STEM: CHALLENGES AND OPPORTUNITIES FOR MATHEMATICS EDUCATION

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Climbing Mountains, Building Bridges is a rich theme for exploring some of the “challenges, obstacles, links, and connections” facing mathematics education within the current STEM climate (Science, Technology, Engineering and Mathematics). This paper first considers some of the issues and debates surrounding the nature of STEM education, including perspectives on its interdisciplinary nature. It is next argued that mathematics is in danger of being overshadowed, in particular by science, in the global urgency to advance STEM competencies in schools and the workforce. Some suggestions are offered for lifting the profile of mathematics education, with examples drawn from two activities on modelling with data in the sixth grade.

INTRODUCTION

In metaphorical terms, we need to lift the level of the peaks of the STEM mountain range, and broaden and elevate the whole of the range at the same time. (Marginson, Tytler, Freeman, & Roberts, 2013, p.72).

A focus on advancing STEM (science, technology, engineering, mathematics) in schools and the workforce is escalating across many nations, with its powerful role across multiple sectors being formally recognised (Honey, Pearson, & Schweingruber, 2014; Harrison, 2012; Marginson et al., 2013; The Royal Society Science Policy Centre, 2014). For example, Australia’s Chief Scientist emphasised in a recent lecture that STEM is “at the core of almost every agenda,” and “the almost universal preoccupation now shaping the world’s plans” (Chubb, 2014). In the United States, the 2013 report from the Committee on STEM Education maintained that “The jobs of the future are STEM jobs”, with STEM competencies increasingly required not only within, but also outside of, specific STEM occupations (National Science and Technology Council, 2013, p. vi). Developing competencies in the STEM disciplines is thus regarded as an urgent goal of many education systems, fuelled in part by perceived or actual shortages in the current and future STEM workforce and also by outcomes from international comparative assessments (e.g., OECD, 2013).

Further evidence of the vested interest in STEM by researchers, educators, industry leaders, and policy makers can be found in the burgeoning of publications devoted to the field (e.g., Honey et al., 2014; National Research Council, 2014; Purzer, Stroble, & Cardella, 2014; the International Journal of STEM Education;
http://www.stemeducationjournal.com/). The biennial international STEM conference (http://stem2014.ubc.ca/) is another example.

Although global interest in STEM from educational and workforce perspectives has proliferated in recent years, the acronym was actually coined in the United States during the 1990s by the National Science Foundation (USA). The combining of the disciplines was seen as “a strategic decision made by scientists, technologists, engineers, and mathematicians to combine forces and create a stronger political voice” (STEM Taskforce Report, 2014, p. 9). Since this time, the debates and dilemmas surrounding STEM employment shortages and STEM education in general have compounded.

One of the current debates is whether there is, indeed, a global shortage of STEM professionals (e.g., Charette, 2013; Hopkins, Forgasz, Corrigan, & Panizzon, 2014; Smith & Gorard, 2011). In arguing for more evidence for these global claims, Hopkins et al. stressed the need to consider tertiary level enrolment trends in the STEM disciplines taking into consideration, among others, ways in which data are collected, courses are classified, and particular subject areas are targeted. Given the complexities of the data used to make claims about STEM shortages, it would seem difficult to draw definitive conclusions. For example, on the one hand, there are Charette’s (2013) extensive analyses of numerous global reports suggesting that the claimed shortages are a myth. On the other hand, there are reports such as that of The Royal Society Science Policy Centre (2014), which conveys employers’ concerns regarding the lack of suitable STEM employees and the estimated one million or more STEM professionals and technicians needed in the United Kingdom by 2020.

The debates on deficiencies in the STEM workforce appear entwined with the urgency for improving STEM education in schools. Irrespective of whether there exist or will be employment shortages, the calls for improved STEM education in schools are not unfounded and cannot be ignored. The STEM disciplines permeate so much of our lives that we cannot afford to neglect the current arguments for their advancement, beginning with the earliest years of school. Charette’s (2013) claim is especially apt in this regard, namely, we do indeed have a STEM crisis but not necessarily with respect to skills shortages. The crisis lies in STEM literacy, that is, students today are not receiving a solid foundation in science, mathematics, and engineering.

This claim for a literacy crisis is underpinned by industry groups and other organisations emphasising the critical role of STEM education in reforming the economy and fuelling innovation (e.g., the Australian Industry Group, Willox, The Australian, 16 Dec., 2014, p. 14). Other reports, such as those from the Australian Office of the Chief Scientist (2013, 2014) and the Australian Council of Learned Academies (Marginson et al., 2013) likewise stress the importance of all students having strong STEM knowledge, skills, and innovative dispositions.
In the remainder of this paper, I first address some of the issues and debates surrounding the nature of STEM education including perspectives on its interdisciplinary nature. I then argue that mathematics is in danger of being overshadowed, in particular by science, in the current international STEM climate. I offer suggestions for lifting the profile of mathematics education and illustrate these ideas by describing two activities that address modelling with data in the sixth grade.

**DEFINING STEM EDUCATION**

One of the factors contributing to the existing debates is the lack of a globally accepted definition of STEM education. Given different national agendas, such education has been interpreted variously, with some discipline areas being given greater attention than others. In acknowledging the lack of an agreed-upon definition, the Californian Department of Education provides a broad perspective on STEM education, namely,

> [STEM]... is used to identify individual subjects, a stand-alone course, a sequence of courses, activities involving any of the four areas, a STEM-related course, or an interconnected or integrated program of study. ([http://www.cde.ca.gov/PD/ca/sc/stemintro.asp](http://www.cde.ca.gov/PD/ca/sc/stemintro.asp))

Debates on what constitutes STEM education range from David Clarke’s (2014) perspective that the four disciplines do not have much in common, to those who advocate commonalities in problem-solving and thinking processes, and more broadly to those advocating a focus on sustained engagement. In his 2014 keynote address at the STEM Conference in Vancouver, Clarke argued that “…it is difficult to recognise that STEM could be the name for a fairly monumental category error. What is it that Science, Technology, Engineering, and Mathematics have in common? One reasonable answer is not much” ([http://stem2014.ubc.ca/conference-details/keynote-speakers/](http://stem2014.ubc.ca/conference-details/keynote-speakers/)). On the other hand, those who embrace definitions of STEM from an interdisciplinary perspective frequently emphasise generic attributes that transcend the disciplines, together with their respective core concepts and skills. The former include critical thinking, problem solving and inquiry processes, teamwork, and design processes, the last of which represents a core engineering link. Other definitions consider STEM education as fostering “sustained engagement with the STEM disciplines where students can become competent contributors and critical participants in a range of STEM-related activities (Burke, Francis, & Shanahan, 2014). Interestingly, Burke et al. consider their approach representative of “the Canadian dialect of STEM education.”

An interdisciplinary approach, however, appears to feature most prominently in STEM definitions, with the Californian Department of Education citing the axiom, “the whole is more than the sum of the parts,” ([http://www.cde.ca.gov/PD/ca/sc/stemintro.asp](http://www.cde.ca.gov/PD/ca/sc/stemintro.asp)) as reflecting this perspective. For example, the STEM Taskforce Report (2014) in the US adopts the strong view that STEM education is far more than a “convenient integration” of its four disciplines,
rather, it encompasses “real-world, problem-based learning” that integrates the disciplines “through cohesive and active teaching and learning approaches” (p. 9). The Report argues that the disciplines “cannot and should not be taught in isolation, just as they do not exist in isolation in the real world or the workforce” (p.9). In supporting their stance, the Report defines STEM literacy with respect to each of the disciplines, demonstrating their interconnections (italics added to mathematics), as follows:

Scientifically literate students use scientific knowledge not only in physics, chemistry, biological sciences, and earth/space sciences to understand the natural world, but they also understand the scientific need for existing and new technologies, how new advances in scientific understanding can be engineered, and how mathematics is used to articulate and solve problems.

Technologically literate students understand that technology is the innovation with or manipulation of our natural resources to help create and satisfy human needs and also to learn how to obtain, utilize, and manage technological tools to solve science, mathematics, and engineering problems.

Students who are literate in engineering understand how past, present, and future technologies are developed through the engineering design process to solve problems. They also see how science and mathematics are used in the creation of these technologies.

Mathematically literate students not only know how to analyze, reason, and communicate ideas effectively; they can also mathematically pose, model, formulate, solve, and interpret questions and solutions in science, technology, and engineering (p.9).

**STATUS OF MATHEMATICS EDUCATION WITHIN STEM**

With the rapid rise of STEM education as an interdisciplinary construct, some researchers have expressed concerns over emerging inequitable discipline representations (e.g., English & Kirshner, 2015; Honey et al., 2014; Moore et al., 2014). As one example, of the 141 regular papers presented at the 2014 STEM conference in Vancouver, 45% were devoted to science, 12% to technology, 9% to engineering, and 16% to mathematics, with the remaining 18% classified as “general” with several papers in this category addressing two or more of the STEM disciplines.

Concerns for the underrepresentation of mathematics cannot be overlooked, especially since influential curriculum documents such as the US Common Core State Standards for Mathematics (http://www.corestandards.org/Math/) and the Next Generation Science Standards (http://www.nextgenscience.org/) are calling for more in-depth connections among the STEM disciplines. This challenge of maintaining equitable discipline representation is especially germane to our discipline, which I maintain needs to have a stronger presence and role alongside the others.
Although reference to science could be interpreted as encompassing mathematics, I nevertheless argue that there is a real danger that science will overshadow the importance of mathematics in today’s world. Indeed, the STEM acronym itself is frequently referred to as simply “science” (e.g., Office of the Chief Scientist, 2014). Even back in 1962, Australia’s former Prime Minister, Sir Robert Menzies, identified “the flowering of science” as “the great distinguishing feature of this [then] century apart from wars and political confusions” (cited by Chubb, 2014). Further, the discipline of science seems to dominate many current STEM reports, as Marginson et al. (2013) indicated. Many nations also refer to the role of STEM education as one that fosters “broad-based scientific literacy” with a key objective in their school programs being “science for all” with increased efforts on lifting science education in the primary, junior, and middle secondary school curricula (Marginson et al., 2013, p. 70). Interestingly, Marginson et al. pointed out that STEM discussions rarely adopt the form of “mathematics for all” even though mathematics underpins the other disciplines (as evident in the discipline definitions cited previously). Marginson et al. thus argued that “the stage of mathematics for all should be shifted further up the educational scale” (p.70). Even the rise in engineering education, commencing in the early school years (e.g., Lachapelle & Cunningham, 2014), would appear to be oriented primarily towards the science strand at the expense of mathematics. Nevertheless, alongside the challenges facing mathematics education are opportunities for its advancement.

Mathematical literacy, in particular, has gained increased attention in recent years, albeit with different interpretations and content emphases. The global importance accorded to this literacy is evident in its inclusion as a major domain in the 2012 PISA (Programme for International Student Assessment, OECD, 2013). It is not surprising then, that as nations reflect on their students’ mathematical achievements, they are questioning the quality of their curricula and the strategic actions needed to enhance the STEM disciplines. It follows that many nations with high international testing outcomes as well as strong STEM agendas have a well-developed curriculum that concentrates on inquiry processes, problem solving, critical thinking, creativity, and innovation as well as “a strong commitment to disciplinary knowledge” (Marginson et al., 2013, p.110). The need to nurture both the generic skills and in-depth conceptual understanding is paramount.

ELEVATING MATHEMATICS EDUCATION ACROSS STEM

The superior international achievements of STEM-focused nations reflect the mathematical literacy assessed in PISA 2012, with the focus on “meeting life needs ... through using and engaging with mathematics, making informed judgements, and understanding the usefulness of mathematics in relation to the demands of life” (Thompson, Hillman, & De Bortoli, 2013). Mathematical literacy is foundational to STEM education, where a facility in dealing with uncertainty and data is central to making evidence-based decisions involving ethical, economic, and environmental dimensions (Office of the Chief Scientist, 2013). Further, with the exponential rise in
digital information within STEM, the ability to handle contradictory and potentially unreliable online data is critical (Lumley & Mendelovits, 2012). More recognition needs to be given to the core role of mathematics in analysing and reasoning with data to make informed decisions and engage in constructive debate about local and global issues (The Royal Society Science Policy Centre, 2014).

With the increasing need to reason effectively with data including entertaining uncertainty and risk, it was timely that the major domain of mathematical literacy within PISA 2012 featured uncertainty and data as one of the four context categories. Given that many nations are striving to achieve social, cultural and economic prosperity in dealing with a rapidly changing and insecure world, greater recognition needs to be given to the foundational role of mathematics, in particular working with data, in building the required knowledge base. Traditional methods in statistics education, which focus on procedural skills rather than conceptual understanding, are inadequate. As several researchers have indicated, the need to develop new approaches to dealing with uncertainty and data, beginning with the earliest years, is paramount (Bargagliotti, 2014; Batanero, Burrill & Reading, 2011; English & Watson, 2015). One approach to elevating mathematics within STEM is modelling with data, which targets the components of a mathematically literate student defined previously.

MODELLING WITH DATA ACROSS STEM

The terms, modelling, and modelling with data, have been variously interpreted and applied in the mathematics education literature (e.g., Borromeo Ferri, 2013; Doerr & English, 2003; English, 2014; Kaiser & Sriraman, 2006; Lehrer, & Schauble, 2005). It is not the intention of this paper to explore these various interpretations; rather, as used here, modelling with data encompasses a focus on both process and product: (a) It follows a process of inquiry involving comprehensive statistical reasoning that draws upon STEM-based concepts, contexts, and questions; and (b) It generates products, (models) that are supported by evidence and are open to informal inferential thinking, which includes recognising uncertainty, detecting variation, and making predictions. Such models may take different forms depending on the nature of the inquiry (e.g., explanatory documentation, persuasive argument, a representation). Because variation is inherent in data (without variation there would be no need for statistics), models are generated in light of the uncertainty that arises from such variation.

In the remainder of this paper, I report on two quite different activities implemented in sixth-grade classes, the first in Cyprus (English & Mousoulides, in press) and the second in Australia (English & Watson, 2014). Together, the activities target the following interdisciplinary knowledge and processes, which I believe need greater representation across the STEM range.

Exploring, posing, and refining investigative questions within STEM contexts;
Applying discipline-based concepts and engineering design in formulating and solving problems;
Planning and undertaking investigations;
Analysing and representing data in multiple ways;
Developing, applying, and assessing evidence-based models;
Understanding informal inference involving variation and uncertainty;
Critically evaluating data-based arguments and conclusions;
Sourcing, evaluating, and communicating information;
Thinking in creative, flexible, and innovative ways.

**Engineering-based Modelling with Data**

Given that the first activity, *Rebuilding the 35W Minneapolis Bridge*, is an engineering-based modelling problem, it is worth highlighting the increased focus on engineering design in the *Next Generation Science Standards: For States, by States* (The National Academies, 2014). Broadening the role of engineering design and elevating it to the same level as scientific inquiry, the Standards define engineering design practices as those that all citizens should develop. The core features of engineering design encompass three main iterative processes, which have the potential to enhance learning across both science and mathematics: (a) defining problems by specifying criteria and constraints for acceptable solutions, (b) generating a number of possible solutions and evaluating these to determine which ones best meet the given problem criteria and constraints, and (c) optimising the solution by systematically testing and refining, including overriding less significant features for the more important.

*Rebuilding the 35W Minneapolis Bridge*

**Participants.** This problem activity was implemented in two 6th-grade classes (12-year-olds, n=48) in a K-6 public school in an urban area of Cyprus. The students had not been exposed to modelling problems of this nature in their regular curriculum.

**Method.** The activity focused on the 2007 structural failure of the 35W Bridge in Minneapolis, Minnesota (adapted from Guzey, Moore, & Roehrig, 2010). In the first session (35-45 minutes), students studied a newspaper article about the bridge collapse as well as a video clip, and answered questions to ensure their understanding of the context and its data. In the second session (1 hr 20 mins - 1 hr 30 mins), students were presented with two tables of data, together with the problem scenario. The first table comprised the key characteristics of the four main bridge types (truss, arch, suspension, cable-stayed), namely, the advantages and disadvantages of each bridge, the span range, the main materials used in construction, and the design effort (low, medium, high). The second table contained two samples of each of the major bridge
types and some of their key features including the total length, the number of car lanes, the construction difficulty, and the building costs (in current values).

The problem scenario explained that the Minnesota Public Works Department urgently needed to construct a new bridge in the same location. The bridge was to comprise a highway with a length of approximately 1000 feet, with a deck of four lanes with additional side lanes. The Department required assistance in creating a way (model) for comparing the different bridge types so as to choose the appropriate one to build across each span. Working in small groups of 3-4 (mixed-achievement in school mathematics), the students drew on the given data to generate, refine, and document their models. The groups were to develop a model that (a) included calculating the cost for each one of the four bridge types (using the given characteristics of the four main bridge types) and (b) would enable selection of the best possible bridge type for the reconstruction of the collapsed bridge. All possible factors related to bridge type, materials used, bridge design, safety, and cost were to be taken into consideration. In the final session (40-50 minutes), each student group explained to their peers their model creations and key findings, which they documented in poster format.

**Data analysis.** Each student group (13 groups in total) was audio taped, while all whole-class discussions were videotaped. The data sources also included students’ worksheets and the researchers’ field notes. Data were analysed using interpretive techniques (Miles & Huberman, 1994), with detailed analysis of all data sources enabling identification of the mathematization and statistical reasoning processes students applied during solution. Students’ cycles of model development, reflecting use of engineering design, were also identified in the analysis.

**Sample of results.** The models students created varied in the number of problem factors considered (cost per surface unit of bridge deck, aesthetics of the various bridge types, bridge design effort, construction difficulty, length), as well as in students’ reasoning with these data, and in the sophistication of the final models generated. I report here on just one student group’s model development, which displayed their reasoning with multidisciplinary components.

The group began the problem by excluding a truss-type bridge explaining that, “The collapsed bridge was a truss one” (Student A) and “Selecting the truss type bridge would make people feel insecure and bring back all those bad memories” (Student B).” The group then decided that a cost model for ranking the different bridge types was needed, but after developing an initial model that involved calculating the average cost (money per square feet of deck) for each bridge type, they decided that it was not the most appropriate solution. The group concluded that the substantial variation in their results for bridges of the same type could be addressed by integrating more factors within their initial model. Their reasoning was as follows:

Student C: Our calculations are correct. There is nothing wrong. The cost is very different.
Student D: There are other things (factors) that are important and influence the cost ... for those (bridges) that are close to sea it is more difficult.

Student C: Yes, like in the Golden Gate Bridge. It is so expensive and not that long.

Student B: Cost is not proportionally related to the surface of the bridge (deck), but also the level of difficulty in constructability, just like in the Golden Gate, is an important factor.

On returning to the key characteristics of the four major bridge types (advantages, bridge span etc.), the group came to the conclusion that all types had their advantages as well as disadvantages. The group thus concluded that a suitable bridge type could not be determined from this set of data alone. The students then moved into the next cycle of their model development as they took further data into consideration. Reflecting on their prior discussion on determining an initial cost model also contributed to their progression to a more comprehensive model.

The students’ next cycle of model development featured a consideration of engineering, scientific, and societal factors. It was decided that these should be incorporated within their earlier model. These additional data included the necessary extra lanes for bridges, bikes, and pedestrians, as well as the difficulty level of each bridge construction. The last factor was determined by dividing the estimated final cost per ft$^2$ by 1.5 for the given examples of the four major bridge types. The group referred to this as the “difficult constructability” factor and specifically created this to provide the same basis of comparison for all bridge types.

The group’s refined model ranked the bridge types from cable-stayed as most favoured, followed by the arch, truss, and suspension bridge types. In deciding on their final model, however, the students were cognizant of scientific and engineering issues, and thus selected the arch type as the best possible solution. They were still concerned about the stability of a cable-stayed bridge for long span bridges.

**Modelling with Data in Developing Statistical Literacy**

**Participants.** The second activity was conducted at the end of a three-year longitudinal study (2012-2014, grades 4-6) on statistical literacy in interdisciplinary contexts, with a focus on informal inference (English & Watson, 2014). For the present activity, four classes of sixth-grade students participated (average age 11 years 10 months, n=89). The students attended a state school situated in an Australian capital city.

**Method.** A foundational feature of the activity was the investigative process, “Four steps to making decisions with data,” which the students had followed in their previous investigations, namely: 1. Posing a question, 2. Collecting data, 3. Analysing (and representing) data, and 4. Making a decision (on the original question), acknowledging uncertainty. Use of the TinkerPlots (Konold & Miller, 2011) software program was a key learning feature of the three-year study. The next
two activity components involved both whole class discussions as well as small group work.

*Are Athletes Getting Better Over Time?*

The first component of the activity (2hrs 30mins - 3hrs 25mins) began with a video clip of *Usain Bolt in the London 2012 Olympics 100m Final* (http://www.youtube.com/watch?v=lacjJVxC5d0). The students then considered the general question, “Are athletes getting better over time?” Students quickly realised that the question needed to be refined in order to answer it statistically and meaningfully (corresponding to Step 1 of “Four steps to making decisions with data”). Over the course of the three-year study, students had come to appreciate that statistical questions require carefully planned investigations and any conclusions drawn from the analysis of the data have a certain degree of uncertainty.

On refining the question in their own way, each group recorded the data they would need to answer their question (corresponding to Step 2). Specifically, students were to record: (a) how/where they would find the required data, (b) whether that data would enable them to answer their question, (c) how confident they would feel in answering their question, and (d) whether they considered their question needed further refinement.

Following a class discussion on how required data cannot always be obtained (due to unavailability or in the present case, time constraints), students were supplied with data rather than sourcing these, as would have been preferred. Each group was presented with 12 data sets of various Olympic Gold Medal results for men’s and women’s freestyle, sprint, running, high, and long jump events. Selecting the appropriate data to answer their question (or if necessary, refining their question first), students were to analyse the data and represent their findings (corresponding to Step 3). Initially they were to sketch a plot of their results, labelling their axes, recording their end points, and indicating the scale they would apply. The students then used the *TinkerPlots* software to generate more detailed representations. On completion of their representation, the students were to respond to the questions, “What does your representation tell you? How does it help to answer your question? How could you improve your representation?”

Moving to the fourth step, students recorded their responses to the following: “From your analysis, what decision/conclusion have you reached? Explain how you reached this conclusion. What evidence do you have to support your conclusion? How certain of your conclusion are you? Explain your answer.” Groups of students shared their conclusions with the class, indicating the data they used, their strategies for analysing their data, and how certain they felt about their conclusion.

Next, students were introduced to a new tool for data analysis, namely, the trend line. The software enabled students to observe improvement over time by drawing a trend
line across the data. Using the Text Box feature of the software, students described
the “trend” or “relationship” in their chosen data set. The trend line was added to
students’ existing repertoire of statistical tools, namely, mean, mode, median, and Hat
Plot, together with their established understanding of representational features in
describing and comparing data sets (e.g., overall shape, outliers, clusters, gaps, etc).

This first component of the activity concluded with a Power Point presentation based
on an article from the Technology, Entertainment and Design Conference (namely, http://tedsummaries.com/2014/05/03/david-epstein-are-athletes-really-getting-faster-better-stronger/ ). The article described how advances in technology have contributed
to athletes’ improved performances. Students were to subsequently reflect on their
prior conclusions and the certainty of their recorded decisions, indicating whether
they regarded these as still justifiable.

Sample of results. As not all data from this activity have been analysed at the time of
writing, examples are drawn from just two classes.

Group responses to Steps 3 and 4 suggested an awareness and appreciation of trends
in the data including any outliers, as well as an appreciation of the uncertainty of
conclusions drawn. For example, one group reported in response to the questions of
Step 3:

Our representation shows us that 100m sprinters are generally becoming faster since
1972. It is a gentle decline from 10:14 sec to 9:63 sec at the London 2012 Olympic
games. However during 1980 Moscow Olympic games someone won with a time of
10:25 which is a distinct outlier. The representation helped us with our answer as it
shows us a clear trend of quicker times. We could improve [our representation] by
making the y axis, the times, more specific to show the exact times.

Responding to the questions of Step 4, this group explained:

We have come to the conclusion that 100m sprinters have become quicker from 1972 -
2012. Our graph has clearly shown the trend of quicker times for gold-medalist. In 1972
the time was 10:14. In 2012 the time was 9:63. The graphs shows [sic] a gentle decline
(Except for the outlier). [We are] Not extremely certain [of our conclusion]. This is
because our time frame does not include all the Olympic games which officially started
in 1896.

Let the Selections Begin!

Method. The second component of the activity, Let the Selections Begin! (1 hr 30
mins - 2hrs) involved developing models for selecting swimming t

eams for the 2016
Olympics. Commencing with the question of whether Australian athletes are also
improving over time, and if so, whether Australia would be likely to win Gold in the
pool at the 2016 Olympics, students again quickly identified difficulties in answering
such a broad question. Given that the nature of the activity involved selecting
Olympic teams from given data sets, the question needed to be refined substantially;
this was achieved through class discussion.
Students were given tables of data (in both printed form and in *TinkerPlots*), for selected swimming competitions during the 2012-2014 time period (personal best times [PB] were included as well as individual race times). Each group was to make its own team selections for the women’s or men’s 100m freestyle relay event for the Rio 2016 Olympics, choosing the 6 swimmers with the best chance of winning Gold for Australia, and providing justification for their choices in a report. Specifically, students were to report on: (a) The data used and how they were analysed (including any representations) to help their team selection; (b) The athletes selected and reasons for selection; (c) How certain they felt that their selected team would be the “best” and why, and (d) The certainty with which they considered their methods of team selection would apply to other swimming and sports events, and why.

**Sample of results.** Interesting insights into the students’ learning emerged in the final part of the activity where student groups reported on the models they had created. The first set of examples is from one class where 11 groups shared their models for team selection. Several students who questioned their peers’ models displayed a critical analysis of how the models were generated and made requests for clarification of terms used, together with justification for conclusions drawn including the supporting data.

Group 11 explained that, in using the data for the women’s 100m freestyle events, they analysed the data “by looking at the athletes’ personal best times and how many times they’ve been to a swimming race.” Explaining further that the latter factor referred to the athletes’ experience, a class member asked, “When you’re talking about experience, what do you mean by that?” followed by, “…which is more important to you, the PBs, the speed, or the experience?” The group indicated the speed.

In describing their model, group 5 stated that they were “75% confident that our team will win the 2016 Rio Olympics.” This claim prompted the peer question, “…how do you know that cause you don’t really have the teams and their times … How can you be any percent sure?” Further questioning about Group 5’s model, which focused primarily on the athletes’ personal best times, included “… do you think your team selection would be more accurate if you take more things into account than just PB?” In replying “yes,” the group was asked what else they might take into consideration, to which they replied, “the events, like the competition events, so like the Olympic Games, the Australian Swimming Championships…” This response elicited further questions and comments including, “How does the type … like where the race is, so if it’s like the Olympic Games or something else, how does that affect the racer?” On giving this point some thought, one Group 5 member responded, “…they’ve got different times so they could have. I’m not too sure.” The other group member elaborated, “Um, maybe it’s like we said. Swimmers, like athletes, can improve over time so maybe we will look at the events as because we think these swimmers could improve.” The peer who posed the question concluded, “So you could have, um,
considered the time they did the other races [previous competitions] and made a better team.”

The second set of examples is from another class (13 groups) where several groups explained why they considered a range of factors in producing their model, not just Personal Best times. Group 8 provides one example:

And to answer this question we used all times of the [female] swimmers and found the averages. So then we ordered the averages from fastest to slowest and we found according to that, the fastest were ... [selected swimmers]. We also took into consideration their age ... it wouldn’t really affect it but just to make sure they were experienced but they were also still like at a good fitness level and ... We focussed on the average, the averages of the times because they basically sum all the swimmers’ results and using their Personal Best would not be very accurate as that had, could basically just be chance that they managed to get such a good time.

In expressing uncertainty in their team selection, a group member explained, "So, we’re fairly certain that the six women that we chose were the fastest in Australia at 100m Freestyle however, we cannot be completely certain as we do not have all of their results for the races they competed in. And also it's still, there is still an element of chance."

Group 13 considered Personal Best times but indicated more factors needed to be taken into account. In colour coding their data table, the group explained:

We organised our data set in a manner so we could organise the times in terms of colours and we saw that Cameron and James had exceptional times. Our third selection was Tommaso D’Orsogna because two of his times got into the green colour which signified a time of 48 seconds. His PB was also green but we didn’t use this mainly as evidence as there was a lot more components to factor in. We averaged all the competitors, all the swimmers' times in terms of events excluding their PB because it could depend on chance rather than, for example it could be just a good day that they achieved their PB and that’s how we selected the other swimmers which were ... [selected swimmers]. The mean was one of our main strategies to choose our swimmers and we are confident with our team, except the decision which included Matthew and Kenneth which had close average times for 100m.

The group expressed confidence in applying their model to other team selections due to its "comprehensive" nature, indicating:

Our strategy could be used to pick other teams in different countries because it is quite comprehensive and it will depend on the events and you’d need, the more events that they could compete in the more accurate the average could be so, it’s one, it could be used, in other teams for choosing. We are quite certain except because this is the best method we could come up with and we also looked at age as well to make sure that um the fitness levels and also that they are around the same age just, and we also noticed
that the young swimmers such as Ned McKendry and Samuel Young [aged 22 and 16 years respectively] had not, were not accepted into the team because of slower times.

CONCLUSIONS

The examples presented in this paper for raising the profile of mathematics education are merely touching the surface of opportunities. Mathematics education provides foundational content and processes that bridge the STEM disciplines. Our challenge is to raise awareness of these contributions and increase the mathematical experiences appearing in STEM documents. Modelling with data, just one example, cuts across the disciplines but is not receiving the recognition it warrants, nor is the potential of applying engineering design in enhancing mathematical problem solving and inquiry. With the rapid rise in engineering education drawing heavily on the science curriculum, it is imperative that mathematics does not become the distant relative. My aim for our international community is to lobby in support of our field as a core player in the advancement of STEM. Mathematics needs to be elevated to the peaks of the STEM mountain range, and we must ensure it remains there with its contributions recognised and lauded.

References


English


