

Ethical Appraisals of Artificial Intelligence in MBA Education: Moral Concern, Social Pressure, Perceived Benefits, and AI Experience

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ABSTRACT

This cross-sectional study examined how MBA students appraise ethical concerns, practical benefits, social expectations, control, and institutional governance related to educational artificial intelligence (AI). The analysis used 275 eligible responses submitted by the prespecified study cut-off. Descriptive statistics, omega and Spearman-Brown reliability, exploratory factor analysis (EFA), rank-based and bootstrap robustness checks, and regression models of ordered AI experience were used. Three exploratory dimensions were retained in 90.4% of 500 bootstrap samples. A proportional-odds reference model improved on the null model, $\chi^2(6) = 17.81$, $p = .007$, but the proportional-odds assumption was rejected, $\chi^2(6) = 17.81$, $p = .007$; threshold-specific models were therefore primary. AI self-efficacy/control was associated with reporting at least moderate rather than none/minimal AI experience (OR = 1.51, 95% CI [1.13, 2.03], $p = .005$), and this result persisted after background adjustment, bootstrap validation, and response-quality screens. In the smaller extensive-experience comparison ($n = 26$), efficiency benefit and perceived ethical-issue frequency were positive exploratory correlates. Concern was highest for data privacy, while governance responses indicated comparatively limited knowledge of personal-data practices. Predictive performance was modest. The findings support clearer task-specific guidance, critical AI literacy, and transparent data practices, but the cross-sectional self-report design does not establish causal adoption effects or validated moral profiles.

1.0 Introduction

Generative artificial intelligence (Gen AI) has come a long way, from a niche technology to a commonplace part of life in higher education. Faculty members use Gen AI to do research, develop courses and course materials, and evaluate student outcomes. Students brainstorm, edit, explain, translate and complete tasks using AI-powered systems. However, institutions are still establishing guidelines for acceptable usage. Evidence from Canada suggests significant but uneven interpretations of AI use across programs and student populations, and students are not entirely clear about academic integrity, privacy, fairness, and institutional expectations (Future Skills Centre, 2024). The question is not just whether students value AI, but how perceived value, ethical concerns, social norms, and confidence in AI applications intersect. The issues related to AI use by students are complex, and how the different dimensions interact is a critical component when it comes to understanding the student side of the academic AI use equation. In particular, the ethics of AI use by students has not been well developed.

Recent scholarship confirms the need for such a perspective centred on ethical responsibility. While AI can contribute to the personalization of and access to positive academic outcomes, the educational value relies on the validity and task fit of the products, and human oversight in the process (Papadakis & Lampropoulos, 2026). Furthermore, evidence from university assessments indicates that AI-generated ratings may not be equivalent to human-trained assessments, rendering fairness and reliability substantive educational issues rather than merely matters of objection (Zacharis & Papadakis, 2025). In student-centred research, students do not view 'AI ethics' as a single attitude; instead, they differentiate among autonomy, justice, explicability, and other ethical aspects (Yang et al., 2025).

Given this range of ethically relevant concerns related to AI use, this study explores student perceptions of ethics in relation to AI use in university settings. Student volunteer responses to a questionnaire explore the range of students' appraisals of AI use, including emotions, perceived social response, and perceived control. This was explored in relation to the types of reasoning involved, though not drawing upon specific philosophical concepts. The students were drawn from a graduate program in business education at a Canadian university; thus, we expected that they would provide relatively insightful, high-level engagement with the conceptual framework and the issues involved.

1.1 The purpose and questions of the research.

The aim is to describe the structure of the ethical and practical appraisals that MBA students hold towards educational AI, to explore the relationship between these appraisals and an ordered measure of prior AI experience, and to summarize separate items on institutional governance. The analysis is guided by three research questions:

RQ1. What are the most salient ethical and institutional components of AI use?

RQ2. What latent ethical dimensions are indicated by the 14 questionnaire appraisal items that focus on guilt, benefits, sanctions, social pressure, attitudes and control?

RQ3. Do moral concerns, social pressure, perceived benefits, self-efficacy/control, and ethical-issue salience correlate with a higher reported level of experience with AI?

2.0 Literature review

2.1 In Higher Education, the opportunities and risks of Generative AI

Research on generative AI in education exhibits a consistent duality. While support for AI-based explanation, feedback, personalization, writing, accessibility, and research tasks is highlighted in reviews and multidisciplinary syntheses, there are also concerns regarding inaccurate output, bias, privacy, overreliance, and academic-integrity risks (Adiguzel et al., 2023; Dwivedi et al., 2023; Kasneci et al., 2023; Montenegro-Rueda et al., 2023). While these sources provide a general opportunity-risk picture, they do not indicate that all uses are educationally useful. Value is a function of the task, quality of the output, the student's verification practices, and the level of human oversight.

Students' work also does not fit neatly into an easy enthusiasm-versus-resistance dichotomy. University students have reported efficiency, personalized support, and learning assistance, along with issues of accuracy, privacy, ethics, and personal development (Chan & Hu, 2023). A comparison between students and teachers also indicates generational differences in interest in using generative AI, but not in verified or responsible use (Chan & Lee, 2023). The educational acceptability of AI should thus be explored in terms of specific activities (e.g., brainstorming, language assistance, tutoring, source synthesis, and the creation of assessed work), rather than simply as a binary user/non-user dichotomy.

2.2 The acceptance of technology, usefulness, and self-efficacy

The perceived usefulness, ease of use, value, facilitating conditions, and confidence are identified as potential factors influencing intention to use and actual use in the technology

acceptance literature. These models have been applied to students' perceptions of learning chatbots and ChatGPT (Al-Abdullatif, 2023; Strzelecki, 2024), and related work has extended the adoption models to incorporate moral obligation, trust, and perceived risk (Chung et al., 2024). As a group, these papers help to distinguish between perceived capability and control and expected performance or efficiency benefits. It also warns against using intention, experience, and observed behavior as synonyms.

The number of people and the context are important. Previous research on performance and effort expectations has explored the acceptance of generative-AI among faculty (Alotaibi & Alayed, 2025; Bilgin & Güngören, 2025), but the results of faculty studies cannot be extrapolated to students. Student research also reveals that the influence the standard acceptance variables is not consistent: Shuhaiber et al. (2025), for instance, found that social influence was not a significant predictor of students' intention to use ChatGPT. Self-efficacy/control and social pressure are thus considered potential factors for analysis in the literature, without making any a priori assumptions about their importance in the current sample.

2.3 Moral concern, guilt and academic integrity

Guilt is a self-conscious moral emotion that can occur when actions seem to be inconsistent with personal values or institutional expectations. With AI-aided assignments, guilt can be a sign of uncertainty about authorship, fairness, disclosure, or adherence to rules, rather than a consistent deontological stance. Guilt, as moral discomfort, obscures the philosophical implications of the affective response and allows for a possible reverse directionality: prior use of AI may influence guilt, and guilt may influence subsequent use (Chan, 2024).

Academic-integrity scholarship reminds us of the significance of context. The boundaries between AI assistance, collaboration, and authorship and subsequent perceptions of misconduct, are becoming more blurred and require more clarity in expectations and assessment design (Cotton et al., 2024; Evangelista, 2025). Experimental and assessment-oriented research also shows that the relevance of ChatGPT depends on the subject of the assessment and the criteria assessors use to evaluate its output (Klyshbekova & Abbott, 2024). Previous studies have revealed a conflict between faculty views and reactions to student academic dishonesty (MacLeod & Eaton, 2020), and Canadian studies have shown that there is no uniform approach to academic integrity education among institutions (Miron et al., 2021). These results are conceptually relevant to personal discomfort and perceived sanctions, but do not support the assumption that either factor is necessarily linked to a decrease in experience with AI.

2.4 Governance, policy and institutional responsibility

The conditions of how students interpret the use of AI are influenced by institutional governance. There is significant variation in the way leading universities are responding to generative AI and assessment (Moorhouse et al., 2023). Previous research in Canada, prior to the mass adoption of generative AI, also revealed differences in the academic-integrity policies of publicly funded universities (Stoesz & Eaton, 2022). In combination with the mixed integrity education reported by Miron et al. (2021), suggests it is important to explore students' perceptions of integrity in institutions as being transparent, open, and clear in relation to data and ethical expectations.

The broader education literature calls for participatory, task-specific and assessment-informed policy development. Research demonstrates the significance of the interconnection among educational practice, institutional policy, and research in the context of the development of generative AI, but the research subjects are not the university's students, but the teachers and education leaders (Chiu, 2024). AI in research supervision also has a strong focus on leadership and shared responsibility (Cowling et al., 2023). These sources provide justification for the governance items under consideration in this

document, but do not constitute evidence that respondents supported a particular institutional policy.

2.5 A bounded and integrated framework and research gap

The literature reviewed indicates that perceived benefits, moral concern, social expectations, and sense of self-efficacy related to student AI use can all co-exist independently. Currently, the evidence is generally related to student experience or, for faculty, institutions, and only a relatively small amount is specific to Canadian MBAs. The framework developed here considers these appraisals as related but empirically separable. Reviewing the outcomes, ethical theory explains how consequences and principles can both be important, while technology-adoption theory explains the proximal perceptions of usefulness, norms, and control. The present data can be used to analyze exploratory dimensions and cross-sectional associations. However, the research cannot be used to validate philosophical profiles, establish causal ordering, or show task-specific AI adoption, all possibilities that future research might usefully examine.

3.0 Method

3.1 Design and setting

In early 2025, MBA students at a Canadian university were invited via email to complete an anonymous online survey expected to take approximately 10 minutes. Recruitment was convenience-based and self-selected. The invitation did not advertise compensation or any other incentive, and the number of students who received it was not documented; therefore, a response rate could not be calculated. The author-specified analytic cutoff was March 22, 2025. The source export contained 311 submissions: 34 records dated June 4 were excluded as post-cutoff, and two of the 277 pre-cutoff records were excluded because consent was not approved, leaving 275 eligible respondents. Three nonstandard consent-export values were checked against the study records and confirmed by the authors as eligible. All 275 retained records matched the analytic file by participant ID. Numeric fields were complete; the optional open-text field had four missing responses and was not used in inferential analyses. Age, country, domestic/international status, and current academic term were not collected.

3.2 Participant characteristics

Most participants selected Female (62.2%), and more than two-thirds selected Master's as their highest qualification (68.7%). Most reported two years or less of experience in MBA programs (94.9%), and 66.2% reported Moderate or Extensive experience with AI in education. Complete distributions using the administered category labels are reported in Table 1.

Table 1: Participant characteristics (N = 275)

Characteristic	Category	<i>n</i>	%
Gender	Female	171	62.2
	Male	98	35.6
	Prefer not to say	4	1.5
	Others	2	0.7
Highest qualification	Master	189	68.7
	Bachelor	78	28.4
	PhD	8	2.9
MBA-program experience	Less than 1 year	76	27.6
	1 year	99	36.0
	2 years	86	31.3
	3 years	14	5.1
AI-in-education experience	None	8	2.9
	Minimal (e.g., exposure to a few tools or concepts)	85	30.9
	Moderate (e.g., regular interaction with AI tools)	156	56.7
	Extensive (e.g., teaching, developing, or heavily using AI tools)	26	9.5

Note. Percentages may not sum to 100 because of rounding. One respondent selected Bachelor, Master, and PhD; because the question asked for the highest qualification and PhD was selected, this response was coded as PhD. The

AI-experience categories reproduce the survey labels; None and Minimal were combined only for regression because the None category contained eight respondents.

3.3 Research ethics

Participation was voluntary and responses were recorded anonymously. The University Canada West Research Ethics Board approved the study on February 13, 2025 (application and ethics agreement no. 202505).

3.4 Instrument and score construction

The questionnaire was adapted from Widyorukmantiyoro et al. (2024) for AI use in MBA studies. The administered anchors were verified against the survey: concern items ranged from 1 (Very unconcerned) to 5 (Very concerned); frequency, appraisal, and governance items used 1 (Never), 2 (Rarely), 3 (Sometimes), 4 (Often), and 5 (Always); and impact items ranged from 1 (No Impact) to 5 (Significant Impact). Because some appraisal and governance stems fit the frequency anchors imperfectly, those responses are treated as ordered numeric ratings and interpreted cautiously. Four theory-guided mean scores were calculated: moral concern/guilt (Question 11, Items 1-4), social pressure (Question 11, Items 9-10), AI self-efficacy/control (Question 11, Items 13-14), and perceived frequency of ethical issues (the five Question 7 ratings). The two perceived-benefit items from Question 11 were analyzed separately because they did not form a well-defined composite. Items concerning fairness, privacy, adequacy, priority, and institutional governance were not treated as validated latent scales. The supplied study records did not document a formal pilot test or cognitive interviews; consequently, all adapted measurement interpretations remain exploratory.

Table 2: Reliability of theory-guided scores (N = 275)

Score	Items	alpha	omega or SB	Bootstrap 95% CI
Moral concern/guilt	4	.933	.933	[.914, .948]
Social pressure	2	.662	.663	[.555, .748]
AI self-efficacy/control	2	.792	.788	[.716, .850]
Perceived frequency of ethical issues	5	.814	.818	[.771, .856]

Note. omega = McDonald's omega total for scores with three or more items; SB = rank-based Spearman-Brown coefficient for two-item scores. Confidence intervals are percentile intervals from 1,000 bootstrap samples.

3.5 Analytical strategy

Analysis proceeded in four stages. First, means, standard deviations, and appropriate upper-category percentages are summarized for concern (Question 6), ethical-issue frequency (Question 7), perceived impact (Question 8), and the four governance ratings (Question 13). The categorical adequacy and priority items (Questions 9 and 12) were summarized with counts and percentages. Second, coefficient alpha was reported alongside McDonald's omega total for scores with at least three items and rank-based Spearman-Brown coefficients for two-item scores; 1,000-sample percentile bootstrap intervals quantified reliability uncertainty. Third, the 14 Question 11 appraisal items were evaluated with EFA using Pearson correlations, the Kaiser-Meyer-Olkin statistic, Bartlett's test, parallel analysis with 1,000 random datasets, maximum-likelihood extraction, and promax oblique rotation. Robustness was assessed with marginal-preserving rank parallel analysis, Tucker congruence, and factor-retention frequencies across 500 case-resampling bootstrap samples.

Finally, the ordered AI-experience outcome included the categories None, Minimal, Moderate, and Extensive. None and Minimal were combined because only eight respondents selected None, producing None/Minimal (n = 93), Moderate (n = 156), and Extensive (n = 26). Standardized predictors were moral concern/guilt, social pressure, AI self-efficacy/control, the performance- and efficiency-benefit items, and perceived frequency of ethical issues. A proportional-odds model was fit as a reference and evaluated with a likelihood-ratio test, a global parallel-lines test, predictor-specific slope tests, variance inflation factors, pseudo-R-

squared indices, ordinal concordance, and 100-fold cross-validation using ranked probability score. Because the parallel-lines assumption was rejected, two threshold-specific logistic models were primary: Moderate/Extensive versus None/Minimal and Extensive versus all lower categories. Case bootstrap validation used 1,000 samples. Sensitivity analyses retained one record per exact duplicate numeric pattern, excluded respondents who selected one response across all 14 appraisal items, and applied a conservative combined screen. Background-adjusted models used the verified qualification and MBA-experience categories. No imputation was required.

4.0 Results

4.1 Ethical concerns, perceived frequency, and educational impact

Concern was highest for data privacy ($M = 4.31$, $SD = 1.02$; 84.7% Somewhat or Very concerned), followed by accountability ($M = 4.08$, $SD = 0.89$; 80.0%), transparency ($M = 3.93$, $SD = 0.95$; 76.0%), and bias ($M = 3.90$, $SD = 0.94$; 72.7%). Among the five frequency items, accessibility had the highest mean ($M = 3.64$, $SD = 1.06$; 53.8% Often or Always), followed by data privacy ($M = 3.56$, $SD = 1.09$; 52.0%). Among the four impact items, adoption of AI tools had the highest mean ($M = 3.77$, $SD = 0.99$; 57.1% Substantial or Significant impact), followed by learning outcomes ($M = 3.61$, $SD = 1.04$; 53.5%). These item sets use different response anchors and are therefore interpreted separately rather than as one salience scale.

Table 3: Separate ethical-issue frequency and impact ratings ($N = 275$)

Item and response type	<i>N</i>	<i>M</i>	<i>SD</i>	% upper two categories
Adoption of AI tools (impact)	275	3.77	0.99	57.1
Accessibility of AI tools (frequency)	275	3.64	1.06	53.8
Learning outcomes (impact)	275	3.61	1.04	53.5
Data privacy (frequency)	275	3.56	1.09	52.0
Trust in AI systems (impact)	275	3.53	1.03	49.1
Accountability (frequency)	275	3.48	1.00	46.9
Faculty teaching practices (impact)	275	3.42	0.99	45.5
Transparency (frequency)	275	3.41	0.96	42.2
Bias (frequency)	275	3.31	0.96	39.6

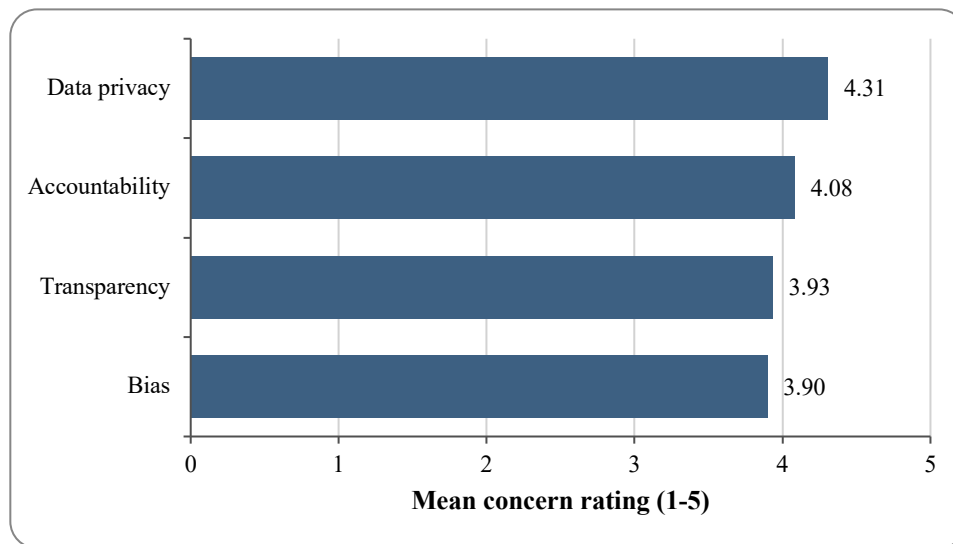


Fig. 1 Mean concern ratings for four AI-related ethical issues ($N = 275$)

Note. Higher bars indicate greater concern on the five-point scale. In Table 3, the upper two categories mean Often/Always for frequency items and Substantial/Significant for impact items.

4.2 Reliability and exploratory factor structure

Moral concern/guilt showed strong internal consistency ($\omega = .933$, bootstrap 95% CI [.914, .948]; $\alpha = .933$). Perceived frequency of ethical issues was also internally consistent ($\omega = .818$, 95% CI [.771, .856]; $\alpha = .814$). Rank-based Spearman-Brown reliability was .788 for AI self-efficacy/control and .663 for social pressure, with bootstrap intervals of [.716, .850] and [.555, .748], respectively. The uncertainty around the social-pressure estimate warrants caution. The two benefit items were retained as separate observed variables because their content and EFA behavior did not support a single score.

The 14-item EFA was factorable: KMO = .858, Bartlett's chi-square(91) = 2065.47, $p < .001$. Pearson and marginal-preserving rank parallel analyses both retained three factors. Factor 1 was characterized by guilt, value conflict, unfairness, and feeling wrong and was labeled moral discomfort. Factor 2 was characterized most strongly by knowledge and control, with smaller loadings for faster tasks and improved grades, and was labeled AI readiness/benefit. Factor 3 was characterized by detection, penalty, and anticipated disapproval and was labeled sanction/social pressure. Factor correlations were -.48 between moral discomfort and readiness/benefit, .64 between moral discomfort and sanction/social pressure, and -.34 between readiness/benefit and sanction/social pressure. Tucker congruence between rank- and Pearson-based solutions ranged from .997 to .999. Three factors were retained in 452 of 500 bootstrap samples (90.4%); two were retained in 46 samples and four in two samples. Median bootstrap congruence was .988, .978, and .975, although lower-tail congruence was weaker for Factors 2 and 3. The factors are therefore described as exploratory dimensions, not validated scales or student profiles.

Table 4: Promax-rotated pattern matrix for the 14 Question 11 appraisal items

Survey item	Wording	F1	F2	F3	h2
Q11.1	Feel guilty using AI	0.87	0.08	0.00	0.69
Q11.2	AI use goes against values	0.90	0.00	-0.06	0.74
Q11.3	AI use feels unfair	1.01	0.09	-0.10	0.84
Q11.4	AI use feels wrong	0.98	0.04	-0.09	0.84
Q11.5	AI use increases grade	-0.06	0.31	0.10	0.10
Q11.6	AI makes tasks faster	-0.01	0.47	0.06	0.22
Q11.7	AI use could be detected	0.02	0.05	0.52	0.27
Q11.8	AI use led to lower grade or penalty	-0.17	0.03	0.83	0.53
Q11.9	Friends or lecturers would disagree	-0.08	-0.01	0.78	0.54
Q11.10	Friends or lecturers would look down on me	0.16	0.02	0.57	0.47
Q11.11	Using AI is not wise	0.40	-0.15	0.31	0.53
Q11.12	Using AI is a bad idea	0.33	-0.23	0.31	0.52
Q11.13	Know how to use AI	-0.05	0.77	0.07	0.60
Q11.14	Can decide how to use AI	0.17	0.87	-0.04	0.67

Note. F1 = moral discomfort; F2 = AI readiness/benefit; F3 = sanction/social pressure. h2 = communality. Loadings at or above |.40| are treated as substantively salient. Pattern coefficients can exceed 1.00 in an oblique solution.

4.3 Associations with ordered AI experience

The ordered outcome comprised 93 respondents in the None/Minimal category (33.8%), 156 in Moderate (56.7%), and 26 in Extensive (9.5%). The proportional-odds reference model improved on the intercept-only model, chi-square(6) = 17.81, $p = .007$, but the global proportional-odds assumption was rejected, chi-square(6) = 17.81, $p = .007$. The predictor-specific diagnostic identified the efficiency-benefit slope as the clearest source of nonproportionality ($p = .006$). Multicollinearity was not problematic (maximum VIF = 1.45). Reference-model explanatory and discriminative performance were modest (McFadden R-squared = .036; Nagelkerke R-squared = .075; ordinal concordance = .634), and 100-fold

cross-validation improved the ranked probability score by only 1.0% relative to the null model. Threshold-specific logistic models were therefore used for primary interpretation.

For reporting at least Moderate rather than None/Minimal experience, the six-predictor model was significant, chi-square(6) = 14.62, $p = .023$. AI self-efficacy/control was the only significant independent predictor: a one-standard-deviation increase was associated with 1.51 times the odds of reporting at least Moderate experience (95% CI [1.13, 2.03], $p = .005$). Moral concern/guilt, social pressure, the two benefit items, and perceived ethical-issue frequency were not significant at this threshold. Predictive performance remained limited (cross-validated AUC = .571; Brier-score improvement over the null model = 0.15%). For Extensive versus all lower categories, the model was significant, chi-square(6) = 21.50, $p = .001$. Efficiency benefit (OR = 1.87, 95% CI [1.05, 3.34], $p = .033$) and perceived ethical-issue frequency (OR = 1.65, 95% CI [1.07, 2.55], $p = .023$) were positive correlates, whereas self-efficacy/control was not significant (OR = 1.33, $p = .258$). Because only 26 respondents were in the Extensive category, these latter associations are exploratory and imprecise.

Table 5: Logistic model for Moderate/Extensive versus None/Minimal AI experience (N = 275)

Standardized predictor	B	SE	p	OR	95% CI for OR
Intercept	0.71	0.13	< .001	2.03	[1.57, 2.63]
Moral concern/guilt	-0.06	0.16	.720	0.94	[0.69, 1.29]
Social pressure	-0.09	0.15	.550	0.91	[0.68, 1.23]
AI self-efficacy/control	0.41	0.15	.005	1.51	[1.13, 2.03]
Performance-benefit item	0.14	0.14	.334	1.15	[0.87, 1.52]
Efficiency-benefit item	-0.14	0.15	.346	0.87	[0.65, 1.16]
Perceived frequency of ethical issues	0.14	0.14	.313	1.15	[0.88, 1.49]

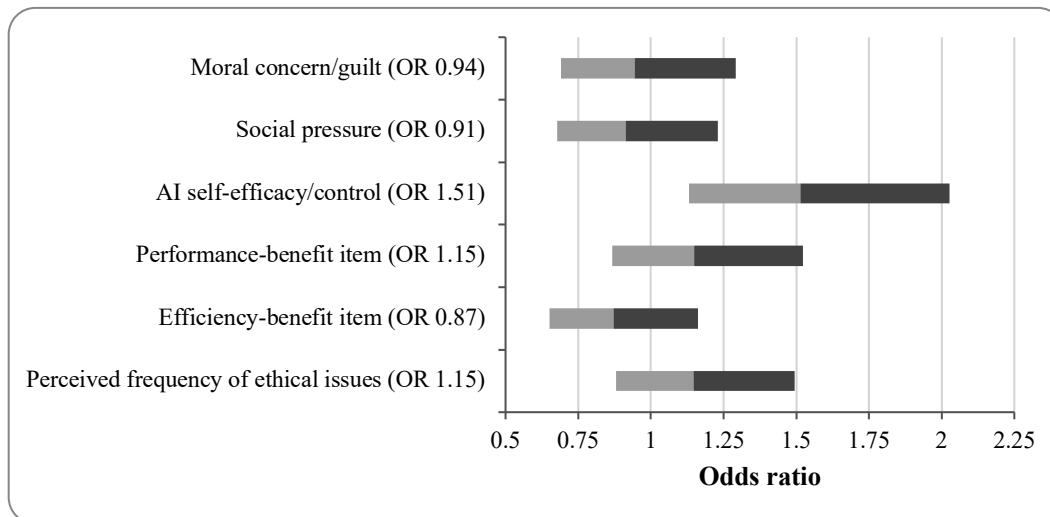


Fig. 2. Odds ratios and 95% confidence intervals for Moderate/Extensive versus None/Minimal AI experience (N = 275)

Note. Predictors were standardized before estimation. Horizontal intervals are 95% confidence intervals, and the light-to-dark transition marks the odds-ratio estimate. The null value is OR = 1.00.

4.4 Robustness and response-quality sensitivity analyses.

Bootstrap validation supported the primary threshold association: the 95% bootstrap interval for the AI self-efficacy/control odds ratio was [1.13, 2.14], and the coefficient was positive in 99.7% of 1,000 samples. Two pairs of respondents (IDs 30/31 and 42/43) had identical responses across every numeric field. Eight respondents selected the same response across all 14 appraisal items, and 12 had a longest identical-response run of at least 10 items. These records were retained in the primary analysis because such patterns can occur among valid respondents and the export did not establish invalidity. The self-

efficacy/control result remained positive after retaining one record per duplicate pair ($n = 273$; $OR = 1.56$, 95% $CI [1.16, 2.09]$, $p = .003$), excluding appraisal straightliners ($n = 267$; $OR = 1.55$, 95% $CI [1.15, 2.09]$, $p = .004$), and applying the conservative screen ($n = 261$; $OR = 1.59$, 95% $CI [1.17, 2.15]$, $p = .003$). The three-factor rank-based solution was retained under every screen, with Tucker congruence of .998 or higher.

Table 6: Sensitivity of the AI self-efficacy/control association at the primary threshold

Analysis	<i>N</i>	OR	95% CI	<i>p</i>
Full sample	275	1.51	[1.13, 2.03]	.005
Deduplicated; retain first exact numeric pattern	273	1.56	[1.16, 2.09]	.003
Exclude 14-item appraisal straightliners	267	1.55	[1.15, 2.09]	.004
Conservative screen: deduplicate and longest run < 10	261	1.59	[1.17, 2.15]	.003

After adjustment for the verified qualification categories (Bachelor, Master, and PhD) and MBA-program experience categories (Less than 1 year, 1 year, 2 years, and 3 years), the AI self-efficacy/control association remained positive ($OR = 1.57$, 95% $CI [1.16, 2.14]$, $p = .004$). The small PhD and 3-year groups make individual background-category coefficients imprecise, so this model is treated as a sensitivity analysis rather than a basis for subgroup claims.

4.5 Institutional-governance ratings

The four Question 13 governance items were reported separately because their stems addressed distinct institutional issues and did not all fit the shared frequency anchors naturally. Mean ratings were 3.75 for the need for ethical assessment, 3.76 for transparency-support tools, 2.70 for knowledge of personal-data practices, and 3.20 for institutional openness. Often or Always was selected by 54.5%, 58.5%, 19.3%, and 35.3%, respectively. On the separate adequacy item, 38.5% selected 'Yes, they are adequately addressed,' 47.6% selected 'Somewhat, but there are gaps,' 10.5% selected 'No,' and 3.3% were unsure. When asked to select the most important AI ethics concern, 40.4% selected data privacy, 26.5% transparency, 20.4% bias, and 12.7% security risks. Together, these descriptive results identify a governance gap around data-practice knowledge and perceived institutional openness, but they do not establish policy preferences or causal effects.

Table 7: Separate institutional-governance ratings ($N = 275$)

Item	<i>N</i>	<i>M</i>	<i>SD</i>	% Often or Always
Need for ethical assessment	275	3.75	1.13	54.5
Transparency-support tools	275	3.76	1.00	58.5
Knowledge of personal-data practices	275	2.70	1.16	19.3
Perceived institutional openness	275	3.20	1.19	35.3

Note. Items are reported separately. The rank-based Spearman-Brown coefficient was .791 for the ethical-assessment/transparency-support pair and .531 for the data-practices/openness pair. The first pair's reliability did not justify combining substantively distinct items, and the second pair's reliability was too weak for a composite.

4.6 Outcomes summary

With regard to the initial research questions, the findings of this research are as follows:

RQ1: What are the most salient ethical and institutional components of AI use?

Ethical Concerns: MBA students expressed the highest level of concern regarding data privacy ($M = 4.31$, $SD = 1.02$; 84.7% somewhat or very concerned). This was followed by accountability ($M = 4.08$), transparency ($M = 3.93$), and bias ($M = 3.90$).

Frequency of Issues: Among specific ethical issues encountered, accessibility of AI tools had the highest perceived frequency ($M = 3.64$; 53.8% reporting "Often" or "Always"), followed closely by data privacy ($M = 3.56$; 52.0%).

Educational Impact: Adoption of AI tools by students and faculty was rated as having the strongest impact on education ($M = 3.77$; 57.1% substantial or significant impact), followed by learning outcomes ($M = 3.61$; 53.5%).

Institutional Governance: Respondents highlighted a high demand for ethical assessments ($M = 3.75$) and transparency tools ($M = 3.76$). However, they reported low knowledge regarding how their personal data is handled ($M = 2.70$; only 19.3% indicating clear knowledge) and modest institutional openness ($M = 3.20$). Overall, 47.6% felt institutional ethical policies had gaps, and 40.4% cited data privacy as their single most important ethics concern.

RQ2: What latent ethical dimensions are indicated by the 14 questionnaire appraisal items?

Exploratory factor analysis (EFA) on the 14 appraisal items identified three distinct, exploratory dimensions (retained across 90.4% of bootstrap samples):

Moral Discomfort (Factor 1): Characterized by personal guilt, value conflict, perceived unfairness, and feelings that using AI for assignments is wrong.

AI Readiness / Benefit (Factor 2): Defined primarily by perceived knowledge and control over AI tools (self-efficacy), with minor loadings on task speed and grade improvements.

Sanction / Social Pressure (Factor 3): Focused on fear of detection, potential grade penalties, and anticipated disapproval or negative judgement from peers and lecturers.

Inter-Factor Relationships: Moral discomfort correlated positively with sanction/social pressure ($r = .64$) and negatively with AI readiness/benefit ($r = -.48$). The study notes these represent empirical exploratory dimensions rather than validated philosophical stances or moral profiles.

RQ3: Do moral concerns, social pressure, perceived benefits, self-efficacy/control, and ethical-issue salience correlate with a higher reported level of AI experience?

Because the global proportional-odds assumption failed, the manuscript evaluated two threshold-specific logistic regression models:

Primary Threshold (Moderate/Extensive vs. None/Minimal Experience): AI self-efficacy/control was the sole significant independent correlate of reporting at least moderate AI experience ($OR = 1.51$, 95% CI [1.13, 2.03], $p = .005$). Moral concern/guilt ($OR = 0.94$), social pressure ($OR = 0.91$), performance benefits ($OR = 1.15$), efficiency benefits ($OR = 0.87$), and ethical-issue salience ($OR = 1.15$) showed no statistically significant independent relationship with experience.

Upper Threshold (Extensive vs. Lower Experience Categories): For the small group reporting extensive experience ($n = 26$), self-efficacy/control was no longer significant ($OR = 1.33$, $p = .258$). Instead, efficiency benefits ($OR = 1.87$, $p = .033$) and perceived ethical-issue frequency ($OR = 1.65$, $p = .023$) emerged as positive exploratory correlates.

Core Conclusion: The analysis did not support the claim that moral concerns or guilt inhibit AI experience. Overall predictive performance across the regression models remained modest.

5.0 Discussion

This study provides an account of MBA students' educational AI appraisals, systematically addressing the three core research questions through descriptive statistics, exploratory factor analysis, and threshold-specific logistic regressions. In response to RQ1, data privacy emerged as the most salient ethical concern ($M = 4.31$, 84.7% concerned), while tool accessibility and data privacy were the most frequently perceived ethical issues, tool adoption and learning outcomes received the highest impact ratings, and institutional governance responses revealed low student knowledge of personal-data practices ($M = 2.70$) alongside significant perceived policy gaps. In response to RQ2, exploratory factor analysis identified three latent appraisal dimensions across the 14 survey items: moral discomfort (guilt, value conflict, unfairness), AI readiness/benefit (knowledge, self-efficacy/control, efficiency), and sanction/social pressure (detection fears, penalties, disapproval). Finally, in response to RQ3, threshold-specific logistic modeling demonstrated that AI self-efficacy/control was the sole statistically significant independent correlate of reporting at least moderate AI experience ($OR = 1.51$, $p = .005$), directly refuting claims that moral concerns or guilt inhibit experience, while efficiency benefits ($OR = 1.87$) and ethical-issue frequency ($OR = 1.65$) served as positive exploratory correlates exclusively at the extensive experience threshold.

These coexisting practical and ethical appraisals align with student reports of learning support alongside concerns about accuracy, privacy, ethics, and personal development (Chan & Hu, 2023), and with reviews describing both educational opportunity and risk (Adiguzel et al., 2023; Dwivedi et al., 2023; Kasneci et al., 2023). The distinct response formats matter: concern, perceived frequency, and impact should not be collapsed into a single measure.

The measurement results clarify what the instrument can and cannot support. Moral discomfort, sanction/social pressure, and readiness/control with benefit indicators appeared as related but distinct dimensions. This pattern is compatible with research that separates moral obligation and risk from usefulness and control (Chung et al., 2024), but compatibility is not validation. Agreement between Pearson and rank-based solutions was very high, and the three-factor solution appeared in 90.4% of bootstrap samples. However, lower-tail congruence was weaker for two factors, some items had low communalities, and the administered frequency anchors fit several appraisal stems awkwardly. The dimensions should therefore remain exploratory rather than being described as philosophical orientations or student profiles.

The original claim that ethical concerns inhibit AI adoption was not supported. The outcome measured self-reported experience level, not task-specific or verified adoption. At the primary threshold, self-efficacy/control was the only independent correlate of reporting at least Moderate experience, consistent with acceptance research that distinguishes capability and control from expected benefit (Al-Abdullatif, 2023; Strzelecki, 2024). At the Extensive threshold, self-efficacy/control was not significant; efficiency benefit and perceived ethical-issue frequency were positive exploratory correlates. This threshold variation is precisely why the failed proportional-odds assumption changes the interpretation: there is no defensible single odds ratio that summarizes every step of AI experience.

The robustness evidence strengthens confidence in the direction of the primary self-efficacy/control result without making it comprehensive. Its coefficient was positive in 99.7% of bootstrap samples and remained similar under duplicate-pattern and straightlining screens, as well as after adjustment for qualification and MBA-program experience. Yet cross-validated discrimination was weak and improvement over the null model was minimal. The model therefore identifies a reproducible sample-level association, not an accurate tool for predicting individual students' AI experience.

The governance results provide a more direct institutional contribution. Most respondents selected Somewhat, but there are gaps when asked whether ethical concerns were adequately addressed, and data privacy was the most frequently selected priority. At the same time, only 19.3% selected Often or Always for knowledge of personal-data practices, and 35.3% did so for institutional openness. Because the shared response anchors do not fit every governance stem naturally, the exact percentages should be read as response-category distributions rather than validated levels of governance quality. Even with that limitation, the pattern is consistent with documented variation in university AI guidance (Moorhouse et al., 2023) and Canadian academic-integrity policy and education (Miron et al., 2021; Stoesz & Eaton, 2022).

5.1 Implications for education

The single most significant empirical finding of the manuscript is that AI self-efficacy/control—a student's practical knowledge and perceived sense of control over AI tools—is the sole statistically significant independent correlate of reporting at least moderate educational AI experience (OR = 1.51, 95% CI [1.13, 2.03], $p = .005$). Crucially, this finding directly refutes the central claim that moral concerns, guilt, or ethical discomfort inhibit AI adoption (OR = 0.94, $p = .720$). While MBA students report high levels of ethical concern—particularly regarding data privacy ($M = 4.31$)—these moral appraisals do not prevent them from using AI tools; instead, technical self-efficacy is the primary leverage point driving student engagement. This finding has important educational implications.

As over time students gain increased exposure to AI tools in the academic environment, through their own experimentation, the actions of peers, and the instructions of their teachers, and learn to apply these tools in the pursuit of personal goals, this study demonstrates that this increased competence is likely to be the dominant framework for managing their AI use. Other moral concerns or ethical issues do not have a significant impact, even though they are a part of student's perceptions regarding their use of AI. This instrumental approach suggests that correct understanding of the use of these tools, especially with regard to academic integrity, is critical in the formation of good ethics in AI applications. As educational institutions approach policy clarity, this needs to be a guiding framework. As well, faculty need to model moral excellence in AI application as well as teach correct, academically responsible, use of AI, as they introduce or implement AI in their classrooms. Clearly, students are not motivated to modify their practices on moral grounds, but if their competence is developed in the context of good rules, appropriate use is more likely to occur.

Potentially, academic institutions might seek to reward good AI usage with more advanced training or access to more sophisticated AI tools. Thus, the implicit pathway to effective instrumental usage (what guides student behaviour) will occur in the context of rewarded correct behaviour.

5.2 Implications for student ethics

Currently the applicability of AI in the academic environment is contested with, as noted above, a lack of institutional clarity regarding appropriate policies. In this study of MBA students, this lack of clarity is confronted by a strong instrumental orientation by students. Policy failure and implicit or explicit institutional and social sanctions do not appear to affect students' adoption of AI. Instead, students' confidence in and competence with AI drive their use. While MBA students might be exceptional with regard to such an instrumental orientation, they may also be typical in their response to the introduction of a new technology. Regardless, in the absence of clear training in the proper use of AI, students will use AI to the extent they are familiar with it. Thus, institutions are required to move quickly to create a pathway of usage excellence that can be transmitted to students.

However, it would remain to be seen whether students would adopt such a pathway if it interfered with their sense of competence or their experience of the efficacy of AI tools in

accomplishing their ends. It also raises questions about students' moral integrity more broadly in graded or achievement-oriented contexts. Instrumental behaviour might be normative, with an AI application being merely a new application. Alternatively, the introduction of Gen AI tools, in the absence of clear moral norms, might open the environment to instrumental applications, while other well-established components of the academic environment remain subject to moral norms even in the face of instrumental efficacy. This would be a valuable framework for future research.

6.0 Restrictions and future studies

The conclusions are limited by several factors. The convenience sample came from one MBA program and may have been affected by self-selection and nonresponse. The number invited was not documented, so a response rate could not be calculated. The sample was predominantly Female and Master-qualified, while age, country, domestic/international status, and current academic term were not collected. Consequently, representativeness and differences across important subgroups cannot be evaluated. The design was cross-sectional and self-reported, so no causal or temporal ordering can be inferred.

Measurement limitations are also substantial. The adapted instrument lacked documented formal pilot or cognitive pretesting in this sample. Social pressure had only moderate two-item reliability, the two benefit items did not justify a composite, governance questions used a shared frequency scale that fit some stems imperfectly, and several domains were represented by single items. Ethical reasoning types were not measured. Although rank-based analysis closely reproduced the Pearson EFA and three factors were retained in 90.4% of bootstrap samples, bootstrap congruence showed uncertainty for Factors 2 and 3. The factors should therefore be considered exploratory dimensions rather than validated scales.

Two duplicate numeric pairs, eight appraisal straightliners, and 12 long identical-response runs were identified. Sensitivity analyses showed that these patterns did not explain the primary result, but the available export lacked timing and platform-quality indicators sufficient to adjudicate every record. Future studies should prespecify quality rules and retain paradata. The primary threshold model improved cross-validated Brier score by only 0.15% over the null model and is not suitable for individual prediction. The smaller Extensive group also produced wider intervals and increases the risk that threshold-specific findings will not replicate.

What you get is a ranked list of AI experiences, not task-specific adoption. Future surveys should differentiate between uses of AI, frequency, disclosure, assessed versus unassessed work, and institutional permission. To study the effect of ethical guidance, AI-literacy instruction, or policy change on guilt, perceived norms, and responsible use over time, a longitudinal or experimental design is required.

However, this study lays the groundwork for future studies on student behaviour. The introduction of Gen AI into the academic environment provides an excellent testing ground for both how policies should be developed and implemented, and exploring how students respond to challenges in the academic environment. The impact of Gen AI cannot be underestimated, and thus, it provides a particularly fertile context for studies into both technological adoption and human moral agency.

7.0 Conclusion

MBA students' appraisals of educational AI were not simply enthusiastic or resistant. The data supported three exploratory dimensions—moral discomfort, readiness/control with benefit indicators, and sanction/social pressure—while concern was especially high for data privacy. AI self-efficacy/control was the only robust independent correlate of reporting at least Moderate rather than None/Minimal AI experience. It was not significant at the smaller Extensive threshold, where efficiency benefit and perceived ethical-issue frequency

emerged as exploratory correlates. Governance responses further indicated limited knowledge of personal-data practices and modest perceived institutional openness. These findings support clearer task-specific expectations, critical AI-literacy education, and more transparent data governance. They do not establish causal adoption pathways, validate moral profiles, or provide accurate individual predictions.

Declaration of generative AI assistance

Generative AI tools were used to support literature search planning, language editing, and the preparation and verification of reproducible analysis code. The authors verified the cited sources, survey coding, statistical outputs, interpretations, and final manuscript and take full responsibility for the work.

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Appendix A. Items Used in the Revised Analysis

Question 6 concern items were coded from 1 (Very unconcerned) to 5 (Very concerned). Questions 7, 11, and 13 used Never, Rarely, Sometimes, Often, and Always, coded 1-5. Question 8 used No Impact, Minimal Impact, Moderate Impact, Substantial Impact, and Significant Impact, coded 1-5. Question 9 assessed whether ethical concerns were adequately addressed, and Question 12 asked respondents to choose the most important listed AI ethics concern. The exact background categories were Male, Female, Others, and Prefer not to say; Bachelor, Master, and PhD; Less than 1 year, 1 year, 2 years, and 3 years; and None, Minimal (e.g., exposure to a few tools or concepts), Moderate (e.g., regular interaction with AI tools), and Extensive (e.g., teaching, developing, or heavily using AI tools). None and Minimal were combined only for regression.

Table A1: Survey items and analytic roles

Survey item	Role	Wording
Q6.1	Concern rating	Bias in AI algorithms
Q6.2	Concern rating	Transparency in AI decision-making
Q6.3	Concern rating	Data privacy
Q6.4	Concern rating	Accountability in AI-driven decision-making
Q8.4	Impact item	Adoption of AI tools by students and faculty
Q7.5	Frequency item	Accessibility of AI tools for all students
Q8.1	Impact item	Learning Outcome (Quality of education and learning experience)
Q7.3	Frequency item	Data privacy
Q7.4	Frequency item	Accountability in AI-driven decision-making
Q7.2	Frequency item	Transparency in AI decision-making
Q8.3	Impact item	Trust in AI systems within education
Q7.1	Frequency item	Bias in AI algorithms
Q8.2	Impact item	Faculty teaching practices
Q9	Adequacy item	Do you feel that ethical concerns are adequately addressed when implementing AI tools in your MBA program?
Q12	Priority item	Which of the following AI ethics concerns do you consider the most important?
Q11.1	Appraisal item	I feel guilty if I used AI to finish my Assignment
Q11.2	Appraisal item	Using AI to complete my assignment goes against my values.
Q11.3	Appraisal item	I feel it's unfair to use AI to finish my Assignment
Q11.4	Appraisal item	I feel wrong when using AI to finish Assignment
Q11.5	Appraisal item	When I used AI, my grading increases
Q11.6	Appraisal item	When I use AI, my task will be faster
Q11.7	Appraisal item	My use of AI could be detected.
Q11.8	Appraisal item	Using AI led to a lower grade or penalty on my assignment.
Q11.9	Appraisal item	When I used AI, most of my friends and lecturers would disagree
Q11.10	Appraisal item	Most of my friends and lecturers would look down on me if I used AI
Q11.11	Appraisal item	I think that the behaviour of using AI is not wise
Q11.12	Appraisal item	I think that the behavior of using AI was a bad idea
Q11.13	Appraisal item	I know how to use AI for my Assignment
Q11.14	Appraisal item	I can decide how I use AI for my assignments.
Q13.1	Governance item	I think there is a need for an ethical assessment of how artificial intelligence systems are used by schools.
Q13.2	Governance item	How often should ethical tools provide a solution for trustworthy conduct of transparency in AI use
Q13.3	Governance item	Do you know at any point in the program how your personal data is collected, processed and what the purposes of its use are?
Q13.4	Governance item	Is the institution being open about the artificial intelligence system, its use and work with personal data