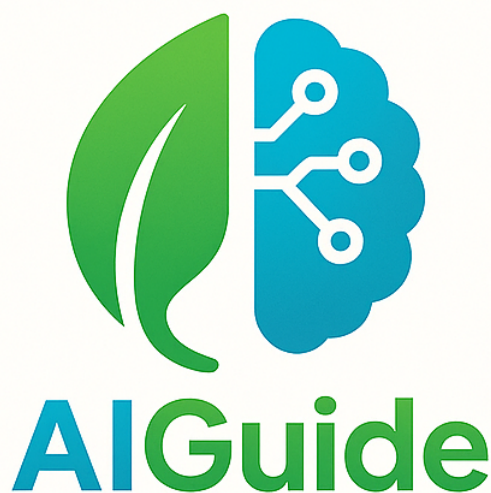




ONLINE COURSE CONTENT

MODULE 3: EVIDENCE-BASED REASONING AND DECISION MAKING

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Artificial Intelligence for Green Understanding, Insights & Decision Empowerment



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A. General Information

Module No	☐ Module1 ☐ Module2 ☒ Module3 ☐ Module4 ☐ Module5
Subtopic	3.2 Evidence-based reasoning and decision making
AI Literacy Component	Data reliability variable identification; argumentation; AI-supported data interpretation
Decision Making Skills	Evidence-based reasoning; data interpretation; decision justification
Teacher Learning Outcome	Collect, prepare, interpret and analyse data or evidence for green decision-making tasks.
Student Transfer Outcome	Justify green decisions with evidence.
Possible AI Tools	Spreadsheets; Orange Data Mining; Power BI; Microsoft Copilot; chatbots (e.g., ChatGPT, Claude, Gemini)
AI Literacy Level	Medium
Estimated Duration	60 minutes

B. Content

Highlights

1. Evidence-based decision-making (EBDM) is a systematic approach that integrates the best available evidence with professional expertise and contextual factors to make informed decisions.
2. EBDM follows a five-step cycle: Ask, Acquire, Appraise, Apply, and Assess — a structure that transfers directly to green decision-making tasks in STEM education.
3. AI literacy — including data reliability assessment, variable identification, argumentation, and AI-supported data interpretation — is a key enabler of evidence-based reasoning.
4. AI tools such as spreadsheets, Orange Data Mining, Power BI, Copilot and chatbots can help teaching staff and students collect, prepare, interpret and analyse data for green decisions.
5. Decisions must be justified with evidence: biases, motivated reasoning and uncritical trust in AI outputs undermine decision quality and must be explicitly addressed in teaching.

Introduction

Evidence-based reasoning and decision-making are critical components of professional development programmes, particularly for university teaching staff who aim to enhance their teaching and research practices. This approach involves the systematic use of the best

available evidence to inform decisions, thereby improving outcomes in various professional contexts. The integration of evidence-based reasoning into professional development can enhance critical thinking, reduce biases, and promote more effective decision-making processes (Kurien et al., 2022; Grawitch et al., 2025).

In the AIGUIDE context, evidence-based reasoning is combined with AI literacy so that STEM teaching staff can collect, prepare, interpret and analyse data or evidence for green decision-making tasks, and so that their students can, in turn, justify green decisions with evidence. This subtopic therefore addresses two intertwined layers: (1) the logic and process of evidence-based reasoning and decision-making, and (2) the AI literacy components — data reliability and variable identification, argumentation, and AI-supported data interpretation — that make this process practical and scalable in the classroom.

1. Understanding Evidence-Based Reasoning and Decision Making (EBDM)

Evidence-based decision-making (EBDM) is a systematic approach that integrates the best available evidence with professional expertise and contextual factors to make informed decisions. This approach is widely applied across domains such as healthcare, education, engineering and organizational management to enhance decision quality and outcomes (Kurien et al., 2022; Leufer & Cleary-Holdforth, 2013).

The importance of evidence-based reasoning in professional practice is well documented:

6. **Professional practice:** In fields like engineering, law and medicine, evidence-based reasoning is crucial for sound decisions. Engineers use it to ensure the safety of designs, while doctors rely on it to determine the best course of action for patient care (Gainsburg et al., 2016).
7. **Educational contexts:** Teachers and administrators use evidence to support learning and make informed decisions about educational practices, constructing and using evidence at levels ranging from classrooms to institutions (Moss & Piety, 2007; Ziebell & Skeat, 2020).
8. **Organizational contexts:** In management settings, evidence-based practice can reduce uncertainty and debias decision-making, and there is a recognised need for more evidence-based curricula to promote critical thinking and structured decision-making (Capezio & Decosta, 2023).

EBDM is not solely reliant on empirical evidence; it also incorporates professional judgment and expertise. This integration is essential for adapting evidence to specific contexts and constraints, as emphasised by the concept of ecological rationality, which balances classical rationality with practical decision-making under real-world conditions (Grawitch et al., 2025). Furthermore, EBDM is a collaborative, social endeavour: effective decisions typically involve

researchers, practitioners and stakeholders whose diverse perspectives enrich the process (HakemZadeh & Rousseau, 2024).

EBDM can also be productively combined with case-based reasoning, in which historical case data complements scientific evidence. This combination is particularly useful for complex problem-solving, because it preserves and reuses strategic knowledge from past decisions alongside current empirical evidence (Lopes & Schiel, 2009; Lopes et al., 2011).

Video: *Evidence-Based Decision Making: A Brief Introduction* (National MCH Workforce Development Center, 2023) — a short, discipline-agnostic primer that frames EBDM the way the text does. <https://mchwdc.unc.edu/evidence-based-decision-making/>

2. The EBDM Process: A Five-Step Cycle

For teaching purposes, the EBDM process can be organised as a five-step cycle that maps directly onto green decision-making tasks (Kurien et al., 2022; Leufer & Cleary-Holdforth, 2013; Ziebell & Skeat, 2020):

1. **Ask:** Identify the problem or decision point and formulate a precise, answerable question (e.g., "Which intervention would most reduce electricity consumption in our laboratory building?").
2. **Acquire:** Search systematically for the best available evidence — measurements, datasets, published studies, institutional records — relevant to the question.
3. **Appraise:** Critically evaluate the quality, reliability and relevance of the evidence, including the identification of key variables and potential sources of bias or error.
4. **Apply:** Integrate the appraised evidence with professional expertise and contextual constraints to reach a justified decision.
5. **Assess:** Evaluate the outcome of the decision and feed the lessons learned back into future decision cycles.

Research on the longitudinal teaching of EBDM shows that implementing this cycle repeatedly over time increases knowledge, skills and confidence among learners, suggesting its effectiveness in educational settings (Martin et al., 2012). In education specifically, evidence-based reasoning has been modelled as a systematic inquiry into student learning that determines necessary interventions and is supported by collaborative practices (Ziebell & Skeat, 2020).

3. AI Literacy for Evidence-Based Green Decision-Making

The integration of AI literacy into education is crucial for developing evidence-based reasoning and decision-making skills. AI literacy encompasses understanding AI systems,

evaluating their implications, and applying AI tools effectively. This framework equips educators and students with the skills needed to interpret data, justify decisions, and engage in green decision-making tasks (Ruiz et al., 2024; Allen & Kendeou, 2024).

The key components of AI literacy for this subtopic are:

6. **Data reliability and variable identification:** Understanding the reliability of data and identifying relevant variables are foundational skills. They enable learners to critically assess data sources and select appropriate variables for analysis, which is crucial for making informed decisions (Ruiz et al., 2024; Mupaikwa, 2026).

7. **AI-supported data interpretation:** AI literacy involves using AI tools to interpret data effectively, understanding how AI algorithms process data, and applying these insights to real-world scenarios such as environmental decision-making tasks (Allen & Kendeou, 2024; Zary, 2024).

8. **Argumentation and decision justification:** Learners interpret data using AI tools and justify their decisions with evidence — a skill critical for logical reasoning and analytical thinking (Lefebvre & Ariane, 2026; Wijaya & Astuty, 2026; Gainsburg et al., 2016).

9. **Ethical considerations:** AI literacy frameworks emphasise data privacy, algorithmic fairness and transparency. Educators and students must be aware of these issues to ensure responsible use of AI technologies (Haider et al., 2025; Choi et al., 2025).

These components can be operationalised with accessible AI tools:

10. **Spreadsheets and Orange Data Mining:** Facilitate data cleaning, analysis and visualisation, helping learners understand complex data sets and derive meaningful insights (Ruiz et al., 2024; Zary, 2024).

11. **Power BI and Microsoft Copilot:** Enable interactive data visualisation and automate repetitive tasks, allowing learners to focus on critical analysis and interpretation (Allen & Kendeou, 2024; Choi et al., 2025).

12. **Chatbots:** Can simulate real-world decision scenarios, act as Socratic questioners ("What evidence supports this claim?"), and provide a controlled environment in which learners practise justifying decisions with evidence (Wijaya & Astuty, 2026).

4. Data Reliability and Variable Identification

Data reliability is a critical aspect of data management and analysis, particularly in the context of AI-supported data interpretation. Identifying the variables that affect data reliability involves understanding the sources of data, the processes involved in data collection, and the methods used for data validation and cleaning (Dawale et al., 2025).

13. **Data source and collection:** The reliability of data is heavily influenced by its source and collection method. Learners should always ask: Where did this data come from? Who collected it, how, and why? (Hao et al., 2017).
14. **Data quality dimensions:** Accuracy, completeness, consistency and timeliness are the key dimensions for assessing data reliability. Addressing missing values and outliers is vital for maintaining high data quality (Dawale et al., 2025).
15. **AI-assisted validation:** AI frameworks that integrate machine learning and large language models can autonomously clean data, identify outliers, and correct semantic discrepancies, improving data quality substantially over traditional methods; AI-driven profiling additionally supports real-time monitoring and anomaly detection (Dawale et al., 2025).
16. **Human oversight:** Despite AI advancements, human analysts are still required to verify AI outputs, particularly in critical decision contexts, to prevent biased findings and untrustworthy behaviour (Kim et al., 2021; Agrawal, 2025).

For teaching staff, this means that any green decision-making task should begin with an explicit data appraisal step: students identify the variables in the dataset, evaluate their reliability, and document data-quality issues before any analysis or interpretation takes place.

5. AI-Supported Data Interpretation and Decision Justification

Once reliable data and relevant variables have been established, AI tools can support the interpretation stage of the EBDM cycle. Learners can use spreadsheets or Orange Data Mining to explore patterns, Power BI to visualise trends, and chatbots to stress-test their interpretations ("What alternative explanations could account for this pattern?").

Crucially, interpretation must lead to justification. Decision justification means being able to state clearly: (1) what was decided, (2) which evidence supports the decision, (3) how the evidence was appraised, and (4) which uncertainties and limitations remain. Justification logic — reasoning explicitly "with reasons" — enables the tracking of evidence for statements and enhances the reliability of assertions (Artemov & Fitting, 2019). Evidential reasoning approaches further show how qualitative and quantitative data can be combined under uncertainty to prioritise and rank decision alternatives (Ahmadzadeh, 2016).

A recurring challenge in evidence-based reasoning is the information gap between what is known and what needs to be known to justify a decision (Sentz & Hemez, 2013). Making this gap explicit is itself a valuable classroom exercise: students state which additional evidence would change their decision, and why.

Video: *Copilot in Power BI Demo* (Microsoft official) — shows natural-language querying and auto-generated visuals that map to the "interpret then justify" step.

https://www.youtube.com/watch?v=wr__6tM5U6I

Orange Data Mining official YouTube channel — a source for the "explore patterns" step referenced in the text. <https://www.youtube.com/@OrangeDataMining>

6. Challenges, Biases and Responsible Use

17. **Bias and motivated reasoning:** Decision-making can be influenced by biases and motivated reasoning, which undermine evidence-based approaches. Addressing these challenges requires a balanced approach that considers both analytical and intuitive thinking (Grawitch et al., 2025).

18. **Balancing evidence and context:** A central challenge in EBDM is balancing empirical evidence with contextual factors and professional judgment, so that decisions are both evidence-based and practically feasible (Grawitch et al., 2025; Lopes et al., 2011).

19. **Implementation barriers:** The integration of evidence-based practices may face resistance due to entrenched traditional practices or lack of resources; adequate training and infrastructure are needed for AI literacy programmes, and disparities in resource access must be addressed (Choi et al., 2025).

20. **Responsible AI use:** Ethical concerns such as algorithmic bias, data privacy and AI hallucination must be explicitly addressed. AI outputs are inputs to human judgment, not substitutes for it; students should always verify AI-generated claims against primary evidence (Haider et al., 2025; Kim et al., 2021).

Video (≈12 min): *Introduction to Cognitive Bias* — Crash Course Scientific Thinking #1 (2026). Covers confirmation, availability, anchoring, hindsight — directly supports the bias/motivated-reasoning paragraph. <https://www.youtube.com/watch?v=d2r7Bk1NlgU>

Video (≈10 min): *Why Large Language Models Hallucinate* — IBM Technology (Martin Keen). Directly supports the "AI hallucination" and "verify AI-generated claims" points. <https://www.youtube.com/watch?v=cfqtFvWOfg0>

7. Anatomy of an effective evidence-analysis prompt

Evidence-based reasoning requires prompts that give the AI enough structure for its answer to be checked and challenged. A well-structured prompt names four things: who the AI should act as (*role*), what it should do (*task*), the situation and data it is working from (*context*), and how the answer should be organised (*expected output*). Making these components explicit gives you a first draft you can critique on the terms you set — and lets students learn the pattern by seeing it applied, not only by being told about it.

Colour key: **Role** **Task** **Context** **Expected output**

Example 1 — Evidence-based interpretation prompt

Act as an energy data analyst helping a STEM class evaluate building efficiency. You have monthly kWh values for three campus buildings together with each building's floor area and occupancy (dataset attached). Identify which building appears least efficient, and support your answer with a small table showing the metric used (e.g., kWh per m² per occupant-month), the calculated value for each building, and the single most important caveat about interpreting that metric.

Example 2 — Follow-up prompt for rival explanations

List three alternative explanations for the high consumption you flagged in Building B (other than lower building efficiency), and for each explanation, state one specific piece of data that would help confirm or rule it out.

Example 2 does not repeat the *role*: in a running chat the analyst voice from Example 1 is still in force. The four-part prompt shape also maps onto the EBDM cycle described in subsection 2 — Example 1 serves *Ask* and *Acquire*, while Example 2 does the *Appraise* work by demanding rival explanations and the evidence that would test them. Staff can use the shape as a diagnostic: a prompt with no expected output tends to skip appraisal and slide straight from *Acquire* to *Apply*.

Compact video summary of Google's prompt-engineering guidance (Task–Context–References–Evaluate–Iterate framing): <https://www.youtube.com/watch?v=o3qfL2fcSx4>

8. 60-Minute Professional Development Session Plan (Workshop for Teaching Staff)

Note on the session structure. The 60-minute plan below describes a professional development (PD) session delivered to STEM higher-education teaching staff — the "participants" in the table are the teachers themselves, not the students in their courses. The session is designed as a synchronous, workshop-style experience (face-to-face or online), in which participants work through AI-supported forecasting, resource-use analysis and a weighted decision matrix as learners, using the same tools and dataset they will later adapt for their own STEM courses. It is not a self-paced e-learning module, nor a lesson plan to be delivered directly to STEM students.

The plan therefore operates at two levels. At the PD level, it is what teaching staff experience during the workshop; at the classroom level, it becomes the blueprint that teachers adapt for their own students. The transfer step is supported in the sections that follow: Section C provides a guideline for constructing an equivalent real-life case in the teacher's own

discipline, and Section D provides a design guideline and student activity card for use with STEM higher-education students. Where the table refers to "participants", "teams" and "the case dataset", these refer to the teaching-staff learners in the PD session; the parallel student-facing materials are those developed via Sections C and D.

Time	Activity	Method / Tools
0–5 min	Welcome and framing: why evidence-based reasoning matters for green decisions; session outcomes.	Short presentation
5–15 min	Mini-lecture: the EBDM five-step cycle (Ask–Acquire–Appraise–Apply–Assess) and its AI literacy components.	Slides; discussion prompts
15–25 min	Real life example walkthrough (Section C): AI-supported evidence for energy decisions; group appraisal of the evidence.	Case handout; guided questions
25–45 min	Hands-on activity: staff work in pairs on the campus energy dataset micro-task from the Interactive Learning Activity (Section D), experiencing the activity as their students would.	Spreadsheet / Orange Data Mining / chatbot
45–55 min	Adaptation workshop: staff sketch a discipline-specific version of the real life example and activity card for their own courses (guidelines in Sections C and D).	Activity Card template; pair work
55–60 min	Wrap-up: key takeaways, reflection question ("What evidence would change your decision?"), next steps.	Plenary discussion

C. Real Life Example

Google DeepMind – AI Data Centre Cooling Optimisation

This example is drawn from the AIGUIDE Best Practices Report, which identified it as a strong industrial case for teaching evidence-based, AI-supported green decision-making in STEM higher education.

The case: Google DeepMind reported a reduction of around 40% in data centre cooling energy consumption through the use of machine learning. The AI system learned from large-scale operational sensor data — real-time facility conditions, temperature fluctuations, energy demand and equipment behaviour — and developed optimisation strategies for this energy-intensive infrastructure. Cooling control moved from experience-based operator settings to a predictive, data-driven approach in which decisions are informed by evidence rather than intuition alone.

Why it fits Subtopic 3.2: The case is a textbook illustration of the EBDM cycle. The question was clearly formulated (how can cooling energy be reduced without compromising equipment safety?); evidence was acquired from thousands of sensors; the reliability of the sensor data and the relevant variables (temperatures, pump speeds, load) had to be identified and appraised; the model's recommendations were applied under human oversight; and outcomes were continuously assessed against measured energy consumption. It also demonstrates why human oversight, verification and domain expertise remain essential — the AI recommendation is an input to a justified human decision, not a replacement for it.

Discussion questions for teaching staff:

1. Which variables did the AI system rely on, and how would you assess the reliability of each data source?
2. What evidence would you require before trusting the AI's recommendation to change a physical control setting?
3. How is the final decision justified, and who is accountable for it — the model or the human operator?
4. How could a scaled-down version of this evidence cycle be reproduced with data available at your own institution?

Activity Guideline: Prepare Your Own Real-Life Example

After discussing the case above, each participant (or discipline-based pair) prepares one real life example from their own subject area, following this guideline:

1. **Select a case (10 min):** Choose a real application in your discipline where data or evidence informs a green/sustainability-related decision (e.g., material selection, process optimisation, land use, water quality, lab resource management). The AIGUIDE Best Practices Report is a recommended source of inspiration (e.g., BrainBox AI for HVAC optimisation, Voltaware for energy intelligence, Carbon Re for cement decarbonisation).
2. **Map it to the EBDM cycle:** Identify for your case the question asked, the evidence acquired, how reliability and variables were appraised, how the decision was applied, and how outcomes were assessed.
3. **Identify the AI component:** State which AI tool or technique supports the evidence work (analysis, prediction, interpretation) and where human judgment enters the decision.
4. **Write 3–4 discussion questions:** Focus on data reliability, variable identification, and decision justification.

5. **Share and peer-review:** Exchange examples with another participant and check: Is the green decision explicit? Is the evidence chain traceable? Could a student justify the decision with the evidence provided?

D. Interactive Learning Activity

The following activity is prepared in the format of the AIGUIDE Student Learning Activity Card Template (WP3-A2-AIGUIDE_Student_Activity_Card_Template_fnl.docx). It is a ready-to-use, student-facing activity that teaching staff can deliver in their own lectures.

Student Learning Activity Card

1. Activity Identification

Module / Unit	Module 3 – Subtopic 3.2: Evidence-based reasoning and decision making		
Activity Code	M3-A2		
Activity Title	Justify It with Evidence: Which Campus Building Should Be Retrofitted First?		
Developing Partner	EGE		
Recommended Duration	60 minutes		
Delivery Mode	In-class Blended	Online synchronous	Online asynchronous
Student Grouping	Individual	Pair	Small group (3–4) Whole class
STEM Context / Discipline	Engineering, energy systems, environmental science, data science (adaptable to any STEM field)		

2. Pedagogical Design

Learning Objective(s)	By the end of this activity, students will be able to: 1. Appraise the reliability of an energy dataset and identify the variables relevant to a green decision. 2. Interpret data using AI tools and formulate an evidence-based recommendation. 3. Justify a green decision with explicit, traceable evidence and acknowledge remaining uncertainties.		
Target AI Literacy Competence	Understanding AI concepts Evaluating AI outputs Ethical/responsible AI use	Using AI tools critically Human-AI decision-making	
Green Decision-Making Focus	Climate change Biodiversity	Energy Waste/circularity	Materials/resources Water
Prerequisite Knowledge	Basic spreadsheet skills; introductory descriptive statistics		

	(mean, trend); familiarity with at least one chatbot.
Key Concepts / Keywords	Evidence-based decision-making; data reliability; variable identification; AI-supported data interpretation; decision justification; energy efficiency.

3. Student Task Design

Student Scenario / Challenge	Your university has budget to retrofit ONE of three campus buildings (Library, Engineering Lab, Dormitory) to reduce energy consumption. You are the student advisory team. Using twelve months of monthly electricity consumption data for the three buildings (plus floor area, occupancy and building age), recommend which building should be retrofitted first — and justify your recommendation with evidence.
Student Instructions	Step 1 – Engage (5 min): Read the scenario, inspect the dataset, and list what you know and what you do not know. Step 2 – Explore (15 min): Appraise data reliability (missing values, outliers, measurement source) and identify decision-relevant variables (e.g., kWh per m², kWh per occupant, seasonal patterns). Use a spreadsheet or Orange Data Mining to compute and visualise them. Step 3 – Explain (15 min): Ask a chatbot to interpret your findings and propose a recommendation. Critically evaluate the AI output: check its claims against your own analysis, and note at least one point where you question or reject it. Step 4 – Extend (15 min): Formulate your team's final recommendation in an evidence-justification table: decision, supporting evidence, appraisal of the evidence, and remaining uncertainties (what additional evidence would change your decision?). Step 5 – Evaluate (10 min): Present your justification to another team; see part 5, Assessment and Evidence.
Input Materials	Dataset (provided by teacher) Case text Article Image/video Policy document
Expected Student Output	Short report Decision matrix Presentation Poster/infographic Reflection Discussion post
Student Deliverable Format	One-page evidence-justification table (spreadsheet or document) + 3–5 sentence reflection on AI use.

4. AI Use and Green Decision-Making

Suggested AI Tool(s)	Spreadsheet (Excel/Google Sheets); Orange Data Mining or Power BI for visualisation; one chatbot (e.g., Copilot, ChatGPT, Claude, Gemini).
AI Prompt / Interaction Guidance	Sample prompts: • "Here are monthly kWh values for three buildings with floor area and occupancy. Which building appears least efficient, and what evidence supports that?"

	• "What alternative explanations could account for the high consumption of Building B?" • "What additional data would you need to make this recommendation more reliable?"
Critical Evaluation Requirement	Students must check AI output for: accuracy bias source quality uncertainty environmental relevance ethical implications
Human Decision Component	The final retrofit recommendation is made by the student team, not the AI. Students must state where they followed, adjusted or rejected the AI's interpretation, and why.
Responsible AI / Ethics Note	AI outputs may contain hallucinated or overconfident claims; all numerical claims must be verified against the dataset. If real building data is used, occupancy data must be anonymised and handled in line with institutional data-privacy rules.

5. Assessment and Evidence

Assessment Method	Checklist Rubric Peer feedback Teacher feedback Self-reflection Quiz
Assessment Criteria	1. Relevance to green decision-making 2. Critical use/evaluation of AI 3. Evidence-based reasoning 4. Clarity of final decision/output
Evidence to Be Collected	Student output Screenshots/log of AI interaction Reflection form Attendance/participation record Teacher observation notes
Success Indicator	At least 70% of student teams deliver a recommendation in which every claim in the justification table is traceable to the dataset or another cited source.
Feedback Questions	1. What did AI help you understand? 2. What AI output did you question or reject? 3. How did your final decision change after evaluation?

6. Implementation Notes

Teacher Preparation	Prepare the three-building dataset in advance (real anonymised campus data if available; otherwise the illustrative dataset supplied with this subtopic — note that illustrative numbers should be adjusted to reflect real institutional conditions before delivery). Verify tool access (spreadsheet software, Orange/Power BI, chatbot accounts).
Timing Plan	Introduction: 5 min Task: 45 min Discussion: 5 min Reflection: 5 min
Accessibility / Inclusion Notes	Provide the dataset in accessible formats; allow the analysis in either a spreadsheet or Orange (visual programming, low-code); balance groups so each team has at least one member comfortable with data tools; permit chatbot use in the local language.

Possible Risks	AI access problems; superficial AI use (copy-pasting AI conclusions without verification); weak or misread data quality.
Mitigation / Backup Plan	Keep printed sample AI outputs for critique if connectivity fails; provide a pre-cleaned backup dataset; require the evidence-justification table so unverified AI claims are visible.
Extension / Follow-up	Teams add a simple cost dimension and re-argue their decision (bridges to Subtopic 3.3 on resource efficiency and trade-off analysis).

Guideline: Design Your Own Interactive Learning Activity

After experiencing the activity above, teaching staff design one interactive learning activity for their own subject area, using the AIGUIDE Student Learning Activity Card Template. The guideline for this design workshop is:

1. **Choose a decision problem (5 min):** Pick a discipline-relevant question in which students must decide something green/sustainability-related on the basis of data or evidence.
2. **Define the evidence:** Identify a dataset, case text or document set students will work with, and note its reliability characteristics (source, quality, known limitations).
3. **Assign the AI role:** Decide where AI enters the task (interpretation, visualisation, critique) and write 2–3 sample prompts. Ensure AI use is transparent and requires critical evaluation of outputs.
4. **Fill in the Activity Card:** Complete all six sections of the template — identification, pedagogical design, task design, AI use, assessment, implementation notes — so that another teacher could run the activity without further explanation.
5. **Check with the completion checklist:** Verify the activity links AI literacy with green decision-making, instructions are concrete and sequenced, expected outputs and assessment evidence are explicit, and accessibility, timing and backup options are considered.
6. **Peer review:** Swap cards with a colleague from a different discipline and give feedback focused on one question: Could your students justify the green decision with evidence after this activity?

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