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Teaching Tip
Using No-Code AI to Teach Machine Learning in Higher Education

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ABSTRACT

With recent advances in artificial intelligence (AI), machine learning (ML) has been identified as particularly useful for organizations seeking to create value from data. However, as ML is commonly associated with technical professions, such as computer science and engineering, incorporating training in the use of ML into non-technical educational programs, such as social sciences courses, is challenging. Here, we present an approach to address this challenge by using no-code AI in a course for university students with diverse educational backgrounds. This approach was tested in an empirical, case-based educational setting, in which students engaged in data collection and trained ML models using a no-code AI platform. In addition, a framework consisting of five principles of instruction (problem-centered learning, activation, demonstration, application, and integration) was applied. This paper contributes to the literature on IS education by providing information for instructors on how to incorporate no-code AI in their courses and insights into the benefits and challenges of using no-code AI tools to support the ML workflow in educational settings.

Keywords: Artificial intelligence, Machine learning, IS education research, Information systems education

1. INTRODUCTION

Machine learning (ML), a subfield of artificial intelligence (AI), focuses on the development, application, and analysis of computer systems capable of learning from experience. In a common variant, supervised ML, a system is shown numerous examples of a type of data, e.g., images or texts describing particular objects or phenomena, to train it to "learn" or recognize patterns in them. The system can then use this learning to predict new "unseen" data, i.e., data it has not previously encountered (Jordan & Mitchell, 2015; Kühl et al., 2022). Leavitt et al. (2021, p. 750) define ML as "a broad subset of artificial intelligence, wherein a computer program applies algorithms and statistical models to construct complex patterns of inference within data" (see also Bishop, 2006).

Massive increases in the processing power of digital technology and available data, in combination with better algorithms, e.g., deep learning algorithms (see Lecun et al., 2015) have set the stage for increases in the use of ML in many contexts (Dwivedi et al., 2021). Accordingly, organizations are increasingly deploying intelligent systems that can process large amounts of data, provide knowledge and insights, and operate autonomously (Simsek et al., 2019; Sturm et al., 2021).

As noted by Ma and Siau (2019, p. 1), "Higher education needs to change and evolve quickly and continuously to prepare students for the upheavals in the job market caused by AI, machine learning, and automation." Among other things, these authors argue that AI must be integrated into academic curricula, and not only those of science, technology, engineering, and mathematics (STEM) departments. However, despite abundant research on applications of AI in educational settings (e.g., Humble & Mozelius, 2022; Luan & Tsai, 2021), much less attention has been paid to instruction of students with non-technical backgrounds in ML's practical use and applications (Kayhan, 2022). As ML is commonly associated with technical professions, such as computer science and engineering, incorporating training in its use into non-technical educational programs, such as business- and management-oriented social sciences and Information Systems (IS) programs, is challenging. Similar issues have been raised in previous research on novel intelligent systems (Liebowitz, 1992, 1995) as educators have sought to integrate their use into business and IS programs. Recently, scholars have identified a need to integrate AI curricula in ways that enable students to develop a sufficient understanding of technology such as ML to apply it without detailed knowledge of AI algorithms (Chen, 2022). In this paper, we assess "no-code" AI platforms' potential utility in an effort to meet this need. In contrast to conventional AI systems, which require significant resources for installation and use, these platforms can be readily applied in educational contexts. Thus, they are easy-to-use and affordable forms of AI, and they guide users through the process of developing and deploying AI models, with no need to learn all about the intricacies associated with complex algorithms (Lins et al., 2021; Richardson & Ojeda, 2022). Hence, in this paper, we pose two research questions (RQs):

RQ1*: How can no-code AI be used to teach ML in non-technical educational programs?*

RQ2*: What are the benefits and challenges of using no-code AI in education?*

As already mentioned, "non-technical" refers here to non-STEM programs, such as business- and management-oriented courses. To answer the RQs, we present a teaching tip based on a case study of a master's level AI for Business course at Umeå University, Sweden, in which qualitative data were collected through interactions with, and observations of, the students. In the remaining sections of the paper: we summarize previous research on no-code software, describe the educational setting, describe the materials and methods used, present the results, discuss them, and finally offer concluding remarks.

2. BACKGROUND: TOWARDS "LIGHTWEIGHT" AI

In this section, we present a brief overview of the ML workflow (subsection 2.1) and then summarize the literature on the emergence of no-code AI platforms (subsection 2.2).

2.1 What is Machine Learning?

ML refers to a broad set of AI applications in which computers build models based on patterns they recognize in datasets and use the models to generate hypotheses about the world. Such models have myriads of uses in problem-solving software exploited in industrial and other organizations (Russell & Norvig, 2022). The general ML workflow (e.g., Chapman et al., 1999; Kelleher & Brendan, 2018; Schröer et al., 2021) begins with the creation of a training dataset from which a machine can learn something (Figure 1). Most applications today are based on supervised learning procedures through which a machine learns from labeled data, e.g., text describing an image, such as a photo or drawing of a dog or cat (Fredriksson et al., 2020). Then the training dataset is processed by an algorithm that "trains" the machine to recognize corresponding patterns. The outcome of this process is an ML model that can be used to make predictions regarding previously unseen data. During the training process, part of a dataset (e.g., 20% of the images in an image classifier case) is reserved for testing the model to avoid problems such as overfitting. Acceptable performance of the model on the test datasets indicates that it may be used to solve problems in real-world contexts, such as organizational settings, if the data provide relevant representations of the things or phenomena that must be recognized to solve the problems.

This description is a somewhat simplified version of the ML workflow. In reality, it takes several iterations of data collection loops and knowledge consolidation processes to create a model that provides meaningful results as experts may have diverging perceptions of what data represent (see Lebovitz et al., 2021 for a detailed discussion on experts' disagreements during data annotation).

2.2 No-Code AI

No-code solutions for software development have been subject to previous research as they enable non-programmers with little or no coding experience to produce various applications (Bhattacharyya & Kumar, 2021; Luo et al., 2021; Lethbridge, 2021; Sahay et al., 2020; Yan, 2021). By adopting low-code principles, enterprises may not only save time and costs but also narrow the gaps between business operations and information technologies, thereby enabling more rapid development and improvements in product and service quality (Rokis & Kirikova, 2022).

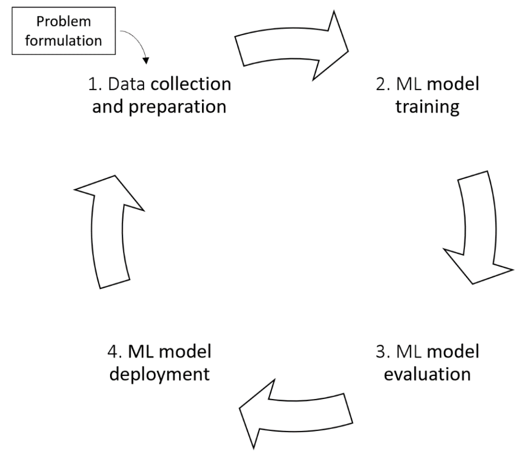

Figure 1. A Simplified Machine Learning Workflow

As noted by Sundberg and Holmström (2022, 2023), a new generation of "lightweight" no-code AI platforms—also known as AI as a service (Lins et al., 2021) or simply AI service (Geske et al., 2021) platforms—enables non-data scientists to train ML models to make predictions. Such platforms may match, or even outperform, coded solutions (Kling et al., 2022). Hence, no-code AI platforms may be widely applied in diverse settings, including citizen science, and as low-cost solutions in emerging markets. In the long run, it has been argued that access to user-friendly, low-code AI could democratize the adoption of these systems and stimulate their multidisciplinary use (How et al., 2021). For example, new "drag-and-drop" interfaces enable anyone to develop, train, and test AI algorithms in a few hours. In combination with a range of open-source solutions and plugins, this vastly simplifies algorithm development and deployment (Coffin, 2021). The advances are so rapid that within two years of Woo (2020, p. 961) stating that "AI might be able to automatically produce code," advances in generative AI, tools such as GitHub Copilot and ChatGPT are enabling code generation based on the input of a user. Computer scientists have always dreamt of writing programs that write themselves, and the dream is becoming a commonplace reality. Recently, academic researchers have also recognized the powerful potential utility of no-code apps in educational settings. For instance, Wang and Wang (2021) argue that no-code (or low-code) app development is transforming traditional software development practices and present a teaching case involving the development of a business app.

3. EDUCATIONAL SETTING

As noted by Holmström et al. (2011), rapid technological developments create challenges for maintaining up-to-date curricula for educating professionals who will work in environments with high levels of technology. They highlight several important issues regarding IS teaching, including the importance of ensuring that the students acquire practically relevant skills through the use of appropriate pedagogical approaches and generic types of knowledge. As AI is being increasingly adopted in diverse domains (Dwivedi et al., 2021), most, if not all, professionals will engage with or be affected by intelligent systems in their careers. However, as mentioned, AI is associated with the need to understand algorithms, and hence, skills rooted in computer science and engineering. This poses challenges for professionals rooted in other disciplines, not because they have nothing to contribute to AI or gain from its use, but because of a lack of fundamental knowledge of how, for example, an ML system works. A potential remedy, also already mentioned, is to use "lightweight" AI (Sundberg & Holmström, 2022) in the form of AI service platforms (Geske et al., 2021; Lins et al., 2021), which are easy to use with little to no installation requirements (as they are cloud-based) and have graphical interfaces that help users to train ML models. Here we present an approach for using such a system, the Peltarion (2022) "no-code" deep learning AI platform (hereafter "the no-code AI platform," or just "the platform"), in a higher education setting at the Department of Informatics, Umeå University, Sweden. The department is part of the university's faculty of social sciences and provides three undergraduate educational programs (on behavioral science with an orientation towards IT environments, digital media production, and system science) and two master programs (on human-computer interaction and IT management), together with individual courses.

The mentioned AI solution enables non-data scientists to upload data and then train and evaluate an ML model that can be deployed via an application programming interface (API). The platform guides users via a graphical interface together with suggestions regarding problem types, workflows, pre-trained models, and iterative improvements. The platform was used in an "AI for Business" course (15 credits) at Umeå University, to give the students hands-on experience in training ML models by engaging in a case-based task. The course is open for students with diverse educational backgrounds, as requirements for enrolment are 90 credits in informatics, computer science, business administration, media and communication studies, pedagogics, psychology, political science, sociology (or equivalent competence). In line with the course curriculum (Umeå University, 2022), the learning objectives of the exercise were to "Account for and explain the role of AI in organizational value creation," by giving the students first-hand experience of training ML models. The educational approach is further described in the following section.

4. MATERIALS AND METHODS

To address the RQs posed in Section 1, we followed a group-based project approach presented by Mathiassen and Purao (2002) in the course, inviting the students to engage in the development of ways of working and participating in communicative activities regarding "real-life" problems. As noted by Leidner and Jarvenpaa (1995), such approaches provide opportunities for students to understand the "messiness" professionals face in the industry, acknowledging the social situatedness of these contexts, and that the problems students will face are "unstructured, ambiguous, and immune to purely technical solutions" (Holmström et al., 2011, p. 2).

We applied the principles of instruction framework advocated by Merrill (2007, 2013) in the educational setting. This incorporates five principles summarized in Table 1: problem-centered learning, activation, demonstration, application, and integration. The framework provides an integrated, multi-strand strategy for teaching students how to solve real-world problems or complete complex real-world tasks.

Principle	Description
Problem-centered learning	Humans learn better when they solve problems, so learning is promoted when learners acquire skills in real-world contexts.
Activation	Learning is promoted when learners activate existing knowledge and skills as foundations for a new skill. An important step here is to start at the learner's level. Activation requires learning activities that stimulate the development of mental models and schemes that can help learners incorporate new knowledge or skills into their existing knowledge framework.
Demonstration	Learning is promoted when learners observe a demonstration of the skill to be learned, e.g., by exposure to examples of good and bad practices.
Application	Learning is promoted when learners apply new skills they have acquired to solve problems. Applying new knowledge or skills to real-world problems is considered almost essential for effective learning.
Integration	Learning is promoted when learners reflect on, discuss, and defend knowledge or skills they have acquired. The effectiveness of a course is enhanced when learners are provided opportunities to discuss and reflect on what they have learned in order to revise, synthesize, recombine, and modify their new knowledge or skills.

Table 1. Principles of the Educational Approach

The case presented to the students described a fictive organization, "WeldCorp," which specialized in welding, seeking to expand and acquire customers in additional geographical markets while retaining and automating quality measures. To assist the company, we invited the students to develop ways to use ML as a tool to assess welding points. The course module described in this paper consisted of a workshop, a Q&A session, supervising sessions, and a final seminar. Its content is further outlined in Section 5.1. Nineteen students attended the course (14 male and five female), with educational backgrounds including bachelor's degrees in business and administration, computer science, and behavioral science. The empirical materials used in the study presented here, as summarized in Table 2, stem from interactions with the students, the no-code AI platform, and teachers' reflections.

These materials allowed us to both provide educators with recommendations for using no-code AI and present interesting findings on the benefits and challenges associated with these platforms' use in educational settings. We identified the benefits and challenges by subjecting the empirical data to thematic analysis (Braun & Clarke 2012; Clarke & Braun 2014) through inductively coding the students' activities during the module. More specifically, we coded the activities undertaken by the students in our empirical setting mentioned and observed in the materials and then aggregated them into themes, informed by the steps in the ML workflow presented in Section 2.1.

Materials	Source(s)
Students' feedback and course evaluations	E-mails, notes taken during the course, written evaluations and feedback from students.
Students' written assignments and presentations	Two written group reports, and two presentations during a final seminar.
Datasets, models and deployments created by the students	The Peltarion (2022) no-code AI platform
Observations	Teachers' experiences and reflections during and after the course

Table 2. Materials and Sources

5. RESULTS: USING NO-CODE AI IN AN EDUCATIONAL CONTEXT

This section is divided into three parts. In line with Lending and Vician (2012), in Section 5.1 we provide a description of our educational procedures to enable instructors to adopt our approach. Then, the benefits of using no-code AI in education are presented in Section 5.2, followed by the challenges we experienced in Section 5.3.

5.1 Detailed Educational Approach

The course module was initiated on December 2, 2021, and the final seminar was held on January 10, 2022. Thus, the duration of the module was a little over a month, including Christmas holiday breaks. The module was initiated with a 3-hour workshop session that included an introduction to ML, followed by a demonstration of the no-code AI platform's functionalities and a description of the group assignment. The information presented and considerations applied in this workshop are summarized in the following text.

As the students came from different backgrounds, it was clearly stated that the workshop would not include a deep examination of phenomena such as neural networks and would focus instead on providing students with sufficient information to get hands-on experience in training ML or deep learning (DL) models. An overview of the current status of ML was presented as increases in the scale of datasets, together with improvements in algorithms and processing speed have increased capabilities for machines to "learn." This included a presentation of:

- A short video showing how neural networks "see" things in image data: https://www.youtube.com/watch?v=xS2G0oolHpo&ab_channel=NOVAPBSOfficial
- Figures from an overview by Hilbert and López (2011) of how the capacities of storing data rapidly shifted from analogue to digital formats.
- A comparison of the world's fastest supercomputer in 1997 (ASCI Red), which reached a speed of 1.8 teraflops, and the SONY Playstation 3 video game console that reached the same speed nine years later.

Then, the differences between supervised, unsupervised, and reinforced ML were briefly presented. We emphasized that the module would focus largely on supervised learning, the basis of most commercial and industrial applications of ML today, so the students would need to engage with data labeling. This is important for two reasons. First, collecting and annotating data are crucial but time-consuming activities that take most of the time spent during ML development (Fredriksson et al., 2020). Second, if this element is neglected or poorly done, the resulting ML models will perform poorly and generate inaccurate, irrelevant, or even harmful results (Sambasivan et al., 2021).

Next, the lecture outlined the kinds of problems that can be solved by using ML. As noted by Kayhan (2022, p. 123), "Many students lack the preparation for the workforce because they cannot conceptualize valid input-output relationships for the problems they propose to solve using ML." Thus, despite the widespread hype surrounding intelligent systems, there is a lack of specificity of the kinds of problems algorithms can actually solve. As noted in Section 2.1, ML is a set of technologies that involve the training of algorithms to create models that can provide predictions concerning previously unseen datasets. Hence, ML cannot solve "general" problems such as "increasing efficiency" or "improving quality": they need specific problem formulations accompanied by relevant datasets. Thus, in this part of the lecture, we presented a checklist for determining whether ML would be suitable to apply:

1. Do you have a use case?
2. Can the use case be solved by AI/ML (or simpler means)?
3. Do you have data?
4. Do you have annotated data?

We also presented examples of various problems/use cases that ML can solve, such as anomaly detection, classification problems (identifying features in texts and images), building chatbots based on text similarity functions, and various regression problems, such as predictions of sales and housing costs. Before demonstrating the functionality of the no-code platform, we described the ML workflow, both generally as shown in Figure 1 and more specifically for the Peltarion platform, as displayed in Figure 2. Although the platform is now discontinued, this workflow (data collection + preparation, training, evaluation and deployment of an ML model) is at the core of most ML development efforts and protocols applied in other no-code AI platforms (such as BigML, Amazon SageMaker, Google AutoML and Teachable Machine).

After presenting the above activities in a traditional lecture, supplemented by visual aids and other materials, we turned our attention to the no-code platform.

Figure 2. The ML Workflow in the No-Code AI Platform

An important step during the use of no-code AI is to check the requirements of the platform of choice in terms of data types (e.g., tabular, images, or text). Familiarity with the selected platform's tools for processing and labeling data is also important. Thus, to provide participating students with an understanding of how the no-code AI platform handled different data types, we used free datasets from Kaggle (2023):

- To explore tabular data, we used the popular "IRIS" dataset, which can be used to predict the species of a flower based on the size of petals and sepals.
- For image data, images of cats and dogs can be used to train a binary classifier. Images of craters on the Moon and/or Mars can be used to train object detectors (if this feature is available in the platform. See Figure 3 for an example).
- Data from the Internet Movie Database (IMDB) can be used to predict whether a text is "positive" or "negative" to train a model that can make predictions based on NLP (natural language processing).

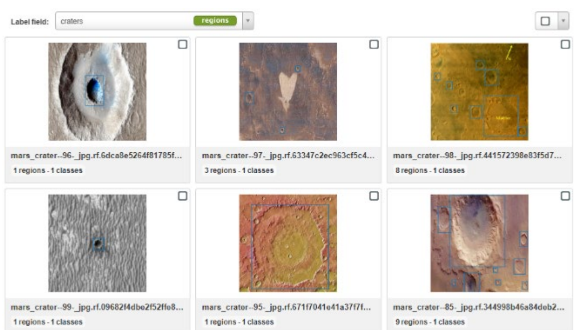

Figure 3. Image Annotation for Object Detection in the BigML Platform

During the demonstration of how to upload data, we briefly described and outlined procedures for various possible formats for tabular and text data (e.g., CSV and npy), but not procedures for connecting to "data warehouses" such as BigQuery or Azure Synapse, as it was irrelevant for the planned task. Instead, we focused more on how to upload image data to the platform, as this was the type of data the students would handle in the following case. An advantage of using no-code AI in such cases is that images can be annotated by placing them in folders that act as labels, compressing them into zip files, and then uploading them to the platform. The platform then takes care of processing and cropping the images to standardized formats. A negative effect, which we informed students about, is that important features near the edges of the images may be cropped.

Then, we demonstrated various examples of ML problems, and their possible solutions using the no-code AI platform. Depending on the type of data involved, the platform suggests certain problems as the user chooses the input (data) and one or more targets (labels). As mentioned, examples of such problems include image classifications and image/text similarity searches. Thus, in this phase, we also displayed examples of ways to use pre-trained ImageNeT-based and NLP-based (e.g., BERT) models for classifying and predicting patterns in images and texts, respectively. The use of pre-trained models relaxes the requirements to use big datasets, as users can fine-tune these models with their own data. Links to online tutorials and datasets (e.g., Kaggle) were uploaded to the course teaching platform, for students who wanted to proceed by experimenting with different types of data and problems.

In another important part of this demonstration, we showed how ML models can be evaluated. This is done by splitting the dataset(s) into a training set and test (and/or validation) set. The algorithm is not exposed to the test set during training, so it can be used to evaluate how a model performs on previously unseen data. Common pitfalls, such as data bias and overfitting, were also introduced during this session. The platform enabled the generation of two indicators that are commonly used for evaluating models: receiver operating characteristic (ROC) curves and confusion matrices, which are especially useful for enhancing students' understanding of the output of ML models, and why their deployment requires careful consideration. Essentially, an image model outputs a probability of what it thinks is present in an image, e.g., "0.76 cat." Depending on the problem at hand, and associated requirements, a threshold can be set to determine how "certain" a model must be before it can classify something. Important measures here include accuracy, recall, and precision. While accuracy is a measure of a model's overall performance, there is always a trade-off between recall and precision. Students can be taught the relevance of this tradeoff using two types of examples: ML-based spam filters, and medical diagnostics. When constructing a spam filter, it is often more important to minimize the number of "false positives" (potentially important emails that end up in the spam filter) than the number of "false negatives" (spam emails that end up in the inbox). Thus, precision is a good measure for such a model, as it assesses whether what is being classified as "spam" really is spam. In contrast, during medical diagnosis, avoiding false negatives is often much more crucial than avoiding false positives (as assessed by a recall measure), because wrongly classifying ill people as healthy can have severe consequences for them. For understanding such issues, knowledge of ROC curves is important because they illustrate three key aspects of ML models. First, they output probabilities (in contrast to "exact knowledge"). Second, configuring these outputs involves active choices of thresholds. Third, these choices entail trade-offs between different evaluation measures.

At the end of the demonstration session, the students were divided into two groups and assigned the problem-centered task of helping "WeldCorp" use ML as an instrument to assess the quality of their welding joints. A rubric for the task provided a backstory, stating that WeldCorp was launched in 1994 in Gothenburg, and subsequent expansion to other Swedish cities led to the CEO experiencing problems with maintaining quality control. So, s/he is now turning to ML for this purpose. The rubric then told the students:

Your assignment is to help WeldCorp sustain its growth by leveraging machine learning. Specifically, your task is to analyze welding images (images of good and bad welding points) to develop a model – using the no-code AI platform – that can be useful for WeldCorp in a quality assurance context.

1. *Describe and justify your choices regarding the data processing, problem selection, and model training in the no-code AI platform.*
2. *Describe how you evaluated your model's predictions. Are they accurate enough to use live for WeldCorp? Why/why not?*
3. *Discuss: What could be done by WeldCorp to improve the model's results? How would they implement this type of solution in their business?*

An important aim during this assignment was to prompt students to think about and justify their choices during training, and the output of their model(s), rather than simply striving to optimize the performance of the model(s). As the module is a part of an AI business course, we also wanted the students to discuss how WeldCorp could integrate AI into their organization.

The students were divided into two groups. The start of the course included a presentation exercise in which the students were asked to state their names and educational background. As two of the students had experience in computer science, we intentionally placed these students in separate groups. To get the students started, they were given a small dataset of 157 images of good and bad welds. The groups were then given enterprise accounts providing access to the no-code AI platform. Before engaging in a similar project, we advise instructors to carefully assess the kinds of user configurations that candidate platforms offer, as their user management options vary, and potential issues must be addressed before the students attempt to use them.

Five days after the initial workshop, a Q&A session was held with the student groups. No instructions were given before this session and the content was largely based on the students' queries. Most questions concerned data. This was consistent with expectations, as models trained using the intentionally limited dataset handed out during the previous session would perform badly, regardless of the platform settings that the students chose. As already mentioned, data collection and processing play a key role in ML, and "there is no AI without data" (Gröger, 2021, p. 98). Illustrative queries from the students concerned the quality of the supplied dataset, tentative workarounds, and image formats. However, the main conclusion the students drew was that more data was needed to train a model that would produce relevant results.

Between the Q&A and final seminar, the students were supposed to email or book appointments with the responsible teachers if they needed supervision. The teachers could observe and aid the students as they uploaded data and then trained and evaluated ML models. After the Q&A session, we observed how the students engaged in data collection and uploaded larger datasets with various images to the platform. As the students aimed to train models based on a binary classification of good and bad welds, they needed two labels ("good" and "bad"). The students applied the procedures previously demonstrated to them, trained several models, and iteratively fine-tuned the platform settings, using several sources of data, including social media, Google image search, and Kaggle.

While the workshop and Q&A session were held on campus, the final seminar was held via Zoom (January 10, 2022) as this was during a time when staff and students at higher education institutions were gradually returning to campus after the COVID-19 pandemic. The written assignment included the following instructions:

You will be presenting your results both in the form of a short paper, max ten pages, and orally in the final seminar. During the seminar, each group will get 30 minutes to present their results. You must also participate actively by answering questions and comments regarding the presentation. Your short paper should begin with a cover page on which you state the names of the group participants, the name of the course, and the semester. It is to be handed in at the start of the seminar.

During discussions in a final seminar, the students were encouraged to reflect upon the ML process, to enable them to integrate their acquired skills. In addition to discussing the ML workflow, the students also proposed ideas for operationalizing their work in a live setting, such as using automated cameras to feed data on welding points for evaluation by the DL model. In this seminar, the teachers mainly played a facilitating role, as the students posed questions and reflected on their results. The students received pass or fail grades for the task. To pass they needed to:

- Present a logically coherent suggestion for WeldCorp, both in writing and orally during the seminar.
- Formulate results and associated discussion in a grammatically correct way and with consistent use of concepts and terms.

The teaching activities outlined above are linked to the five instruction principles and summarized in Table 3. Depending on the course, and available data and case(s), these activities can be varied. For example, the workshop can be divided into two separate events, with an initial lecture focusing on theoretical aspects of ML, followed by a more hands-on workshop. Moreover, the group case can be presented as an individual or pair-wise task, although this might neglect the collective character of data work.

5.2 The Benefits of Using No-Code AI in Education

This subsection presents the observed benefits of using no-code AI to teach ML, which are described below and summarized in Table 4.

5.2.1 Benefit 1: Visualization of Data and Provision of a Graphical Interface for Uploading Data. As already mentioned, a crucial and time-consuming part of working with ML is collecting and processing data. As the no-code AI platform automated many parts of the ML workflow, students had time to spend during the exercise on consideration and labeling of the data. This was an anticipated and important part of the task, especially as previous studies have highlighted tensions among people involved in labeling data for supervised learning (Lebovitz et al., 2021).

In their course evaluations and written feedback, the students heavily emphasized an increase in their awareness of the importance of data, and how the no-code approach enabled them to focus on important features of the datasets used, potential flaws in them, and problem-solving rather than model-optimization, as illustrated by the following three quotations:

Principle	Description
Problem-centered learning	The students were presented with a case of a welding company, WeldCorp, seeking to expand and scale up its business while improving quality control. To help these efforts they were encouraged to apply ML to differentiate between good and bad weld points.
Activation	Since the students had diverse educational backgrounds (business and administration, computer science, and behavioral science), we chose to use a no-code AI platform. This enabled them to incorporate previous skills and work during the course, even if they lacked previous experience in data science.
Demonstration	We showed the students several examples of ways to train ML models via the no-code AI platform. Students were encouraged to take tutorials and experiment with different types of open datasets (e.g., table, text, and image-based), and problems that can be accessed through the platform.
Application	The students were divided into two groups, and each student was given access to an enterprise account enabling them to use the no-code AI platform to address a new type of problem by applying the previously demonstrated procedures.
Integration	Students were encouraged to reflect on their learning during the final seminar in both a survey and the course evaluation. During the final seminar, they were also expected to learn from each other by preparing questions for the other group.

Table 3. Activities That We and the Students Engaged in, Linked to the Five Principles of Instruction

"I've obtained practical knowledge and experience of the impact of data. And I've seen the impact of flaws in the dataset first-hand. Thus, I think this was an optimal learning method considering our (and my) educational background." – *Student Evaluation*.

"[I've learnt] that data matters! The choice, generating and cleansing of data is crucial." – *Student Evaluation*.

"For me, the barrier to understanding the practical use of AI (or to ever try it myself) has been my lack of programming and coding skills. With the no-code approach, I got the opportunity to try experiments and thus got a "black-boxed" grasp of how it works. With that, I could focus on the problem that I wanted to solve, the learning dataset and its effect on the results, and also on the result itself. So, I think I learned more about AI in this course than I have in all the other courses combined, and that is without any code." – *Student Evaluation*.

Both groups chose to label their images in a binary fashion as "good" or "bad." To establish the consensus required for creating "ground truths," one of the groups formalized the data labeling process in their report with a "weld quality framework." The other group strongly engaged in data augmentation as they extended their dataset 4 to 5-fold by manipulating the images by zooming, cutting, and rotating them. These slightly different approaches were displayed in the results and reflected upon in the student reports. While the group that applied data augmentation focused more on the performance of the models they created, and thus achieved better measures (lower rates of false positives or negatives), the other group focused more on trying to explain the output of the models they created, i.e., why the models made certain predictions.

5.2.2 Benefit 2: Access to a Portfolio of Pre-Trained Models, Tutorials, and Datasets, as Well as the Automatic Selection and Fine-Tuning of Algorithm(s) for Training. Both groups ended up using a pre-trained model (EfficientNetB0) to solve an image classification problem (single label) in the platform. Each group formed training, validation, and test sets, respectively, containing 80%, 10%, and 10% of their full datasets (images), which is common practice and a default option in the platform. The students refined their models' outputs in two ways. First, they iteratively adjusted settings in the platform, such as increasing the training rate (with careful monitoring of the variances of performance measures of the predictions generated by splitting the dataset to avoid overtraining the model). The platform assists such adjustment by suggesting settings to enhance the models' performance, e.g., switching to a different pre-trained model, and modifying the learning rate (Figure 4).

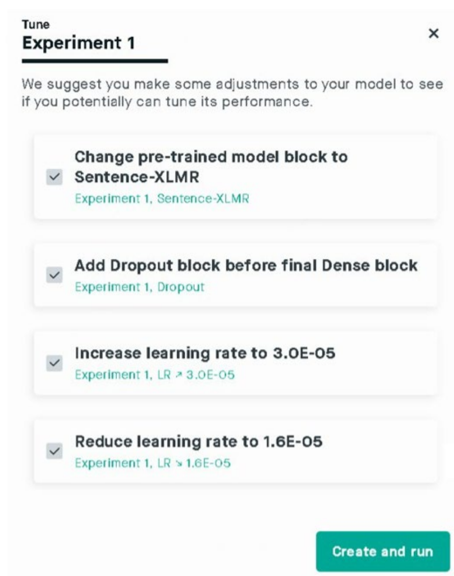

Figure 4. Suggestions to Improve Model Performance

5.2.3 Benefit 3: Visual Interface for Evaluating and Comparing the Performance of Models (e.g., Through ROC Curve- and Confusion Matrix-Based Analyses). Second, as particularly strongly emphasized by one of the groups, the students strove to ensure the data included were contextually relevant and suitable for WeldCorp's purposes. This was done after they received output from the ML model in the form of confusion matrices and ROC curves (Figures 5 and 6) and could assess whether certain types of images were incorrectly classified, identify potential biases in the data, and signs of model overtraining. Examples mentioned during the final seminar were images of painted welds, which would not be relevant in the industrial context they imagined.

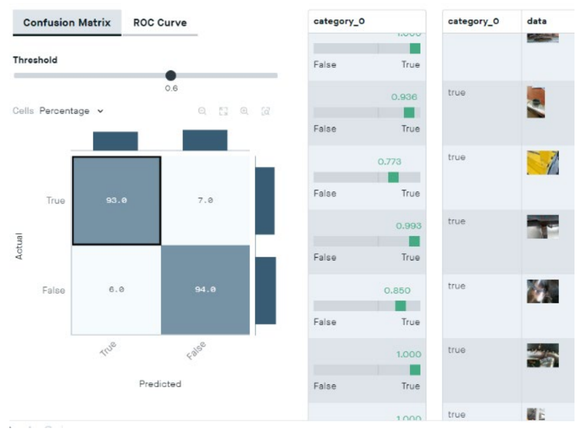

Figure 5. Illustrative Model Evaluation Output

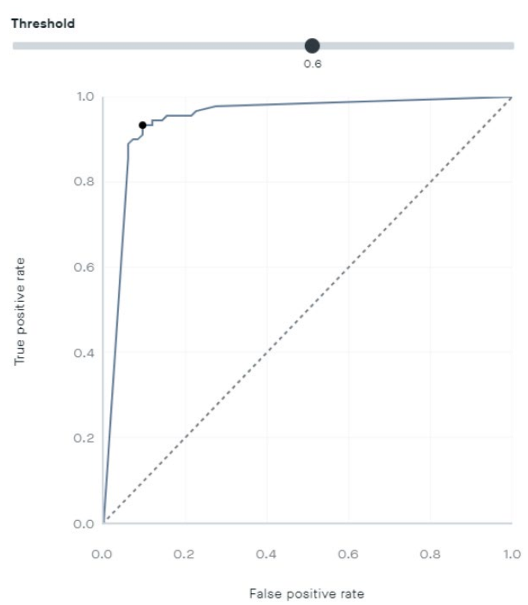

Figure 6. ROC-Curve From One of the Student Reports

Available features briefly mentioned in the course included tools to deploy the models created in the platform. This was not relevant to the assigned task, as the students were not expected to integrate their solution in a live environment; we presented a few paths to do so. Examples included plugins for common software (such as Excel, Google Sheets, and Bubble) and the ability to call APIs for easy integration of a model in an operating environment. The platform also includes a graphical interface for predicting new images, as shown in Figure 7. We used this function during the final seminar to show the students how their models performed on selected images of good and bad welds.

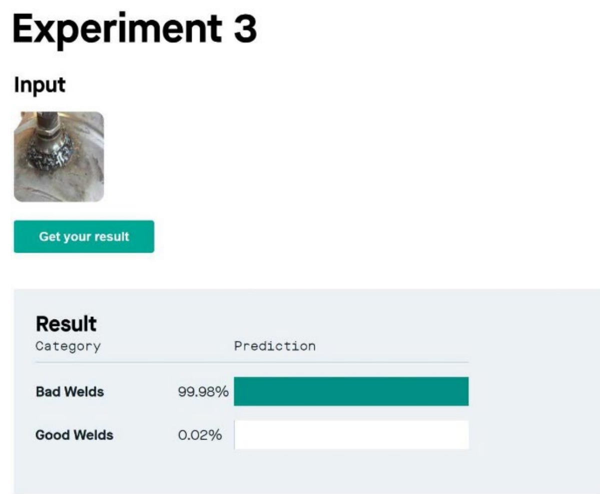

Figure 7. Results of a Test of a Model's Performance on Unseen Data During the Final Seminar

Thus, by simplifying parts of the ML workflow related to training, evaluating, and deploying models, learners can focus on data collection and interpreting outputs of the models to gain a sense of whether the chosen approach is suitable and feasible rather than engaging in model optimization. Based on our materials, we generated themes in the form of distinct ways that no-code AI facilitates learning about ML. These themes are described in Table 4.

ML workflow	Role of no-code AI
Data collection / preparation	Provision of a graphical interface for visualization, uploading, and processing data.
Model training	Access to a portfolio of pre-trained models, tutorials and datasets, as well as automatic selection and fine-tuning of one or more algorithm(s) for training.
Evaluation	Visual interface for evaluating and comparing the performance of models (e.g., through ROC curve- and confusion matrix-based analyses).
Deployment	APIs with complementary plugins to aid integration in organizational settings.

Table 4. How No-Code AI Can Facilitate Learning About ML

5.3 Challenges With Using No-Code AI in Education

Our approach was not free of challenges, including three summarized here. First, it is important to formulate a live case in terms of ML and make a preliminary judgement of the feasibility of the students collecting the necessary data during the task. Finding an appropriate case may be time consuming, but data repositories, such as Kaggle, may aid this process. Second, as mentioned, the teachers also encountered challenges related to user management routines before the module started and needed help from the platform owners to set up separate organizations for the students. These challenges highlight the importance of considering and addressing potential user management issues in advance and choosing an appropriate platform for the intended purposes. The market for these platforms is rapidly evolving. While the Peltarion platform is now discontinued, several alternatives are available, such as BigML, HuggingFace, and solutions from large tech companies (e.g., Microsoft Azure, Amazon SageMaker, Google AutoML, and Teachable Machine). These often come in both free and paid versions. For individual use, the free versions may be suitable for smaller tasks and datasets. A common advantage of paid versions is the incorporation of more collaborative features, which enables re-use and comparisons of student projects over the years. Whichever platform and version is chosen, it is also important to ensure that students do not upload sensitive data, depending on the regulatory context of the educational setting. Third, the student feedback included proposals that groups should be smaller in future versions of the course, as they experienced difficulties in engaging everyone simultaneously when using the platform.

6. CONCLUDING DISCUSSION

As the no-code approach enabled students to engage in collective data work the selected empirical setting provided an ideal opportunity to address our two questions:

RQ1: *How can no-code AI be used to teach ML in non-technical educational programs?*

RQ2: *What are the benefits and challenges of using no-code AI in education?*

We answer RQ1 by proposing a problem-centered approach to using no-code AI in higher education, with instruction to teachers. Regarding RQ2, we show how no-code AI can help to guide students through the ML workflow (data processing, model training, evaluation, and deployment), and present important challenges (ML case construction, platform selection and user management, and student group composition) that we encountered during the course.

Our contribution to the IS education literature is two-fold. First, we provide information for instructors on how to incorporate no-code AI in their courses. Second, we provide insights into the benefits and challenges of using no-code AI tools to support the ML workflow in educational settings.

Through this study, we have set the stage for incorporating a new generation of AI tools in IS curricula by showing how they can be used to support students in analyzing live cases, particularly in conjunction with an approach based on principles of instruction. By doing so, in this paper, we have proposed an innovative solution to an IS teaching need, grounded in theory and tested in an educational setting (Lending & Vician, 2012). The novelty of our approach is the application of tools that are usually only accessible to computer scientists to problems related to business practices and phenomena addressed in social sciences. As the no-code AI tools available are rapidly increasing and evolving (a few, of many, examples of contemporary no-code or low-code solutions that support the ML workflow include BigML, Huggingface, and Teachable Machine), we urge educators to keep track of this development and find approaches to implement such tools in their curricula, in combination with lessons on how to use AI in effective and responsible ways.

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