**AI Privacy, Policies, and Biases**

**Privacy**

The main topic of replacing Graduate Assistants (GAs) with AI graders and tutors at TMU involves critical considerations regarding privacy, policies, and biases that could significantly impact students, faculty, and the institution’s reputation. As AI systems rely heavily on training and processing a large amount of data in order to work, this can cause protecting and assuring private information becomes a big challenge. Although the core goal is to help utilize the convenience and ease as well as speed up the process, this data often includes sensitive student information, such as personal identifiers, academic performance, and behavioral patterns, which must be securely stored and processed. Mishandling this data could lead to breaches of confidentiality, violating student trust and legal frameworks such as Canada’s **Personal Information Protection and Electronic Documents Act (PIPEDA)** or even international regulations like the **General Data Protection Regulation (GDPR)**. For example, Marda and Narayan (2021) emphasize the risks of improperly securing educational data, highlighting cases where weak privacy measures led to widespread breaches. Without stringent protections, students could lose faith in the institution’s ability to protect their personal information, hindering the perceived legitimacy of AI in education.

**Policies**

Strong policies governing the use of AI are critical to ensure its integration is consistent with TMU's commitment to equity and academic integrity, as outlined in Policy 60. One of the major issues of AI is that it may sometimes place efficiency higher than fairness, resulting in oversights that may harm student outcomes. There are obvious reasons why AI is used the most when it comes to auto-grading scenarios: while AI may be the best at identifying surface-level errors or applying standard rubrics, it might struggle to evaluate more subjective aspects of student work, such as creativity or the quality of arguments. For example, AI will be the best grader when it comes to a test that includes only multiple choices, but when grading an essay or a project for a fashion student, then the principles will not be enough, and objective human opinions will be required. Moreover, instructors and GAs frequently adjust and are flexible in their feedback based on the conditions and the scenarios for each of them, a quality that current AI technologies lack. Binns et al. (2018) argue that regulatory frameworks should include mechanisms to audit AI decisions, hold developers accountable for errors, and ensure equity across diverse student populations. Without these safeguards, students may question the credibility of their grades, leading to dissatisfaction and potential disputes.

**Biases**

Equally concerning is the potential for **bias** in AI systems, which could aggravate existing inequities within the student body. Although the same algorithm and structure create consensus on a single standard evaluation metric, AI tools are only as unbiased as the data on which they are trained, and training data sets often reflect social biases. For instance, Mehrabi et al. (2021) show that AI grading systems can unintentionally penalize students from underrepresented backgrounds due to biases embedded in the data or the design of the algorithms. A typical example is the 2020 UK grading controversy, where an algorithm used during the COVID-19 pandemic downgraded students from low-income areas, causing widespread backlash. While GAs can adapt their evaluations to account for individual circumstances, AI tools lack this contextual understanding. This rigidity might disadvantage students who communicate their ideas in non-standard ways or come from diverse cultural backgrounds. For example, international students may have different reflective perspectives when the topic is about culture and customs, especially with domestic standards at the location where AI gets the data.

Furthermore, the biases could extend beyond automated AI grading and AI tutoring, which could disproportionately benefit students whose learning styles align with the AI’s programmed responses. AI in some ways helps students research information faster or have an overall understanding of new knowledge. Noble (2018) illustrates how algorithmic systems in education often reinforce systemic inequalities by favoring groups that align with dominant cultural norms. TMU must recognize that these biases may cause students who already face challenges in higher education to feel more struggle. Resulting in the fact that AI tools which can provide many supportive benefits, become less effective than humans in promoting an inclusive learning environment.

To reduce these dangers, TMU should conduct more rigorous testing of AI tools before and after deployment, invest in diverse training datasets, and guarantee that monitoring mechanisms allow instructors and staff to appeal AI choices. Additionally, the university must establish transparent policies regarding data use, consent, and accountability, as recommended by legal scholars and AI ethicists. Considering that the increase in costs and complexity will be more costly than the benefit that these measures can bring, it would be more comprehensive to negate some of the financial benefits that prompted the proposal.

In summary, although TMU's goal of maximizing costs and improving the student experience more quickly and promptly through AI is worth considering, the potential disadvantages involved cannot be ignored. to privacy, policy enforcement, and bias. If these issues are not adequately addressed, this change could harm trust, equity and student outcomes, ultimately weakening the school's reputation.

1. Binns, R., Veale, M., Van Kleek, M., & Shadbolt, N. (2018). **'It's reducing a human being to a percentage': Perceptions of justice in algorithmic decisions.** *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*, 1–14. https://doi.org/10.1145/3173574.3173951
2. Marda, V., & Narayan, A. (2021). **Data governance in education: Implications for privacy and equity.** *Data & Policy, 3*, e24. https://doi.org/10.1017/dap.2021.24
3. Mehrabi, N., Morstatter, F., Saxena, N., Lerman, K., & Galstyan, A. (2021). **A survey on bias and fairness in machine learning.** *ACM Computing Surveys, 54*(6), 1–35. https://doi.org/10.1145/3457607
4. Noble, S. U. (2018). **Algorithms of oppression: How search engines reinforce racism.** NYU Press.