

AI Readiness Diagnostic Findings



Step 6: Basic Recommendations



Step 6 Overview

To find out how **you** can benefit from examining your institution through a '**data and AI lens**', contact our **AI & Data Science team** at hello@educateventures.com

- Once machine learning has been applied to your data, and you've identified the **patterns** and **relationships** between data sources, you can use **human intelligence** to relate these patterns to the particulars of your **challenge**
- For a simplified example: in an educational or educational business setting, that might mean discovering several different patterns, such as **student profiles**, through your application of machine learning, and then **relating** those profiles to answers from a **student survey**. You might discover:
 - How **confident** each of the different student profiles are when in particular teaching sessions
 - Do some profiles **interact** or **learn more** in peer-to-peer sessions?
 - How do the different profiles respond to **feedback**; is there a correlation between **engagement with feedback** and **increased knowledge retention**?
 - Has any **additional technology** boosted student

confidence based on those profiles?

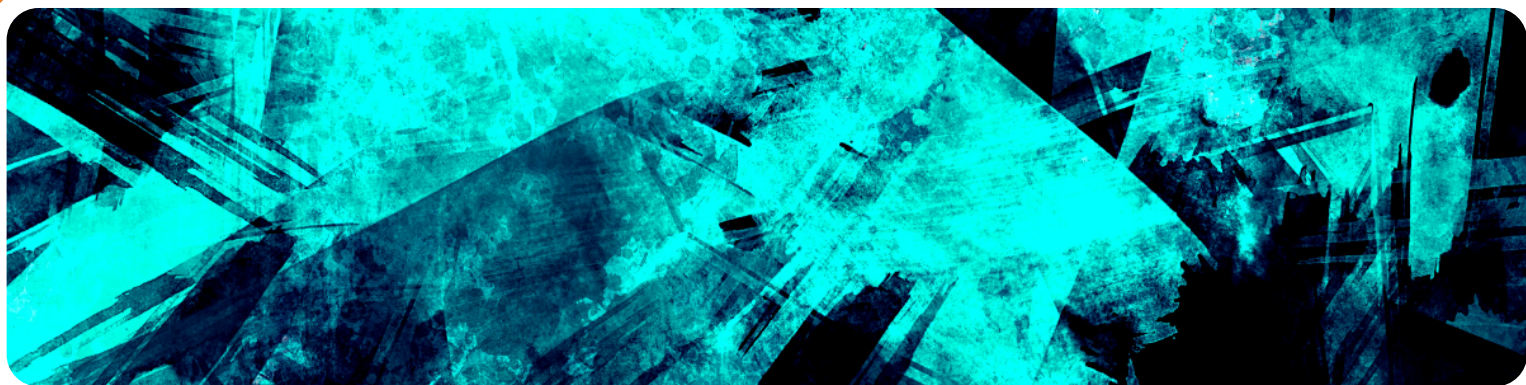
- Imagine how useful it might be to have all that **siloed, unconnected data** that you had at the beginning of the whole process now working in concert to show you patterns you hadn't even thought to look for in, for instance, **budgeting** and **spending**, or **teacher** or **student confidence**, **learning behaviours**, **recruitment**, **marking**, **timetabling**, or **administration**
- Acting on those findings, and being confident at an **organisational level** that how you are tackling your challenge is **supported by the data**, is a great and rewarding feeling, and moreover, it can help you **organise** your institution in a tighter, more methodical manner, and understand the challenge better, so that you are not falling into **traps**, **constructing misconceptions**, or making mistakes with **similar challenges** in your school
- **Key Takeaway:**
 - Including **human intelligence** at all stages of the process of leveraging AI, from **articulating your challenge**, to **cleaning** and **organising your data**, will mean that at the end of the AI Readiness exercise, you're able to materially address and improve the **conditions** in which your challenge appears, you're able to understand it in greater **depth**, and actually do something to **solve** it for people

Recommendation: What to do with the findings from AI applied to data

SUMMARY: having found **patterns** in the data from an **unsupervised machine learning algorithm**, the **next step** is to ask how these **patterns** relate to the **other data** we have access to

- Learning from the analysis of the data related to our challenge is **crucial**. Revisit **Step 2** in the AI Readiness Framework to find out how and why a particular challenge is selected. Recall that our particular fictional challenge was around **maintaining the quality of teaching and learning online** during the **pandemic**
- To illustrate how we prepared our data for analysis, we used the analogy of **cooking**, and the baking of raspberry souffles, drawing attention to the fact that not all cooking methods are right for all **occasions**. The choice depends on the sorts of **ingredients** (the data) that we have, and the sorts of **end product** we want to produce

- The same is true for **machine learning**. We had to do a huge amount of **processing** before we got to the stage of being able to apply machine learning AI to the data. Cleaning and processing the data could take approximately **90%** of your time
- Using the context of our fictional challenge, we produced four **datasets** (revisit **Step 5** in the AI Readiness Framework to see how these datasets were produced), and we had our four different sorts of datasets in the same way that we had our **ingredients** in the kitchen scenario
- How do we get those datasets and turn them into something from which we can **learn**? How do we take those ingredients and turn them into our **souffles**? In our case it's about understanding what the data can tell us about the **challenge** that we've identified. And not only that, but what this process and outcome can tell us in order to help us understand **AI**, and the **potential** of AI for us and for our organisation



- In order to learn more about our **challenge** from the **output** from that unsupervised machine learning algorithm, the **question** we should ask now is:
 - Could it be that our patterns of clustered data relate to other data that we have access to?**
- For example, could it be that this clustered data relates to data from the **survey** that we conducted that told us **confidence levels** (amongst other things) for our students?
- Could it be that there's a **difference** in the confidence levels of students in the different **profiles**? What might that mean for the **suitability** of this type of interaction for different sorts of students?
- We don't know. This is not a question of **causation**, we're not saying that confidence levels **cause** particular profiles, but we're looking to see if there's a **relationship** between the confidence levels of the students and the **nature** of the profile they are part of
- If we think about the **lowest level of confidence** here – and in this example we're saying that we've seen a relationship between this **level of confidence** and **membership of the group** who were **mainly working online** and **mainly in whole group sessions**: is that something that has an impact on students' **confidence**? We don't know, whereas the students **learning at home** and **using not just the online environment, but also some additional technology** have a much **higher rating** in their confidence

- We have our integrated, cleaned, collated, **datasets**, but we can also explore the **individual parts** of that dataset to see what we can learn from **both** those **individual parts** and from the **whole of the data**
- Reflecting on the model below, we can ask a fundamental question related to our fictional challenge: **what is there to learn about the consistency of teaching and learning in online interactions during the pandemic?**



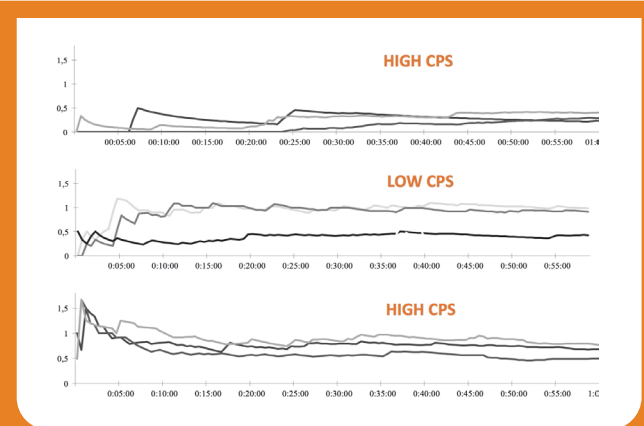
Recommendation: Identifying relationships

One of the factors that we know from **existing psychology research literature** is that for students whose **eye gaze** is **synchronised**, a **correlation** arises between that synchronisation and **effective collaborative problem solving**.

That does **not** mean that just because students are looking at the **same thing**, or looking at the **same person**, they are collaborating effectively, but you can think of it as one little **signifier** – one data **snapshot** - that could be an **ingredient** in finding out whether students are collaborating effectively or not.

In a study performed at UCL, data was taken from eye tracking and eye gaze, and analysed to see whether not only is the student looking at the same thing or person, but also if they are **active**, **semi-active**, or **passive**, when working with other students in trying to build an interactive toy together.

Analysing those datasets produced the **graphs** in the image. The detail is not important for this preamble, but each graph represents **different groups of three students**. When the lines in each graph were **closest together**, that was when students had **synchronicity** in the direction of their **eye gaze**. The graphs factor in very small **time intervals** of 5 seconds. The evaluator, as part of the research study, identified groups as being either **highly effective** at collaborative problem solving, or **low**.



- If we could also add this kind of **multimodal data** to our datasets in the example challenge we're exploring (that of maintaining the quality of teaching and learning online during the pandemic) we can **learn** a great deal more about our data
- For instance, we might be able to code such **eye tracking** and **eye gaze data** as having a **value** of:
 - **Two**, when one student is looking at another student
 - **Three**, when a student is looking at the screen
 - **One**, when students are looking at the same thing
 - **Zero**, when a student was looking at something else
- In our example challenge, we're dealing with **online learning**, so measuring all this could be difficult - many of our interactions are online - but perhaps in a smaller Zoom breakout room it would be possible to measure this
- If we think about how we can add in the analysis of the eye tracking data, where we'll be able to identify the **synchronicity** of different students' focus of gaze, with some

of the **profiles** we have clustered in the **recommendation above**, maybe we can learn something interesting

- Bearing in mind that a student gets a **higher score** for concentrating on the screen, and **nothing** for looking at something that isn't on the screen or another individual, if we take an **average score**, it would be interesting to see whether there is any **alignment** with our clustered profiles
- This is all just an **example** of how this kind of data can be immensely helpful and valuable in understanding what's happening in a **learning interaction**, both for a school and an educational business that has similar data. We could combine what we've got from our **confidence level data**, with these **eye gaze and synchronicity scores** and see if there was any additional information. Do they map to our four profiles in an interesting way?
- A **rich picture** of what is happening is starting to emerge, gathered from the data that has been analysed so far using an unsupervised machine learning algorithm, and then looking at the survey data individually

Who can help me?

*We are specialists in **ethical AI solutions** for schools and education and training businesses - **contact our team for help***

The EDUCATE AI and Data Science team was formed to consult on and co-design ethical AI solutions to complex problems in data-driven technology ventures and schools. Our team of computer scientists, educationalists, and world-renowned experts can take you from zero AI to a comprehensive evidence-led strategy and beyond, with effective, scalable AI-powered teaching and learning solutions.

To find out how you can benefit from examining your institution through a '**data and AI lens**', and leveraging the transformational power of AI to tackle your challenges, contact the **AI and Data Science Team** at EDUCATE Ventures Research at hello@educateventures.com.

Thanks for reading!

- The EDUCATE Ventures Research Team
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Further Reading

Below you can find a selection of resources, books, podcasts, webinars, and research papers appropriate to your stage of AI Readiness. Good luck!

- [AI for School Teachers, Byte-Sized Edition](#)
 - An easy-to-read 10-page byte-sized summary of the book of the same name, written by Professors Rose Luckin, Mutlu Cukurova, and Headteacher Karine George, members of the senior team actively developing and using the AI Readiness Framework from which these recommendations derive
- [Radio 4 Explores AI in Education](#)
 - The Learning Revolution is a new three-part BBC Radio 4 series on the future of education, created by education expert Alex Beard. The second episode looks at how teaching itself is becoming revolutionised by technology. As part of this, Century Tech's Founder Priya Lakhani took Alex to Shireland Collegiate Academy in Birmingham to see how their AI is improving the way students learn

