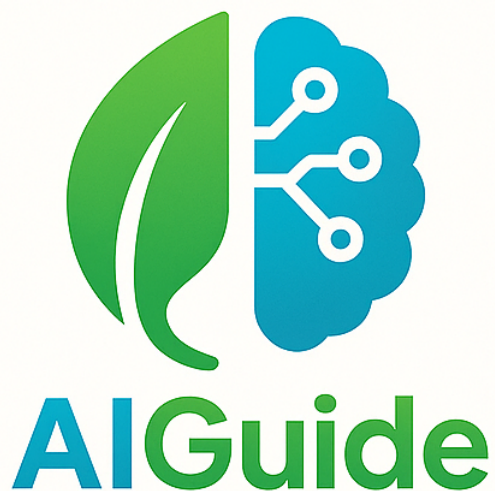




ONLINE COURSE CONTENT

MODULE 3: RESOURCE AND ENERGY EFFICIENCY FOCUSED DECISIONS

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Artificial Intelligence for Green Understanding, Insights & Decision Empowerment



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Table of Contents

A. General Information.....	3
B. Content.....	3
Highlights.....	3
Introduction.....	3
1. Why Energy and Resource Efficiency Decisions Matter	4
2. AI-Supported Energy Forecasting	5
3. Resource-Use Analysis.....	5
4. Trade-Off Analysis and Decision Frameworks.....	6
5. AI Tools for This Subtopic	6
6. Responsible and Critical Use	7
7. Anatomy of an effective efficiency-analysis prompt.....	7
8. 60-Minute Professional Development Session Plan (Workshop for Teaching Staff)	8
C. Real Life Example.....	9
Case: Renewing a University Computer Laboratory	9
Activity Guideline: Prepare Your Own Real-Life Example	10
D. Interactive Learning Activity	11
1. Activity Identification	11
2. Pedagogical Design	12
3. Student Task Design	12
4. AI Use and Green Decision-Making.....	14
5. Assessment and Evidence	15
6. Implementation Notes.....	15
Partner Completion Checklist.....	16
References	17

A. General Information

Module No	☐ Module1 ☐ Module2 ☒ Module3 ☐ Module4 ☐ Module5
Subtopic 3.3.	Resource and energy efficiency focused decisions
AI Literacy Component	AI-supported energy forecasting; resource-use analysis; and trade-off analysis;
Decision Making Skills	Energy/resource efficiency decision
Teacher Learning Outcome	Compare resource-efficiency and energy-related decision alternatives using AI- supported analysis
Student Transfer Outcome	decide the resources according to efficiency and sustainability criteria
Possible AI Tools	Orange Data Mining; Excel/Sheets AI features; energy calculators
AI Literacy Level	Medium
Estimated Duration	60 minutes

B. Content

Highlights

1. Resource and energy efficiency decisions require comparing alternatives against multiple, often competing criteria such as cost, energy consumption, performance and sustainability.
2. AI-supported energy forecasting (e.g., machine learning models such as LSTM and temporal convolutional networks) enables accurate prediction of energy demand and supply, supporting proactive planning.
3. Resource-use analysis with AI identifies where, when and how energy and materials are consumed, revealing inefficiencies that are invisible in aggregate data.
4. Trade-off analysis, supported by weighted decision matrices and multi-criteria decision-making (MCDM) techniques, turns forecasts and consumption data into transparent, justifiable decisions.
5. Accessible tools — Orange Data Mining, Excel/Google Sheets AI features and online energy calculators — allow teaching staff and students to perform these analyses without programming skills.
6. AI itself consumes energy; responsible use requires weighing the footprint of AI solutions against the efficiency gains they deliver.

Introduction

Universities, laboratories and engineering workplaces constantly face decisions about how to use limited resources: Which equipment should be replaced? How should heating, cooling and computing loads be scheduled? Which of several technically feasible options is the most efficient and sustainable? These are rarely single-criterion choices. Energy consumption,

purchase and operating cost, performance, lifetime, maintainability and environmental impact pull in different directions, and a defensible decision requires making these trade-offs explicit.

This subtopic builds on the evidence-based reasoning skills developed in Subtopic 3.2 and moves one step further: from interpreting data to comparing decision alternatives. The teacher learning outcome is to compare resource-efficiency and energy-related decision alternatives using AI-supported analysis; the student transfer outcome is to decide on resources according to efficiency and sustainability criteria. Three AI literacy components support these outcomes: AI-supported energy forecasting, resource-use analysis and trade-off analysis.

Throughout the session, participants work with tools that are realistic for classroom use — Orange Data Mining, the AI features of Excel/Google Sheets and freely available energy calculators — so that what is learned in the professional development session can be transferred directly to their own STEM courses.

1. Why Energy and Resource Efficiency Decisions Matter

Energy efficiency is a policy priority as well as an operational concern. The European Union's "Energy Efficiency First" (EEF) principle requires that demand-side efficiency options be considered as genuine alternatives to supply-side investments, with their environmental and employment benefits explicitly evaluated in decision-making processes (Zondag et al., 2021; Yu et al., 2022). In practice, however, organizations face well-documented barriers: high project costs, lack of time and insufficient understanding of project requirements, particularly in medium-sized organizations (Marques et al., 2019). Decision processes also often overlook the systemic and dynamic nature of efficiency measures, which limits the benefits actually realized (Martins et al., 2022). Holistic frameworks that consider processes and their interdependencies — rather than isolated devices — help avoid such conflicts and embed energy metrics into everyday decision support (Herrmann et al., 2011).

For STEM educators the message is twofold. First, efficiency-focused decision-making is a professional competence their graduates will need in industry, where computer-assisted decision systems already optimize energy and resource use in domains from chemical processing (Meshalkin et al., 2021) to food production (Lutska et al., 2023). Second, the reasoning pattern itself — define criteria, gather evidence, compare alternatives, justify the choice — is teachable, and AI tools make it accessible at classroom scale.

The Interreg REEF project — a page explaining the EE1 principle with short explanatory videos.: <https://www.interregeurope.eu/reef>

Interview with Robert Nuij (European Commission) — an executive-level overview of how the EED works.: <https://revolve.media/interviews/the-european-commission-energy-goals>

2. AI-Supported Energy Forecasting

Forecasting is the starting point of most efficiency decisions: before choosing between alternatives, one must estimate future demand and supply. Machine learning and deep learning techniques, including Long Short-Term Memory (LSTM) networks and Temporal Convolutional Networks (TCNs), achieve high accuracy in predicting energy demand and renewable production such as solar and wind output, outperforming traditional statistical models (Umunawuike et al., 2025; Manoj, 2025). Accurate forecasts support renewable integration, grid stability and predictive maintenance, and are used at industrial scale by companies such as Siemens and Tesla (Umunawuike et al., 2025).

In the classroom, the same logic can be demonstrated at a much simpler level: a monthly electricity-consumption series for a campus building can be forecast with Excel's FORECAST.ETS function or a linear/tree model in Orange Data Mining. The pedagogical point is not the algorithm itself but the practice of basing a decision on a data-driven estimate of the future rather than on intuition — and of asking how reliable that estimate is.

γιδεο: YouTube — "Time Series Forecasting of Electricity Consumption using LSTM" (30 Days ML Projects series, hands-on):<https://www.youtube.com/watch?v=JcKhO7I3CWA>

MDPI open-access article, LSTM/GRU comparison (available for in-class theoretical background):<https://www.mdpi.com/1424-8220/22/11/4062>

3. Resource-Use Analysis

Resource-use analysis answers the question "where do our energy and materials actually go?". AI-based frameworks dynamically allocate computing resources and have reduced energy consumption by up to 15.7% compared with traditional methods in cloud environments (Manoj, 2025), while AI-driven energy management systems combine demand forecasting with optimization models to improve efficiency and renewable integration in smart grids (Aleemoddin et al., 2025). Broader applications include smart buildings, industrial process optimization and precision agriculture, where AI combined with IoT sensing enables precise prediction and control of consumption patterns (Goel, 2024).

For teaching purposes, resource-use analysis can be practiced with data students can genuinely obtain: laboratory equipment power ratings and usage hours, computer-lab occupancy logs, or building meter readings. Visualizing this data (pivot tables, Orange visualizations) typically reveals a small number of dominant consumers — an insight that reframes the decision problem before any alternative is compared.

4. Trade-Off Analysis and Decision Frameworks

Once demand is forecast and consumption is understood, the core decision task is comparing alternatives that are better on some criteria and worse on others. Multi-criteria decision-making (MCDM) provides the formal machinery: for example, combining intuitionistic fuzzy sets with MCDM techniques has been used to optimize energy efficiency in smart factories while balancing renewable-energy use and production efficiency (Anjum et al., 2025). A classroom-friendly version of the same idea is the weighted decision matrix:

7. Define the decision alternatives (typically 2–4 realistic options).
8. Define the evaluation criteria (e.g., energy consumption, cost, performance, lifetime/e-waste, maintainability).
9. Assign a weight to each criterion reflecting institutional or project priorities (weights sum to 1 or 100%).
10. Score each alternative on each criterion on a common scale (e.g., 1–5), using forecasts and consumption data as evidence.
11. Compute weighted totals, compare, and — critically — test how sensitive the ranking is to changes in weights or scores.

Two further points deserve attention. First, trade-off analysis applies to AI itself: AI systems consume significant energy, and organizations must balance the footprint of AI solutions against the efficiency gains they promise; evidence suggests that organizations committed to clean-energy goals are in fact more likely to adopt energy-efficient AI practices (Glavas, 2025). Techniques such as model pruning, quantization and compression reduce the energy demand of AI models while preserving performance (Bayoumi et al., 2026), and green AI architectures have demonstrated measurable reductions in energy consumption and improvements in resource recovery (Ranpara, 2025). Second, AI models support trade-off reasoning by detecting complex patterns and producing predictions that optimize operations, reduce costs and accelerate the transition to cleaner energy (Rojek et al., 2023) — but the weighting of criteria remains a human, value-laden judgement that students should learn to make explicit and defend.

5. AI Tools for This Subtopic

12. **Orange Data Mining:** open-source visual workflows for loading consumption data, building simple forecasting models (linear regression, trees) and visualizing results without coding.

<https://orangedatamining.com/blog/orange-youtube-tutorials/>

13. **Excel / Google Sheets AI features:** FORECAST.ETS, trendlines, Analyze Data / Explore, and Copilot/Gemini assistance for building the weighted decision matrix and sensitivity checks.

<https://www.myonlinetraininghub.com/excel-functions/excel-forecast-ets-function>

14. **Energy calculators:** free online calculators for appliance consumption, CO₂-equivalent emissions and lifecycle cost, used to generate evidence for scoring alternatives.

15. **AI chatbots (supporting role):** generating candidate criteria, stress-testing weightings ("what changes if energy price doubles?") and drafting justification texts — always subject to verification against the data.

6. Responsible and Critical Use

Participants should model for their students the habits of responsible AI use: check the provenance and quality of consumption data; treat AI-generated forecasts as estimates with uncertainty, not facts; report the assumptions behind weights and scores; and acknowledge the energy and emissions cost of AI tools themselves (Alsajri, 2025). Data privacy, computational cost and regulatory compliance remain real barriers to AI adoption in the energy sector (Umunawuike et al., 2025) and belong in any honest classroom discussion of these methods.

Offered Multimedia: https://managenergy.ec.europa.eu/document/download/9a5aff7f-97ce-4d4f-ae88-b38070db98f8_en?filename=EnergyandAI%20%281%29.pdf

7. Anatomy of an effective efficiency-analysis prompt

The responsible and critical use described above depends on prompts that give the AI enough structure to be checkable. A well-structured prompt names four things: who the AI should act as (*role*), what it should do (*task*), the situation it is working in (*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 — Prompt for widening the decision criteria

Act as an energy analyst advising on a university computer-laboratory renewal. Suggest three additional criteria for comparing energy-efficiency alternatives, beyond up-front cost and rated power draw, as a bulleted list where each item names the criterion, the specific data it would require, and a plausible source for that data.

Example 2 — Follow-up prompt for a sensitivity check

Identify which criterion weights in our decision matrix should change if electricity prices doubled over the equipment's expected lifetime, and for each weight change give one sentence of reasoning and one number that would falsify the reasoning.

Example 2 does not repeat the *role*: in a running chat the energy-analyst voice from Example 1 is still in force. Notice how the four-part shape supports the responsible use described in subsection 6 — every criterion, data source, weight change, or number the AI returns is something the student is now expected to verify. A prompt that omits *expected output* tends to produce fluent prose with nothing specific to check.

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	Phase	Participants' activity	Tools / Materials
0–5 min	Welcome & framing	Present the subtopic outcomes; connect to Subtopic 3.2 (evidence) and to participants' own institutional decisions.	Slides; General Information table
5–15 min	Mini-lecture	Core concepts: energy forecasting, resource-use analysis, trade-off analysis; the weighted decision matrix; Energy Efficiency First principle.	Slides; Section B content
15–30 min	Guided demo	Forecast a building's monthly electricity use (Excel FORECAST.ETS or Orange); inspect consumption breakdown;	Excel/Sheets; Orange Data Mining; sample dataset

		introduce the case dataset.	
30–50 min	Group work	Teams of 3–4 complete the computer-lab trade-off matrix (Section C), adjust weights, run a sensitivity check and prepare a 1-minute justification.	Matrix template; energy calculators; chatbot (optional)
50–57 min	Discussion & transfer	Groups present decisions; compare rankings under different weightings; discuss how to adapt the case to each participant's discipline (Sections C and D guidelines).	Whiteboard / shared doc
57–60 min	Wrap-up & assessment	Exit ticket: one criterion, one weight and one data source participants would use in their own course case.	Exit ticket form

C. Real Life Example

The case below is a classroom-scale scenario constructed for training purposes; it is not an entry from the AIGUIDE Best Practices Report (WP2-A3). It does, however, mirror the AI-supported energy-optimisation reasoning documented in that report — see, in particular, Google DeepMind (data-centre cooling), BrainBox AI (building HVAC) and Voltaware (household energy intelligence) in §5 – Industry Application. Instructors adapting the case for their own courses may draw evidence, benchmarks and performance figures from those documented real-world examples.

Case: Renewing a University Computer Laboratory

A STEM faculty must decide how to renew a 30-seat computer laboratory whose desktops are seven years old. The laboratory runs about 2,000 hours per year. Facility meter data show the lab accounts for a disproportionate share of the building's electricity use, and a forecast of next year's consumption (Excel FORECAST.ETS on 36 months of meter readings) projects a further 6% increase under current equipment. Three alternatives are on the table:

16. Alternative A — Replace all desktops with new energy-efficient desktops (high performance, moderate energy savings, high purchase cost).
17. Alternative B — Replace desktops with thin clients connected to a central server (large energy savings, moderate cost, adequate performance for most courses).
18. Alternative C — Keep current PCs, apply aggressive power management and staggered scheduling (lowest cost, smallest energy savings, declining performance and rising maintenance).

The faculty's energy team agrees on five criteria and weights, then scores each alternative from 1 (worst) to 5 (best) using power measurements, vendor specifications and an online energy/lifecycle-cost calculator:

Criterion	Weight	A: New desktops	B: Thin clients	C: Extend life
Energy consumption	0.30	3	5	2
Total cost (purchase + operation)	0.25	2	3	5
Performance for coursework	0.20	5	3	2
Lifetime & e-waste impact	0.15	3	4	4
Maintainability	0.10	4	4	2
Weighted total	1.00	3.25	3.85	3.05

With these weights, Alternative B (thin clients) ranks first. A sensitivity check shows the result is robust to moderate changes: only if the performance weight rises above roughly 0.35 does Alternative A overtake B — a finding the team reports openly in its recommendation. Note: all figures in this matrix are illustrative for training purposes; before live delivery they should be replaced or validated with real institutional data and priorities.

Activity Guideline: Prepare Your Own Real-Life Example

After working through the case, each participant (or discipline pair) prepares an equivalent example from their own subject area, following these steps:

19. Pick a decision: identify a genuine resource/energy decision in your discipline (e.g., pump selection in mechanical engineering, reagent or solvent choice in chemistry, algorithm/server choice in computing, irrigation strategy in agriculture, material choice in civil engineering).
20. Locate data: name at least one realistic data source students could access (equipment datasheets, meter or sensor readings, open datasets, energy calculators).
21. Define 2–3 alternatives and 4–6 criteria: ensure at least one criterion concerns energy or resource consumption and one concerns sustainability or environmental impact.
22. Choose the AI support: state where forecasting (Excel/Orange), consumption analysis or chatbot support will enter the task.
23. Draft the matrix: prepare a weighted decision matrix template with your criteria and proposed weights; mark any placeholder numbers clearly.
24. Plan the justification: define what an acceptable student justification looks like (references to data, explicit weights, a sensitivity remark).

Participants exchange drafts in pairs for peer feedback (5 minutes each) using three questions: Are the alternatives realistic? Are the criteria measurable with the named data? Is the AI support meaningful rather than decorative?

D. Interactive Learning Activity

Student Learning Activity Card

For partner-developed course activities to be completed by students

Project	Artificial Intelligence for Green Understanding, Insights & Decision Empowerment
Purpose	Standard template for designing student-facing activities within AIGUIDE course modules
Target users	Partner organisations / module developers
End users	STEM higher education students, guided by STEM higher education teachers
Version / Date	V1 / 12.07.2026

How to use this template: Create one completed Activity Card for each student activity. The card should be concise, operational, and directly usable by a STEM higher education teacher. Each activity must connect AI literacy with green/environmental decision-making and include clear evidence of completion.

1. Activity Identification

Module / Unit	Module 3 – AI-Enhanced Green Decision-Making; Subtopic 3.3 – Resource and energy efficiency focused decisions
Activity Code	M3-A3.3-S1
Activity Title	The Energy Trade-Off Challenge
Developing Partner	EGE
Recommended Duration	60 min in-class (scalable 45–90 min)
Delivery Mode	In-class Online synchronous Online asynchronous Blended
Student Grouping	Individual Pair Small group (teams of 3–4) Whole class
STEM Context / Discipline	Energy systems / general STEM. The core case is a university computer laboratory; the guideline in Subtopic 3.3 Section D shows how to adapt it to any STEM discipline (e.g., pump selection in mechanical engineering, solvent choice in chemistry, server choice in computing).

2. Pedagogical Design

Learning Objective(s)	By the end of this activity, students will be able to: 1. Produce a short-term energy-consumption forecast from real or realistic data using an AI-supported tool. 2. Compare resource and energy efficiency decision alternatives using a weighted decision matrix and a sensitivity check. 3. Decide on resources according to efficiency and sustainability criteria and justify the decision with evidence.
Target AI Literacy Competence	Understanding AI concepts Using AI tools critically Evaluating AI outputs Human-AI decision-making Ethical/responsible AI use
Green Decision-Making Focus	Climate change Energy Materials/resources Biodiversity Waste/circularity Water Other: _____
Prerequisite Knowledge	Basic spreadsheet skills (formulas, charts); descriptive statistics; the evidence-interpretation skills from Subtopic 3.2 (reading a dataset, questioning data quality).
Key Concepts / Keywords	Energy forecasting; resource-use analysis; trade-off analysis; weighted decision matrix; multi-criteria decision-making (MCDM); sensitivity analysis; sustainability criteria; AI output verification.

3. Student Task Design

Student Scenario / Challenge	Your university must renew a 30-seat computer laboratory whose desktops are seven years old and account for a disproportionate share of the building's electricity use. Your team is an advisory group that must recommend one of three alternatives: (A) replace all desktops with new energy-efficient desktops; (B) switch to thin clients with a central server; (C) keep the current PCs with aggressive power management and scheduling. Different stakeholder groups weight the decision criteria differently — and your team must defend its recommendation with data.
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Student Instructions	Step 1 – Engage (5–10 min): Examine the monthly meter readings showing the laboratory’s share of building electricity use. Discuss in your team: which alternative do you expect to win, and why? Record your team’s initial vote and one assumption behind it — you will revisit both at the end. Step 2 – Explore (15 min): Using the provided dataset (36 months of meter readings), build a forecast of next year’s consumption with Excel/Sheets FORECAST.ETS (or the prepared Orange Data Mining workflow). Identify the two largest consumption drivers in the data and note one data-quality concern (missing months, outliers, unclear units). Step 3 – Explain (15 min): Complete the weighted decision matrix for the three alternatives using your team’s assigned stakeholder weight profile (e.g., budget-constrained faculty, carbon-neutral campus office, student experience committee). Score each alternative 1–5 per criterion using the forecast, equipment specifications and an energy calculator as evidence. Compute the weighted totals and explain, in your own words, why the ranking came out as it did — and whether it matches your Step 1 intuition. Step 4 – Extend (10 min): Test how robust your recommendation is: swap weight profiles with another team, or ask an AI chatbot “which criterion weights should change if electricity prices doubled, and why?” — then verify the suggestion against your data. Prepare a 2-minute pitch: your recommendation, the key evidence, and how the result would change under a different weighting. Step 5 – Evaluate: See part 5, Assessment and Evidence.
Input Materials	Dataset Case text Article Image/video Policy document Other: weighted-matrix template; stakeholder weight-profile cards; equipment specification sheets
Expected Student Output	Short report Decision matrix Presentation

	Poster/infographic Reflection Discussion post Other: _____
Student Deliverable Format	Completed weighted decision matrix (spreadsheet file, one sheet, weights summing to 1.00); 2-minute team pitch (oral or max 3 slides); individual written reflection of max 200 words answering the three feedback questions in part 5.

4. AI Use and Green Decision-Making

Suggested AI Tool(s)	Excel / Google Sheets AI features (FORECAST.ETS, trendlines, Analyze Data/Explore); Orange Data Mining (prepared workflow); free online energy/lifecycle-cost calculators; AI chatbot (optional, supporting role only).
AI Prompt / Interaction Guidance	Sample prompts: • “Suggest additional criteria for comparing energy-efficiency alternatives for a university computer laboratory, and state what data each criterion would require.” • “If electricity prices doubled, which criterion weights in our decision matrix should change, and why?” • “List three data-quality problems that are common in building electricity meter data.” Rule: every number or claim suggested by the AI must be verified against the dataset or a named source before it enters the matrix.
Critical Evaluation Requirement	Students must check AI output for: accuracy bias source quality uncertainty environmental relevance ethical implications
Human Decision Component	The AI forecasts and the chatbot suggestions are inputs only. Students themselves must (1) set or adopt the criterion weights and make the value judgements they encode explicit, (2) score each alternative with evidence, (3) choose the recommended alternative, and (4) defend it — including stating under which weighting their recommendation would change.
Responsible AI / Ethics Note	Forecasts are uncertain estimates, not facts — report their assumptions. Chatbots can hallucinate plausible-looking numbers; verification is mandatory. Do not enter

	personal or institutionally sensitive data into external AI tools. Note that AI tools themselves consume energy: using them is a trade-off decision too.
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5. Assessment and Evidence

Assessment Method	Checklist Rubric Peer feedback Teacher feedback Self-reflection Quiz
Assessment Criteria	1. Relevance to green decision-making (efficiency and sustainability criteria present and weighted) 2. Critical use/evaluation of AI (forecast correctly built; AI suggestions verified) 3. Evidence-based reasoning (scores traceable to data, specifications or calculator results) 4. Clarity of final decision/output (explicit recommendation with a sensitivity remark)
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 teams submit a complete matrix with explicit weights and a correct sensitivity remark; every student justifies the team decision with at least two data points in the individual reflection.
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 and test the dataset (36 monthly meter readings, 20–100 rows, opens in Excel/Sheets and Orange); prepare the matrix template with formulas; print 3–4 stakeholder weight-profile cards and verify in advance that they produce genuinely different rankings; test tool access on classroom devices; prepare one worked example.
Timing Plan	Introduction: 10 min Task: 40 min (Engage 5–10, Explore 15, Explain 15, Extend 10 — overlaps absorbed in group pacing) Discussion: 7 min Reflection: 3 min

Accessibility / Inclusion Notes	Form mixed-skill teams (at least one confident spreadsheet user per team); provide the matrix template with pre-built formulas so no team is blocked by spreadsheet mechanics; offer a printed dataset and glossary of key terms for language support; roles within teams (data analyst, matrix keeper, presenter) can rotate to balance participation.
Possible Risks	AI tool or internet access failure; teams copying chatbot output without verification; weight profiles accidentally producing identical rankings; dataset too complex for the time available.
Mitigation / Backup Plan	Keep an offline spreadsheet with a pre-built forecast and matrix; bring printed sample AI outputs for the Extend step; pre-test weight profiles; a reduced 12-month dataset as fallback.
Extension / Follow-up	Apply the same method to a real, current decision at your institution and compare with the actual outcome; connect to Subtopic 3.4 by adding a policy constraint (e.g., a campus carbon-neutrality target) as an additional criterion.

Partner Completion Checklist

No.	Checklist Item	Completed
1	One Activity Card is prepared for each student activity.	Yes
2	The activity is written for students	Yes
3	The activity clearly links AI literacy with green/environmental decision-making.	Yes
4	Student instructions are concrete and sequenced.	Yes
5	AI use is transparent, and ethically framed.	Yes
6	The expected student output and assessment evidence are explicit.	Yes
7	The activity can be implemented by a STEM higher education teacher without further explanation.	Yes
8	Accessibility, timing, and backup options are considered.	Yes

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