Assessing the Effects of AI-driven Tools on Productivity in Academia

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Abstract

The field of AI has exploded in the last decade, and innovation has come from both industry and academia. Like many fields that are technology driven, the rapid growth, availability of resources and widespread use have outpaced policymaking [1]. Ironically, this has also been the case in academia where discussions on fair usage, ethics and quality control have taken place but no clear, definitive answers are apparent with many organizations trying to cobble together best practices, on-the-fly [2]. Such discussions are often ill informed, relying on anecdotal expertise, and may lack data to back up "gut" feelings or simply be an extension of current policies. This type of approach will always lag the unique challenges presented rather than echo current usage. Additionally, the use of AI is not an endpoint in and of itself. AI should be used to increase productivity. In academia, productivity can be measured in terms of both volume and quality [3]. Specifically, 'productivity' is defined in the novel context of Four Pillars of Academic Productivity (4PoAP). In defining the 4PoAP Framework in the context of education, particular attention will be given to topics in the use of Generative AI. It is the aim of this study to provide a perceptual framework in which comparisons may be made on the productive use of AI by comparing usage by students and faculty (both technical and non-technical users). While the use of AI is ever-evolving, some comparisons may persist over the longer term. Our methodology takes a quantitative approach to gauging perceived performance. We find largely agreement between faculty and students, though key differences exist and should inform policy-making through maximum stakeholder engagement.

Keywords: *Technology, education, artificial intelligence, productivity, perception, policy.*

1. Introduction

In recent decades productivity in Canada, as well as in several other OECD countries, has been extremely lackluster. The government has been trying to rectify this, and with the widespread availability of generative AI, particularly Large Language Models (LLMs), there appears to be an opportunity to finally address this. Existing models for productivity improvement already exist, and they can be updated to incorporate AI. While arguably easier to use than many technologies, there is still a need to teach people how to make use of AI, and academia is the obvious epicenter for such learning. The United Nations, via UNESCO, under its Education 2030 Agenda, identify 4 main areas under which AI and academic productivity dovetail, namely, 1) inclusivity and equitability, 2) leveraging AI for education, 3) job readiness under AI, and 4) transparency and auditability in educational data [4]. Various studies have found that LLMs can preferentially help weaker persons both native English-speaking [5] and not [6]. However, it is not simply a matter of using AI and expecting gains in productivity. One large scale study found that while access led to usage, that did not translate into academic productivity [7]. When considering AI adoption within academia, there are myriad ethical and practical considerations that must be factored into any AI policies and AI usage. Understanding how faculty and students regard, use, and understand AI will have to be understood before policies can be refined and optimized. The study that follows will compare faculty and student usage and considerations of artificial intelligence, as well as their existing thoughts on current AI policies in college.

1.1 Four Pillars of Academic Productivty

The Four Pillars of Productivity (4POP) framework was originally designed to calibrate an organization in such a way so as to foster continuous improvement and enhanced productivity. This was accomplished by aligning culture, strategy, operations, technology and innovation to create winning conditions throughout the enterprise [8]. With the advent of generative AI, this model has to be updated to reflect the new reality faced by organizations, as the technology component has now become a centrepiece of any operation. One of the most obvious use-cases for AI is in education, as students are already embracing it [9], and personalized AI tutors will almost certainly change learning as we have known it [10, 11]. That being the case, 4POP is being updated specifically to focus on Academia, now referred to as the *Four*

Pillars of Academic Productivity (4PoAP). The foundation and pillars of the model can be applied to impacted stakeholders.

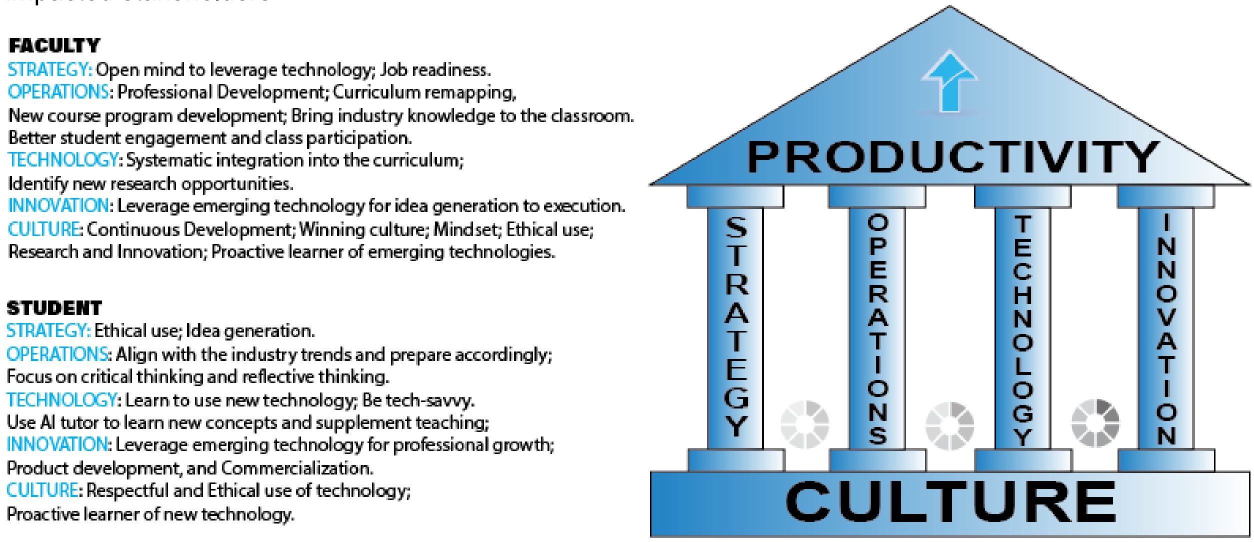

Fig. 1. Four Pillars of Academic Productivity

Any organization, particularly academic ones, should be looking to incorporate AI into their larger strategy or else risk being left behind. At least in the short-term, AI could serve as a point of differentiation as it is incorporated into an institution's digitization. Decision-makers should, and will, be using AI to ingest and summarize vast amounts of data before executing any strategy. Strategy has historically been viewed as having at least a 5-year time horizon, but in the age of AI change is so rapid that it simply is not possible to plan that far ahead [12]. Therefore, academic institutions will have to be very deliberate about defining a strategic intent that is generic enough that it will apply in a fluid environment, but can still serve as a guiding principle when making operational decisions. This typically means choosing where one sits on the trade-off spectrum of low-cost commodity versus high-cost differentiated offering. In academia, for example, this is usually expressed as a low-acceptance rate, but expensive prestige college, versus a higher admission rate with typically lower tuition fees.

Outside of technology, operations are the organizational aspect most impacted by Artificial Intelligence. In some cases, AI will replace entire functions previously done by humans [13]. In academia, the way that students are assessed will have to be revised to account for the fact that AI exists. Some skills will be less important than they were previously, while others have been promoted in the skill hierarchy [14]. It is unclear if bias, hallucination, and other AI errors can be entirely eliminated, and at least for the time being it is absolutely necessary that anybody working with AI must be capable of double-checking its output. Realignment of skills taught with those demanded by industry is always necessary, and with rapid change the frequency of such realignment must increase.

While AI has dominated the vast majority of conversations surrounding technology in recent years, there are many technological decisions outside of AI that an organization has to make in order to maximize its productivity. Amongst those decisions are the selection of tools such as Customer Relationship management (CRM) and Enterprise Resource Planning software, and lately the Canadian government has been providing funding to help with the adoption of such non-AI digital technologies. There are also industry-specific decisions that must be factored in, such as the choice of a Learning Management System (LMS) in academia. Despite it not being such LMS' main selling point, a few of these do incorporate AI nowadays [15]. However, the technology selection must weigh the suitability of the platform for the desired use-case against all else. Now more than ever, cybersecurity is one of the most consequential technology decisions an organization has to make. Data privacy and user trust are all dependent upon sufficiently establishing cybersecurity. Academia has to make use of and handle sensitive student, faculty, and staff data, and the legal and financial consequences for inadequate cybersecurity leading to data breaches can be significant. AI provides yet another attack surface that malicious actors will be looking to exploit, and because of its recency, is quite possibly the least secure if it has any exposure to sensitive data.

There is a misconception that innovation is entirely a matter of talent and luck [16]. Innovation has to be encouraged to increase likelihood of success, and it must also be sought out at all levels of an operation. Getting everyone involved in sharing suggestions, questioning why things are currently done the way they are, and experimenting with other methods and processes will eventually result in continuous improvement. In academia this means the learning community (students, faculty, administration, and other staff) should be conditioned to seek out better ways of doing things. This may be one of AI's greatest uses. Anyone with new ideas can ask the AI to support or refute them, to determine if they are worth implementing.

Culture is the foundation of all good organizations. Good cultures typically endure for a very long time, and bad ones usually fail reasonably fast [17]. There is no single correct culture, but a winning culture usually has some combination of the following elements: top-down support for innovation, idea-sharing, rewards and bonuses for improvements, and a flat-hierarchy when it comes to valuing ideas (there is still an organizational hierarchy of course, but ideas have to be weighed based on merit rather than ideator/provenance/origin) [18]. In general, good cultures also have people take pride in their work, while also enjoying their work. In academia, new waves of students come in every semester, which makes establishing continuity of culture even more important. People will conform to a culture, so making sure that culture is producing the right kind of incentives is an absolute prerequisite for long-term success. Only the organizational cultural foundation of 4PoAP remains largely unchanged by AI, while the four pillars will all be affected by it. Fundamentally, however, the need to align the four pillars is still essential for productivity. Having the pillars all supporting in parallel, facing in the same direction towards the same goal is the key to repeatable productivity and innovation improvements.

2. Methodology

Faculty (response rate 31%, n_f=11) and students (11%, n_s=263) at Loyalist College in Toronto were anonymously queried over two weeks using parallel, standard cross-sectional survey design (taking 5-10 minutes). They were identically presented 27 multiple-choice (with 'other' option) and open-ended, non-branching questions in simple English but for minor modification of language by role (e.g. an instructor's prime duty read 'teaching' while a student's read 'studying') and for ease (for non-native English speakers). Faculty had two additional questions pertaining to perception of student work, with no converse analogue for students. Categorical/ordinal questions (requiring separate treatment below) were non-technical with definitions/interpretations left to the respondent.

Histograms were used to compare and visualize analogous distributions. Natural Likert scale orderings and language-balanced categories were sometimes complicated by distinct "not sure", "neutral" or "n/a" bins requiring contextual handling. Likert responses were reduced binomially by (e.g. AI usage uptake's five-category reduction to a binary 'Yes/No' comparison). Disparate group sizes, ordinal vs. categorical scales, and skewed distributions required a variety of analytical tools. Wilson score intervals were chosen (due to small, asymmetric samples) for a proportion, $\hat{p}$, samples of size, n, and $Z_{\alpha=0.05}$:

$$\frac{\hat{p}+\frac{1}{2n}z_{\propto}^2}{1+\frac{1}{n}z_{\propto}^2} \pm \frac{z_{\propto}}{1+\frac{1}{n}z_{\propto}^2}\sqrt{\frac{\hat{p}(1-\hat{p})}{n}+\frac{z_{\propto}^2}{4n^2}}.$$

The non-parametric Mann-Whitney (MW) U-test was selected (not require normality, and robust against size disparity), allowing for group response ordinality comparison. The test constructs the null hypothesis, H_0, stating faculty and student cohorts have responses coming from the same underlying distribution, the alternative being, H_0 is false. The MW test relies on neither mean nor median for comparison. While the responses appear discrete, they actually belong to a continuous scale we are sampling discretely (e.g. there is a continuum between "strongly agree" and "agree"). Even if untrue, at the very least, the scale has an ordering. The MW procedure involves calculating an unbiased *U*-statistic:

$$U = min\left[U_f = n_f n_s + \frac{n_f(n_f+1)}{2} - R_f, U_s = n_f n_s + \frac{n_s(n_s+1)}{2} - R_s\right],$$

where R_i is the summed rank of group i's elements from the larger pooled ranking of both groups. The ranking is accomplished by encoding order to numerical rank. The *U*-statistic is compared to a critical value (here, *Z-score* with significance 0.05, due to a large pooling size) following the standard hypothesis testing procedure, in this case, the *Z*-score (significance was taken as 0.05). The matter of MW effect size was reported using Cliff's delta and confirmed using rank-biserial correlation. Cliff's delta is calculated as:

$$CD = \frac{\sum_{i,j}[x_i>x_j]-[x_i<x_j]}{n_f n_s},$$

where bracketed quantities are 1, if the relation holds, and 0, otherwise. The simplest procedure used a dominance matrix, and two axial cohorts were individual member pairwise-compared for size per CD, with all entries then averaged. Rank-biserial correlation is quite straightforward:

$$r = \frac{2U}{n_f n_s}\text{-}1, r \in [-1,1],$$

indicating no relationship when r=0. Following standard practice, a confidence interval (CI) about CD was created and further refined using the procedure outlined in [19].

Apart from this, Venn diagrams, word clouds, doughnut, violin and cumulative frequency charts were used to help visualize. Other methods such as ordinal regression and bootstrapping were ruled out as unnecessarily complicated and redundant.

3. Results

Faculty & students show roughly similar proportions (~1/2 have strong exposure) of familiarity with AI tools (figure 2a) with few students and no faculty having weak AI exposure. Despite this, the presence of students unexposed to AI results in a Cliff's Delta of 0.76 ± 0.02 indicating a mostly minor degree of distributional overlap, confirmed by an extremely small MW test p-value showing differences are significant. Using the improved CI, taking into account distributional skew (asymmetry), this changes to [0.11, 0.14] which takes into account the few students who are not AI aware. Though both cohorts show some positive familiarity with AI use, actual reported usage (figure 2b) is higher amongst faculty (82% vs 28%), with much (44%) of the gap occupied by student uncertainty. A closer, granular look at the frequency of use shows that for faculty, the mode is 'very frequent' vs. students centred symmetrically around 'somewhat'. Statistical significance is again confirmed by the various metrics and CD=0.92±0.008 (even stronger effect than for familiarity). We cannot directly examine correlation between familiarity and frequency (the survey was anonymous), but distributionally, there is moderate correlation for faculty and strong correlation for students.

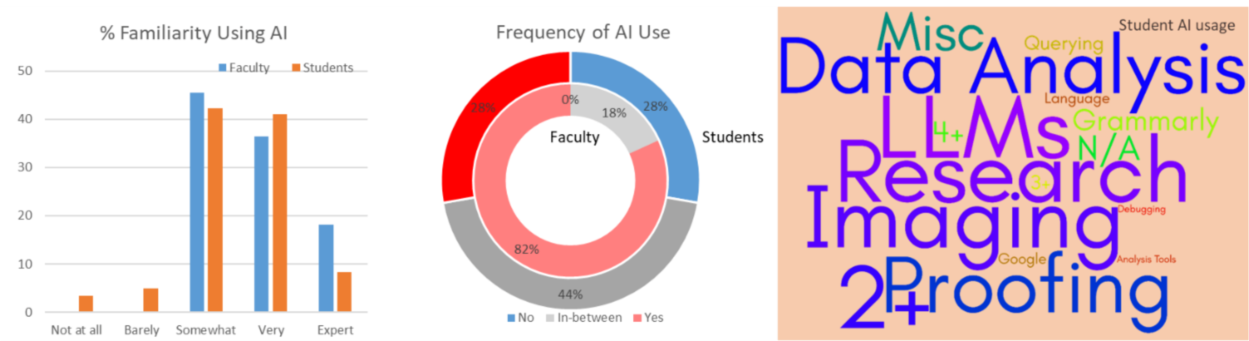

Fig. 2. (a) Familiarity using AI **(b)** Frequency of AI use **(c)** Student AI usage by type

The word cloud (figure 2c) shows LLMs and research tool types are the main types used by students (faculty largely corresponding). Cohorts showed roughly equal proportions by use case (figure 3a), prominently, research/learning, brainstorming, problem solving, and summarizing, and content generation (faculty).

Reported impact on productivity (figure 3b) and quality (figure 3c) was higher for both cohorts (faculty more than students) though some faculty reported a decrease and some students no change.

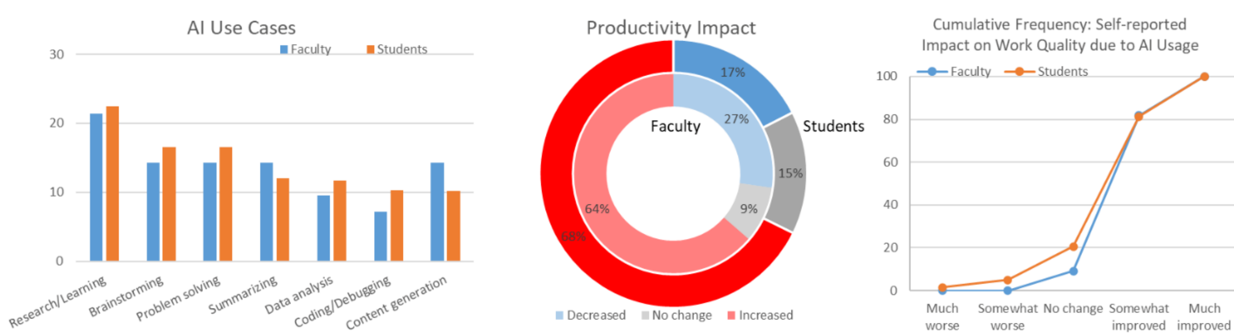

Fig. 3. (a) AI use cases **(b)** Reported impact on productivity **(c)** Reported impact on quality

In addition to self-reporting, faculty were asked to evaluate student performance using AI. Figure 4a shows a correspondence in student self-perception versus faculty with the overall pattern roughly matching though the CD interval falls within [0.11, 0.13] which does not include zero but is small. However unlike in their own work, faculty report some deterioration (10% drop in 'Somewhat improved' and all of 'No change', with completely shifting to the 'worse' categories) of quality in student work (CD unchanged).

Respondents reported relative comfort (figure 4b) in using AI except for some students who felt lost. When asked instead if they felt confident (figure 4b), there was a shift towards the middle of the distribution from the positive side for all. Exploration of guidelines was undertaken with questions on clarity (figure 4c) and sufficiency (not shown) with respect to official college guidelines. All faculty and most students responded affirmatively with only 7% responding negatively. When it came to sufficiency of guidelines, faculty largely (~90%) felt the guidelines were sufficient, but students (40%) did not. Using the binomial classes, the 95% Wilson CI for the faculty is (0.62, 0.98) indicating a large spread and overlapping with students (0.52, 0.67). The guidelines set in place deal largely with the ethical use of AI and should engage all stakeholders.

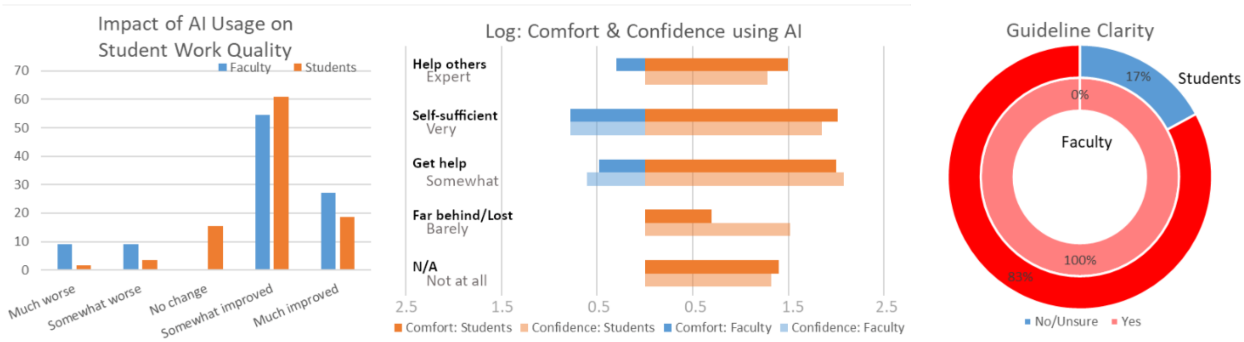

Fig. 4. (a) Perceived impact on quality **(b)** Comfort in using AI **(c)** Clarity on guidelines

Respondents experienced issues surrounding ethics and/or quality control (figure 5). A small majority (55%) of faculty are concerned with ethical and/or quality control issues using AI. Of them, all are concerned most with QC issues, while 2/3 of them have ethical concerns, 28% unconcerned, and 18% unsure. Student ratios are almost inverted with only 38% concerned (15% for QC, 6% with ethics, 17% for both -less than half the faculty's rate), and a relatively large portion, 24%, unsure.

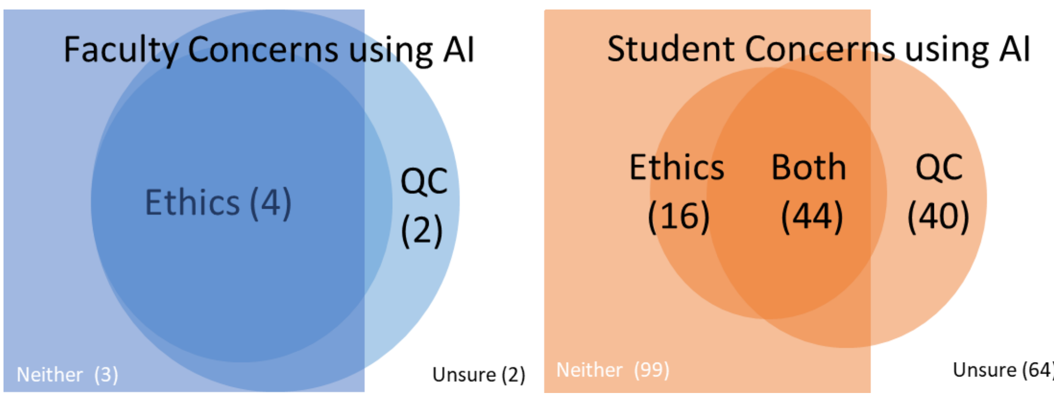

Fig. 5. Faculty and student concerns in AI usage

When following up on accuracy (not shown), cohorts were asked about methods to verify accuracy. All faculty responded, but only 62% of students did. Of respondents, most (faculty 64%, students 56%) felt there was some need to ensure accuracy and had some method (primarily cross-checking and proof-reading). Still, a large portion (27% of faculty, 15% of students) were certain to not check, and substantially, 9% of faculty and 29% of students, were uncertain if checking was needed. Cohorts were also asked to what extent they rely upon unchecked AI (figure 6a). All skewed towards not relying, though there were some (13%) students who did so with regularity. If both accuracy and reliance are reduced binomially, the 95% CI overlap. For accuracy, faculty (0.24, 0.76) encompasses student (0.32, 0.49), while for reliance, faculty (0.15, 0.65) encompasses student (0.49, 0.61).

Open-ended responses (not shown) on how AI has influenced specific roles (for faculty, teaching methods/curriculum design, and students, learning methods/studying) showed some difference. Students' main uses were in research/ideation, learning/comprehension, also reflecting a diversity of categories (10 in total). Faculty's largest category by far was content creation, followed by feedback/suggestions, with only 7 categories (not statistically significant). When they were further asked how they thought students used AI, they overestimated usage (by 37%) but ranked correctly, primarily research/brainstorming. They greatly over-estimated (175%) content creation/writing (also ranked correctly). Several other uses (proofing, summarizing, learning, and studying) were missed.

Asked if the use of AI had an impact on student performance (figure 6b) (the definition left open with responses positive, negative, or both), students felt 2:1 AI enhanced their work rather than detracted, a slim 4% unclear about it. Faculty felt 3:2 work was enhanced with a large 37% unclear. This was extended to perception on usage in academia overall (figure 6c), which received a positive outlook (2.5 times higher for faculty than students), a mixed outlook (similar for both groups), with some students (but no faculty) with a negative outlook. Uncertainty was high amongst students at 18%.

Among challenges faced using AI (not shown), students were primarily concerned with low quality results, followed by improper usage, then ethics, misinterpreted prompts, untrustworthiness, and accessibility though some students faced no challenges. Faculty concerns were similar but ranked equally and loss of motivation was added as an issue. Further to challenges they were asked what the institution should do for them (not shown). All parties primarily asked for training (in ethical usage, with practical hands-on approaches, subject matter/curricular uses, fact-checking, preserving criticality/creativity, maintaining academic success, understanding how AI works, and ethics), clearer guidelines (rules, ethical usage, privacy etc.), free access (to paid AI), and for the institution to deal with student misuse (better detection and limit usage). Some felt nothing was needed, and others requesting different, more precise guidelines. Faculty wishes were more uniform (without guideline concerns but wanting the College to encourage use).

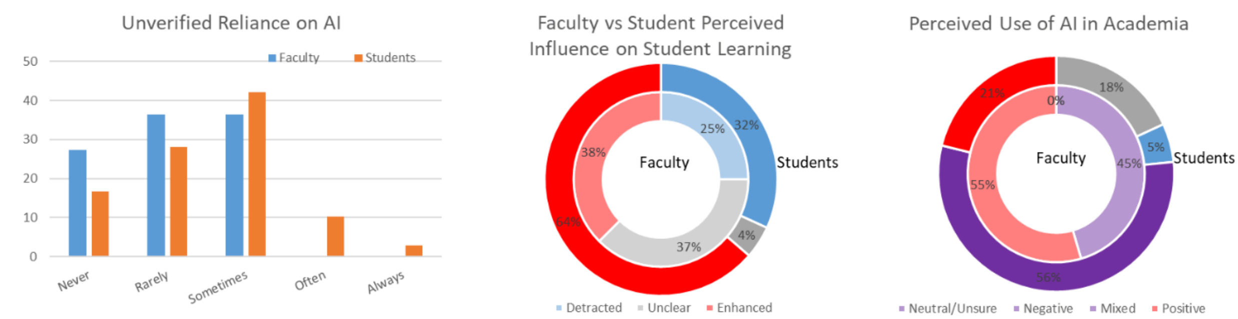

Fig. 6. (a) Using unverified AI **(b)** Perceived quality in learning **(c)** Perceived quality in academia

With respect to academia keeping up with AI, almost half of faculty felt it was (not shown), with 55% either unsure or disagreeing. Students were more optimistic with 2/3 believing it was keeping up, and 27% unsure with only 5% believing otherwise.

When asked to choose (constrained) if they used prompt engineering (definition not given) techniques, respondents skewed towards more use than less (faculty significantly more so than students).

On whether or not AI can replace or aid in instruction (figure 7a), AI was selected (faculty, unanimously) in an auxiliary capacity. Of the student body, though some did feel AI can replace an instructor, the skew was toward preferred human instruction. The p-value was quite low and Cliff's delta was 0.91±0.008.

AI reliability/trustworthiness (not shown), revealed differences (low p-value and CD=0.92±0.008) where faculty felt it was good but needed double-checking versus students who had predominantly mixed feelings. Faculty tended to avoid the extremes while students did not shy away from them with some feeling AI is terrible and others, great.

Cohorts were asked if AI was useful (figure 7b) and if they needed to use it. Faculty completely thought it was useful, and mostly felt it was essential (2.7 times the 'useful but not essential' category). On the other hand, of those students who recognized AI as useful (84%), 7.5 times as many felt it was not needed as opposed to essential.

Finally, under open feedback, faculty commented that AI is a great assist but cannot replace instructors, and over-reliance might lead to laziness and loss of critical thinking skills. AI needs to be adopted into the curriculum. Students echoed the above and also added the need for more discussion on verification, ethics and real-world applications.

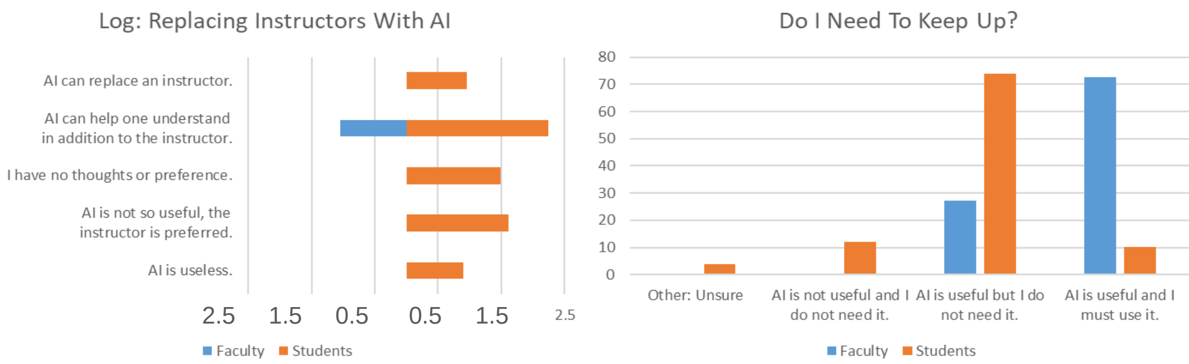

Fig. 7. (a) Human vs. AI instruction **(b)** AI use and adoption

4. Discussion & Conclusion

Given the recency of widespread AI uptake, and the relative equal sophistication among non-technical students and faculty, there might not be an expectation of AI disparity. Some differences were observed but when taking into account asymmetry and sample size, these differences diminish. In any case, there is a great opportunity for all stakeholders to grow with AI together. Generally speaking, faculty tends to have more exposure to AI and typically they use it for tasks relevant to teaching such as generating content. Students also use AI for knowledge-gathering and learning tasks such as ideation and summarization, as well as in problem solving. They do not report widespread use in content generation. It is unsurprising that the largest platform cohorts use are LLMs. So, for prompt engineering, it is concerning students lag faculty.

When it comes to academic productivity and quality of work, all parties report on the plus side probably signaling a change in pedagogical paradigm (perception trumps KPIs). Nonetheless, a longer term cross-sectional or longitudinal study is required to see evolution in the fast-paced AI landscape. This does not mean blanket policy instruction should apply. The results clearly show there are still significant groups (e.g. students) for whom AI decreases productivity and some for whom quality is worsened or who feel lost when it comes to AI. The same can be said for accuracy of, and reliance on, AI. Furthermore, self-perception does not necessarily align with evaluator perception (faculty tend to believe in diminished student output quality) which can lead to biases in grading for example. It should not be assumed that one party is in the right. Faculty grossly over-estimated the role of AI in student content creation -which happens to be one of their own prime usages, and simultaneously missed many other reported uses. In fact, there is disparity even in how faculty sees its own work compared to students', with bias towards enhancement of the former.

Regarding policy development, frameworks need to include all stakeholders. Results show while faculty largely find the guidelines clear and sufficient, students do not, with some requesting clear, real-world examples and separation of ethics and privacy issues. Surprisingly, students feel enforcement is important. There is a diversity of concern not only across groups (ethical and quality control), but even within groups not all faculty are singular and also certainly not in the student body.

Risks require further study before they become real. Chief among concerns are ethics, trust, access (training, and physical), and loss of motivation in critical thinking. There is enough substantial believe that academia is not keeping up with the evolution of AI, and there is no overall concern for AI replacing faculty. There is general belief that it needs incorporation into curricula, so it makes sense that AI serve as adjunct.

Though survey results inherently suffer many generic problems/biases, in an academic setting where there is a policy on the use of the very subject of the survey, much of the above results may be skewed by perceived 'correct' answers or fear of consequences for having used AI and other typical shortcomings despite privacy policy, assurances of anonymity etc.). Misalignments obviate the need for metrics and further research avenues should include metrics related specifically to AI in academic productivity (e.g. time spent on tasks such as learning/studying/solving, grading activities/trends, quantity of research outputs etc.), with an eye towards quality control. Cohort studies will help answer questions on direct correlation (e.g. frequency vs. familiarity, quality as a function of prompt engineering etc.). Expansion into granular measures of successful AI use across various fields and by user type (creatives vs technical) will help pinpoint policy/strategies. Further drill down is needed (e.g. determining if lack of guideline awareness is a communications breakdown and if so, exactly where; comparing (non-)technical cohorts).

In brief, though perceptual agreement (on guidance received, accuracy, reliance, challenges, and wishes) was found between faculty and student bodies, sufficient differences do exist between and within groups, to reject the null hypothesis (marginally for familiarity, confidence, preferred mode of instruction, trust/reliability, ability of academia to keep up, perceived quality in others' work and productivity; strongly for exposure, concerns, use type, performance impact, use of prompt engineering, use in academia, quality control, quality of own work, comfort and utilty/need), so disparity must be considered.

In a hierarchy, if the party in charge does not perceive correctly/uniformly, the risk of AI-tunnel-vision (believing all experience AI the way we do) combined with the increasing presence of AI in academia, makes negative sequelae (e.g. unethical use, mistrust, and loss of motivation in critical thinking) of AI-inequality (gaps in access and understanding) a high-stakes matter. Unsubstantiated belief in increased production and high quality can lead to false security and poor learning outcomes. Clearly, policy development must be made carefully, with widespread consultation, empathy, and frequent testing using metrics.

Though not addressed in this study, in addition to faculty and students there is another important group that should be researched in a subsequent study regarding AI usage: academic administration. It is generally accepted that effective change requires top-down buy-in, and this will presumably be the case for AI too, but a further study is warranted to verify this. Based on the findings, 4PoAP has been applied to each stakeholder group in the college (student, faculty, staff, and administration) to aid in AI adoption and policy creation. This study does address that generally productivity is thought to be improved through the use of AI, but perhaps further research should be done to also prove the veracity of this belief.

REFERENCES

[1] Wang H., Dang A., Wu Z., & Mac S., "Generative AI in higher education: Seeing ChatGPT through universities' policies, resources, and guidelines", Computers and Education: Artificial Intelligence, 2024, 100326.
[2] Da Mota M., "Toward an AI policy framework for research institutions", Artificial Intelligence, 2024.
[3] Abramo G., & D'Angelo C. A., "How do you define and measure research productivity?", Scientometrics 101, 2014, 1129–1144.
[4] Pedro, Francesc, et al., "Artificial intelligence in education: Challenges and opportunities for sustainable development", Working Papers on Education Policy, Paris, UNESCO, 2019.
[5] Noy, S., & Zhang, W., "Experimental evidence on the productivity effects of generative artificial intelligence", Science, 381, 2023, 187-192. DOI:10.1126/science.adh2586
[6] Syahrin, S., and Akmal, N., "Navigating the Artificial Intelligence Frontier: Perceptions of Instructors, Students, and Administrative Staff on the Role of Artificial Intelligence in Education in the Sultanate of Oman", Arab World English Journal, 2024, 73-89. DOI: https://dx.doi.org/10.24093/awej/ChatGPT.4
[7] Segbenya, Senyametor, et al., "Modelling the influence of antecedents of artificial intelligence on academic productivity in higher education: a mixed method approach", Cogent Education, Taylor & Francis Group, 2024, (11:1), 2387943, DOI: 10.1080/2331186X.2024.2387943.
[8] Chowdhury M., "Four Pillars of Productivity: A Systematic Solution for Canadian Small and Medium Sized Businesses", International Journal on Interdisciplinary Studies in Business, Technology, and Education, U.S.A., 2016, 2333-598.
[9] Mark D., "Analysis: Did the demand for ChatGPT plunge because students left for summer break?", OnlineEducation.com, 2024. . Retrieved from https://www.onlineeducation.com/features/chatgpt-demand-declines-in-the-summer.
[10] Domeyer A., "Education for all: An interview with Dr. Sven Schütt", McKinsey & Company, 2024. Retrieved from https://www.mckinsey.com/industries/education/our-insights/education-for-all-an-interview-with-dr-sven-schutt#/.
[11] Shabbir A., Rizvi S., Alam M.M., & Su'ud M.M., "Beyond boundaries: Navigating the positive potential of ChatGPT, empowering education in underdeveloped corners of the world", Heliyon, Vol. 10, No. 16, 2024, https://doi.org/10.1016/j.heliyon.2024.e35845.
[12] Ruiz G., & Ortiz K., "Application of artificial intelligence techniques in the administrative management of higher education institutions: An analysis of their effectiveness in process optimization and strategic decision making", Revista Científica Interdisciplinaria Investigación y Saberes, Vol. 13, No. 2, 2023, 66–83
[13] Aleru G.E., "Impact of artificial intelligence on job performance of higher education managers in state-owned universities in South-South", American Research Journal of Contemporary Issues, Vol. 1, No. 3, 2023, 109–120.
[14] Salih S., Husain O., Hamdan M., Abdelsalam S., Elshafie H., & Motwakel A., "Transforming education with AI: A systematic review of ChatGPT's role in learning, academic practices, and institutional adoption", Results in Engineering, Vol. 138, Article 103837, 2025, https://doi.org/10.1016/j.rineng.2024.10383.

[15] Ritala P., Aaltonen P., Ruokonen M., & Nemeh A., “Developing industrial AI capabilities: An organisational learning perspective”, Technovation, Vol. 138, Article 103120, 2024, https://doi.org/10.1016/j.technovation.2024.103120
[16] Nieminen J., “21 common innovation myths & misconceptions debunked”, Idea to Value, 2021, Retrieved from https://www.ideatovalue.com/inno/jessenieminen/2021/06/21-common-innovation-myths-misconceptions-debunked/
[17] PricewaterhouseCoopers, “Global Culture Survey 2021 Report”, PwC. Retrieved from https://www.pwc.com/gx/en/issues/upskilling/global-culture-survey-2021/global-culture-survey-2021-report.html.
[18] Austlid S., & Elfström J., “Sharing is Caring: A Qualitative Study of Idea-sharing in Large Organizations”, University of Gothenburg, Gothenburg, Sweden, 2021. Retrieved from https://gupea.ub.gu.se/bitstream/handle/2077/69116/gupea_2077_69116_1.pdf.
[19] Feng D., & Cliff N., “Monte Carlo Evaluation of Ordinal d with Improved Confidence Interval”, Journal of Modern Applied Statistical Methods, Vol. 3, Iss. 2, Article 6, 2004. DOI: 10.22237/jmasm/1099267560.