**Literature review – main points**

**1. Background**

Beck et al. (2015) provide a good overview on the different components that go into an Intelligent Tutoring System (ITS), which each requires different inputs and presents different challenges in terms of how it should be designed:

1. The **Student Model** – the information here reflects the system's belief of the learner's current knowledge state.

* Popular models include, for example, an overlay model of student knowledge (where a student’s knowledge is thought of as a subset of the teachers’ knowledge). However, this model might not reflect beliefs that are not part of the expert's knowledge base.

1. **Pedagogical Module** – a model of the teaching process, containing information about when to review, when to present a new topic and which topic to present.

* It uses information from the student model to determine what aspects of the domain knowledge should be presented to the learner.

1. **Domain Knowledge** – contains information the tutor is teaching.
2. **Communications Module** – the design of the communication flow between student and tutor.

* Important questions here include: how should the material be presented to the student in the most effective way?

1. **Expert Model** – a model of how someone skilled in a particular domain represents the knowledge. For example, in terms of online tasks, a tutor might compare the learner's solution to the expert's solution to pinpoint the places where the learner had difficulties.

**2. Educational Data Mining & Learning Analytics**

2.1 Overview

**Educational data mining (EDM)** has emerged as a research area to analyse unique data that arise in educational settings, with a view to resolve educational research issues (Romero and Ventura, 2013). This has been propelled by the rise of big data (where datasets are too large to be analysed by typical software), online learning and political demands for increased educational performance (Ferguson, 2012).

Some unique aspects of educational data include its specific hierarchies of data (at the keystroke level, answer level, session level, student level, classroom level, and school level) which each reveal different behaviours and levels of detail. There are also issues of time and context (Baker, 2010).

The main techniques within EDM are summarised below (Baker, 2010; Romero and Ventura, 2013; Clow, 2013):

|  |  |  |
| --- | --- | --- |
| **Method** | **Goal** | **Applications & examples** |
| Predictive modelling | Develop a model which can infer a single aspect of the data (predicted variable) from some combination of other aspects of the data (predictor variables). | Applications:   * Detecting student behaviors (e.g., gaming the system, off-task behavior). * Predicting and understanding student educational outcomes.   Example: Course Signals project at Purdue University predicted the chance of a student failing the course, allowing professors refer students to support services. |
| Cluster analysis | Find data points that naturally group together, splitting the full data set into a set of categories. | Applications:   * Discovery of new student behavior patterns; * Investigating similarities and differences between schools. |
| Relationship mining | Identify relationships between variables and (usually) to encode them in rules for later use. | Applications:   * Identify relationships in learners’ behavior patterns – diagnosing students’ learning difficulties or mistakes that frequently occur together. * Discovering which pedagogical strategies lead to more effective/ robust learning.   Example: Beck and Mostow (2008) used learning decomposition, a type of relationship mining, to determine the relative efficacy of different types of learning opportunities. They fit exponential learning curves to performance data, relating student success to the amount of each type of pedagogical support a student has received. The weight of each type of support then indicated its relative success. |
| Discovery with models | A previously validated model of a phenomenon is developed with prediction, clustering, or knowledge engineering. It is then used as a component for further prediction or relationship mining. | Applications: (analysis of research question across wide variety of contexts). |
| Distillation of data for human judgment | Data is distilled to enable a human to quickly identify or classify features of the data. | Applications:   * Human identification of patterns in student learning, behavior, or collaboration. * Labelling data for use in later development of prediction model. |

Other applications include:

* **Social Network Analysis (SNA**), which analyses and measures the relationships between entities in networked information. For EDM, it can be used to interpret and analyze the relations in collaborative tasks and interactions with communication tools.
* **Outlier detection**, which can be used in EDM to detect students with learning difficulties, deviations in the learner’s or educator’s actions or behaviors, and for detecting irregular learning processes.

Within the interpretation of results, Romero and Ventura (2013) highlight that the preferred systems for EDM are **white-box** DM models (which show the computation process, unlike black-box models). **Recommender** systems are also highlighted as being useful for non-expert data users, as it provides tailored suggestions about the results and how to apply them, rather than the entire DM model (Clow, 2013).

**Learning analytics (LA)** is a field strongly related to EDM with much overlap. Nevertheless, Ferguson (2012) differentiates the two in terms of their goals – while EDM seeks to extract value from big sets of learning-related data, LA mainly seeks to optimise opportunities for online learning (thus it does not necessarily rely on large datasets). In terms of drawing on artificial intelligence, LA primarily utilises machine learning techniques to detect patterns in data (Cooper, 2012).

Some other LA applications include the use of natural language processing and latent semantic analysis, which has made it possible to analyse textual qualitative data (Clow, 2013).

* For example, Larusson and White (2012) developed a “Point of Originality” tool which tracked how students developed originality in their use of key concepts over the course of numerous writing assignments. A trial of this tool on a computing course showed a strong correlation between originality scores using the tool and grades achieved for the final assessment.
* Similarly, several frameworks for analysing the nature of educational dialogue (particularly on online educational discussion) have been developed (Mercer and Littleton, 2007; Ferguson and Buckingham Shum, 2011). It has been used to identify where exploratory talk takes place, to highlight the most useful student discussions.

**Dynamic assessment** is another technique that has been studied, though much of the research focuses on its use within language learning. Fieldwork-based studies such as Kao and Kuo’s (2021) has shown that dynamic assessment poses the following benefits:

* More in-depth understanding of areas of curricula that students face.
* Prompt students to find correct answers with greater self-initiative (by offering hints to guide to the correct answer).
* In showing students’ actual scores and mediated scores (i.e. correct answers with prompts from the technology), it reveals the learning potential of students. This might reveal how students are likely to respond to future instruction – being slower or faster at understanding feedback.

2.2. Possible future developments

Wayman et al. (2010) strongly argues that the future of student data systems will be contingent upon the ability of school districts to acquire *interoperable* and *modular* data systems. This is because schools are better off buying commercial data systems due to the difficulty of building a system, and buying commercially would also allow for economies of scale (ibid).

In turn, these systems would need to be interoperable and modular to allow schools to adopt systems specifically tailored to their needs.

* Interoperability refers to data system interoperability, which would allow disparate systems to exchange data. This would be necessary when educational institutions wish to piece together independent systems to address their specific data needs.
  + Example: the Schools Interoperability Framework (SIF; <https://www.a4l.org/page/SIFSpecifications>), is an international data-sharing open specification initiative, with requirements for educational data to adhere to. Adherence to the framework would enable diverse applications to interact and share data.
* Modularity of data management software would allow schools to use certain parts and not others to suit their needs.

Current technological advancements in education includes (Wayman et al., 2010):

* Dynamic measurement which goes beyond measuring right or wrong answers and analyses other forms of student behaviour – this is linked to big data and EDM due to the amount of information collected.
  + Example: Tsai and Wu (2021) tracked student eye behaviour while completing an online task.
* Use of mobile devices which is changing how teachers and students interact.
* Intelligent or push technologies offers automatic recommendations based upon the data at hand. These technologies are becoming increasingly capable at tapping into practice-based, tacit knowledge (professional intuition).

**3. Barriers to adoption of data use/AI**

3.1 General challenges in using AI (McKinsey / Chui et al., 2018)

* **Need for data labelling:** current AI models still require supervised learning where humans must label and categorize the underlying data – this can be a sizable and error-prone chore.
* AI training requires **large training data sets**.
* AI systems present **explainability problems** – this refers to instances where the software does not provide explanations as to why certain choices are undertaken.
  + This could be a particular challenge in education where regulation and accountability is important.
* **Low generalizability of AI learning**: AI models have difficulty carrying their experiences from one set of circumstances to another.
* Data and algorithms remained **biased** despite data appearing objective – skewed data poses a particular challenge by resulting in biased AI learning.

3.2 Challenges of adopting data-driven decision making (DDDM) in education

Schildkamp (2019) breaks down the use of data in education into distinct steps: goal setting, data collection, sense-making, action. Within each, teachers and students face significant barriers and ethical considerations.

* Goal setting
  + Data use in education needs to be approached with specific goals or hypotheses in mind – however, Kippers et al. (2018) found that Dutch teachers struggled a lot in setting a plausible and measurable purpose in using educational data. Utilising data without a clear goal can then lead to issues later on in identifying useful patterns in the data, or forming a clear action plan.
* Data collection
  + **Informal data** (e.g. classroom discussions) is often neglected.
  + Certain forms of data is **easier to collect** (e.g. test data) which may lead to goal displacement – schools only focusing on goals they have data on.
* Sense-making
  + Teachers trust data more when they have acc**ess to the databases themselves** rather than reports generated from the data – likely due to the ability to explore and learn (Datnow and Hubbard, 2016).
  + **Collaboration** between teachers leads to more effective data use by allowing for greater inquiry about their teaching methods as a whole (Datnow and Hubbard, 2016).
  + Sense-making is not a straightforward process and data can be **interpreted differently** by different school staff (e.g. when data is fit into pre-existing beliefs, lack of data triangulation).
* Action
  + Data is often used to improve curricula, assessment and instruction. However, it might also be used in ways that are **not meaningful**, for instance in strategic ways (data manipulated to attain goals) or symbolically (does not lead to any action).
  + While teachers might have good ideas on how to take action, they might not actually have the **ability** to enact changes (Kippers et al., 2018).
  + There are some aspects of students and learning that are **simply out of teachers’ control** – e.g. childhood health issues, lack of parental support (Mandinacha and Jimerson, 2016). A learning analytics study by Jovanović et al. (2021) also found that most of the variance in student academic success were due to factors internal to students (i.e. learners' motivation, prior knowledge, and affective states) as opposed to external factors (i.e. teacher's role and availability of feedback).

*Other factors affecting data use (some underlying social/cultural factors)*

* Training programs for data use
  + Datnow and Hubbard (2016) highlight that teacher training programs need to focus more on what teachers **should do with data** once they have it, rather than just training them to access the data system. They also suggest that training needs to be **ongoing and continuous** to meet changing needs.
* Data use culture
  + **Overemphasis on accountability** and seeing student data as numbers to meet accountability goals rather than a record of student progress can lead to negative outcomes.
* Perceptions of what data and teaching means
  + Data use often focuses solely on **achievement and the deficits** of student capabilities, but can also highlight students’ strengths (Park et al., 2013).
  + Some teachers see the **performance of students as based on their inherent abilities** and thus might not view achievement data as useful to improving their teaching (Datnow and Hubbard, 2016; Schildkamp and Kuiper, 2010).
    - This can be reinforced by external policy demands (e.g. the USA’s No Child Left Behind policy which places more pressure on schools to meet achievement standards).
  + Teachers also differ in their views of the **purpose of assessment**, which affects how they view assessment data – Remesal (2011) highlights four distinct orientations: assessment for teaching, learning, accountability, and accreditation.
* School leadership
  + School **principals’ vision and leadership** has been shown to be important in setting tone of how the school views and handles data.
  + School cultures and practices are also important in setting up **trust** so that teachers do not view student data as something that will be used against them (e.g. for teaching evaluations and comparisons) (Datnow and Hubbard, 2016).

**4. Research gaps in data use for education**

4.1 The involvement of students in data use (“Student-involved data use”: SIDU)

Within the **sense making** process of data use, Schildkamp (2019) highlights that most attention is focused on teachers’ use of data, and not on policymakers or students. Similarly, there has been little attention paid to interactions between stakeholders within data use. These interactions take place within a vast range of settings – for instance, online vs. classrooms – which yield different outcomes and data needs.

Turning towards specific stakeholders, the field of academic analytics somewhat covers the decisions made by policymakers (Ferguson, 2012), and thus a particularly under-researched group remains **students.** Yet, student involvement is critical, particularly when linked to with achievement goal theory. The theory suggests that learners with “growth” orientation mindsets see failures as a process, while those with a ‘‘performance’’ orientation see feedback as verification of their inherent abilities (Jimerson and Reames, 2015). SIDU might then be able to nudge students towards “growth” mindsets.

However, as Jimerson and Reames (2015) highlight, the current lack of rigorous SIDU research might lead to haphazard student involvement with data, inadvertently reinforcing “performance” mindsets. Thus, they suggest that research must go beyond describing methods to involve students (e.g. policy best practices), but to study the process as it unfolds – asking how the students are involved, or what characterizes the conversations between teachers and students in the process.

4.2 Other gaps in data use research

*Methodological issues*

* A major gap in research is that studies are too theoretical and do not study in-depth classroom processes and thus where opportunities for data use might arise. In this sense, the practice of data use within schools is ahead of the research on data use (Jimerson and Reames, 2015).
  + Thus, Schildkamp (2019) proposes a new methodology of classroom observations for research in this area.
* Studies also often do not follow the use of data after it is collected to examine its impact on teaching. Questions that often remain unanswered are:
  + *Were intervention actions implemented after data is collected?*
  + *Did the actions lead to the desired effects among the different stakeholders?*
  + *Was the goal, as stated in the beginning of the process, reached?*

*Research themes (Mandinacha and Jimerson, 2016)*

* **Data skills need to be better integrated with educational content knowledge and pedagogical knowledge:** teachers need a baseline of each skill; data specialists are unlikely to have the teaching experience to effectively meld the two practices.
* **The choices of educators:** more analysis needs to be made done into *why* educators engage in certain practices (e.g. SIDU) and what they think happens within the process. This would allow researchers to understand the needs of teachers rather than assuming that data leads to improved teaching.
* **Definitions of effective teaching and models for how data use can contribute to it**: relatedly, the definition of what “effective teaching” means and how it can be measured is not explicit in the literature. Current work often presents a surface view of data use as inherently beneficial to teaching, but does not outline which aspects of the teaching process it should be used for.
  + This might lead to further resistance to the adoption of data use by teachers, if they do not understand why they need to engage in data use as the benefits do not seem explicit.
* **Better models for professional learning and collaboration processes for data literacy:**
  + While many studies advocate for greater training for teachers in terms of data use, there is little said about where and when such training should take place (e.g. should it be continuous training?).
  + This could be linked to theories on user acceptance of information technology (Venkatesh et al., 2003) and technology acceptance models (TAM).

**Possible research topics**

Some of the most relevant data mining/learning analytics techniques to KiteSense might include:

* Predictive modelling and relationship mining
* Recommender systems
* Distillation of data for human judgment
* Dynamic assessment

Specific research topics (based on research gaps)

* What are the underlying relationships in educational data that can be discovered without pre-defined hypotheses?
  + *Schildkamp (2019) highlighted that one important aspect of big data is that it often contains new patterns in the data that might not be identified with traditional hypotheses.*
  + *However, this might be difficult to explore experimentally without specific data mining software? Maybe can research EDM journals on their findings though it might be quite technical.*
* Are all parts of education and learning well captured by data? Or are there some things that data just cannot address? *(A broader question)*
* Conducting observational research on classroom practices to understand the thought processes and needs of educators.
  + Useful questions might be: what do educators hope to achieve when they implement data-based decision making? Do their actions follow through and why/why not?
* Similarly, observational research would be useful within student use of data – how does the presentation of data to students affect their morale, learning and classroom habits etc.?
* Beyond the findings from dynamic assessment (e.g. Kao and Kuo, 2021) or new learning analytics techniques (e.g. Tsai and Wu (2021) using eye tracking data), investigate the effect of such data on teaching practices – what do teachers actually do with this information after obtaining it?

**Resources**

**Key journals**

* Computers & Education (<https://www.sciencedirect.com/journal/computers-and-education>)
* Internet and Higher Education (<https://www.sciencedirect.com/journal/the-internet-and-higher-education>)
* Journal of Educational Data Mining (<https://jedm.educationaldatamining.org/index.php/JEDM>)
* Studies in Educational Evaluation (<https://www.sciencedirect.com/journal/studies-in-educational-evaluation>)
* Teaching and Teacher Education (<https://www.sciencedirect.com/journal/teaching-and-teacher-education>)
* Interactive Learning Environments (<https://www.tandfonline.com/toc/nile20/current>)

**Research groups and societies**

* Society for Learning Analytics Research – SoLAR (<https://www.solaresearch.org/>)
  + Research group at UC Irvine; they conduct an annual conference on learning analytics – the International Conference on Learning Analytics & Knowledge.
* International Educational Data Mining Society (<https://educationaldatamining.org/>)
  + They host an annual conference on educational data mining: <https://educationaldatamining.org/edm2021/>

**Readings**

Social media & learning

Sarapin and Morris (2015) Faculty and Facebook friending: Instructor–student online social communication from the professor's perspective

Hosen et al. (2021) Individual motivation and social media influence on student knowledge sharing and learning performance: Evidence from an emerging economy

Intelligent Tutoring Systems / online learning

Beck et al. (2005) Applications of AI in Education

Baker (2010) Data Mining [International Encyclopedia of Education]

Wayman et al. (2010) Student Data Systems and Their Use for Educational Improvement *[International Encyclopedia of Education]*

Wang (2014) Developing an assessment-centered e-Learning system for improving student learning effectiveness

Lima et al. (2021) Contrasting levels of student engagement in blended and non-blended learning scenarios

Educational Data Mining / Learning Analytics

Beck and Mostow (2008) How who should practice: Using learning decomposition to evaluate the efficacy of different types of practice for different types of students

Cooper (2012) A Brief History of Analytics (<http://publications.cetis.org.uk/wp-content/uploads/2012/12/Analytics-Brief-History-Vol-1-No9.pdf>)

Ferguson (2012) Learning analytics: drivers, developments and challenges

Brookings Institution/West (2012) Big Data for Education: Data Mining, Data Analytics, and Web Dashboards

Romero and Ventura (2013) Data mining in education

Clow (2013) An overview of learning analytics

Jovanović et al. (2021) Students matter the most in learning analytics: The effects of internal and instructional conditions in predicting academic success

Tsai and Wu (2021) Visual search patterns, information selection strategies, and information anxiety for online information problem solving

Kao and Kuo (2021) Diagnosing l2 English learners’ listening difficulties and learning needs through computerized dynamic assessment

Data Use in Education

Schildkamp (2014) Exploring data use practices around Europe: Identifying enablers and barriers

Jimerson and Reames (2015) Student-Involved Data Use: Establishing the Evidence Base

Kippers et al. (2018) Data Literacy: What Do Educators Learn and Struggle with during a Data Use Intervention?

Datnow and Hubbard (2016) Teacher Capacity for and Beliefs about Data-Driven Decision Making: A Literature Review of International Research

Mandinacha and Jimerson (2016) Teachers learning how to use data: A synthesis of the issues and what is known

Schildkamp (2019) Data-based decision-making for school improvement- Research insights and gaps

Singapore Education System

Chua and Gopinathan (2015) A Critique of Knowledge-Based Economies: A Case Study of Singapore Education Stakeholders

Lee et al. (2016) An ecological view of conceptualising change in the Singapore Education System

Others

Tulbure (2011) Do different learning styles require differentiated teaching strategies?

McKinsey/Chui et al. (2018) What AI can and can’t do (yet) for your business (<https://www.mckinsey.com/business-functions/mckinsey-analytics/our-insights/what-ai-can-and-cant-do-yet-for-your-business>)