HUMANE ARTIFICIAL INTELLIGENCE IN REAL ESTATE EDUCATION (AIREE) STEVEN BOYD

CQUniversity, Australia

ABSTRACT

AI in education (AIED) has the potential to close the achievement gap between students due to individual or social differences. The goal of AIED K-12 is to develop systems that enable personalized flexible and engaging learning and to automate mundane teaching tasks such as assessment and feedback.

This research identifies the potential benefits in AI adoption. The review extends to consider the risks and potential for unintended consequences by employing AI in real estate education. The later part of the research merges the AIED pillars of ethics, human rights, and a partnering framework for valuation, to create a partnering framework for real estate education. The AIREE partnering framework is presented for subsequent analysis.

Key words: AI in education, AIREE, partnering framework, real estate education

INTRODUCTION

Artificial intelligence will shape our future more powerfully than any other innovation this century. Anyone who does not understand it will soon find themselves feeling left behind, waking up in a world full of technology that feels more and more like magic. (Maini and Sabri, 2017, p.3).

This world of magic, enhanced by artificial intelligence (AI), is upon us. Many of the, now arbitrary, hurdles set by Grace, Salvatier, Dafoe, Zhang, and Evans (2018), such as translating languages, authoring high-school essays, driving trucks, and working in retail have been achieved with current advances in machine learning. Machine learning enables computers to learn on their own, identifying patterns in observed data, building models that explain the world, and predicting things without having explicit pre-programmed rules and models (Maini and Sabri 2017).

Since the 1970s, Artificial Intelligence in Education (AIED) has grown to encompass the application of the technology to learning and instruction (Southgate, Blackmore, Pieschl, Grimes, McGuire, & Smithers 2018). According to Southgate et al. (2018) AIED has the potential to close the achievement gap between students due to individual or social differences. The goal of AIED K-12 is to develop systems that enable personalized flexible and engaging learning and to automate mundane teaching tasks such as assessment and feedback. In higher education automation pursuits have AI learning to author essays for students with other systems attempting to authentic assessments and provide feedback. Through AI smart content creation, learnings are tailored and updated as markets and practices change. Algorithmic 'nudging' embedded in the systems, can influence a student's emotional state, engaging them deeper in their learning (Southgate et al. 2018).

This research extends beyond the benefits and barriers to embedding AI in education. The review considers the role of AI as a partner or even teacher in real estate education. It specifically contemplates how to partner with a system that is not human, one that exhibits influence and power without empathy. The later part of the research merges the AIED pillars of ethics, human rights, and a framework designed for real estate valuation, to create a humane partnering framework for real estate education.

PREVIOUS RESEARCH

The review looks again at what past research can tell us about the role of AI as a learner and a teacher in the future of real estate education. It extends to contemplate how to partner with an intelligent, but artificial system, one that exhibits influence and power but acts without empathy. In this review intelligent artificial systems are referred to as learners, teachers, partners, and peers, roles traditionally reserved for human, natural intelligence.

AI in real estate

AI refers to intelligence demonstrated by something artificial, or not endemic in a natural environment, such as a computer or other device or application, that functions '... as if possessing human intelligence' (Macmillan Publishers Australia 2021). Introducing human like intelligence or cognition into systems with existing and emerging power relations can lead to efficiency gains, in ways not expected with consequences not envisaged.

Acceptance of AI within disciplines and professions is by no means uniform, or a given. For example, Abidoye, Ma and Lee (2021) and Wilkinson (2018) suggest property valuers should see AI as a strategic partner instead of a threat. That said, in Abidoye et al. (2021) survey of Australian property valuers they found most valuers disagree and strongly disagree that AI should be more widely adopted in Australia. The explicit acceptance or not of AI may be a moot point given the dominance of such systems in forecasting and suggesting as evidenced in the flood of published research into machine learning and real estate markets.

AI learner

Providing artificial systems with access to data and helping them learn, may be our destiny whether we intend to advance machine learning or not. For example, in their review of emerging technologies, Starr et al. (2020) say our human survival in this rapidly changing [Real Estate 4.0] environment requires us to embrace opportunity and 'learn to experiment with emerging and maturing technologies' (p. 165). They take this further concluding '... new technologies are bound to be disruptive to the industry, reskilling and upskilling empowers real estate professionals to become as cutting edge and successful as the technologies evolving within the profession' (p. 165). Starr et al. (2020) are not alone embracing AI. In an Australian context Abidoye et al. (2021) call upon professional bodies to promote AI valuation methods to enable a sustainable practice.

AI would make a challenging learner, one that may achieve its goal or set outcome in a way that is unexpected with consequences not envisaged. Southgate et al. (2018) refer to the opaque nature of deep machine learning making it difficult to understand how and why an AI makes its decisions. Even though some decisions are hidden, as Viriato (2019) refers to in a 'black box', or lack of transparency in how a prediction is generated, there is still a need to trust the AI learner. Cajias (2020) refer to the deployment of AI as 'trusting the models you trained and integrating their results into your decision processes' (p.16). As explained by Cajias (2020), machine learning may find clarity and accuracy outside our established theory and data source, such as:

when applying a machine learning method to estimate the relationship, the machine will do everything to minimise the forecasting error. That means that it might be the case that Twitter, Facebook, and the amount of rain are better predictors of rents than the size, location, or the age of the dwellings (p.18).

In this way an AI student will 'challenge the econometrician to consider statistical-causality and econometricethical principles more intensely than ever' (Cajias 2020, p.18).

AI teacher

Artificial intelligence in education (AIED) has grown as a specialised interdisciplinary field to encompass the application of the technology to learning and instruction (Southgate et al. 2018). Jimenez and Boser (2021) acknowledge AI can help students learn better and faster as they get back on track faster by alerting teachers to problems the naked eye cannot see. According to Southgate et al. (2018) AIED has a broader scope with potential to close the achievement gap between students due to individual or social differences. The goal of AIED for education from Kindy to the end of school, year 12, (K-12) is to develop systems that enable personalized flexible and engaging learning and to automate mundane teaching tasks such as assessment and feedback (Southgate et al. 2018).

AIED focuses on developing intelligent tutoring systems, virtual pedagogical agents that function as a peer or instructor, embodied AI robots, and 'smart' classrooms (Southgate et al. 2018). Intelligent tutoring systems (ITS) simulate one-on-one human tutoring with similar reported positive effects on learning as human tutors, however Southgate et al. (2018) urge caution, noting it may not be suitable for all learners. Pedagogical agents refer to virtual characters, or avatars, integrated into learning technologies to facilitate instruction. They are created to add a social, emotional, and motivational component to learning technologies and to communicate with learners in natural human-like ways (Southgate et al. 2018). Southgate et al. (2018) relate smart learning environments to those with wireless communication, personal digital devices, sensors, and learning platforms that connect with each other to provide input into AI systems. The AI is then enabled to make decisions about regulating physical aspects of the environment (e.g., climate control) or learning systems. Adaptive learning

can use AI to alter the type of learning tasks, the difficulty of learning tasks, or the interface, to suit the needs of individual learners or groups (Southgate et al. 2018).

The computer-based learning environments adopted in higher education have the potential to capture significant amounts of data about how learners perform and engage with these systems. The analysis of that is the domain of learning analytics. Through learning analytics and education mining, with deep learning using artificial neural networks, content creation and learnings may be tailored and updated (Southgate et al. 2018) as markets and practices change. This setting of content and learning, presents an array of ethical questions and potential impacts on the students and their human rights. For example, AI recommender systems, such as the system Netflix uses, purposed to suggest academic pathways, can learn bias, and oppose human rights in recommending pathways for students to pursue (Jimenez and Boser 2021). Bias in testing, AI, and big data will always exist and therefore, limiting bias may be the wrong goal (Jimenez and Boser 2021). Instead, Jimenez and Boser (2021), propose:

policymakers who oversee testing systems must ask themselves how much and what type of bias is tolerable, as well as how to ensure that bias does not disproportionately affect students based on race, ethnicity, income, disability, or English learner status (p.5)

Another issue for the AI teacher, or lecturer, is the algorithmic 'nudging'. Nudging is embedded in AI systems for education, and affective computing applications to influence a person's emotional state. These engagement systems raise concerns about respect for the right of humans to make their own choices based on sufficient information (Southgate et al. 2018).

AI partner or peer

Before embracing or engaging with AI there are a series of ethical considerations. With respect to digitisation, Landau-Ward and Porter (Porter et al. 2019) support Kitchin's (2014) assertion 'digital disruptions cannot be viewed as simply neutral technologies that replace existing analogue processes, but are instead fundamentally social and political processes entwined with existing and emerging power relations' (Kitchin's 2014, cited in Porter et al. 2019). Braesemann and Baum (2020) echo these concerns discussing the importance and substantial efficiency gains from PropTech innovations while acknowledging their potential to 'change the whole fabric of the real estate market' (p. 20). They speak of datafied markets characterised by oligopolistic market structures, with a few firms or even monopolies offering the sole digital service available. To prevent the accumulation of market power Braesemann and Baum (2020) say 'users and owners of real estate need to become aware of the value of the data they are generating in renting, buying, or managing real estate' (p.20).

The socio political and power concerns shared by Landau-Ward and Porter (Porter et al. 2019) and Braesemann and Baum (2020) present an opportunity to exert power, control and influence over both, people, and machines (Wagner 2021). In discussing dark, or empathy deficient, approaches to management Wagner (2021) speaks of automation taking away a humanistic point of view, resulting in less criticism and leaders losing touch with what is right and what is wrong. Further, he introduces a greater threat with 'compared to automation, an even more important lever for the dark traits may be augmentation through AI' (Wagner 2021, p.2). Wagner (2021) says control of AI presents 'a new means of power, a new managerial tool that can be used for good as well as for bad purposes...' (pp.2-3).

The scary, or dark side of AI has been explored with the development of Norman, the world's first psychopath artificial system, according to the developers MIT Media Lab and Scalable Cooperation (MIT) (No date). According to MIT, Norman's psychopathic inkblot interpretations are the result of teaching the machine learning algorithm with biased data. Kumar, Singh, Bhatanagar and Jyoti (2019) speak of AI training requiring a controlled environment with correct and appropriate data provided. In supporting their view, they share how AI may be modified to accomplish something damaging on its pathway toward accomplishing its set objectives.

Engaging with intelligent systems

There are many complex and nuanced issues related to the design, implementation, and governance of AIpowered systems for education (Southgate et al. 2018; and Jimenez and Boser 2021). Some of the questions raised in this review of past research, including those around human rights are addressed in more detail in the IEEE Global Initiative on Ethics of Autonomous and Intelligent Systems publication 'Ethically Aligned Design: A Vision for Prioritizing Human Well-being with Autonomous and Intelligent Systems'. The IEEE

RMIT Classification: Trusted

publication seeks to establish societal and policy guidelines for autonomous and intelligent systems to remain human-centric, serving humanity's values and ethical principles (Institute of Electrical and Electronics Engineers 2017). The Australian Human Rights Commission have similarly shared a technical paper 'Addressing the problem of algorithmic bias', that presents questions (see Lattimore, O'Callaghan, Paleologos, Reid, Santow, Sargeant, & Thomsen 2020, p.55) and six consumer outcomes to promote responsible business use of AI and data (Lattimore et al. 2020). The Lattimore et al. (2020) consumer outcomes are presented in Table 1: Consumer Policy Research Centre consumer outcomes.

| Table 1: Consumer Policy Research C | Centre consumer outcomes |
|--|--------------------------|
|--|--------------------------|

| pu | Accessibility | Markets are inclusive, and all consumers have the right to access this technology and its application on an equal basis with others. |
|---|--------------------------------------|---|
| which would ss use of AI and | Accountability | Consumers have a clear route for seeking explanations and accessing appropriate redress from a responsible party if things go wrong. |
| nes, which iiness use | Agency | Consumers are empowered to exercise autonomy and freedom of choice in their interactions with technologies such as AI systems and the use of their personal data. |
| r outcon sible bus | Transparency | People are made aware when they are the subject of a decision-making process that uses an AI system. |
| CPRC consumer outcomes, w promote responsible business data, include: | Understandability and explainability | Individuals subject to these decisions are entitled to a meaningful, comprehensible explanation of the AI system and its decision-making process. |
| | Sustainability | Long-term implications of technology on consumers are considered and addressed throughout design and implementation. |

(Lattimore et al. 2020, p.57)

With respect to AIED Southgate et al. (2018) propose five pillars of ethical AI, being awareness, explainability, fairness, transparency, and accountability. They apply these to the design, implementation and governance of AI interventions as presented in Figure 1: Applying the Five Pillars of AI ethics to school education.

[Figure 1: Applying the Five Pillars of AI ethics to school education]

In real estate, Boyd (2021) designed an intelligent system partnering framework (ISPF) for the practice of valuation. The framework considered barriers and learnings from AI adoption in real estate as well as Sheehy et al. (2020) suggested series of pragmatic solutions for dealing with psychopaths. The ISPF, as presented in Figure 2: Intelligent systems partnering framework, presents five stages, reading from left to right. The first stage relates to identification of the AI, or intelligent system. It also captures interventions that have potential to share data or analysis for unidentified intelligent systems to utilise.

[Figure 2: Intelligent systems partnering framework]

The Australian Human Rights consumer outcomes, Southgate et al. (2018) AIED ethical pillars and the real estate ISPF by Boyd (2021) provide a foundation to guide AI use and partnering in real estate education. Through merging these outcomes, pillars and frameworks, a new intelligent system partnering framework for AIREE can emerge.

Framework Design for AIREE

The merged framework presents as an extension and modification to the Boyd (2021) ISPF. The initial identification stage (I) of the framework requires the proposed system to meet all the Human Rights consumer outcomes of: Accessibility; Accountability; Agency; Transparency; Understandability and explainability; and Sustainability (Lattimore et al. 2020). The fourth, due diligence (DD), stage of the framework incorporates a requirement to pass the AIREE DD. In this framework the AIREE due DD closely mirrors the questions presented regarding governance in Southgate et al. (2020) AIED pillars. This scope of the DD is focused on the following five questions being:

- 1. Is there a rigorous process for seeking user consent?
- 2. Do educators have access to independent technical expertise?

- 3. Does the system promote fairness?
- 4. Is the system transparent?
- 5. Are there protocols in place to respond and prevent harm?

The final question, requiring protocols to respond and prevent harm, is actioned in the final management (M) stage of the new framework. Specifically, if the system does not perform as prescribed, then there is a directive to initiate protocols to respond to potential harm and discontinue use. The AIREE partnering framework, Figure 1: AIREE Intelligent systems partnering framework, is presented.

Figure 1: AIREE Intelligent systems partnering framework

| Identification (I) | | Control (C) | Viability and suitability (V) | | Due Diligence (D) | | Management (M) | | |
|--|-------------------------------|---|-------------------------------|--|---|--|----------------|--|---|
| I1. Intelligent system or information sharer? Consider, is the proposed intervention an intelligent system or does the system have the potential to share your data or analysis? If so, does it meet all the Human Rights consumer outcomes of: 1. Accessibility | | C1. Do you have full control of the intervention? Consider, has it been developed internally or purchased for exclusive use? | Yes (V1) | V1. Do the projected benefits outweigh the anticipated costs and need for periodic human monitoring ? | | D1. Does the intervention pass AIREE due diligence, being? 1. Is there a rigorous process for seeking user consent? 2. Do educators have access to independent technical expertise? 3. Does the system promote fairness? 4. Is the system transparent? 5. Are there protocols in | Yes (M1) | M1. Does the system perform as prescribed? | |
| Accountability Agency Transparency Understandability and explainability Sustainability | | | No (C2) | | No (I1) | place to respond and prevent harm? 6. Can the intervention be acquired retaining full control? and 7. Can you set the performance benchmarks? | No (I1) | | uue) |
| | acquisition process) Yes (C1) | | Yes (V2) | V2. Do the projected benefits outweigh the anticipated costs and need for sustained human monitoring ? | | D2. Does the intervention pass AIREE due diligence? Can the intervention be acquired on terms that mirror an employment agreement? And | Yes (M2) | M2. Does the system perform as prescribed? Consider, has the role changed and are the same | Yes (continue) |
| | | | No (C3) | | No (11) | can you set performance benchmarks? | No (I1) | - system controls in place? | respond to ntinue – 11) |
| | | C3. Does a system or another person control the intervention? Consider, does another person or system set the terms and conditions for use? | Yes (V3) | V3. Do the projected benefits outweigh the anticipated costs, need for sustained human monitoring, and opportunity cost of intellectual property? | ⁽¹⁾ ⁽²⁾ | | Yes | M3. Does the system perform as prescribed? Consider if the role and terms and conditions have materially | No (initiate protocols to respond to potential harm and discontinue – II) |
| | No (alt. ac | | No (I1) | | No (I1) | | No (I1) | changed? | No (initiat notential h |

(Boyd 2022)

This framework provides a means for real estate educators to engage and learn with AI. The AIREE framework presents five stages. The first relates to identification of the AI, or intelligent system, and the potential to share and impact human rights. The second stage assisting with categorisation of the level of control afforded with the intelligent system. The control afforded to the AI determines the pathway through the final three stages. Viability and suitability relate to the cost benefit and promote the inclusion of human monitoring as a one of the costs. The due diligence stage relates to governance and the AIED pillars (Southgate et al. 2020). The final, management, stage relates to performance and if future analysis is required.

Further research and limitations

This research extends to the design of a partnering framework to inform the adoption and design of AI in real estate education. A defining and controversial aspect in exploratory and qualitative research of this nature relates to the active role of the researcher and their influence. With the main aim of qualitative research being to discover the perceptions and experiences of the participants so that the researcher can then extract themes (Levy 2006), the researcher becomes embedded in their study. As such, the interpretive nature of the research approach is affected by the researcher's interpretations, leading to potential misrepresentations of information, however unintentional (Brown 1992).

The AIREE framework is a novel addition by the author. While the framework was structured with consideration given to published research findings, specifically AI in education and property, there has been no empirical testing. Further research is necessary to provide justification for frameworks relevance in real estate education and research into engaging with intelligent systems.

CONCLUSIONS

As Maini and Sabri (2017) share, 'Artificial intelligence will shape our future more powerfully than any other innovation this century' (p.3). In higher education learning can be automatically tailored and made more engaging, potentially closing the achievement gap between students due to individual or social differences. That said, while AI promises to enhance learning and education, some systems have the potential to threaten the human rights of their students and users.

This research provides a means for real estate educators to engage and learn with AI. The AIREE framework presents five stages. The first relates to identification of the AI, or intelligent system, with the second stage assisting with categorisation of the level of control afforded with the intelligent system. This categorisation determines the pathway to the final three stages, viability and suitability, due diligence, and management.

Through understanding the role of AI in real estate education we take a step towards an augmented and 'magic' learning experience that can close the achievement gap between students due to individual or social differences. But we must take these steps with caution and move from traditionally held perspectives that partnering in business and political activities relates to entities or people, not AI. As our engagement and partnership with AI progresses, we will be reminded that shared goals do not necessarily lead to a shared path or empathetic relationship.

REFERENCES

Abidoye, R., Ma, J., & Lee, C.I. (2021) Barriers, drivers and prospects of the adoption of artificial intelligence property valuation methods in practice, Pacific Rim Property Research Journal, https://doi.org/10.1080/14445921.2021.2001724

Baum, A., Saull, A., & Braesemann, F. (2020). PropTech 2020: the future of real estate, viewed 18 July 2021, https://www.sbs.ox.ac.uk/sites/default/files/2020-02/proptech2020.pdf

Boyd, S. (2021). Partnering with intelligent systems to enhance the practice of property valuation, proceedings from the 2021 Virtual ASRES-GCREC-AREUEA Joint International Real Estate Conference, 18-21 July.

Braesemann, F., & Baum, A. (2020). PropTech: Turning Real Estate into a Data-Driven Market?, viewed 18 July 2021, https://ssrn.com/abstract=3607238 or http://dx.doi.org/10.2139/ssrn.3607238

Brown, A. (1992). 'Design experiments: theoretical and methodological challenges in creating complex interventions in classroom settings'. Journal of Learning Sciences. 2:2. 141–178.

Cajias, M. (2021). Artificial intelligence and real estate - not just an evolution, a real game changer. Journal of Property Investment & Finance, 39(1), 15–18. https://doi.org/10.1108/JPIF-06-2020-0063

Grace, K., Salvatier, J., Dafoe, A., Zhang, B., & Evans, O. (2018). When will AI exceed human performance? Evidence from AI experts. Journal of Artificial Intelligence Research, 62, 729-754.

Institute of Electrical and Electronics Engineers. (2017). Ethically Aligned Design A Vision for Prioritizing Wellbeing with Artificial Intelligence And Autonomous Systems, Version 2, report, viewed 11 September 2022, http://www.standards.ieee.org/develop/indconn/ec/autonomous_systems.html.

Jimenez, L., and Boser, U. (2021). Future of Testing in Education: Artificial Intelligence, Center for American Progress, report, viewed 11 September 2022, https://www.americanprogress.org/article/future-testing-education-artificial-intelligence/#:~:text=challenges%20of%20AI-

,Artificial%20intelligence%20can%20help%20students%20learn%20better%20and%20faster%20when,the %20naked%20eye%20cannot%20see.

Kumar, G., Singh, G., Bhatanagar, V., & Jyoti, K. (2019). 'Scary dark side of artificial intelligence: a perilous contrivance to mankind'. Humanities & Social Sciences Reviews, 7(5), 1097-1103.

Lattimore, F., O'Callaghan, S., Paleologos, Z., Reid, A., Santow, E., Sargeant, H., & Thomsen, A. (2020). Using artificial intelligence to make decisions: Addressing the problem of algorithmic bias. Australian Human Rights Commission.

Levy, D. (2006). 'Qualitative methodology and grounded theory in property research'. Pacific Rim Property Research Journal. 12:4, 369–388.

Macmillan Publishers Australia. (2021) Macquarie Dictionary, website, viewed 12 August 2021, https://www.macquariedictionary.com.au/features/word/search/?search_word_type=Dictionary&word=Artifi cial+Intelligence

Maini, V., & Sabri, S. (2017). Machine learning for humans. Online: https://medium. com/machine-learning-for-humans.

MIT media Lab and Scalable Cooperation. (Unknown). Norman World's first psychopath AI, website, viewed 30 June 2021, http://norman-ai.mit.edu/

Porter, L., Fields, D., Landau-Ward, A., Rogers, D., Sadowski, J., Maalsen, S., Kitchin, R., Dawkins, O., Young, G. & Bates, L.K. (2019). 'Planning, Land and Housing in the Digital Data Revolution/The Politics of Digital Transformations of Housing/Digital Innovations, PropTech and Housing – the View from Melbourne/Digital Housing and Renters: Disrupting the Australian Rental Bond System and Tenant Advocacy/Prospects for an Intelligent Planning System/What are the Prospects for a Politically Intelligent Planning System?', Planning Theory & Practice, 20:4, 575-603, DOI: 10.1080/14649357.2019.1651997

Sheehy, B., Boddy, C., & Murphy, B. (2020). 'Corporate Law and Corporate Psychopaths. Psychiatry', Psychology and Law, 2020, (June 26,2020), https://ssrn.com/abstract=3668064

Southgate, E., Blackmore, K., Pieschl, S., Grimes, S., McGuire, J. & Smithers, K. (2018). Artificial intelligence and emerging technologies (virtual, augmented and mixed reality) in schools: A research report. Newcastle:

University of Newcastle, Australia. https://www.education.gov.au/supporting-family-school-community-partnerships-learning/resources/ai-schools-report

Starr, C.W, Saginor, J., & Worzala, E. (2020). 'The rise of PropTech: emerging industrial technologies and their impact on real estate', Journal of Property Investment & Finance, Vol. 39 No. 2, pp. 157-169. https://doi.org/10.1108/JPIF-08-2020-0090

Viriato, J. C. (2019). AI and machine learning in real estate investment. The Journal of Portfolio Management, 45(7), 43-54.

Wagner, D.N (2021). 'Artificial Intelligence and the dark side of management', ROBONOMICS: The Journal of the Automated Economy, 1,10. https://journal.robonomics.science/index.php/rj/article/view/10/2

Wilkinson, S., Antoniades, H., & Halvitigala, D. (2018). The future of the Australian valuation profession. Property Management, 36(3), 333–344.

Email contact: s.boyd@cqu.edu.au

TABLE AND FIGURES

Figure 1: Applying the Five Pillars of AI ethics to school education

| | Design | Implementation | Governance | | | |
|----------------|--|---|--|--|--|--|
| Awareness | How have the manufacturers of system engaged with the education stakeholders to raise awareness of AI, its limitations, potential and risks? | Have students and parents/caregivers been made aware of the type of data harvesting and sharing arrangements required by the system? | Is there a rigorous process for seeking parental consent and student assent before systems are deployed? | | | |
| Explainability | Is the system designed to explain to students, parents and teachers its purpose, process, decisions and outcomes in an accessible way? | What opportunities, approaches and public forums are available for students and parents to explore, explain and share information and experiences of AI in schooling? | Do policy-makers, procurement officers, and school leaders have access to appropriate independent technical expertise to explain and advise on AI systems? | | | |
| Fairness | Has the issue of potential bias in the design of the system been proactively addressed and documented? | How will school address potential inequalities in an AI world? Does the system use autonomous experimentation and could this create an unfair burden on students and teachers? Does the AI system introduce unjust and punitive types and levels of surveillance on students and teachers? | What procedures and policies are there to ensure that AI systems positively address rather than exacerbate inequity, discrimination and prejudice in education? What evidence is there that an AI system can be used to address equity concerns in schools? | | | |
| Transparency | Is the system designed and implemented for traceability, verifiability, non-deception and honesty and intelligibility? | Can students, teacher, parents and community inspect and have opportunities to respond to AI systems training and decision making in ways that are intelligible or authentically empowering to them? | How will those in governance or procurement positions ensure genuine traceability, verifiability, non-deception and honesty, and intelligibility of AI systems prior to purchase and during implementation? How will transparency be operationalised if harm occurs? | | | |
| Accountability | Have the designer and vendor of an AI system clearly articulated their responsibilities to ethical use of AI? What systems do they have to ensure ethical accountability? | Who is accountable for the procurement of ethical AI? Is there a school and system wide procedure for reporting and responding to AI harm? Do all stakeholders in the school community know about and how to access the above procedure? | What protocols are in place to respond to prevent and respond to harm? What early warning systems are there that harm may be occurring that can trigger action? | | | |

(Southgate et al. 2018, pp48-49)

| Identification (I) | | Control (C) | | Viability and suitability (V) | Due Diligence (D) | |
|---|----------------------|---|---|--|--|--|
| 11. Intelligent system or information sharer ? Consider, is the proposed intervention an intelligent system <u>or</u> does the system | | C1. Do you have full control of the intervention? Consider, has it been developed internally or purchased for exclusive use? | Yes (V1) | V1. Do the projected benefits outweigh the anticipated costs and need for periodic human monitoring ? | Yes (D1) | D1. Does the intervention pass a sceptical due diligence ? Can the intervention be acquired retaining full control ? A |
| have the potential to share your data or analysis? | | | No (C2) | | No (I1) | can you set the performa benchmarks? |
| | Yes (C1) | C2. Do you share control of the intervention? Consider, can you set the role and determine what the system can and cannot do? | an you \sum_{α}^{∞} outweigh the anticipated costs what \sum_{α}^{∞} and need for sustained humar | Yes (D2) | D2. Does the intervention pass a sceptical due diligence ? Can the intervention be acquired terms that mirror an | |
| | cess) | | No (C3) | | No (I1) | employment agreement? And can you set performance benchmarl |
| | acquisition process) | C3. Does a system or another person control the intervention? Consider, does another person or system set the terms and conditions for use? | Yes (V3) | V3. Do the projected benefits outweigh the anticipated costs, need for sustained human monitoring, and opportunity cost of intellectual property? | Yes (D3) | D3. Does the intervention pass a sceptical due diligence ? And can you s performance benchmar |
| | No (alt. | | | | | |

Figure 2: Intelligent systems partnering framework

(Boyd 2022)