and important tasks are carried out by higher-level or more experienced lab technicians. Thus students might feel sufficiently educated whereas the workplace system is serving as an ecology adapting to particular gaps or weaknesses in apprentices' knowledge. Such adaptivity and division of labour also has another side: we were told about lab technicians with an affinity for statistics who were given the opportunity to develop their statistical knowledge and become the team's statistics expert.

One of the main problems we observed is the discrepancy between how statistical measures and techniques are typically represented at school on the one hand, and how they are used in practice on the other. In course materials standard deviation and the t-test are typically represented in a symbolic language with ∑-signs–a language that is inaccessible to most vocational students. Our impression from observations and previous research (Bakker et al., 2009) is that many teachers and trainers think the essence of, say, a t-test is captured by its formula, just like the mean by its calculation, and that they see little opportunity to represent such concepts alternatively, or emphasize their meaning in usage. However, what intermediate-level employees need to know about such techniques is what their purpose is and how they should be interpreted when produced by a computer system, and some conditions of usage. To us it seems sufficient for student lab technicians who do not plan to attend higher professional education to know that a t-test is useful for comparing means of data sets (e.g., to check if a new instrument is as accurate as the standard), and what it means that there is a significant difference, more concretely that there is a small chance of two types of error. The little time attributed to teaching the t-test (typically one lesson) is perhaps better spent on such insights, including how to perform a t-test in Excel, than on explaining and applying the formula.

The problem of representation of such statistical concepts and tests is also reported by Bakker et al. (2009) in the context of process improvement in a car factory. To avoid the symbolic language about process capability indices, they designed relatively simple, visual computer tools with which employees could get a sense of what these indices conveyed, and how their indices could be manipulated by changing mean, control limits or specification limits. These tools proved to facilitate communication between employees with diverse educational background. We therefore expect that it is in principle possible to convey the practical usage and implications of many statistical concepts and techniques in the context of work without anxiety-evoking formulae. In mathematics education there is a tradition of democratizing powerful ideas (Hegedus & Lesh, 2008) through carefully designed computer tools, so that more people can gain from some practical understanding of them. Statistics education research should in our view continue this line of research, especially in vocational settings.

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