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Towards Pedagogy Supporting Ethics in Modelling

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Abstract

Education for concepts such as ethics and societal responsibility that are critical in building robust and applicable mathematical and statistical models do currently exist in isolation but have not been incorporated into the mainstream curricula at the school or university level. This is partially due to the split between fields (such as mathematics, statistics, and computer science) in an educational setting but also the speed with which education is able to keep up with industry and its requirements. I argue that principles and frameworks of socially responsible modelling should begin at school level and that this would mean that ethics and real-life modelling are introduced much earlier than is currently done. Integrating these concepts with philosophical principles of society and ethics would ensure suitable foundations for future modellers and users of technology to build upon.

Keywords: pedagogy, education, analysis, ethics, modelling, mathematics

Definitions Used within this paper

In this paper the terms *analysis*, *data science*, *machine learning*, *AI*, and *modelling* have been used to indicate the process by which one examines the world around them, collects data, creates an algorithm or programme, and produces output data. With this output data one is able to either make decisions, such as in credit cards, or make predictions, such as in finance. This process constitutes a definition of modelling. A modeller is modelling an aspect of the world around them. Terms such as analyst, data scientist or AI practitioner would all fall under the umbrella term of modeller. The fact that modelling is not widely understood as a specialty and is instead referred to as machine learning, data science, or AI means that a common language is currently not in use in order to understand the modelling process.

The modelling pipeline consists of guidelines such as those used by the AQuA[1] Book (Analytical Quality Assurance) [24]. The AQuA book details the process a modeller can follow that guides a modeller from model concept to model implementation via a route such as the following:

- Data Collection
- Topology of model
- Model Construction
- Model testing/Validation/Verification
- Model testing
- Production of paperwork for users and audit
- User testing
- Audit

This process contains, from start to finish, critical ethical considerations and implementation. For example, the collected data has to be appropriate and representative of society but also understood to actually be reflective of society. If we cannot understand the ethics of using data that is taken from a society that behaves in certain ways and that this will affect any outcome from the model, then it can become an obsession for modellers to try to reverse engineer data and the model to try to make it representative of an idealistic society. The avoidance of inherent issues in data such as gender bias, racist tendencies or factors that impact the data that might not seem appropriate all have to be understood within the context of society. In addition, robust and ethical modelling considers the impact of the model on society and ensure that testing is carried out so as not to disadvantage society upon implementation. The ethical part of modelling cannot be extracted from the technical process and indeed requires subject matter experts and interdisciplinary working for it to succeed. Where this paper discusses modelling, it is considered that the ethical process should be fully embedded into the modelling process, they are not separate.

[1] The AQuA (analytical quality assurance) book is the current best practice guidance for the UK Government

This process should be supplemented by adequate facilities for modellers to challenge any issues within the model and to be able to communicate with an interdisciplinary team, stakeholders and their board [45].

1. Introduction

At present in the UK, in industry and academia, there is a lack of definition of what an analytical professional in modelling looks like. Indeed, the UK military roadmap for 2022 [67] discusses a new cyber capability which will need resourcing with analytical specialists from inception. Indeed, Vasileios stated that "a skills gap in the domains of data science [. . .] is observed" [21]. However, the current education system does not yet have capability to produce the modellers of the future. This is partially because technology has moved so quickly over the last decade that even legislation and regulation are struggling to keep up [19, 51, 1]. Since 2010 statistics has seemingly split into multiple fields; data science in 2015 , then machine learning in 2017, and AI in 2019 [51]. All of these involve currently recruitable roles within industry but many do not have a good definition [57] and some require "exaggerated technical skills for Data Scientist Positions" [59]. For example, a professional could be asked for a decade of experience and multiple programming languages. Not only do businesses not know what to ask for in terms of competencies but they are also struggling to find the right people [27]. This is exacerbated by the lack of professional pathways from university to industry to demonstrate, by professional body recognition or otherwise, what skills one has and if the person in question has the ability to build robust models. Subjects taught in academia are historically separated, and so someone who has studied mathematics may not have studied ethics, programming, or modelling. In order for progress to be made in technological development the educational system is a critical enabler and "education must keep up with the change to have our next generation to survive" [43].

Modelling is currently undertaken in technical sciences at university, but the subject benchmark statements that govern teaching and assessment[2]

[2] Subject Benchmark Statements describe the nature of study and the academic standards expected of graduates in specific subject areas. They show what graduates might

are not current [47]. Even today the UK higher education system does not yet have benchmark statements for teaching and assessing AI, data science, or machine learning. Where there is provision for AI and Data Science within degree courses, ethics is not generally highlighted as a key concept. As such there can be a lack of focus on the teaching of modelling and ethics as specific skills. The skills required to use a basic statistical model, for example, would not be sufficient to start from scratch and build an ethical model reflecting real-world scenarios with which to inform policy or organisational decision making. This is a skill in itself and includes such aspects as awareness of data quality, ethics, user implementation problems, context, human factors, and an understanding of the environment that the model is being created in [24]. As the field of analytics has progressed so quickly in the last decade, modules such as those covering AI have simply been added onto Maths or Computing degrees rather than being fully detailed as key areas of study or driving new, more integrated, courses of study.

This paper posits that critical themes within education such as ethics and robust modelling are being overlooked and indeed gaps at primary, secondary, and tertiary educational levels need to be addressed. Implementing and integrating these key concepts from school level is essential so that modelling can be undertaken robustly to avoid damage to society. Indeed, crucial areas of context surrounding a model such as assumptions, caveats, quality assurance and answering the right questions with constructive challenge become a cultural fixture [28, 71]. Assumptions and caveats give the user and developer information on what the model can be used for, its limitations and where the model should not be used. This is critical information to ensure that, not only are the models used correctly and explainable to all stakeholders, but that the output is not used in a misleading or incorrect manner. In order to be able to establish assumptions and caveats around a model one must first understand the ethical foundations and potential ethical consequences of that model. Important information such as data required to run the model and how the model processes this data alongside fitness for purpose of any output would be potentially included in assumptions and caveats.

reasonably be expected to know, do and understand at the end of their studies

These skills and a suite of transparent paperwork accompanying models[3] not only helps practitioners of technology but also users of rapidly developing technology. Fedushko *et al.* remind us that AI and ML is already used by pupils in the classroom whether they are competent in understanding the impact or not [15]. In addition, leadership and soft skills are not generally focussed on in academia but these skills are crucial to ensure that a cultural shift can take place in academia and the workplace. This is essential in order to promote continuous improvement in analysis, such as the introduction of robust and ethics modelling, within organisations [45].

The addition of key concepts throughout the educational system and the updating of potentially outdated curricula is key to ensuring a functional and ethical society where modelling is concerned. But more than this, if decisions are made by models that are not robust and, in any way, harmful the very functioning of society could be under threat. Where every citizen is ultimately a user of technology it is imperative that those that develop it are ethical and socially responsible in the development of technology.

The next section in this paper (§2) covers problems experienced within industry as shown by an empirical study by Holstein *et al.*, [25]. Then we analyse issues encountered within the education system. Here we discuss the importance of relevant and robustly trained practitioners and how current gaps can be addressed. We examine the education system in the UK and, where it is lacking, we propose how amendments can ensure that the next generation of working age can be trained to ensure we have well trained professionals available. The role of professional bodies is also examined as a route to risk mitigation of AI and also for training of professionals in the workforce. We then recommend ways forward and conclude.

2. Current challenges in Industry due to a lack of educational provision

Walden found that there is a substantial gap between what academia teaches students and what industry needs students to be able to do once the join the

[3] Paperwork such as user guide, assumptions, caveats, model topology, testing results, output ranges, validation and verification

workforce. Walden asks "Are we teaching what the students need in order to be successful in their new careers?" [70].

In 2019 Holstein *et al.* [25] performed a study that determined that practitioners were facing significant challenges, some of which seemed to originate from lack of basic modelling methodology or understanding of aspects such as data collection. Additionally, a lack of process meant ethical considerations could not be addressed. It might be assumed that these skills are taught in the education system, but they were nevertheless being cited as challenges by practitioners. In this section the findings from Holstein *et al.* [25] are summarised.

Holstein *et al.* [25] found that practitioners struggled with the application of regulation to their work. Either they were not aware of it or struggled to balance competing pieces of regulation. Increasingly ethics was quoted in the study as being an emerging, but critical, topic for societal acceptability of model implementation and development. Holstein at al. [25] highlighted challenges outside of the traditional model development pipeline; such as not being able to recruit correctly skilled staff.

The following results from the 2019 study by Holstein *et al.* [16] begin to illustrate the plethora of issues now found in industry where modelling is being undertaken.

- In the survey undertaken on practitioners "52% of the respondents who answered the question stated that that communication tools would be "Very" or "Extremely" useful" [16]. This would allow modellers and practitioners to speak in the same language in order to understand one another. This indicates the need for a shared language and interdisciplinary working within modelling.
- "A majority (60%) of survey respondents, out of the 25% who indicated their team has some control over data collection processes, stated that having active guidance on how to collect and process data would be "Very" useful" [25]. Not being able to collect and process data correctly not only produces a concern over regulatory breaches but whether the model is suited to the intended purpose.
- "51% of survey respondents stated that they discovered serious issues only after deploying a system in the real world. The fact that only after

deployment serious issues were found indicates a lack of model testing throughout the development process. This is a critical undertaking in order to establish a model which, when deployed, has been thoroughly tested in order to minimise harm

- Many respondents stated that "they do not currently have fairness metrics against which they can monitor performance and progress" [16]. This is a crucial omission as the respondents cannot currently determine if their model is far or robust.
- 71% stated that they would welcome tools to help their team understand potential "UX side effects caused by implementing a particular strategy for addressing a fairness issue"[4] Implementing a fix may also lead to adverse results therefore testing is imperative.
- Over half of practitioners stated that they would welcome "tools to help them collect further data to address fairness issues and that estimation of the required number of data points was difficult" [16]. Here a statistician would need to be involved in interdisciplinary working to be able to perform the complex calculations for validation samples collection.
- Most practitioners struggled with accounting for human bias within development of models. 69% of those who responded were currently attempting to mitigate these biases [25]. This is a very complex area and involves disciplines such as psychology and philosophy. Human biases can be very difficult to detect, and code does not behave in the way a human may consider it to due to lack of experience and context that would be assumed in a Human world view. Therefore, this is a very difficult area to address.

Within the UK education system there is no opportunity to develop a common language or discuss ethical considerations in modelling as it is not part of the teaching diet. In not being able to develop basic skills such as data collection for real world models, practitioners are then seen to struggle to

[4] Fairness in machine learning is often described in a statistical manner and consists of mitigating unfair biases in developing models [11, 16].

develop robust modelling. The fact that practitioners can be unaware of ethical considerations until real world deployment is part of the reason for the number of recent legal challenges due to ethical issues. For example, modellers may not have considered the data and how robust it is, the testing of the model may not have been designed properly or indeed have been through enough to indicate processing issues, and perhaps most problematic of all, the modellers may not have realised that the output would be detrimental to society due to a lack of understanding of how the model works. In the results from the Holstein study [16] we see numerous requests for help in terms of tools to understand what is happening in their own modelling. This paper posits that this is a request for training and education as the tools asked for are ones that help define fairness, metrics or ethical considerations. These complex concepts cannot be readily applied in tools and there is no quick fix. This type of understanding relies on ethical education.

3. Problems in Modelling Methodology

At present there is no definitive modelling guidance that can guide a modeller through the process from data collection to model implementation in a comprehensive manner. However, there are elements of best practices in existence. In the UK, for example, the AQuA book does try to fill this gap [24]. The AQuA book is the guidance for best practise in modelling as constructed by experts in UK Government. The modelling pipeline, to the best of the authors knowledge, has not been laid down in a suitable format for the breadth of modelling being undertaken from Mathematics, Statistics [5, 31], Machine Leaning (ML) or Artificial Intelligence (AI) [10]. It appears to be assumed that aspects such as critical thinking, contextual analysis, ethical considerations and testing of models is somehow inherent in the education system or within professional training done by professional bodies. With no particular body or institution taking accountability it is difficult to see how progress could occur.

Concepts such as ethics, context, validation,[5] verification [24], and other

[5] Validation and Verification (V&V) is the process whereby a model is tested to ensure the data is robust, the results are robust and that the model does what we expected it to

contextual considerations should still be present agnostic of the modelling method. However, this is not addressed well in industry [25] or in education [47, 66] and as a result many modellers would not have been taught how to model robustly nor with a knowledge of ethics. Neither would modellers have received support professionally to undertake this. This is borne out in the extent of the legal cases seen in the past few years both from private industry and the public sector such as: decisions made about credit card approvals, for example, were thought to be arbitrary until an algorithm, designed and implemented in order to make these decisions [14, 49] was seen to be discriminatory. Decisions, whether it be what school a child goes to or whether one is eligible for a credit card or loan [61], ultimately shape society. From providing the evidence to support major investment decisions [2] to individual services for citizens [12, 22, 36, 56, 9], models can have major implications for society. It is therefore vital that the models used are fit for purpose. Balancing societal impact and supporting innovation, so that society's right to benefit from science is protected [45, 19, 33], and limiting the potential harms associated with poorly-designed modelling is challenging [13, 41].

4. The fundamental principles of modelling methodology

Good modelling is underpinned by (but not limited to) the following foundations:

- Data Collection relevant to the problem (where undertaken)
- Data collected in a statistically robust manner (where undertaken) [16]
- Choosing the correct technology with which use this data/build a model [32]
- Building a robust model based on the data [72]
- Unit testing the model (as is already undertaken in the IT and software industry) [72, 52]
- Testing the full output of the model [24]

- Sensitivity Testing[6] [24]
- Validation and Verification of the model [24]
- Prior tests of model deployment with real data [24]
- Monitoring the model when deployed

Figure 1 illustrates how traditionally software development pipelines have been separate to purely technical, mathematical or statistical development pipelines.

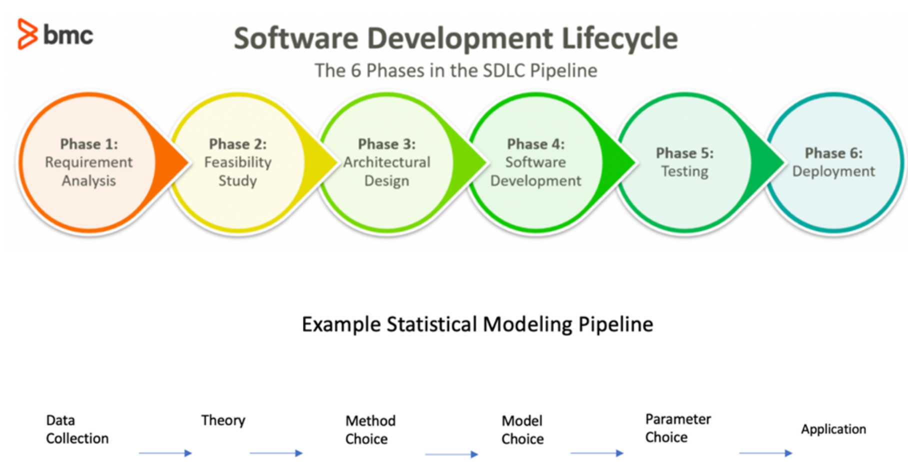

Figure 1: Traditional separate pipelines per discipline (Pipeline 1 ref:[39])

Figure 2 illustrates that current models are based not only within the technical, but also within software development and that a new modelling process or pipeline is now necessary. This improved and combined approach ensures that ethics can be considered throughout the development of the model and also throughout user testing. It guides modellers through the overarching principles that govern ethical modelling and suggests how to approach modelling for robust results.

[6]Sensitivity testing is when the input is changed slightly in order to see the impact on the output data, this helps check for consistency of output

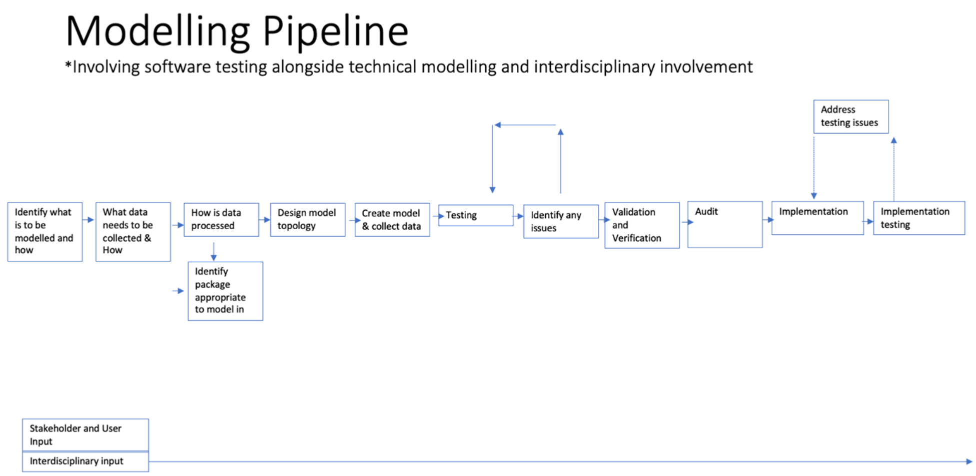

Figure 2: Example Mixed Modelling Pipeline

Underpinning skills such as critical thinking and contextual analysis are fundamental because without these it is difficult to model the real world. Aspects such as what data to use, what software to use and how should the data be processed as the foundations of model development. Modelling the real world is able to be deconstructed into separate self-contained subjects such as distribution modelling [65] or data architectures [62], but because these subjects are split across multiple curricula such as ICT and Statistics, it is difficult or impossible to align the skills across multiple disciplines. In addition, a well-prepared student would require critical thinking and contextual skills that are currently not taught across technical subjects to be able to understand how their model might impact society. These skills are crucial in order for modellers to have a general understanding of the society in which we operate. Society and its actions drive the patterns in the data we collect, fairly or unfairly, and the results of our models and how they impact on society will also be closely tied to an understanding of the society we intend to implement them within. The next section discusses what is currently taught within the UK Education system and identifies gaps within modelling methodology.

5. Where does the UK Educational System fall short and how can this be mitigated?

The UK education system is split into 3 separate stages. 1. Primary to Junior (Age 5-11) where basic principles are taught in preparation for later learning; 2. High School (11-18) where subjects are very tightly delineated and there is not much cross over between them (the age 11-16 education range is named secondary education and the range of teaching encompassing the age 16-18 is called A-Levels); and 3. Tertiary education or University (18-22) which encompasses specific degree subjects taught in depth with very little crossover. Subject benchmark statements are the educational guidance and prescription that govern the teaching of A-Levels and university education.

5.1. Secondary Education (A-Levels)

Secondary education is generally separated into non-overlapping subjects. The Secondary Curriculum [48] for mathematics, statistics and computer science is concentrated wholly on very technical aspects of the subject [54]. This means modelling consequences and implementation issues are not necessarily taught, thus leaving ethics out of the educational pathway. Indeed, statistics is taught but is allocated a very small amount of teaching time and does not include robust data collection, ethical or modelling considerations, despite students constructing basic models. The word "model' is mentioned within the secondary curriculum in terms of mathematical models such as algebra and formal mathematical representations [44]. This leaves students lacking a wider consideration and appreciation of modelling at school leaving age.

A-Levels are more even defined in terms of nuanced subject areas. Here we might find modelling undertaken in Mathematics, Statistics or Economics [66, 29]. Students would be familiar with the mathematics taught at secondary school but the onus on providing the wider context would now shift to the A-Level teacher in conjunction with subject specific content. A look into some of the A-Level requirements for teaching across the technical disciplines reveals the omission of teaching in areas such as context and ethics. Despite this being addressed in isolated areas across the globe, currently there is no joined up approach or widespread use of this theory [66, 3, 37].

The A Level Subject Content for Business does not mention modelling and ethics are mentioned in relation to business activities and personnel only [64, 26]. The subject content for Economics starts to discuss model limitations but does not go into detail on this. As stated in the A Level Subject Content for Economics, "Economics develop a critical approach to economic models of enquiry, recognising the limitations of economic models" [63]. The subject content for computer science [62] mentions data models but it is unclear whether this is in relation to computational architecture or data modelling. Modelling for a specific purpose is mentioned but this would indicate an understanding of ethics and robust data collection would be required [62]. In Statistics, where we might most expect modelling content to reside, modelling the real world is mentioned as an outcome. Neither ethics, robust data collection nor contextual model testing, validation or verification are mentioned. Indeed, the requirement for assessment is technical in nature and the testing of models appears to pertain only to the technical testing of distribution modelling [62].

The benchmark statements for many subjects have not been updated since 2016 according to the subject content papers. Subjects not updated since 2016 include maths, further maths, and statistics [66]. This is concerning because the most rapid technological development and application is within these specific subjects. The statistics subject content paper [65] states that the correct technological method will be taught depending on the model. If the model methodologies are simply distributional and technical then we would not expect this fundamental theory to change overly much but real-life modelling has developed at an extremely fast pace since 2016 and where once, we might have used excel we now use R or python frequently in the public sphere and in industry. Where we once used statistical methods we might now use Machine Learning [8] and AI based systems [10, 18]. This lack of updated teaching content and assessment criteria puts students at risk of being out of date in their specialism before they even access the workplace. This is even more problematic when some students may now leave education and go straight to the workplace without further study. In the workplace newly graduated Secondary Students may be required to build models.

5.2. Subject Benchmark Statements

The curriculum takes time to catch up with real world developments due to the slow pace at which boards sit and agree how update the subject benchmark statements. This lack of timely updating of subject content does not help modellers to utilise the rapid development of technology. In the last few decades technology has raced ahead in development [6]. Not only have multiple programming languages and user interfaces been developed worldwide, but ethics has become an integral part of model and software development [68]. This rapid development and ethical requirement is currently not reflected in higher education programmes of study. As Subject Benchmark Statements are reviewed only every seven years and by a chosen group of academics, we cannot be certain that the needs of modellers are well represented [38].

The benchmark statement for mathematics, statistics and operation research [48] is one such example. One might argue that with such diverse disciplines the statement should be split by discipline. Indeed, in 2019 the statement was amended to highlight data science courses. This statement now becomes confusing in that too many disciplines, with their own requirements and teaching burdens and assessments are represented within it. The subject benchmark statement for mathematics states that "all branches of mathematics, statistics and operational research are dynamic, vibrant subjects which permeate most areas of modern society" [48]. This is confusing as it indicates that the content should be updated more regularly given the rapid development of the area. Additionally the statement below indicates that mathematics and associated disciplines are now critically interwoven with other subjects : "The use of mathematics, statistics and operational research in subjects such as physics, engineering, psychology and management is well established; however, much research in subjects such as biology, economics, political science and sociology is now also heavily reliant on mathematics, statistics and operational research applications" [48]. This begs the question why interdisciplinary working and ethical and robust outcomes are not featured heavily within the curriculum given the serious consequences of models currently being built.

The problem with subject benchmark statements not being updated in concert with the rapid development of technology is that some academic courses are being developed by institutions so rapidly that they not held to account by a subject benchmark statement. Assessment and teaching can therefore not be formally regulated or inspected by the QAA or other government mechanisms. Students are simply taught what the academic institution would like to teach them. Whether the material is appropriate or not is not questioned. We see from the study by Holstein *et al.* [25] that modellers in industry are still not gaining the skills they need and that the education system would be best placed to mitigate this. This shows a clear gap between the understanding of what needs to be taught in the UK educational system and what the academic community actually teach.

The quote below illustrates new modules and courses that include computer science, mathematics, or data science are being created but not necessarily included on a subject benchmark statement due to the lengthy delay between updated of the statements. "Mathematics, statistics and operational research courses have been sufficiently flexible to adapt quickly to innovations ..." and that "The practice of rapid development of new courses is to be encouraged and is indicative of the dynamic and evolving nature of mathematics, statistics and operational research" [48] This indicates that with the volume of new content being described and the interdisciplinary nature of the content it is not enough to attempt to capture multiple disciplines in one benchmark statement moving forwards. The quote below admits the variability but the lack of appetite to split the benchmark statements to accommodate this. "Although mathematics, statistics and operational research is a very broad grouping of subjects, it is possible to deal with the entire subject area within a single Subject Benchmark Statement, provided that users of this document bear in mind that there is very wide variability among the courses that come within its scope" [48].

Where ethics is mentioned once within the entire benchmark statement it is discussed under general skills and in the context of personal data. No further ethical modelling considerations are made despite stating that Statistics in particular is using data to model "knowledge of ethical issues, where appropriate, including the need for sensitivity in handling data of a personal nature" [48]. Indeed, the section on Modelling is no where near granular enough despite being the area that has caused a huge amount of legal scrutiny and challenge as well as disadvantage to society in the past few years.

Currently there are no subject benchmark statements for Data Science, Machine Learning or Artificial Intelligence.

Next, we examine the subject benchmark statements for Computing and Mathematics.

5.3. Subject Benchmark Statement for Mathematics, Statistics and Operational Research

This benchmark statement is vague and unable to convey the granularity required to understand the teaching and assessment in multiple subjects. Indeed, the statement speaks of "examples of other titles [for courses involving operations research] include business decision methods, business systems modelling, management science and business analytics" [48]. This makes it difficult to know under what remit the interdisciplinary part of the work is being taught.

In examples of what students might be expected to do the spectrum is vast, from constrained techniques to physics and differential equation systems. Despite the differing approaches and requirements for this variety of models there is no granularity here on subject specific approach. The statement appears to show a lack of understanding of the modelling pipeline.

In the section dedicated to modelling only two points appear. The first is to state that "Modelling is the activity of constructing a mathematical representation of a process or structure" [48]. This is not always true and would depend on what is being modelled and how. Much modelling is representative of real life. The following statement does not seem to be supported by the rest of the subject content statement in terms of requirements for teaching and assessment.

> "All graduates of practice-based courses and many from theory-based courses have knowledge and understanding of a range of modelling techniques and their conditions and limitations, and of the need to validate and revise models. Graduates also know how to use models to analyse, and as far as possible solve, the underlying problem or to consider a range of scenarios resulting from modifications to it, as well as how to interpret the results of these analyses." [48]

Indeed this area is so large it is covered in part by the entire Aqua Book Series [24]. It would be expected that this area might be broken down further given the importance of modelling. The only mention of ethics in the statement is that the graduate should be aware of "knowledge of ethical issues" [48]. What the ethical issues are is not explained.

The statement covers too many disciplines. Disciplines that are suitably large in their own right and would benefit from being contained their own statement. In addition, critical areas are missed such as ethics, verification, validation and modelling process.

5.4. Subject Benchmark Statement for Computing

The computing subject benchmark statement, although not directly involved with mathematical or statistical modelling is the only one that addresses risks with model implementation. This is the only statement which describes risks pertinent to the implementation of models (here referred to as computing systems) such as "the ability to recognise any risks and safety aspects that may be involved in the deployment of computing systems within a given context" [47] which is critical for model construction. This is the only subject to address constraints found in real world modelling such as a budget and what assumptions and caveats apply. The benchmark statement states that "the ability to critically evaluate and analyse complex problems, including those with incomplete information, and devise appropriate solutions, within the constraints of a budget" [47].

The benchmark statement for computing goes further to state that a graduate should "recognise the professional, economic, social, environmental, moral and ethical issues" [47] but only in the context of "the sustainable exploitation of computer technology" [47]. The graduate should however, be "guided by the adoption of appropriate professional, ethical and legal practises". However, these practises are not stated [47].

The computing benchmark statement does mention the following but applies no further detail. Students should "apply appropriate practices within a professional, legal and ethical framework" [47]. Although these critical parts of modelling are mentioned they are not contextualised or detailed.

5.5. Higher Education Teaching

In the study by Boon *et al.* [6] it is stated that results highlight a need for teacher training courses in order to train teachers to include ethical philosophy units within the curriculum. “This represents a sustainable way to support professional practice and enhance teacher quality, by preparing and equipping teachers with techniques to explore and teach complex ethical issues in the classroom”. One reason given for this need was that teachers were ill prepared by their training to broach ethical dilemmas and felt quite unprepared to do so in the classroom [6].

Boon *et al.* suggested that “to address the gap in teacher expertise to debate ethical dilemmas when teaching sensitive issues, pre-service teacher training programs must include a focus on ethics which elaborates the connections between ethics and science to help teachers deal with the challenges they meet in the classroom” [6].

5.6. Summary

The secondary education system in the UK stops at collecting basic data sets, which is not enough for modellers to build complex models in industry. This issue is exacerbated by little analysis of the contextual or ethical context of the data or the final implemented model. The tertiary education system benchmark statements are vague and limited in approach to each discipline. Additionally, Teachers in secondary and higher education are not generally trained in the teaching of ethics . This leaves critical parts of the modelling pipeline spread across disciplines instead of being brought together into a comprehensive pipeline. It is for this reason that good modelling involves a few more steps than those taught within the education system and these extra steps are what can act to guard society against negative impacts of technology.

6. A study illustrating the disconnect between the tertiary pedagogic curriculum and industry needs

In a study by Walden *et al.* [70] educational provision was compared to industry requirements to determine if there were any disconnects between academia and practitioners in industry where skills were absent or lacking.

Walden *et al.* [70] examined the top 25 universities and their coherence with industry requirements. The schools that were ranked in the Top 25 had a composite match of 88.7% match between what industry says they need and what academia says that they are teaching" [70]. Walden *et al.* [70] compared the syllabi from seventy-eight colleges and universities in the USA. The comparison involved comparing course content to the requirements in job announcements for entry level supply chain management positions. These positions were advertised over a five month period on major job sites such as Careerbuilder.com, Monster.com, and Indeed.com. The results of this comparison revealed a major disconnect between what was being taught in the introductory courses and what industry was looking for [70]. Only a 44% match between the syllabi topics and the job announcements topics for the non-Top 25 schools was found. However, in this study the Top 25 schools demonstrated an 88% match between what industry stated they required in new supply chain graduates and what the top schools were teaching. Walden *et al.* [70] states that this "has applications to physical sciences, engineering, and business and may have applications in schools of education" [70]. If Universities are not teaching relevant material to equip the graduate for the workplace, then not only do we do graduates a disservice but we cause ripple effects into the resulting inappropriately skilled job market. This has implications in that clearly the top 25 universities were able to interact with industry and/or understand the requirements for a fast-moving workplace whereas non-top 25 universities were not.

7. Ethics and the curriculum

In a US-centred study on Lajoie *et al.* [35] the integration of ethics into the technical curriculum was examined. Lajoie *et al.* "produced a study aimed at the promotion of training professional and aspiring engineers in North America with the integrated critical thinking skills they need to ethically assess the social and cultural impacts of the technologies they design, develop, and deploy" [35]. Lajoie *et al.* "performed a qualitative analysis of all selected articles to identify the main educational objectives and curricular approaches they presented, and findings were organized according to five major themes that emerged: previous interventions, institutional barriers, curriculum development, student perceptions, and pedagogical needs" [35]. Indeed, a study by Walczak *et al.* [69] found that barriers to ethics education are as follows:

- The curriculum is already full, and there is little room for ethics education,
- Faculty lack adequate training for teaching ethics,
- There are too few incentives to incorporate ethics into the curriculum,
- Policies about academic dishonesty are inconsistent,
- Institutional growth is taxing existing resources.

Both faculty and administrators noted that these obstacles not only provided challenges to teaching ethics, but they also deterred faculty from incorporating ethics into the curriculum [69]. The recommendations however, were similar to those of Lajoie at al [35]

- Integrate curricular and co-curricular activities,
- Collaborate across disciplines and divisions to create content around ethics education,
- Offer incentives to faculty for training or curricular innovation, and
- Present consistent policies among faculty and staff regarding academic dishonesty [69].

Lajoie *et al.* [35] found that collaboration, internships with industry and interdisciplinary or cross faculty seminars had the potential to help widen the scope of education and understanding of those in technical subject areas in higher education. Mitcham *et al.* [40] also support the teaching of ethics embedded into a curriculum for the technical sciences as ethics is currently an unacknowledged aspect of the curriculum. Mulhearn *et al.* [42] caution that "Increased investment in ethics education has prompted a variety of instructional objectives and frameworks. Yet, no systematic procedure to classify these varying instructional approaches has been attempted" [42].

This is an area of critical future research to ensure consistency of teaching across the disciplines in areas such as ethics, modelling and robust technical output. Grosz *et al.* propose a framework to embed ethics throughout the curriculum employs a distributed pedagogy that makes ethical reasoning an integral component of courses throughout the standard computer science curriculum so that “Students learn ways to identify ethical implications of technology and to reason clearly about them while they are learning ways to develop and implement algorithms, design interactive systems, and code” [23]. However, this does not go far enough to address the sciences as a whole.

8. What role do Professional Bodies play

Professional bodies could play an important role in training and certifying professionals in modelling. If we assume that this should be the remit of a Mathematics or Statistics body, we could refer to the Royal Statistical Society of the Institute of Mathematics, or even the Science Council. However, at this stage the educational pipeline is complete and so training would have to reintegrate ethics and modelling considerations into material already assimilated. It is possible to allocate modelling as a skilled profession with relevant recognition; alongside domain specific educational resources, courses and tools and specialised professional bodies. However, any gaps in practitioner knowledge would then have to be filled before certification resulting in further training courses at the practitioner’s expense.

From studies such as Walden *et al.* [70] it is clear that it is currently difficult to attract the right talent or top talent. The Royal Statistical Society [50] is moving towards formalising achievements and training with allocation of a designation for Data Scientist but this is in the development stages currently. This designation only allows for a very small strata of professional of an undefined role of “Data Scientist’ to obtain a lower-level accreditation and so does not go far enough or provide accurate definition of who can apply and what the accreditation means for industry. This does not appear to be applicable to a more generalist Modelling Professional role. The Science Council provides a Chartered Scientist designation but this is not specifically directed towards modelling practitioners [55]. Therefore, there is a gap that might be filled with a professional body catering to developing and designating modelling practitioners of the future. The link between academia and industry must be a closer collaboration as development moves forwards [13, 3, 55, 2, 20, 30].

9. Recommendations

The issues within the current UK education system and the subsequent disconnect to industry are multiple. Below are recommendations to move towards a more joined up approach in order to benefit students and industry.

- To bring ethics into the curriculum could be achieved in a straightforward manner. The area of ethics is the remit of a philosophy course, which is not taught widely as a subject in schools in the UK. However, all students do take Mathematics and as the ethics issues discussed in this paper are involved with modelling it would be preferable to link the teaching of modelling skills and ethical behaviours. Ethical value systems are needed around human behaviour as well as ICT [43].
- For Industry to work alongside professional bodies and academia in order to facilitate the rapidly changing requirements for new graduates. In order for graduates to succeed, and to buoy the economy, the workplace needs to have the modellers it requires. We must ensure that graduates skills meet the needs of industry [25, 70].
- Professional Bodies are able to certify in two ways. Firstly, the body can certify that the degree the modeller undertook was fit for purpose and included such aspects as discussed in this paper. Secondly the body could charter or certify individuals who meet the criteria of modellers. This would help to identify those qualified to undertake modelling and a profession and give industry confidence of this [17].
- The Higher Education system is critical to ensuring that programmes of study are relevant, robust and are updated regularly. These programmes of study must take account of rapidly developing technology so that graduates can both access the workplace but meet the requirements of industry. Students, Industry and the nation's economy are

disadvantaged if we do not find a way to facilitate this. However, Higher Education can only be as good as the foundations it is set upon. Therefore, if the primary and secondary curriculums are not delivering what is required for the modellers of the future then we must ensure a joined-up approach in education.

- Best practice in modelling is critical to implementation of robust and relevant technology in society. Therefore, best practise should be sought out and taught through Higher Education [29] and trained by Professional Bodies and industry [4]. Charterships and professional standing would help to determine which modellers have achieved this critical level of understanding.

- Industry requirements should reflect the education system. A next step could be to survey industry to see what the companies that are recruiting for our graduates are looking for. This could be done through a survey of companies through the school's career centre or through a review of job announcements posted on the major recruiting websites [70, 46, 53].

- Benchmark Statements use the terms "validation and verification" [24, page 25], but this does not take into account industry standards of validation and verification, which are large drivers of poor modelling in the modeller study. The statements also do not define the terms being used. Therefore, it is uncertain what type of modelling is used. Interpretation is a key part of modelling [7, 58] and one that modellers ask for more support in order to deal with uncertainty, predictions and to improve their modelling.

10. Conclusion

It is important to address gaps at secondary and tertiary educational levels. It would then be possible to implement training in this area from school level. Complex concepts such as assumptions, caveats, quality assurance and answering the right questions with constructive challenge would then become a cultural fixture. Subject Benchmark Statements can be updated in Higher Education so that it is clear that ethics, context and the modelling lifecycle must be covered. In addition, leadership and soft skills should be taught so that a cultural shift and continuous improvement mentality occurs downstream within organisations.

In this paper we have examined the current state of the education system in the UK in terms of ethics, modelling and interdisciplinary teaching and learning. It has become clear that the current education system is not working with industry to ensure the next generation of professionals is adequately qualified to undertake robust and ethical modelling as well as prepare students and professionals for the potential rapid developments in technology and coding. The current system is outdated and, not being agile, unable to keep up with advances in technology. There is a lack of ethics teaching within curriculums and the lack of coordination between sciences such as Mathematics, Operational Research and Statistics within individual benchmark statements does not help to create granular courses fit for purpose with relevant assessments and teaching diets.

There is a requirement for further work to close the gaps between education and industry and ensure students get the correct education to allow them to flourish in industry. In a rapidly developing world where students will certainly be using, or be beholden to, AI and ML technology, whether they develop it or not, it is critical to ensure every student has some understanding of new technology. Future work could include the updating and individualising of subject benchmark statements along with an enquiry into the usefulness of the current educational provision to industry. The gaps between industry requirements for professionals and the current skills level of students is a critical area of action. We have to ensure that the next generation of modellers can produce robust and ethical modelling to avoid the plethora of legal challenge we have seen in recent times. Discussions with relevant professional bodies and industry could also help to close the existing gap between industry requirements and education.

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