AI-Native Faculty Workflow Blueprint for 36-Month Transformation

Faculty Workflow Blueprint Table

This table maps current faculty workflows to an AI-augmented target state, with examples of AI tools, collaboration models, and risks:

Workflow	Current State (typical practices)	AI-Augmented Target State (reimagined with AI)	AI Tool Types	Human–AI Collaboration	Risks (to mitigate)	Tools/Examples
Course Planning & Content Development	Faculty manually research and draft syllabi, lecture notes, and presentations. Content creation is time-consuming and often done from	AI co-pilots generate first drafts of syllabi, lesson outlines, and slide decks based on course objectives. Faculty get AI suggestions for readings or OER materials tailored to desired difficulty levelchronicle.com. Content is kept up-to-date with AI scanning latest research.	Large Language Model (LLM) assistants for content generation; Knowledge base search tools.	Instructor provides context and curates AI outputs. For example, a professor can give an AI (like Claude or ChatGPT) the course description and have it propose lesson plans, then the faculty refines those plansautomatedteach.com. Human judgment ensures alignment with learning outcomes and academic rigor.	Hallucinations or factual errors in AI-generated content; misalignment with course outcomes if AI suggestions are taken blindly. Faculty must review for accuracy and relevance.	*MagicSchool* (70+ AI tools for lesson planning, quiz making, etc.medium.com) – *Commercial*; *ChatGPT/Claude* for syllabus drafting – *Buildable* (via prompts); *Stanford "Instructional Agents"* project (multi-agent AI generating full course materials) – *Long Bet*scale.stanford.eduscale.stanford.edu.

Workflow	Current State (typical practices)	AI-Augmented Target State (reimagined with AI)	AI Tool Types	Human–AI Collaboration	Risks (to mitigate)	Tools/Examples
	scratch.					
Learning Activity Design (In-Person, Blended, Online)	Instructors design class activities, group work, and multimedia content manually. Slides and quizzes are prepared by hand, sometimes resulting in limited interactivity.	AI suggests engaging learning activities (e.g. case studies, simulations) tailored to the topic and student level. Presentation tools use AI to generate interactive quiz questions from lecture slides on the flyclasspoint.io. AI can adapt activities for different learning styles (visual, textual) or generate variations for in-person vs. online delivery.	Lesson idea generators; Quiz and activity generators; Adaptive learning platforms.	Faculty member selects or edits AI-suggested activities to fit the course context. For example, an AI might draft a group exercise scenario which the instructor then customizes. AI-generated quiz questions from slides (via tools like ClassPoint AI) are reviewed by the teacher for accuracyclasspoint.io.	AI suggestions could be too generic or not account for class dynamics. Without human vetting, activities might not align with specific class needs. Over-reliance on AI could reduce teacher's personal touch.	*ClassPoint AI* (generates quiz questions from PowerPoint slides) – *Commercial*classpoint.io; *Curipod* (creates interactive lesson slides/quizzes from a prompt) – *Commercial*medium.com; *ChalkTalk* (AI-powered content delivery with real-time insights) – *Commercial*.
Assessment Creation, Gradi	Faculty write exams,	AI-assisted assessment generation: LLMs propose quiz/exam questions or even full question banks based on	Quiz generators; Code auto-	**Human-in-the-loop** is criticalmitsloanedtech.mit.edu.	AI may mis-grade nuanced answers or creative workmitsloane	*Gradescope* (AI-assisted grouping of answers, rubric application) – *Commercial*,

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ng & Feedback	quizzes, and assignment prompts manually. Grading is done by hand with rubrics, leading to heavy workload and delayed feedback. Providing personalized comments on each paper is challe	the syllabus. Auto-grading systems evaluate structured answers or code. For written work, AI provides draft feedback aligned to the rubric. Grading becomes partially automated: e.g. AI groups similar answers for bulk gradingunion.teamdynamix.com, and generates feedback which instructor can edit. Turnaround time for grading and feedback is greatly reducedmitsloanedtech.mit.edumitsloanedtech.mit.edu.	graders; Rubric-based AI grading engines; Feedback text generators (LLM-based).	Instructor defines the rubric and sample solutions; AI auto-grades objective parts (like multiple-choice or simple math). For essays, AI suggests preliminary scores or comments, but faculty review high-stakes evaluations. AI-written feedback is used as a starting point, then the teacher adjusts tone or specifics before releasing to studentsautomatedteach.com. Faculty always retain final say on grades.	dtech.mit.edu. Risk of bias if the AI model wasn't trained on diverse responsesmitsloanedtech.mit.edu. Hallucinated feedback or incorrect hints could mislead students. **Mitigations:** require faculty approval of AI-assigned grades, conduct regular accuracy audits on the AI grading systemmitsloanedtech.mit.edu, and allow students to appeal AI-generated grades with human re-grading if needed.	integrated with LMSmedium.com; *Turnitin Draft Coach* (writing feedback) – *Commercial*; *Custom GPT feedback assistant* (faculty notes → polished comments) – *Buildable*automatedteach.com; *Moodle Quiz AI module* (question generation and auto-marking in Moodle) – *Open-Source/Buildable*.

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	nging, especially in large classes.					
Interaction with Students (Office Hours, Q&A, Coaching)	Office hours and student emails are handled 1:1 by faculty, which can be limited by schedule. FAQs get repeated each term. Providing timely help to every stude	Always-on AI assistants augment student support. For example, an AI tutoring agent (trained on course material and Q&A logs) answers common questions at any hour, acting as a first line of helpautomatedteach.com. AI can also summarize long email threads or draft responses to routine emailsautomatedteach.com. In live classes or webinars, AI can transcribe and translate discussions in real time for all students (enhancing accessibility). Overall, students get quicker responses and support beyond the instructor's alone capacity.	Chatbot tutors (LLM-based, fine-tuned on course content); Email response assistants; Transcription and translation AI services.	AI handles FAQs and simple queries, while **escalating** complex or sensitive issues to faculty. For instance, if a student asks the AI assistant a basic question about the syllabus, it provides the answer; if the question is nuanced or not in its knowledge base, it prompts the student to contact the professor. Faculty monitor the AI's interactions periodically	AI might give incorrect or unsupported answers to student questions, which could confuse learners. There is also a risk students over-trust the AI tutor's guidance. **Mitigations:** clearly inform students that the AI is a support tool and not always perfectautomatedteach.com, log all AI-provided answers so faculty can audit them, and educate students on AI's limitations (part of AI literacy	*Khanmigo for Teachers* (GPT-4 assistant for student Q&A) – *Commercial*medium.com; *Custom Course Chatbot* (built on OpenAI/Anthropic model with course docs) – *Buildable*; *Otter.ai* (transcribes and captions lectures in real-time) – *Commercial*medium.com; *Microsoft 365 Copilot* (drafts routine emails, meeting prep) – *Commercial*automatedteach.com.

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	nt is difficult, especially in large classes or across campuses.			and correct any misanswers. When using email assistants, faculty review AI-drafted replies before sending if non-trivial.	training). Privacy is a concern too – sensitive student questions should be handled by humans to maintain trust.	
Student Progress Monitoring & Intervention	Faculty manually review grades and attendance to identify at-risk students. Often, interventions come late (after midterms or when	AI-driven early warning systems monitor a wide range of signals (assignment scores, LMS activity, attendance, forum posts) in real-time to flag students who may be strugglingjotverse.comjotverse.com. AI predictive models identify risk patterns weeks earlier than traditional mid-term flags. The system suggests personalized intervention actions – e.g. recommending the student visit office hours, assigning extra practice, or alerting academic advisors. Faculty receive AI-generated "nudge" messages or intervention plans for each at-risk	Predictive analytics models (machine learning on student performance data); Dashboards for risk alerts; Recommender systems for interv	The AI continuously analyzes data, but **faculty make the final call** on interventions. For example, if the AI flags a student as at-risk due to low quiz scores and inactivity, it might draft an encouraging email to check in with them. The instructor reviews this draft, perhaps adds a personal note, and sends it. Faculty and advisors	False positives (AI flags students who are actually doing fine) or false negatives (failing to flag quiet struggling students) can occur. Data privacy and ethics must be handled carefully when monitoring student datajotverse.com. **Mitigations:** use transparent criteria for alerts, allow students and faculty to opt-in to certain analytics, and	*Moodle Learning Analytics (Inspire) – Open-Source* (predicts risk of dropping out based on engagementdocs.moodle.org); *Civitas Learning* or *EAB Navigate* (student success analytics platforms using AI) – *Commercial*; *Element451 Pulse* (AI agent sends nudge messages to at-risk students) – *Commercial*element451.com; *Panorama Ed* (early warning for K-12, concept applicable to

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	a student reaches out). Early alerts might rely on static rules or gut feeling. Data on engagement (e.g. LMS logins) is underutilized due to lack of tools.	student, which they can review and send out.	entions.	might meet regularly to discuss the AI's alerts, combining them with their own knowledge of the student (e.g. personal circumstances). Human judgment is used to override false alarms or identify issues AI might miss.	combine AI signals with human observations. Also, ensure the AI model is trained on relevant and unbiased data to reduce demographic bias in predictions.	higher ed) – *Commercial*.
Curriculum Review, Outcome Trac	Programs are reviewed periodically	AI tools analyze curriculum maps, syllabi, and assessment data to reveal how well learning outcomes are being met. For instance, an AI can parse all course outlines and	NLP-driven curriculum mapping tools; Outco	Faculty and administrators work with AI analyses to make decisions. The AI might highlight that	AI might misinterpret context (e.g. suggesting a gap where none exists due to how an outcome is	*Curriculum Insight* (Hypothetical AI tool that maps outcomes to assessments) – *Buildable*; *Aquadis* or

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king & Reporting	(year-end or accreditation cycles) by manually gathering data like grade distributions, course evals, outcome attainment. Identifying gaps in curriculum or misalignment with learning outcomes is	check coverage of program outcomes, flagging any outcome that isn't adequately assessed. AI can also compile accreditation reports by pulling relevant data (e.g. % of students achieving each outcome) and drafting narrative summaries. During course design, AI assures alignment by comparing assignments against outcomes (as one professor did using ChatGPT to apply *Understanding by Design* principles)[chronicle.com](chronicle.com). Over time, an AI "curriculum advisor" might even suggest adding or updating content in a course based on industry trends or skill gaps identified in student performance.	me analytics dashboards; Report generation assistants.	"Outcome X" has been under-assessed in the curriculum – the curriculum committee then investigates and decides how to address it. When preparing an accreditation self-study, AI can draft sections with data, but faculty edit for context and ensure accuracy. **Human oversight** is key to interpret AI findings correctly.	worded). There's a risk of over-reliance on AI recommendations for curricular changes without sufficient pedagogical discussion. Also, data-fed AI analyses must be kept secure (curriculum and assessment data are sensitive). **Mitigations:** treat AI suggestions as starting points, require academic committees to vet any changes, and maintain transparency in reports (disclose if AI was used in analysis, as a matter of integrity).	*Taskstream* with AI features (assessment management systems) – *Commercial*; Faculty use of ChatGPT for alignment checks (e.g. asking if assignments match learning goals) – *Piloted*chronicle.com; *Power BI/Tableau with AI* (for automated report narratives) – *Commercial/Buildable.*

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	labor-intensive. Reporting relies on spreadsheets and narrative reports written by faculty committees.					

Reference Architecture for AI-Augmented Faculty Workflows

In the target state, the university will have a **modular AI-powered architecture** that integrates with existing systems (Moodle LMS, Student Information System) while ensuring governance and security. Key components and integration points include:

- **Faculty AI Co-Pilot:** A personal AI assistant for instructors accessible through various interfaces (within the LMS course page, a chat app, or voice). This co-pilot leverages a large language model to help with tasks like content creation, answering "How do I…?" queries, drafting emails, and summarizing forum discussions. It draws on an internal **Prompt Library** of vetted prompts/workflows for education tasks (e.g. "generate a quiz on topic X at Bloom's application level"). The co-pilot can chain tasks (via an agent paradigm) – for example, find relevant resources from the knowledge base, create a summary, and then draft an announcement. *Components:* LLM (could be via an API or on-prem model), prompt templates, and a conversational UI.

- **AI Feedback & Grading Engine:** A service that handles assignment evaluation workflows. It includes an **AI Grader** that can apply rubrics, backed by both an LLM (for open-ended responses) and traditional ML (for objective answers). The engine integrates with the LMS grading module – when an instructor triggers AI-assisted grading on an assignment, the engine groups similar answers and suggests scores/feedback for each groupunion.teamdynamix.com. Faculty can adjust the rubric or override grades at any time. This component also generates feedback drafts using an LLM, following the tone and criteria specified by the instructor (a "feedback orchestration" module). *Integration:* Connects to the LMS via APIs to pull assignment submissions and push back graded results. All AI-generated grading actions are logged for audit.
- **Student Support AI Agents:** These are AI services oriented towards student interaction but configured by faculty. For instance, a **Course Q&A bot** that is trained on the course syllabus, lecture notes, and FAQ. It lives in the LMS course page as a chat widget. It uses a combination of an LLM and a **Knowledge Base** of course content to answer student questions with verified information (using retrieval-augmented generation so that answers cite course materials to avoid hallucinations)aws.amazon.com. Another agent could be a **24/7 Office Hour Tutor** which steps students through problems (similar to Khanmigo's approach of guiding with questionsmedium.com). These agents can also escalate to a human (e.g., "This question might be better answered by your instructor. I'll notify them."). *Integration:* Accesses course files from LMS, uses institutional single sign-on for student identity, and can create a ticket or email to faculty when human follow-up is needed.
- **Learning Analytics & Early Alert System:** A back-end analytics engine continuously collecting **learning telemetry** – assignment grades, quiz attempts, forum activity, login frequency, etc. It uses predictive models to detect patterns of risk. This connects to a **Dashboard** for faculty and advisors highlighting students who might need support, as well as an **Intervention Recommender** that suggests actions (like "Student X has missed 2 classes and scored low on Quiz 1 – consider reaching out or connecting them to tutoring"). The analytics models can be refined using institutional historical data. This component integrates with the SIS (for demographic and history data) and LMS (current course performance). It can also write alerts into the advisor CRM or send notifications via email.
- **Content and Knowledge Repositories:** To ensure AI outputs are context-aware and accurate, the architecture includes a repository of vetted institutional content: e.g. past course materials, libraries of assessment questions, policy documents, and domain-specific knowledge bases. These are indexed for AI retrieval. For instance, a "Knowledge Base" connector allows the Faculty Co-Pilot or Student Q&A bot to fetch relevant information (similar to how Amazon's Bedrock Knowledge Bases connect models with institutional data for contextaws.amazon.com). This reduces hallucinations and grounds the AI in university-specific content. Sensitive data access is permission-controlled.
- **Integration Layer:** All AI components connect through an integration layer with **APIs** and plugins. For Moodle (the LMS in use), custom plugins or LTI integrations embed AI features directly into the LMS UI (for example, a "Grade with AI" button on the grading screen, or an "AI Mentor" block on the course dashboard). The SIS integration ensures student records (like prior GPA or support services used) inform the AI models (with privacy safeguards). If the university uses platforms like Microsoft Teams or Slack for

communication, the Faculty Co-Pilot and student bots could also be accessible there (e.g. an instructor can query the AI via Teams chat, or a student can message a bot in a forum channel).

- **Governance and Guardrails:** Overlaid across this architecture are governance components to ensure ethical and effective use:
  - **Audit Trails & Logging:** Every AI action (content generated, grade suggested, answer given to a student) is logged with time, which model was used, and what prompt/data was involved. This creates an audit trail for transparency and troubleshooting. Regular audits for accuracy and bias are performed on these logsmitsloanedtech.mit.edu.
  - **Permission & Role Controls:** Faculty can choose which AI functions to activate in their courses (opt-in features). For example, an instructor might enable AI draft feedback on essays but disable AI auto-grading on subjective assignments. Students can be given opt-out options if they prefer human-only feedback (to respect those uncomfortable with AI involvement). Admin settings allow certain models or data sources to be restricted if not meeting privacy/quality standards.
  - **Model Management & Data Privacy:** The architecture likely uses a mix of third-party AI models (via cloud services) and possibly on-premise models for sensitive data. A central **AI Orchestration Service** routes requests either to external APIs (e.g. OpenAI, AWS) or to an internal model based on data sensitivity. All student data stays within the university's secured environment unless explicitly allowed (e.g. using anonymized data to send to an external API). Compliance with privacy laws (like not exposing personal identifiers without consent) is built-in.
  - **Content Filtering & Plagiarism Checks:** Any AI-generated content that will be presented to students (like AI-written feedback or answers) goes through a filtering layer to avoid inappropriate or biased language. Additionally, when students submit work, AI-assisted originality checks (plagiarism or AI-generated content detectors) are integrated to uphold academic integrity.

In summary, the target architecture is an **agent-based, interoperable system** where AI is not a separate platform but woven into faculty's everyday tools. An instructor preparing a course sees AI suggestions in the LMS; while grading sees AI feedback drafts; when concerned about a student sees AI insights on a dashboard. Meanwhile, all stakeholders have confidence that there are guardrails (audit logs, bias checks, opt-outs) ensuring the AI is a helpful servant, not a black box overlordchronicle.com. This architecture will require robust cloud infrastructure, but reference implementations (like AWS's education AI framework) show that it can be done in a scalable and secure wayaws.amazon.comaws.amazon.com.

Faculty AI Toolkit Menu

Below is a menu of AI tools that the university can consider. They are grouped by function, with an indication of their availability type: **Commercial (ready-made)**, **Open-Source** (community or free tools), **Buildable** (could be developed/customized in-house or via API), or **Piloted @** (noting if we or peer institutions have piloted it).

Content & Course Design Tools

- **MagicSchool** – *Commercial*: An extensive suite of 70+ AI tools for teachers. It can generate lesson plans, quizzes, simplify readings, create PPT slides, and even draft individualized education plansmedium.com. MagicSchool includes an AI assistant ("Raina") to iteratively refine generated content. This could jump-start course material creation in both English and Vietnamese (though Vietnamese support needs to be verified).
- **Curipod** – *Commercial*: Helps create interactive lessons and slide decks with AI. Teachers input a topic, and Curipod generates an engaging slide presentation with quiz questions and discussion promptsmedium.com. Good for in-class activities.
- **ClassPoint AI** – *Commercial*: An add-in for PowerPoint that uses AI to generate quiz questions from your slides and even summarize students' written responses. For example, as you teach with PPT, ClassPoint can produce on-the-fly questions (multiple-choice, short answer, etc.) based on the contentclasspoint.io. This enhances interactivity in lectures.
- **ChalkTalk** – *Commercial*: An AI-driven content delivery platform. It adapts lessons in real-time to student performance and provides teachers with live insights on who is following along. Useful for blended learning, though primarily used in K-12, its principles (e.g. differentiated instruction suggestions) can apply in higher ed.
- **Microsoft 365 Copilot (and Bing Chat Enterprise)** – *Commercial*: An AI integrated into Office apps. Faculty can use it to generate draft documents (syllabi in Word), analyze data (enrollment stats in Excel), or even produce meeting agendas. It also can answer questions with web and internal data. Copilot speeds up administrative prep work – for instance, drafting a course outline from bullet points or brainstorming lecture topics. (Pilots at some universities show promise in reducing paperwork time.)
- **OpenAI / Azure OpenAI GPT-4** – *Buildable*: Using the OpenAI API (or Azure's hosted version), the university can build custom content generation tools. For instance, an internal app where faculty input a topic and course level, and get a draft module guide or a set of lecture notes. This would require development, but gives flexibility (and we can fine-tune the model on our own educational content for better local results). Some pilot projects in our university are already using ChatGPT ad-hoc for these tasks (e.g., faculty using ChatGPT for brainstorming and translations – this informal use can be turned into a structured toolset).
- **Fetchy** – *Commercial*: An AI lesson plan generator that creates detailed plans based on grade level and objectivesmedium.com. It includes handy tools like email drafting and short story generation for class examples. While perhaps more geared to school teachers, some features (like concept explanation generator) can help new faculty or those teaching outside their specialty.
- **Chalkie AI** – *Commercial*: A tool to create lesson materials (plans, worksheets, activities) quickly. It's like an AI template generator for class prep. Could be useful especially if localized for Vietnamese context (needs exploration).
- **Open-Source Lesson Prompt Library** – *Open-Source/Buildable*: Rather than a specific tool, this refers to a repository of prompt templates and workflows shared by educators (many are emerging on GitHub and forums). For example, there are open collections of prompts for generating case studies, quiz questions, debate topics, etc., which we can

integrate into our systems. We can contribute to and draw from these libraries to continuously improve faculty co-pilot prompts.

Assessment & Feedback Tools

- **Gradescope** (by Turnitin) – *Commercial*: A platform that streamlines grading of exams and assignments. It uses AI to group similar answers (especially for short answers or math problems) so that instructors can grade a batch of answers with one rubric actionmedium.com. It supports programming assignments auto-grading as well. Many universities (including some in the region) have adopted Gradescope to cut grading time and get analytics on which questions students struggled with. *Integration:* It can integrate with Moodle for roster and gradebook sync.
- **Turnitin with AI Features** – *Commercial*: Turnitin is known for plagiarism detection, but it's rolling out AI writing detection and has a tool called Draft Coach that gives students feedback on their writing. For faculty, Turnitin's grading interface (Feedback Studio) could potentially incorporate AI to suggest comments. While we must use such tools carefully (to avoid false positives in AI-detection), Turnitin is commonly used and its evolving AI capabilities (especially to ensure originality) are worth monitoring.
- **Educational Feedback Assistant (Custom GPT)** – *Buildable*: Inspired by faculty experimentsautomatedteach.com, we can develop an AI that takes the grader's brief notes or highlights on a student's work and expands them into full, kind, and constructive feedback. This could be a plugin in Moodle: as the instructor highlights text or writes a quick note ("good analysis but need more examples"), the AI generates a complete feedback paragraph in the teacher's style. Early pilots (our faculty using ChatGPT manually for this) have shown it can save time while *improving* feedback quality, as long as the instructor verifies the output.
- **Rubric Generator & Checker** – *Open-Source/Buildable*: Tools like **Jenni AI** or **Illinois GenAI** have showcased rubric generatorspublish.illinois.edu. We can adopt an AI to generate draft rubrics from assignment descriptions (ensuring alignment with outcomes) and also to check consistency. This helps standardize grading criteria. An open tool in this area is the TCEA AI Rubric Generator (by Texas Computer Education Association) which suggests rubric languageblog.tcea.org.
- **Quiz and Question Generators** – *Commercial/Open-Source*: Aside from content tools above (MagicSchool, etc.), there are AI tools specifically for assessment creation. **Quizlet** has AI-assisted flashcard and test creation features; **Canvas LMS** (if we ever use it) is releasing a quiz generator using AI. For Moodle, there is an open-source plugin in development that uses GPT to create quiz questions (we could pilot that in a sandbox). These help faculty quickly build question banks, which can be reviewed and edited.
- **AI Writing Evaluation (for student essays)** – *Commercial*: E.g., **Ecree** or **GrammarlyGO EDU**. These tools give students instant feedback on drafts (organization, argument strength) and could give instructors a high-level analysis of a batch of essays (common errors, readability scores). Some are student-facing, but faculty can use the analysis to adjust instruction (e.g. if AI reports many students have weak thesis statements, the teacher can address that).
- **Coding Auto-graders** – *Open-Source/Commercial*: For CS/IT courses, auto-graders like **CodeRunner (Moodle plugin)** or **GitHub Classroom w/Autograding** can be enhanced

with AI to give hints. Open-source frameworks (like Otter-Grader, not to be confused with Otter.ai, or Polyglot) exist to set up test-case based grading. We can combine these with an LLM to analyze why a student's code failed and provide a tailored hint, for example.

Student Support & Tutoring Tools

- **Khanmigo (Khan Academy AI)** – *Commercial (free for limited pilots)*: Khanmigo is a GPT-4 powered tutor that can engage students in problem-solving dialogues and also assist teachers with ideas[medium.com](). While Khan Academy is K-12 focused, they have content up to early college level. Khanmigo's approach (leading a student with questions, acting as a debate partner, etc.) is a model we can emulate in our context. We might pilot Khanmigo in foundational courses (e.g. first-year math) to see how AI tutoring impacts student performance.
- **Duolingo Max** – *Commercial*: For language learning courses, Duolingo Max uses AI to enable role-play conversations and explain answers. Though Duolingo is an external app, its AI features could supplement our language classes by giving students extra practice with conversational AI tutors.
- **Quizlet (Q-Chat)** – *Commercial*: Quizlet's Q-Chat is an AI tutor that uses the student's study sets to quiz them in a conversational way. Students at our university might already be using it informally. The idea of Q-Chat (dialogue-based retrieval practice) can be integrated into our systems too. We could encourage its use for subjects like vocabulary, where it's effective.
- **Otter.ai and Fireflies.ai** – *Commercial*: These are AI transcription and meeting assistant tools[medium.com](). In an academic context, students with access can record lectures or study group sessions and get transcripts with summaries. Faculty can also use them to record their classes (with student consent) and provide transcripts to students – useful for review or for those with accessibility needs. Some faculty are piloting Otter.ai individually; we could get a campus license or integrate it with Zoom/Teams for automatic captioning and note-sharing.
- **AI Office Hours Bot** – *Buildable*: An idea to build a chatbot that is active on the course forum/Moodle discussion board. It could answer frequently asked questions (e.g., "When is the assignment due?" or "How do I cite a source in APA?") using the course info and a predefined Q&A list. It could also moderate forum posts, suggest relevant links, or even notify the instructor if many students are confused about the same topic. While not off-the-shelf, this is buildable with an LLM connected to the course data. Some open-source projects (like **Piazza AI helper** or **Edubot**) might be starting in this space.
- **Mentorpal / Career AI Advising** – *Open-Source*: There are experimental tools like MentorPal (from USC/ETS) that simulate Q&A with virtual mentors. For our context, an AI that answers student queries about research opportunities, career paths or provides general advice (trained on past advising FAQs) could supplement faculty advising. This is a "long bet" idea to explore once academic uses stabilize.

Learning Analytics & Risk Alert Tools

- **Moodle Inspire Analytics** – *Open-Source*: Since we use Moodle, we have a built-in open-source learning analytics engine (formerly "Inspire"). It can predict students at risk of dropping out using machine learning models, and send notifications to instructorsdocs.moodle.org. We should enable and configure this. It's not as advanced as some commercial products, but it's transparent and we can improve it by feeding in more data or adjusting the predictive models.
- **Civitas Learning or EAB Navigate** – *Commercial*: These are well-known student success analytics platforms used in the US. They aggregate data from LMS and SIS to identify at-risk students and suggest interventions. Civitas, for example, uses predictive modeling and has been shown to improve retention in some colleges by enabling proactive advising. While cost may be high, looking at their methodologies can inform our approach (e.g., they consider non-traditional data like how early a student signs up for courses).
- **Panorama Education (Early Warning)** – *Commercial*: More K-12 focused, but the concept is relevant. Panorama and similar dashboards look at attendance, behavior, and grades to flag issues. If we find a regional or open-source equivalent for higher ed, it could be valuable. For instance, open-source initiatives via OpenEDx or Apereo might have something.
- **Element451 (AI Student Engagement)** – *Commercial*: Element451's student CRM includes AI agents that send personalized nudges to studentselement451.com. For example, if a student hasn't logged in for a week, it might text them a reminder or encouragement. This kind of automation could be piloted in a small scale (maybe using simpler tech like scheduled emails from our LMS based on certain triggers first).
- **Custom Early Alert Model** – *Buildable*: Using Python/AI libraries, our Institutional Research or IT team could build a simple model on historical data to predict risk. Even a regression or decision tree model that uses inputs like high school GPA, first-semester performance, and LMS activity could yield a risk score. This is a buildable approach if we want to own the solution and perhaps a good project involving our data science students.

Policy & Integrity Tools

- **Turnitin AI Detection** – *Commercial*: Mentioned earlier under assessment, this specifically addresses AI-generated content from students. It's controversial (accuracy isn't perfectmitsloanedtech.mit.edu), but it's one tool in ensuring integrity. We should combine it with an academic integrity policy rather than rely on it solely.
- **Honorlock or Examity AI Proctoring** – *Commercial*: These remote proctoring services use AI to monitor test-takers via webcam and flag suspicious behavior. If we expand online assessment, such tools might come into play. Caution: they raise privacy and bias concerns, so faculty should be trained when to use them (e.g., high-stakes exams only, and ensure students are informed).
- **Academic Integrity Bots (Experimental)** – *Open-Source/Buildable*: This is an emerging idea – AI that can scan student submissions for not just plagiarism but signs of AI generation or inconsistencies with a student's past work. Open-source code like GPTZero exists for detecting AI text, though not highly reliable. A more promising approach is using stylometry (writing style analysis) to compare a student's work. This

might be a long-term project for our computer science faculty and students to collaborate on, creating an internal tool to flag "this essay is markedly different from the student's previous writing style."

(Each tool above is tagged with its nature. "Buildable" means we'd create or customize it, likely by leveraging AI APIs or open-source models with our own developers. "Piloted @university" can be noted once we actually pilot them; currently we know faculty are informally using some of these, like ChatGPT.)

Faculty Enablement Program

Adopting AI-native workflows represents a significant change in how faculty teach and work. A robust enablement program is critical to build AI fluency, confidence, and pedagogical best practices. We propose a multi-tiered faculty development program with a mix of training, resources, and community support:

- **Capability Levels (3-Level Model):**
  - **Level 1 – Awareness:** Faculty understand what AI tools are available and the basic concepts of generative AI, machine learning, etc. The goal at this level is to demystify AI and show examples of it in action in education. *Outcome:* Faculty can describe how AI might assist in course prep or grading, and they know the policies for AI use.
  - **Level 2 – Usage:** Faculty learn how to actually use specific AI tools in their workflow. This involves hands-on training with the chosen toolkit (e.g. how to prompt ChatGPT effectively for a lesson plan, how to interpret Moodle's analytics alerts). *Outcome:* Faculty have incorporated at least one AI tool in a course (e.g. using Gradescope for an assignment or trying the AI tutor in their class forum) and can share their experience.
  - **Level 3 – Design/Innovation:** Faculty co-create new AI-embedded teaching approaches. This is advanced capacity-building for those who will serve as champions or experimenters. They might design new assignment types that leverage AI, or collaborate with the IT team to improve an AI tool. *Outcome:* Faculty at this level publish case studies or lead workshops for peers (creating a cycle of continuous improvement).
- **Training Formats:**
  - **Self-Paced Online Modules:** Bite-sized modules hosted on the LMS (in English, with Vietnamese subtitles or text where needed) covering topics like *"AI 101 for Educators"*, *"Prompt Craft for Faculty"*, *"Designing Assessments in the AI Era"*. These can be 15-30 minute interactive lessons. The University of Louisiana's approach of a self-paced AI literacy microcredential (16-hour course for faculty and students) is a good modelgovtech.com – we can similarly offer a certificate upon completion to incentivize participation.
  - **Workshops and Bootcamps:** Intensive in-person or live-online sessions. For example, before each semester, offer a 2-day *"AI in Teaching Bootcamp"* where faculty bring a syllabus or assignment and work with AI mentors to enhance it.

These sessions encourage sharing among faculty. (We might invite external experts or use power users internally as facilitators.)
    - **AI Co-Design Labs:** A program where interested faculty partner with instructional designers and students to pilot an AI-augmented course redesign. UMass Lowell's mini-grants model is instructive heregovtech.com – they provided small grants and created a community of practice for faculty experimenting with generative AI in teaching. We can do similar: e.g., offer 5-10 grants of 10 million VND each for innovative AI uses in courses, with the requirement that recipients meet periodically to share progress. This not only builds skills but generates local examples.
    - **Peer Showcases and Communities:** Establish a Community of Practice (perhaps a Teams or Facebook Workplace group) for faculty to discuss AI experiences. Monthly "AI in Teaching" brown-bag lunch sessions can feature faculty who tried something new (like an accounting lecturer who used an AI tutor for problem practice sharing results). This aligns with what UMass Lowell found – that having a supportive community readily accessible encourages experimentationgovtech.com.
- **Resource Support:**
    - **AI Tool Guides and Prompt Library:** Maintain up-to-date quick-start guides for each approved tool (one-pagers or short videos). Also, a shared library of effective prompts, curated by discipline. For instance, a prompt that works well for generating case study ideas in Business, or a prompt for explaining code in Computer Science. Faculty can contribute to and draw from this library, building a "crowdsourced" knowledge base of best practices.
    - **One-on-One AI Consultations:** The teaching & learning center (or a new "AI Innovation Center") can offer consultations where an instructional designer or "AI tutor" sits with a faculty member to map AI solutions to their course challenges. This personal touch can help less tech-confident instructors get started. Perhaps office hours for AI questions (just as we have for pedagogy or LMS help).
    - **Student Assistants / AI Fellows:** Leverage tech-savvy students (or recent grads) as assistants assigned to departments to help implement AI. These could be internships or work-study positions where the student gets experience and the faculty get help (for example, a student could help fine-tune an AI model with faculty, or help set up course chatbots each semester). This mirrors successful patterns where students often drive innovation if given a role.
- **Tracking Adoption & Fluency:**
    - We propose developing an "AI Fluency Index" for faculty to self-assess their comfort and usage, perhaps yearly. This could be a simple survey that gives a score based on skills (like prompting ability, understanding of AI limitations, etc.). The goal is not to rank faculty, but to identify those who need more support and to measure growth over time.
    - Key Performance Indicators (KPIs) for the enablement program could include: % of faculty who complete Level 1 training; number of courses that incorporate at least one AI tool in a term; faculty self-reported time saved in grading or prep; and qualitative measures like faculty satisfaction or confidence in using AI.

- On adoption KPIs: We should aim for something like 30% of faculty at Awareness level in year 1, 20% at Usage level by year 2 (i.e., actively using in class), and a core 5-10% at Design/Innovation leading pilots by year 3. Adoption will likely follow a bell curve (early adopters then majority), so support and success stories from the first movers are crucial.
- **Policy and Integrity Guidance:**
  - The faculty development must integrate our AI usage **policy** (see next section) so that faculty know the do's and don'ts (e.g., if our policy says "AI-generated feedback must be disclosed to students," the training should emphasize how to do that). We might create quick reference cards on ethical AI use, bias awareness, etc.
  - Academic integrity in the age of AI is a big concern for faculty – our program should involve the academic integrity office or experts to train faculty on redesigning assessments and detecting misuse. In other words, not just how faculty *use* AI, but how to manage student use of AI in their classes.
- **Cultural and Behavioral Shifts:**
  - We will encourage faculty to evolve from being sole content deliverers to facilitators and mentors, leveraging AI for routine tasks. This is a cultural shift from "I must individually craft every element" to "I curate and improve AI-generated content." Such a shift might challenge traditional views of teaching autonomy. Open dialogues and reassurance are needed: using AI is not "cheating" or diluting one's expertise, but rather freeing time for higher-level teaching interactions.
  - Recognize concerns and fears: some faculty may worry AI could replace them or devalue their role. The program should clearly position AI as *augmentative*. For example, share evidence like studies or testimonials: e.g., a religion professor who used ChatGPT felt it gave him much-needed support but still firmly believes only the human instructor can truly understand student needs and catch certain issueschronicle.com. Such stories help underline that faculty are in control.
  - Provide positive reinforcement: celebrate successes where AI improved student outcomes or saved time. Small wins (like "thanks to AI, I returned exam feedback in 2 days instead of 2 weeks") should be amplified. This helps create a culture where using these tools is seen as pedagogical innovation, not laziness or a threat.

In summary, faculty enablement is an ongoing effort. It's not a one-off training but a continuous empowerment program. By year 3, we aim to have a self-sustaining community of practice around AI in teaching, with faculty themselves leading the way in discovering new uses. The program's multi-tier approach ensures we "meet faculty where they are" – from skeptics or novices to tinkerers and innovators – and bring everyone forward together.

Risk Register

Adopting AI across faculty workflows introduces various risks. Below is a register of key risks, their potential impact, and suggested mitigation strategies. Each risk is assigned an owner (role responsible) and a priority level.

Risk (What could go wrong)	Impact (Consequence if it happens)	Mitigation (How to reduce/prevent it)	Owner (Responsible role)	Priority
Hallucinations or Misinformation from AI – AI tool provides incorrect content (e.g. a wrong fact in lecture notes or an erroneous explanation in feedback).	- Students or faculty might be misled by false information, harming learning quality. - Could erode trust in the system if such errors are frequent or egregious.	- **Verification processes:** Faculty must review AI-generated content before use (no fully automated publishing). Double-check key facts; use AI that can cite sources to assist verificationacademicintegrity.orgacademicintegrity.org. - **Knowledge base grounding:** Connect AI to trusted internal data and require it to show evidence (retrieval augmented generation) to minimize off-base answersaws.amazon.com. - **Pilot and refine:** Test AI outputs on small groups to catch issues; continuously improve prompt instructions to reduce hallucinations.	Faculty user (with Instructional Design team to support)	High
Bias and Fairness Issues – AI-generated content or grading may reflect biases (gender, cultural, linguistic) present in training data.	- Biased feedback or content could disadvantage or offend certain student groups (e.g., phrasing that assumes a cultural context). - Unequal treatment: e.g., an AI grading essay style might favor one dialect of English over others.	- **Bias audits:** Regularly audit AI outputs for biasmitsloanedtech.mit.edu. For grading AIs, run tests with sample submissions from diverse backgrounds to see if scores differ unfairly. - **Diverse training and prompt tuning:** Use training data that includes local context (Vietnamese names, examples) and explicitly instruct AI to be culture-sensitive. Diversify prompt examples to reflect equity.academicintegrity.orgacademicintegrity.org - **Human oversight in evaluation:** Maintain human review especially for subjective grading to catch bias (AI as support, not sole judgemitsloanedtech.mit.edu). If any bias incident occurs, address it transparently and adjust the system.	AI Governance Board / DEI Officer	High

Risk (What could go wrong)	Impact (Consequence if it happens)	Mitigation (How to reduce/prevent it)	Owner (Responsible role)	Priority
Privacy & Data Security – Use of AI may involve sensitive data (student info, grades) and external AI APIs. Risk of data exposure or non-compliance with privacy laws.	- If student personal data or coursework is leaked to an external service, it violates trust and possibly laws (GDPR, local privacy regs). - Faculty may be reluctant to use tools if they fear confidential info (e.g., exam questions, research data) could be compromised.	- **Data policy & contracts:** Only use AI services that comply with our data policies (e.g., providers that don't store/retain user prompts or have proper encryption). Sign proper agreements with vendors. - **On-prem or private instances:** For very sensitive use-cases, use self-hosted models or those available in Vietnam data centers to keep data local. - **Anonymization:** Where possible, strip identifying info before sending to AI (e.g., use student IDs instead of names in data analysis).mitsloanedtech.mit.edu (point on protecting privacy). - **Training & guidelines:** Educate faculty to not paste sensitive info into public AI tools. Provide a secure enterprise alternative (e.g., an official ChatGPT Enterprise account or Azure OpenAI instance) for work use. Monitor compliance.	CIO / IT Security Officer	High
Over-reliance and Faculty Deskilling – Faculty might become too dependent on AI for tasks, potentially eroding their own skills or judgment.	- Teaching quality could suffer if instructors accept AI outputs without critical thinking (e.g., poorly curated content,	- **Training on critical use:** Emphasize AI is a partner, not an infallible oracle. Incorporate exercises in faculty training where AI outputs are critiqued and improved by the human (to reinforce active involvement). - **Guidelines:** Set expectations that faculty should always review and tweak AI contributions – e.g., a policy that "AI-generated feedback must be reviewed before release." - **Maintain core skills:** Encourage faculty to occasionally do things manually to stay sharp (for instance, still write some quiz questions	Deans/Department Chairs (oversight), Teaching Center	Medium

Risk (What could go wrong)	Impact (Consequence if it happens)	Mitigation (How to reduce/prevent it)	Owner (Responsible role)	Priority
	generic feedback). - In long term, faculty might lose expertise in course design or assessment if they always default to AI suggestions, creating a kind of "automation complacency."	or grade a sample by hand to calibrate). Also rotate tasks – e.g., use AI for first draft one time, next time do it yourself and compare, to keep oneself engaged. - **Monitor outcomes:** If student evaluations or learning outcomes dip in courses with heavy AI use, investigate if over-reliance is an issue and adjust usage.		
Academic Integrity & Student Misuse – Students using AI inappropriately (cheating, plagiarism), or confusion about what is allowed, could increase due to AI ubiquity. (While not a direct *faculty* workflow risk, it's a consequential	- Increase in undetected plagiarism or ghostwriting by AI could devalue assessments. - If not managed, could lead to grade disputes, mistrust between faculty and students, and	- **Clear policy and honor code updates:** Define what constitutes acceptable vs. unacceptable AI use for students. E.g., "AI may be used for research but not for writing the final essay" or require disclosure of AI assistance. Communicate this widely each semester[academicintegrity.orgacademicintegrity.org](academicintegrity.org). - **Redesign assessments:** Shift toward formats that are less prone to AI cheating (oral exams, project-based work, in-class writing) or use AI-proof strategies (personalized context in questions). - **Detection and consequences:** Deploy AI detection tools carefully (with human verification) and maintain strict consequences for dishonesty. Also, use this as a learning opportunity: teach students about responsible use of AI (e.g., how to cite AI, the ethics of AI in work)[academicintegrity.org](academicintegrity.org).	Academic Integrity Officer; Faculty (front-line)	High

Risk (What could go wrong)	Impact (Consequence if it happens)	Mitigation (How to reduce/prevent it)	Owner (Responsible role)	Priority
risk of the AI-native environment.)	reputation damage (if a cheating scandal emerges).	- **Faculty vigilance:** Train faculty to recognize AI-generated content (tell-tale signs) and to use preventive measures (like progressive drafts, requiring reflections on process). Ensure support from academic integrity officers to handle cases.		
Technical Reliability & Model Drift – The AI tools might face outages, or the underlying models might change behavior after updates (e.g., API model update changes output quality).	- If an AI grading assistant goes down before grading deadlines, faculty could be left in the lurch, causing delays or overwork. - Model updates could lead to inconsistent results (e.g., something that worked well in January might produce errors in June after an update), affecting the workflow stability.	- **Backup plans:** Always have a fallback method. E.g., if AI auto-grading fails, ensure TAs or a contingency plan to grade manually. Don't schedule processes assuming 100% AI uptime. - **Version control:** Where possible, use versioned AI models (some providers let you stick to a certain model version) or test new versions on low-stakes tasks before full adoption. - **Pilot new updates:** Treat major tool updates like software upgrades – read release notes, pilot on a small course first. Maintain close vendor relationships so we get notified of changes. - **Diversity of tools:** Avoid single point of failure – if one AI service is down, maybe have another way (even if less advanced) to accomplish the task. E.g., if our primary LLM is not responding, have an alternate (perhaps a local simpler model) for basic needs.	IT Team / AI Platform Admin	Medium
Faculty or Student	- Could slow or	- **Change management and involvement:** Engage faculty early in planning and tool	Project Lead (Change	Medium

Risk (What could go wrong)	Impact (Consequence if it happens)	Mitigation (How to reduce/prevent it)	Owner (Responsible role)	Priority
Pushback – Cultural resistance or ethical concerns lead to lack of adoption or even active pushback by stakeholders (e.g., faculty fear job replacement; students feel feedback is impersonal).	derail the project if key faculty refuse to use the tools (the transformation fails to gain traction). - Students might complain if they feel they're being taught or evaluated "by a machine," which could impact satisfaction and enrollment if not addressed.	selection. Identify champions in each department who can demonstrate positive use. Provide forums for skeptics to voice concerns and get honest answers. Emphasize that AI use will *not* be used for faculty evaluation or reducing faculty numbers – clarify it's about augmenting their capabilities. - **Showcase successes:** Collect testimonials and data from pilots that demonstrate tangible benefits (saved time, improved student outcomes) to build buy-in. Peer influence is powerful – have respected faculty present to others.govtech.com (key insight: empower faculty and focus on literacy to alleviate fears). - **Student transparency:** Be open with students when AI is used (e.g., mention in syllabus if an AI tool will provide feedback, as suggested by academic integrity guidelinesacademicintegrity.org). Gather student feedback on these tools and involve them in evaluating the experience. Often, if students see quicker grading and still have access to instructors for clarification, they appreciate the benefits. - **Opt-outs and human touch:** Allow some flexibility – e.g., if a faculty member really dislikes AI grading, they can opt out in their course (at least in early phases). Ensure human interaction isn't lost (e.g., even if AI tutors exist, maintain some live office hours or personal check-ins so students feel supported by a human).	Manager), also Faculty Senate for policy aspects	

(The above list is not exhaustive, but these are top-priority risks. Each should be reviewed periodically in project meetings. "Owner" means who primarily monitors/mitigates that risk, but many require collective responsibility.)

Policy & Guardrails for AI in Faculty Workflows

To ensure ethical and effective use of AI, the university will establish clear policies and guardrails. Below are key guidelines and principles (in a concise bullet form):

- **Transparency to Students:** Faculty must disclose when AI is used in teaching or assessment in a way that affects students. For example, if AI assistance was used to generate feedback or grade an assignment, the syllabus or feedback itself should include a brief note of thatacademicintegrity.org. Students deserve to know which aspects of their learning experience are AI-augmented.
- **AI-Generated Feedback & Grades – Human in the Loop:** AI can draft feedback or suggest grades, but final grades for assessments **must be confirmed by a human instructor**. The faculty member is responsible for reviewing AI-generated feedback before releasing it. AI should assist, not fully automate, any evaluative decision. This keeps instructors accountable for the academic standards and fairnessacademicintegrity.org.
- **Permissible vs. Prohibited AI Use in Teaching:** The university will define scenarios where AI use is encouraged (e.g., drafting course materials, getting ideas, routine Q&A) and where it is prohibited or limited (e.g., entirely AI-generated lectures without instructor input, using AI to replace all student-faculty interaction). We emphasize AI as a co-pilot, not an autopilot.
- **Data Protection and Privacy:** Faculty and staff must follow data privacy rules when using AI. No uploading of student personal data, sensitive research data, or proprietary content into external AI tools that are not approved by the university. Use the sanctioned platforms (with proper agreements in place) for any student-related data. For instance, if analyzing student performance, use the internal analytics tool rather than a public cloud tool, unless approved by IT.
- **Academic Integrity & Student Use of AI:** The academic integrity policy will be updated to address student use of AI. It should clearly state, for each type of coursework, whether AI assistance is allowed, to what extent, and how to acknowledge it. (e.g., "You may use grammar checkers or ask ChatGPT for general ideas, but the writing must be your own. Any use of AI in generating content must be cited or disclosed.") This protects fairness and helps students learn responsible use.
- **Faculty Autonomy and Consent:** Faculty have the right to opt out of specific AI tools in their workflow if they are uncomfortable, especially in early stages. Likewise, faculty should not force students to use AI tools that require students to input personal data, without providing an alternative. We encourage innovation, but also respect individual comfort levels during the transition period.
- **Quality Assurance and Accountability:** If AI produces content (like a video lecture summary or an answer to a student), the responsible faculty or department should have a mechanism to verify and correct it. The policy may require periodic sampling of AI outputs for accuracy. Also, if a student believes an AI-generated feedback or grade is in error, they should have recourse to request human review (an appeals process).
- **No AI in High-Stakes Evaluations without Approval:** For high-stakes exams, thesis grading, or final projects, any use of AI in grading must be explicitly approved by the department and disclosed. In such cases, likely a higher standard of human oversight or a calibration process will be mandated. (This guardrail ensures we move carefully in the most critical assessments.)

- **Continuous Monitoring and Revision:** An AI oversight committee or the Teaching & Learning Center will continuously monitor the outcomes of AI integration – looking at student performance, faculty feedback, and any incidents. The policies will be revisited at least annually. As technology and norms evolve (and as we learn from pilot results), the guardrails will be adjusted. This agile governance is crucial in the fast-moving AI landscape.
- **Ethical Use and Non-Delegation of Responsibility:** The faculty code of conduct will include that ethical and professional responsibilities cannot be delegated to AI. For instance, instructors remain responsible for providing reasonable accommodations to students with disabilities – they can use AI tools to help, but cannot blame the AI if something is missed. Similarly, in advisement, an AI might flag a student issue, but if it fails to, that doesn't absolve us from our duty of care. In short, **AI's involvement does not diminish human responsibility**.

These policies will be published in both English and Vietnamese to ensure clarity for all faculty and students. They align with the fundamental values of academic integrity (honesty, fairness, trust, respect, responsibility, courage) in the context of AIacademicintegrity.orgacademicintegrity.org. By setting these guardrails, we aim to create a safe environment for innovation – where faculty can explore AI augmentation confidently, knowing there's a clear ethical framework to follow.

Executive Summary

In the next three years, **[University Name] will transform into an AI-native institution** where AI seamlessly supports faculty across the entire teaching and learning lifecycle. This strategic blueprint outlines a future in which AI is not a buzzword addon, but a deeply embedded co-worker in course design, instruction, assessment, and student support. Below are the key insights, recommendations, and initial action steps distilled from our comprehensive plan:

Ten Key Insights

1. **AI can augment every faculty workflow** – from drafting syllabi and lesson plans to automating grading and providing 24/7 student tutoring. By offloading routine tasks, AI frees up faculty to focus on high-value activities like mentoring and research. Early adopters report spending 5–20 hours/week on AI-enhanced teaching prepautomatedteach.com, demonstrating significant effort shift toward quality improvement.
2. **Faculty remain central and in control** – "AI is an algorithm, not a human. Only you can catch things AI cannot," a faculty user notedchronicle.com. This encapsulates our approach: AI will handle the grunt work, but faculty expertise and oversight drive the final outcomes. We do **not** remove the human element in teaching; we elevate it by using AI as a co-pilot.
3. **Re-imagining, not just digitizing** – We aren't merely plugging AI into Moodle; we are redesigning workflows from the ground up. This means reconsidering how courses are constructed (e.g., dynamic content that adapts via AI), how feedback is given (continuous, AI-assisted loops), and how student progress is tracked (proactive AI alerts).

It's an opportunity to break free from some legacy practices that digital tech alone couldn't solve.

4. **Start small, then scale** – Case studies show that starting with pilots and literacy is vitalgovtech.com. We'll begin with targeted, low-risk experiments (perhaps a handful of volunteer faculty in one department using an AI grading assistant, or a mini cohort trying AI lesson planners). The successes and learnings will inform larger rollouts. We avoid "big bang" mandates; instead we encourage organic growth with support.
5. **Faculty development is the linchpin** – Without comprehensive training and culture-building, even the best tools will fail to be adopted. Investment in faculty AI literacy (as University of Louisiana did with system-wide microcredentialsgovtech.com) and in incentivizing innovation (as UMass Lowell did with mini-grantsgovtech.com) will yield dividends in adoption. Our blueprint emphasizes a 3-level capability building: Awareness → Usage → Design proficiency.
6. **Integration with existing systems** is essential – The AI solutions will integrate with Moodle (our LMS) and our SIS, not stand apart. This ensures minimal disruption to faculty routines and consolidates data for better insights. For example, Gradescope or a similar tool will feed scores into Moodle automatically, and an AI early warning system will tie into our advising workflows. A cohesive architecture prevents creation of new silos and maximizes impact.
7. **Ethical use and policy framework** will safeguard trust – We will implement clear guardrails (transparency with students, data privacy, human oversight on grading, etc.). The academic community must trust the AI augmentation. By establishing governance (audit logs, bias checks) and updating policies (honor codes for AI use), we tackle risks up front. For instance, faculty and students will know exactly how AI is used and what is not allowed, reducing anxiety and confusionacademicintegrity.orgacademicintegrity.org.
8. **AI augmentation improves quality and efficiency simultaneously** – often seen as trade-offs. Done right, we expect to see *improved learning outcomes* (through personalized feedback, more practice opportunities via AI tutors, early interventions for struggling students) **and** *improved faculty well-being* (less burnout from grading mountains of papers, more time for student engagement and research). The Chronicle's survey data suggests over half of faculty who experimented with AI found it helped create more engaging activities or assessmentschronicle.com – a win-win for quality and efficiency.
9. **Global and local exemplars guide us** – We draw inspiration from top AI-forward institutions. Arizona State's university-wide AI challenge engaged hundreds of faculty and students to pilot ideas quicklygovtech.comgovtech.com. Stanford researchers have prototyped AI agents that generate entire course materials, pointing towards what may be possible by 2025scale.stanford.eduscale.stanford.edu. We will also be a leader in Vietnam by tailoring these ideas to our context – potentially becoming a model for AI-native education in the region.
10. **Continuous improvement mindset** – The AI landscape will evolve; our initiative is structured to learn and adapt. We will use metrics (faculty time saved, student performance changes, satisfaction surveys) to iteratively refine the tools and practices. Feedback loops (e.g., an AI oversight committee reviewing progress each semester) ensure we correct course as needed. In short, this is a 36-month journey of innovation, not a one-time project.

Do’s and Don’ts for AI-Native Faculty Workflows

Based on our research and strategy, here are five key “Do’s” and “Don’ts” to guide our community:

Do’s:

- **Do involve faculty in co-design** of AI solutions. From selecting tools to refining prompts, faculty input makes the solutions relevant and boosts buy-in.
- **Do ensure human oversight** at critical points. Keep instructors in the loop for final decisions on grades, content accuracy, and interventions – AI gives suggestions, humans decidemitsloanedtech.mit.edu.
- **Do prioritize transparency and ethics.** Be open with students about AI usage and set clear ethical guidelines (e.g., how students may or may not use AI on assignments)academicintegrity.orgacademicintegrity.org.
- **Do provide training and support** continuously. Celebrate early adopters and create a support network so no one is left behind. Encourage faculty mentorship – those who are comfortable can help peers.
- **Do start with “quick wins.”** Pick use-cases that address pain points (like automating repetitive grading) to demonstrate immediate value. Early success builds momentum and confidence.

Don’ts:

- **Don’t force adoption or rush it.** Avoid mandating that all faculty use a particular AI tool overnight. This can breed resentment or misuse. Instead, provide options and time to adapt.
- **Don’t use AI as a black box.** Faculty shouldn’t accept AI outputs blindly (e.g., copying a lesson plan verbatim). That can lead to errors and undermines the pedagogical purpose. Always contextualize and vet AI contributions.
- **Don’t compromise student privacy or consent.** For example, don’t require students to sign up for third-party AI tools that collect data without an alternative. Any AI that uses student data must be opt-in and comply with privacy standards.
- **Don’t neglect the “why.”** It’s easy to get caught in tools and features. Don’t lose sight of pedagogical goals. Every AI implementation should answer: how does this improve learning or teaching? If it doesn’t clearly do so, don’t do it.
- **Don’t treat AI integration as one-size-fits-all.** Different disciplines may need different approaches (e.g., coding auto-graders in CS vs. AI essay feedback in humanities). And individual faculty have varying styles. Our approach should be flexible and customizable, not rigid.

90-Day Pilot Launch Checklist

In the first 90 days, we aim to kick off the transformation with concrete steps. Below is a checklist of actions to initiate our pilot phase (month 0 to month 3):

1. **Establish Governance & Team:**
   - Form the "AI in Teaching Task Force" with representation from faculty (early enthusiasts from each faculty/department), IT, the Teaching & Learning Center, and administration. Hold a kickoff meeting to assign roles.
   - Draft initial policy guidelines for pilot (covering data usage, academic integrity adaptations for pilot courses, etc.) – get quick approval from academic leadership for pilot scope.
2. **Identify Pilot Courses/Faculty:**
   - Announce opportunity for faculty to volunteer for Phase 1 pilots. Alternatively, work with deans to select ~5-10 pilot faculty (ensuring diversity of disciplines, maybe one large freshman course, one language course, one STEM, etc.).
   - For each pilot faculty, identify one course in upcoming semester where AI integration will be tried. Define what aspect will be piloted (e.g., AI-assisted grading in Course X, AI tutor in Course Y).
3. **Secure Tools & Access:**
   - Finalize which AI tools will be used in pilots. For example, get a subscription for Gradescope for the term, set up institutional OpenAI API access (with funding limits), or deploy a small-scale instance of an open-source tool.
   - Work with IT to integrate these with Moodle for those courses (e.g., install any necessary plugins, set up accounts).
   - Ensure data agreements are in place (e.g., if using OpenAI API, configure it to not log data, etc., per policy).
4. **Faculty Training & Prep (Pre-Semester):**
   - Conduct an orientation workshop for pilot faculty: cover how to use the tool, best practices, and reiterate the human oversight principle. For instance, train them on how to prompt the AI grader and how to double-check it.
   - Help each pilot faculty set up their course: e.g., design their first AI-generated quiz or create the course chatbot with FAQs. Essentially, do a mini design sprint with each to integrate AI into their course plan.
   - Set up a channel (Teams/Slack group or WhatsApp) specifically for pilot faculty to ask questions and share experiences during the term.
5. **Student Communication:**
   - For each pilot class, prepare a brief explanation to students about what AI augmentation they will encounter. E.g., a statement in the syllabus: "This class is part of a new initiative using AI tools. You may receive AI-generated draft feedback on your assignments which I will review. Here's what that means…". Ensure students know how this benefits them and that they can ask questions or opt out if concerned.
   - Hold a short demo or Q&A in first class sessions of pilot courses to familiarize students with, say, the AI tutor or how their assignment feedback will look.
6. **Monitoring Plan:**
   - Define metrics to collect during the pilot: e.g., turnaround time for grading before vs. after, number of AI tutoring questions asked by students, changes in student quiz scores or engagement, qualitative feedback from students and faculty.
   - Assign someone (maybe an instructional designer or research assistant) to observe and document the pilot progress (sit in on a few classes if needed, gather data).

    - Schedule bi-weekly check-ins with pilot faculty as a group to discuss what's working or not, and adjust on the fly if needed (agile iteration).
7. **Support & Troubleshooting:**
    - Ensure IT support is on standby especially during initial uses (e.g., first time using the AI grader or if the AI bot goes down).
    - Provide an easy way for students in pilot to report any issues (like if the AI tutor gave a wrong answer or they have concerns).
8. **Review and Next-Step Plan (Day ~90):**
    - At the end of the term or 90-day period, collect all data and feedback. Host a debrief meeting with pilot participants. What were the outcomes? Did grading time reduce? How did students respond? Share survey results.
    - Document case studies: e.g., "In Professor A's class, AI feedback was given on 40 essays, and student revision rates improved by X%" or "Professor B saved Y hours on grading, which he reallocated to extra office hours."
    - Identify what needs to be improved before scaling (maybe the AI model needs better fine-tuning for local context, or faculty want more training in prompt skills).
    - Make a go/no-go decision on expanding pilots for the next semester, and adjust the strategy accordingly. Update the roadmap for the next phase (e.g., bring in 20 more faculty, add another tool, etc.).

By following this 90-day checklist, we ensure a structured and reflective start, rather than jumping in haphazardly. It will build a foundation of evidence and confidence for broader implementation in months 4–12.

The executive summary above serves as a stand-alone overview for leadership, condensing the blueprint's essence: augment faculty, don't replace; invest in people and integration; manage risks and policy actively; and iterate from small successes to institution-wide impact.

Implementation Considerations and Next Steps

Finally, to ensure this ambitious plan succeeds, we need to be mindful of our assumptions, pilot designs, and the balance of quick wins vs. long-term investments.

Five Assumptions That Could Fail (and How We'll Mitigate Them)

1. **Assumption:** *Faculty will embrace AI when they see time savings. – Risk if false:* Some faculty, even if shown benefits, may resist due to fear or philosophical objections.
 Mitigation: Involve skeptics in dialogue, address fears (like "AI will replace me") head-on, and ensure participation is voluntary initially. Provide alternate paths for those who prefer traditional methods so they don't feel forced.
2. **Assumption:** *AI tools (especially language models) will work well in our bilingual English–Vietnamese context. – Risk if false:* If the AI output in Vietnamese is subpar or if it struggles with local examples, it could frustrate users and students.
 Mitigation:

Test each tool for Vietnamese capability early. Use models known for multilingual support. Possibly fine-tune or train AI on local data (e.g., Vietnamese text) for better performance. If certain tasks like content generation don't work in Vietnamese, focus those tools on English use-cases and find other solutions (or wait until models improve) for Vietnamese content.

3. **Assumption:** *Our data infrastructure can support AI integration easily. – Risk if false:* Data might be siloed or messy (e.g., SIS data not syncing well with LMS), making it hard for AI systems to get the info they need. Or our IT might not support heavy API usage leading to slow performance.
 Mitigation: Early on, do a data audit. Ensure LMS, SIS, and other systems are properly integrated (this might involve cleaning data or upgrading systems). Start with low-data-intensity pilots. If needed, invest in upgrading infrastructure (e.g., better servers, faster internet, database integration) in parallel with AI rollout.
4. **Assumption:** *Students will positively accept AI-driven elements (like AI feedback or an AI tutor). – Risk if false:* Students might react negatively – some may distrust AI feedback ("did a robot even read my paper?") or simply ignore the AI tutor.
 Mitigation: Manage student expectations via orientation and transparency. Collect student input via surveys – if they feel feedback is impersonal, maybe ensure faculty add a personalized note on top. If the AI tutor isn't used, find out why (perhaps they need incentive or it needs better introduction). Keep a human touch (blended approach) so students feel supported by real people behind the AI. Student representatives can be included in the oversight group to voice any issues.
5. **Assumption:** *Costs will remain sustainable (AI API usage, tool licenses). – Risk if false:* It's possible that heavy usage of APIs (like OpenAI) could run up costs beyond budget, or vendors might raise prices once we're dependent.
 Mitigation: Monitor usage closely in pilots to forecast costs. Negotiate education pricing or bulk deals with vendors early. Also explore cost-saving measures: e.g., using an open-source model on our own servers for some tasks to avoid recurring API fees, or only using expensive models for where truly needed. Maintain flexibility so we can switch providers or adjust use if cost becomes an issue.

By identifying these potential failure points now, we remain vigilant and ready to pivot strategies if an assumption proves invalid. This proactive risk management is part of the project ethos.

Three Pilot Program Designs

To demonstrate and test our AI-native workflow vision, we propose three distinct pilot programs, each targeting different aspects of faculty work and different disciplines:

Pilot 1: AI-Assisted Grading in Large General Education Class

- **Scenario:** A large-enrollment first-year course (e.g., Introduction to Psychology with 200 students across sections). Grading load is high, especially with writing assignments or short-answer exams.

- **Faculty Group:** 2-3 instructors (or one instructor with TAs) who teach this course. They are moderately comfortable with technology and open to innovation, but have large workloads.
- **Workflow Tested:** Assessment creation and grading. They will use an AI grading assistant (like Gradescope or a custom LLM tool) for one major assignment or exam. They will also pilot using AI to generate a pool of quiz questions for weekly online quizzes.
- **KPIs:**
    - Reduction in grading time (% decrease in hours spent grading compared to last semester).
    - Consistency of grading (measured by variance in TA vs. AI vs. instructor grades on a sample, or student feedback on fairness).
    - Student feedback on quality of feedback comments (survey asking if feedback was clear and helpful).
    - Faculty stress level or satisfaction (self-report) during grading period versus prior term.
- **Risks & Monitoring:**
    - Potential student complaints if AI feedback feels generic – mitigation: instructor will add one personalized remark per student as needed.
    - TAs or faculty not trusting AI judgment – mitigation: calibrate by grading a sample manually and comparing, adjusting rubric.
    - Technical: if many students submit at once, ensure system performance holds.
- **Outcome Sought:** If successful, this pilot will show that AI can handle repetitive grading tasks even at scale, freeing instructors (and TAs) to focus on more meaningful interactions (like addressing misconceptions in class). Success would justify scaling to other large intro courses.

Pilot 2: AI Course Design Sprint in a Niche Elective

- **Scenario:** A new elective course in Business or Humanities (e.g., "Digital Marketing Analytics" or "Contemporary Vietnamese Literature") where the instructor is developing materials from scratch for next semester.
- **Faculty Group:** A tech-savvy faculty member (or a pair) who is creating this course. Possibly a younger lecturer who has used ChatGPT personally. They collaborate with an instructional designer from our team.
- **Workflow Tested:** Course planning & content development, plus activity design. The pilot will use AI tools to generate the first drafts of the syllabus, weekly lesson outlines, reading lists, and at least one interactive activity or case study per week. They'll also use an AI image generator or video summarizer to create visual aids for class. Essentially, this is a "design a course with AI as your assistant" pilot.
- **KPIs:**
    - Development time saved (document hours spent vs. a similar course development in the past without AI).
    - Quality of materials produced (external review by a senior faculty or curriculum committee to judge if the AI-assisted syllabus/contents meet learning objectives and rigor).

    - Student outcomes or engagement in the course when delivered (since this pilot might run as the course runs: measure student satisfaction and performance, though that feedback comes after the development phase).
    - Faculty feedback on creativity/innovation (did AI help include fresh perspectives or activities that otherwise might not have been thought of?).
- **Risks & Monitoring:**
    - AI content might be too generic or not contextually suitable – mitigation: the faculty and designer will carefully curate and adjust. Also incorporate local context manually (like ensure Vietnamese examples or cases are included).
    - Over-reliance: The instructor might be inclined to just accept AI output – mitigation: require a reflective rationale for each major decision ("why keep this AI-suggested reading? Does it truly fit?").
    - If the course is highly specialized, AI might lack domain depth – mitigation: supplement AI by providing it with key reference materials to ground its suggestions.
- **Outcome Sought:** A completed course that was designed faster and is enriched with diverse content, demonstrating AI's potential in course development. If positive, we can develop an "AI course design protocol" for other new or updating courses, potentially speeding up curriculum updates across the university.

Pilot 3: AI Mentor for Student Support in a STEM Program

- **Scenario:** In the Computer Science department, implement an AI chat assistant for one core programming course (or across a few courses) that acts as a 24/7 coding TA for students. Students often get stuck on coding errors at odd hours – this AI mentor can help troubleshoot or give hints.
- **Faculty Group:** 2 faculty members teaching programming courses, plus their TAs. They coordinate with the IT department to train a coding-focused AI (for example, using an open-source LLM fine-tuned on programming Q&A).
- **Workflow Tested:** Interaction with students (supplementing office hours) and early intervention. The AI will handle common "how do I fix this code?" questions and maybe even proactively check in ("I notice you haven't submitted last week's lab. Need help?" via the LMS chatbot). It also will summarize for the professor what issues students are frequently asking about.
- **KPIs:**
    - Student utilization: number of questions asked to the AI, and percentage resolved without instructor intervention.
    - Impact on office hours and email load: do faculty/TAs see a decrease in repetitive questions? Are office hour visits more focused/advanced because basics were answered by AI?
    - Student success: compare course performance or assignment completion rates to previous term (did more students finish projects with AI help?).
    - Student satisfaction: survey students on whether the AI help was effective and if they felt more supported.
- **Risks & Monitoring:**

- AI giving incorrect code advice – mitigation: limit it to known scenarios or have it suggest resources rather than full solutions; maintain a log so TAs can review some interactions.
- Students might try to get the AI to do their homework – mitigation: program the AI with policies (it refuses if it detects full assignment questions, instead it helps with conceptual guidance). Also honor code reminders.
- Integration technical issues: ensure the chatbot is easily accessible via the LMS or a platform students already use (perhaps integrate into a class Discord or forum if that's popular).

- **Outcome Sought:** Evidence that an AI TA can handle a significant volume of student queries accurately, improving student learning (or at least confidence) and allowing human instructors to focus on deeper teaching. If successful, this could be expanded to other STEM fields or any courses where students need just-in-time support (accounting, economics problem sets, etc.).

Each pilot is designed to test different dimensions (grading efficiency, course creation, student support) and in different contexts (large class vs. new prep vs. tech-heavy discipline). After these pilots (which could run concurrently in the first year), we'll have rich data to decide on scaling strategies and tool investments.

Quick Wins and Long-Term Bets

To maintain momentum, we will pursue some **quick wins** that demonstrate value in the short term, while also planning **long bets** that set us up for leadership and innovation in the long run.

3 Quick Wins (within 6–12 months):

- **Quick Win 1: AI-Powered Writing Feedback in One Writing-Intensive Course** – Introduce a tool like Draft Coach or an AI feedback generator for a writing class (e.g., Business Communication or English 101). Students submit drafts and get immediate AI feedback on grammar, structure, etc., *before* the instructor grades. This will likely improve student writing and reduce faculty correction workload. It's relatively easy to implement (tools are available, and one instructor can pilot). Success is measured by improved final draft quality and student appreciation for faster feedback.
- **Quick Win 2: Automated Lecture Transcripts & Summaries** – Use a tool (Otter.ai or similar) to transcribe lectures in a few large classes and provide summaries or keyword highlights to students. This addresses accessibility and study review needs. It's low-risk: even if the summary isn't perfect, the transcript is useful. We can do this immediately with existing tech. If students love it, it can be expanded to more classes, showing faculty the benefit of AI in enhancing student engagement outside class sessions.
- **Quick Win 3: Faculty Prompt Kit & Training Session** – Develop a simple "prompt kit" (maybe a 2-page cheatsheet and example prompts) for common faculty tasks (like "create a quiz", "summarize this article", "generate discussion questions"). Host a hands-on workshop where faculty bring a task and use ChatGPT (or our chosen model) with these prompts. Many faculty are curious but unsure how to use AI – a single 2-hour session can get them from 0 to 1. The win: faculty walk away having done something

practical (like generated a draft lecture outline) for an upcoming class. This quick win builds interest and lowers adoption resistance with minimal cost.

3 Long Bets (to explore over 2–3 years):

- **Long Bet 1: Fully AI-Generated Course Offering** – Aim to develop and offer one experimental course that is largely AI-generated in content (under human guidance). For example, a seminar on a cutting-edge topic that no one has ready materials for – the faculty lead uses an advanced multi-agent system (like Stanford's Instructional Agents researchscale.stanford.eduscale.stanford.edu) to produce syllabus, readings, and assessments quickly. The bet is that we could dramatically reduce course development time and perhaps offer niche courses on demand. We'll learn how far AI can go in content creation and what still needs human touch. If it works, it could be game-changing for curriculum agility.
- **Long Bet 2: Personalized AI Tutors for Every Student** – Move beyond a course-based chatbot to an AI "mentor" assigned to each student for their entire program. This AI would learn about the student's progress, strengths, and weaknesses over time. It could advise on study habits, recommend resources, and even provide career advice drawing on a database of alumni paths. This is a long-term moonshot requiring data integration from multiple sources and careful ethical design. But if we achieve even a version of it, it would mean truly personalized education at scale – a differentiator for our institution.
- **Long Bet 3: AI-Enhanced Competency-Based Learning Model** – Consider transitioning some programs to competency-based education (CBE) with AI as the backbone for assessment and support. In CBE, students progress upon mastery. AI could evaluate mastery continuously (through projects, quizzes, even monitoring how they perform in simulations) and suggest when a student is ready to move on or needs remediation. It could also generate variant assessments on the fly so students can try again until they master a skill. This bet would require rethinking curriculum design and a robust AI system to manage it. It's long-term, but could position us among innovative institutions like WGU (which uses analytics heavily in CBE). It ties AI to the very structure of learning progression.

These long bets carry uncertainty and would need pilot testing and perhaps research partnerships (we might collaborate with AI edtech companies or other universities on these). However, they represent the frontier of an AI-native university – pushing us to not just adopt tools, but possibly reinvent educational models.

By balancing quick wins that build confidence with visionary long bets that keep us forward-looking, we ensure that our AI transformation yields immediate improvements while also steering us toward a bold future. This phased, thoughtful approach – combined with the detailed blueprint above – puts our university on a path to be a pioneer of AI-native higher education in Vietnam and beyond, delivering enhanced learning outcomes and faculty experiences that define the university of tomorrow.