Guardrails or Growth? How Agricultural Education Faculty Frame AI Use in Syllabi

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Introduction

The rapid integration of artificial intelligence (AI) tools into higher education has created an urgent need for faculty to establish clear expectations regarding appropriate student use of these technologies (Chan, 2023; Crompton & Burke, 2023). Within agricultural education programs, preparing future teachers requires both theoretical knowledge and practical skill development, faculty are establishing varying expectations for AI use as they navigate academic integrity concerns with pedagogical benefits (McDonald et al., 2024). Despite growing attention to AI policy development in higher education broadly (Brandon et al., 2023), little is known about how agricultural education faculty communicate AI use expectations through syllabus statements across different institutions and course types. Understanding these communicated expectations is critical for ensuring consistency in teacher preparation programs and equipping future educators to navigate emerging technologies in educational settings (Miao & Cukurova, 2024). The purpose of this study was to examine how university agricultural education faculty communicate expectations about AI use in their course syllabi. Two research questions guided our study. 1. How do agricultural education faculty frame acceptable use of AI in their syllabus statements, and what tone do they employ when addressing AI?, 2. What consequences and rationales do agricultural education faculty communicate regarding AI use in their syllabi? This study utilized Entman's (1993) framing theory as the analytical lens for examining syllabus statements. Framing theory suggests that communicators select certain aspects of reality and make them more salient in a text to promote problem definitions, moral evaluations, and treatment recommendations (Entman, 1993). This framework provided a lens to understand how faculty communicate AI use expectations to students through policy language.

Methodology

This study used qualitative content analysis (Fraenkel et al., 2023) to examine AI use expectations communicated in agricultural education faculty syllabus statements. A sampling frame of agricultural education faculty members was developed by utilizing the list of programs from the American Association of Agricultural Educators, which was then cross-referenced with individual program websites. Participants were purposively sampled (Fraenkel, 2023) and invited to complete an online questionnaire through Qualtrics. Data collection occurred between December 2025 to January 2026. It was sent to 138 participants and 69 usable responses were collected (50% response rate). The survey asked participants to provide their AI statements and 44 participants provided theirs. Of the 44 syllabi, 9 were independently created, 29 were used or adapted from their department or institution statements, 4 collaborated with their colleagues to create a shared statement and 2 used or modified a statement recommended by an external resource. Limitations included purposive sampling, which limited generalizability beyond the study population; response bias, as only faculty who chose to participate shared their policies; and temporal constraints, as data reflected policies at a single point during rapid AI policy evolution (Fraenkel et al., 2023). The coding framework was developed from existing literature and included four primary categories: (1) tone (prohibitive, cautionary, neutral, supportive) , (2)

acceptable use frames (none, general use, task-specific, tool-specific) (Corbin, 2025), (3) consequences of improper use (none, general academic integrity, course-level consequences, institutional-level consequences) (Grassini, 2023), and (4) purpose or rationale for policy (none, academic integrity protection, learning support, professional skill development, administrative/compliance-oriented) (Hooper & Lunn, 2024). Two researchers independently coded all 44 syllabus statements. ReCal2 was used to calculate intercoder reliability, which was found to be acceptable ranging from .81 to .95. (Krippendorff, 2006). Data were analyzed using frequencies and percentages to describe the occurrence of each code across syllabus statements.

Results/Findings

Cautionary tone dominated (*f* = 26*,* 59.1%), with fewer supportive (*f* = 10*,* 22.7%), prohibitive (*f* = 4, 9.1%), or neutral (*f* = 3, 6.8%) statements. Task-specific acceptable use was most common (*f* = 25, 56.8%), followed by general use (*f* = 21, 47.7%); however, 34.1% (*f* = 15) also included prohibitive language specifying no acceptable use. Most statements (*f* = 25, 56.8%) did not mention consequences; when included, institutional-level consequences (*f* = 17, 38.6%) were most frequent. Rationales were largely absent (*f* = 22, 50%), with academic integrity protection (*f* = 13, 29.5%) and learning support (*f* = 12, 27.3%) most commonly provided.

Conclusions, Implications and Recommendations

Agricultural education faculty predominantly communicated guarded AI expectations but provided limited pedagogical rationales or consequences, suggesting incomplete policy frames that may inadequately prepare preservice teachers. Through Entman's (1993) framing theory lens, faculty define the problem (AI requires caution) but often fail to provide moral evaluation (why caution matters) or treatment recommendations (consequences for violations). While academic integrity protection emerged as the most common rationale when provided, the absence of rationales in most statements indicates preservice teachers may not understand why AI boundaries exist, hindering their ability to develop informed approaches as future educators. Faculty face tensions between academic integrity and pedagogical benefits (McDonald et al., 2024); however, many communicate caution without helping students navigate this complexity, highlighting a need to move beyond rules toward helping preservice teachers understand principles guiding appropriate AI integration (Chan, 2023; Miao & Cukurova, 2024). Agricultural education faculty should explicitly articulate pedagogical rationales connecting AI expectations to learning objectives and position AI literacy as an essential competency rather than solely an academic integrity concern (Miao & Cukurova, 2024). Teacher preparation programs should also consider developing shared AI policy frameworks to ensure consistency across courses. Future research should explore preservice teachers' perceptions of instructor AI policies to determine whether current syllabus statements adequately prepare them to develop informed approaches to AI integration.

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