Towards a Framework for Learning Content Analysis in K-12 AI/ML Education

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***Abstract*—In recent years, an explosion of interest in AI has resulted in many K-12 resources being developed for teachers and students. However, there is limited research on how these resources can be used by teachers effectively. This paper is a work-in-progress innovative practice study in which we categorised 307 AI/ML teaching resources across our proposed SEAME framework: (i) Social & Ethical; (ii) Application; (iii) Model, and; (iv) Engine. We found that the majority of resources focused on the Application and Model levels, with the Engine and Social & Ethical levels less well covered. We found little consensus across resources about what to teach and how. Similarly, we found few examples of professional development resources indicative of the challenges teachers face in teaching about AI. We propose that the SEAME framework provides an innovative starting point for teachers and researchers to review resources and consider what a progression of AI-related concepts and skills might look like that is comprehensive and simple to use.**

***Index Terms*—K-12, computing education, AI, ML**

I. Introduction

Though artificial intelligence (AI) increasingly permeates different aspects of public life, the systems and processes behind the uses of AI are not widely understood [1]. Efforts to support K-12 AI education are limited but growing [2], [3]. Additionally, there is limited research on the impact of K-12 AI learning initiatives [4]. This presents an exciting challenge for computing education researchers and teachers alike to consider how aspects of AI and machine learning (ML) could be taught in computing education. In addition, a broad consensus on which AI/ML concepts and skills should be taught and learnt is yet to be reached [5]. Analysing currently available resources provided us with a starting point to consider how resources could be categorised to better support teaching and learning in this area.

II. Related work

A. Teaching about AI

Multiple attempts have been made to define the competencies needed to be "AI literate" and how these might be taught [2], [6], [4], [7], [8], [9], [10]. For K-12, the AI4K12 working group [2] defined the "5 Big Ideas" in AI (perception, representation and reasoning, learning, natural interaction, and societal impact). [10] took an alternative approach by inductively analysing 30 K-12 instructional units on ML. They identified 12 ML topics (e.g., neural networks), 13 ML applications (e.g., sentiment analysis), and 7 ML processes (e.g., model evaluation). Likewise, [6] reviewed interdisciplinary literature that contained elements of AI/ML and found many resources required prerequisite knowledge (e.g., statistics or mathematics).

However, consensus among the AI education research community has yet to be reached as some have questioned the comprehensiveness of existing frameworks. For example, [11] argue that most AI literacy frameworks fail to capture data science (or "data literacy") concepts and skills. Moreover, a "common language" [12, p. 101] is missing to characterise and discuss AI/ML teaching resources.

Though teaching and learning about AI in educational contexts has gained significant traction in recent years, there is still limited research of the landscape of AI learning in K-12 contexts [5]. Supporting teachers to implement AI/ML lessons is an additional challenge as AI/ML is not a widespread requirement in many contemporary computing education curricula. In this paper, we investigate how the landscape of AI resources could be analysed to better support the design and research of lessons about AI/ML.

III. Aims and research questions

We set out to survey the landscape of resources available to support K-12 teaching and learning about AI/ML. By reviewing available resources, we aim to help teachers navigate the complex topic of AI/ML. Our research questions are:

- RQ1: What resources are available to support K-12 teaching and learning about AI/ML?
- RQ2: How useful is the SEAME framework in reviewing AI/ML teaching resources?

IV. Methodology

In the context of a fast moving, complex field, a summative content analysis approach was considered appropriate to identify research gaps in relation to the emerging practice [13] and link the results to the landscape of AI/ML educational resources in which they were produced [14]. We conducted a category-based analysis where we presented what the SEAME categorisation could tell us about the current landscape of resources, followed by a case-oriented analysis of how the framework applies to two case studies [15].

A. Protocol

1) Research question 1 (RQ1): To answer our first research question, we started with five most recent AI literature reviews [6], [10], [16], [17], [18] and all resources mentioned in these literature reviews were added to the data set.

Additional resources were sourced through other means: (1) Suggested resources from a research seminar series on teaching AI that were previously crowd-sourced and freely available online[1]; (2) a Google web search looking for "AI teaching resources" (undertaken 2nd Feb 2022). Resources were included based on the following criteria:

1) freely available;
2) available for download between January and March 2022 (period of analysis);
3) taught about some aspect of AI or ML;
4) suitable for learners under the age of 18;
5) available in English.

Using these criteria, we "snow-balled" [19] further resources that were mentioned in the candidate reviews. A pragmatic decision was taken to stop collecting at 500 resources, with the aim of capturing a representative snapshot in time of available resources rather than conducting an exhaustive search.

2) Research question 2 (RQ2): To answer our second research question, the full set of resources was categorised across the SEAME framework, and according to target age, target audience, type of resource and software or hardware requirements. Where a single resource contained individual lessons, activities or sub-units, these were split into separate resources and categorised individually.

B. Validation

Four authors worked on the categorisation of the final 487 resources (13 duplicates deleted). 180 resources were excluded based on the inclusion criteria. Two authors categorised the full set and then two further authors dual-coded a 40% sample. Inter-rater reliability was calculated as .76 (Cohen's Kappa coefficient), a substantial agreement between researchers [20].

V. Framework

A. Overall

We were inspired by Falkner and Vivian [21] who analysed resources in K-12 CS education in Australia. We set out to report on the existing field of AI resources without providing a judgement on the quality of resources. In doing so, we devised and used a content analysis framework, the SEAME framework, that categorises the high-level focus of an AI/ML teaching and learning resource: Social & Ethical (SE), Application (A), Model (M) or Engine (E) (or SEAME) [22]. The proposed framework is based on an existing framework created for K-12 teacher AI/ML professional development (see [23] for diagram and further details). The SEAME framework provides a simple breakdown of the AI subject matter. The levels represent a separation of content as it emerges from existing AI resources as analysed by the researchers.

[1] https://www.raspberrypi.org/ai-ml-data-science-education-resources/

TABLE I
TOTAL RESOURCES ACROSS THE SEAME FRAMEWORK

SE	A	M	E	Excluded	Total
130 (42%)	246 (80%)	185 (60%)	83 (27%)	180	487

1) Social & Ethical (SE): The first level of the SEAME framework refers to the social and ethical dimensions of AI. This highlights the impact of AI/ML on everyday life and its ethical implications in wider society. Resources categorised at this level introduce students to issues such as privacy or bias concerns, the impact of AI on employment or misinformation.

2) Application (A): The second level refers to the use of AI applications. At this level, students do not need to understand how AI engines work, nor how to train models, but they will engage with applications that call an AI component. Resources at this level might include using, amending or even building AI applications by using AI extensions that are embedded in popular programming environments (e.g. *Scratch*).

3) Model (M): The third level refers to the underlying AI model (M) or training of models. This includes the learning paradigms of ML (i.e., supervised, unsupervised or reinforcement learning). Resources categorised at this level focus on sourcing and preparing data for model training, including data collecting, cleaning, classifying, visualising, and testing.

4) Engine (E): The fourth level refers to the underlying engines (E) or algorithms used to create AI systems. This includes a focus on the basic workings of neural networks, generative adversarial networks (or GANs) and decision trees etc. This is the most hidden level, which may be black-boxed if an application calls an ML component.

Resources can be situated at one or more levels simultaneously. The four levels of the SEAME framework do not indicate a hierarchy or sequence, nor do they suggest that resources are best situated at one (or all) of the four levels. Instead, the framework represents a comprehensive high-level categorisation which covers all aspects of AI [11], as well as providing a "common language" to discuss AI resources from different perspectives [12, p. 101]. In addition, the SEAME framework offers a simple way of reviewing the breadth of learning objectives, completeness and level-specific vocabulary of individual resources.

VI. Results

A. Quantitative results

In total, 307 resources were categorised according to target age, target audience, type of resource, and software or hardware requirements. Within each category, the resources were further categorised across the SEAME framework. Overall, we found most resources (80%) focus on the Application (A) level, over half (60%) on the Model (M) level, under half (42%) on the Social & Ethical (SE) level and under a third (27%) on the Engine (E) level (Table I).

TABLE II
TARGET AGE GROUPS ACROSS THE SEAME FRAMEWORK

Age in years	SE	A	M	E	Total
0 - 11	8 (53%)	12 (80%)	13 (87%)	7 (47%)	15 (5%)
11 - 18	60 (58%)	86 (83%)	48 (46%)	25 (24%)	104 (35%)
all ages	41 (43%)	73 (76%)	57 (59%)	27 (28%)	96 (31%)
not specified	20 (46%)	77 (87%)	66 (74%)	24 (27%)	89 (29%)

TABLE III
TARGET AUDIENCE RESOURCES ACROSS THE SEAME FRAMEWORK

Audience	SE	A	M	E	Total
student	28 (40%)	58 (83%)	38 (54%)	20 (29%)	70 (23%)
teacher and student	83 (49%)	140 (82%)	121 (71%)	48 (28%)	170 (56%)
anyone	9 (17%)	39 (75%)	24 (46%)	16 (31%)	52 (17%)
teacher PD	10 (83%)	9 (75%)	4 (33%)	4 (33%)	12 (4%)

1) Target age groups: We consolidated 32 age ranges as specified by the resources into four age groups (Table II). Only 15 out of 307 resources were explicitly designed for learners under 11 years. Of these 15 resources, almost half (7) were aimed the Engine (E) level, which is higher than the average across all 307 resources (27%). Most resources (185, 60%) were not aligned with a specific target age group.

2) Target audience: The target audience categories (Table III) distinguish between resources aimed directly at students (23%), those directed at teachers and students (56%), resources designed for anyone to use (17%), and resources aimed at teacher professional development (PD) (4%). Within the 12 (4%) resources for teacher PD, 10 (83%) cover the Social & Ethical (SE) level and 9 (75%) cover the Application (A) level. In contrast, the Machine (M) and Engine (E) levels are only covered by 4 (33%) resources, suggesting an imbalanced focus in PD content.

3) Type of resources: Resources were also categorised according to their type (Table IV). The distribution of teacher guide/curriculum resources across the SEAME framework points to a high emphasis of the Application (A) and Model (M) levels at 87% and 68%, respectively, as opposed to the Engine (E) and Social & Ethical (SE) levels at 23% and 49% respectively. The online activity and worksheet/tutorial resources, which tend to be more practical, have a lower-than-average coverage of the Social & Ethical (SE) level at only 27% but a higher than average Engine (E) level coverage at 38%. In contrast, 65% of the lesson plan resources include Social & Ethical (SE) content.

4) Software or hardware used: From our analysis of resource types 18 resources (6%) were classified as AI tools (Table IV). However, some AI tools were often used across other resource types, such as lesson plans, online activities or curricula. Examples of AI tools include the *Scratch* programming environment or AI applications such as *Quick, Draw!*. Hardware examples include robotics such as *Cozmo Robots* or the *Raspberry Pi* computer. We found that most resources (67%) make use of software tools while only 5% of resources use hardware tools (Table V). The remaining 28% of resources that do not include any software or hardware are either unplugged activities, books or purely theoretical explanations. The distribution of resources which use software across the SEAME framework heavily emphasises the Application (A) and Model (M) levels at 91% and 75% respectively as opposed to the Engine (E) level and Social & Ethical (SE) level coverage at 24% and 41% respectively.

TABLE IV
NUMBER OF RESOURCE TYPES ACROSS THE SEAME FRAMEWORK

Type	SE	A	M	E	Total
curriculum/ guide	45 (49%)	80 (87%)	63 (68%)	21 (23%)	92 (30%)
lesson plan	40 (65%)	48 (77%)	36 (58%)	15 (24%)	62 (20%)
worksheet/ tutorial	12 (27%)	37 (82%)	25 (56%)	17 (38%)	45 (15%)
online activity	8 (27%)	23 (77%)	22 (73%)	9 (30%)	30 (10%)
blog/ article	8 (20%)	31 (76%)	23 (56%)	11 (27%)	41 (14%)
AI tool	6 (33%)	15 (83%)	10 (56%)	3 (17%)	18 (6%)
webinar	8 (80%)	8 (80%)	2 (20%)	3 (30%)	10 (3%)
event	3 (60%)	5 (100%)	4 (80%)	2 (40%)	5 (2%)

TABLE V
SOFTWARE OR HARDWARE USED ACROSS THE SEAME FRAMEWORK

	SE	A	M	E	Total
software	84 (41%)	186 (91%)	153 (75%)	49 (24%)	205 (67%)
hardware	6 (43%)	13 (93%)	2 (14%)	2 (14%)	14 (5%)

B. Qualitative results

In this section, we present two case studies that show how resources cover different areas of SEAME framework. We also illustrate how resources were split up to disaggregate learning content and analyse these at a finer level of granularity.

1) Case study 1: The DAILy curriculum [24] is a 30-hour curriculum designed to develop middle school students' AI literacy. The curriculum incorporates learning activities at all levels of the SEAME framework, with each unit covering one or more levels. For example, the *Supervised Machine Learning* unit specifically focuses on the Engine (E) level by tasking students to role-play nodes in an unplugged classifying activity. Another unit, *GANs* [24], focuses on the Model (M) level by using ML models trained on different data to convert line artwork into original artwork. Finally, the curriculum focuses on the Social & Ethical (SE) dimensions by asking students to consider ideas of fairness and bias when looking at applications of AI.

2) Case study 2: AI and COVID-19 [25] is a teaching unit that focuses on the Social & Ethical (SE) level of AI by exploring the role of AI during the COVID-19 pandemic. The unit challenges students to consider its wider implications in their everyday lives, such as in medicine, games, and fashion. The unit forms part of a larger high school curriculum, *AI4ALL* [25]. The full curriculum is designed to develop the AI literacy of students with no prior programming or mathematics experience by focusing on the impacts of AI on students' everyday lives, their futures and wider society.

3) Summary: The resources detailed above represent two examples of how the learning content of different resource types (a curriculum, a unit) can be analysed using the SEAME framework. Moreover, they exemplify how the learning focus of each resource can be situated within a single level or overlap multiple levels of the framework.

C. Limitations and mitigating actions

The resources reviewed are a non-exhaustive snapshot in time of the AI/ML material available. While we cannot guarantee a representative sample, we have used a diverse range of sources to mitigate this limitation.

VII. Discussion

A. What resources are available to support K-12 teaching and learning about AI/ML?

Our analysis presents a complex picture of the landscape of AI resources with little concern for age-appropriateness or progression through topics, lack of appropriate teacher PD support, and an imbalance in terms of the areas of AI covered. These findings align with other recent work [12], [17], [26]. Where no target age is given, it might indicate a desire to create resources which are accessible without any knowledge prerequisites. However, teachers must then consider how best to incorporate resources into lessons. Likewise, only 4% of resources are designed for professional development despite over half of resources (56%) specifying a teacher/student audience. Research in K-12 CS education paints a similar fragmented picture at this stage of maturity [21], [27], [28].

B. How useful is the SEAME framework in reviewing AI/ML teaching resources?

Using SEAME highlighted the imbalance of levels across resources, with over a quarter of resources (27%) focusing on the Engine (E) and over 80% focusing on the Application (A) levels. Similar content gaps are highlighted by others [26], [4], [12]. Our results (Section VI-A3) indicated that practice-based resource types, such as online activities and worksheets/tutorials, have better coverage of the Engine (E) level, with instructional-based materials such as lesson plans including more Social & Ethical (SE) content.

Our analysis gave insights into how learning content overlaps different levels of the framework. When looking at resources that only cover a single level, 10 resources focused solely on the Engine (E) level, 12 on the Model (M) level, 46 on the Application (A) level and 5 on the Social & Ethical (SE) level. The remaining 234 resources covered at least two levels together. Additionally, we found only 28 of the 307 resources (9%) covered all levels, reflecting prior literature [12]. The focus on one or multiple levels might be indicative of the depth to which each resource focuses on its learning objectives. For example, from the 130 resources covering the Social & Ethical (SE) level, 121 resources also focused on the Application (A) level, 75 on the Model (M) level and 32 on the Engine (E) level. This points to the fact that in the design of resources so far, the SE level is predominantly presented alongside applications of AI in the world. However, it is less explained in combination with the Engine (E) and Model (M) level. This arguably misses an opportunity to explain the ways in which social and ethical issues are both created and potentially avoided in the building and training of AI systems.

The SEAME framework also highlighted the ways in which "black-boxing" is used as a scaffolding strategy [29], which is important in a novel and complex domain. For example, in the *Cooking with Neural Networks* resource from *KidsCode-Jeunesse*, we noted how AI is explained at the Engine (E) level, with a focus on neural networks. The resource hides the Model (M), Application (A), and Social & Ethical (SE) levels in order to focus on the underlying AI/ML systems at work.

Using the SEAME framework, we were able to discern between the distinct yet overlapping levels of AI and how resources focused on some levels while abstracting others. The framework can also be used by teachers when looking for content, by researchers looking to analyse the content of existing resources, and for resource developers to consider for which levels they wish to make their content suitable.

VIII. Conclusion

Our categorisation of AI resources found little support for teachers, such as lesson documentation or professional development, despite most resources being targeted at classroom use. We suggest that the SEAME framework provides an intuitive way to determine the core focus of AI/ML resources. In reviewing the usefulness of the SEAME framework, we found it afforded a practical evaluation of the levels, indicating that each level is a simple view, yet that overall it is a comprehensive framework. We found that the framework can be useful for researchers to analyse AI/ML resources to reveal gaps and overlaps of resources. For example, researchers may use the SEAME framework to discern whether some age groups have more learning activities at one level than another and investigate whether this changes over time. The framework serves as a reminder to consider all aspects of AI in all stages of learning. Finally, a simple yet comprehensive framework can help teachers navigate a complex topic, where there is a plethora of material for them to consider for classroom use.

In future work, we intend to consider the learning goals within each level of the SEAME framework. We would also like to conduct further in depth analysis of the resources with respect to the learning contexts, pedagogical approaches and quality of resources to address gaps found in the literature [26]. We would also like to consider the impact of the reviewed resources as they relate to the teaching and learning of AI. Our intention with the SEAME model is that it could be used by teachers, researchers, and resource developers to consider whether and how resources span one or more levels. In doing so, it offers a common language for thinking about the learning focus of resources. Finally, we propose that the SEAME model may be used towards reaching consensus goals for AI education, similar to work conducted in CS education [30].

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