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Quantifying Digital Competency Gains for Environmental Health: A Paired Pre-Post Evaluation of Applied Data Analytics Training

[1] Syazwan Aizat Ismail; [2] Abd Muhaimin Bin Amiruddin
[1] Senior Lecturer, National Poison Centre, Universiti Sains Malaysia, 11800, Gelugor, Pulau Pinang, Malaysia
[2] Senior Lecturer, Department of Environmental Management, Faculty of Forestry and Environmental Studies, Universiti Putra Malaysia

Corresponding Author: Syazwan Aizat Ismail

Abstract: The operational demands of modern environmental health necessitate that practitioners master digital data acquisition, automation, and visualization tools. This study reports the quantitative findings of a course evaluation conducted on a cohort of environmental science undergraduates (N=45) following a targeted training module. The module utilized practical cloud-based tools, including App Sheet for mobile data collection, Google Looker Studio for visualization, Google Apps Script for API integration with services like the Open Weather API, and Wokwi for IoT prototyping. Using a paired pre- and post-test design with a 5-point Likert scale, we assessed gains across three domains: Knowledge (K), Behavioural Intent (B), and Confidence/Attitude (C). Results showed statistically significant improvements across all domains. Knowledge saw the largest mean gain (+1.61 points, $p<0.001$), with understanding of APIs and Dashboard Goals increasing by +2.00 ($p=0.001$). Behavioural intent to apply these skills increased by +0.96, specifically emphasizing the intent to automate repetitive tasks (+1.25, $p=0.028$). Confidence/Attitude gained +0.45, driven by increased belief in the career necessity of data analytics tools (+0.62, $p=0.011$). This evaluation confirms the curriculum's success in rapidly building technical competence and promoting a proactive, data-driven mindset essential for contemporary environmental health practice.

Keywords: Digital competency, environmental health, data analytics, App Sheet, Looker Studio, paired t-test, course evaluation, IoT, Environmental Health Surveillance Analytics, EMSA

1. Introduction

The traditional paradigm of environmental health (EH) practice, reliant on static reports and periodic manual monitoring, is rapidly being overtaken by the demands of continuous, real-time digital surveillance. The foundation of effective environmental health management is shifting from intermittent manual sampling to continuous, real-time surveillance powered by the Internet of Things (IoT) and accessible open data streams [1]. Modern challenges, such as climate-driven health risks and infectious disease outbreaks, require professionals who are adept at managing the entire data lifecycle: from the collection of data via networked sensors (IoT) and open-source application programming interfaces (APIs) to the automated processing and clear communication of findings through dynamic dashboards [2, 3, 4, 5]. The core challenge for environmental health pedagogy is thus the integration of applied digital competency to bridge this growing technical skills gap.

1.1 The necessity of digital literacy in environmental health

Digital competency in EH extends beyond basic spreadsheet skills; it encompasses the ability to design data solutions, manage large-scale data streams, and leverage automation to increase operational efficiency [5]. Reputable agencies now emphasize the need for EH professionals to be proficient in data wrangling, cloud computation, and the ethical deployment of technologies to support timely decision-making [6]. However, many existing curricula still lag, resulting in graduates who are theoretically strong but practically unprepared for the data-intensive environments they face [7]. Professionals are now required to manage the entire data lifecycle: connecting to data sources (APIs), automating processing pipelines, and communicating findings through dynamic dashboards [2, 4].

1.2 Low-code solutions and pedagogical innovation

To address this knowledge-to-practice gap, pedagogical approaches must prioritize hands-on, experiential learning using tools that provide high functionality with a low barrier to entry. Low-code and no-code platforms, such as AppSheet and Google Apps Script, allow students to design and deploy functional applications and automation pipelines without extensive programming knowledge, fostering self-efficacy and innovation [8, 9]. The subsequent visualization of this self-collected, live data using tools like Google Looker studio enhances the understanding of data translation, shifting visualization from a reporting task to a risk communication tool [3, 5]. To address this evolving technical demand, an intensive course module was developed focusing on applied digital tools relevant to environmental fieldwork.

This module was structured around several low-barrier-to-entry, cloud-based platforms:

- **AppSheet:** Used to prototype no-code mobile applications for rigorous, standardized, and geo-tagged field data collection.
- **Google Looker Studio:** Utilized for developing interactive dashboards to visualize and communicate complex environmental trends.
- **Google Apps Script:** Employed for scripting and automating data transfer, including making API calls to external open data sources.
- **Wokwi:** Used for simulating basic IoT sensor prototypes and demonstrating real-time data flow concepts.

1.3 Research Objective

This study presents a quantitative evaluation of the module's effectiveness, using a paired pre-post design to measure student competency gains and provide empirical evidence for curriculum validation and quality improvement. Specifically, this study aims to quantify the statistically significant changes across three key domains: Knowledge (K), Behavioural Intent (B), and Confidence/Attitude (C), following the intensive training intervention.

2. Methodology

2.1. Study design and participants

This paper reports the results of a single-group, paired pre-test and post-test course evaluation intended for internal quality improvement and curriculum assessment. The target population was a cohort of undergraduate environmental science students (N=45) who completed the dedicated Environmental Data Analytics module.

2.2. Intervention and curriculum structure

The Environmental Data Analytics module was delivered as a 1 day intensive course unit, comprising 8 hours of practical, hands-on instruction. The pedagogical design was rooted in constructivist learning theory, where students actively built a complete, functional EH data pipeline from scratch, moving from: 1) data generation (Wokwi simulation); 2) mobile data collection (AppSheet application design); 3) automation and data enrichment (Google Apps Script and OpenWeather API integration); to 4) dashboard visualization (Google Looker studio). This scaffolded approach ensured that the theoretical concepts were immediately translated into functional products.

2.3. Educational tools utilized in the intervention

The course module provided intensive, hands-on instruction focusing on creating a fully functional environmental data pipeline, utilizing the following specific tools (Table 1).

Table 1. Tool and platform use for the intervention

Tool/ Platform	Function in Course	Environmental Health Relevance
Google Sheets	Primary cloud-based database and organizational back-end for all applications.	Teaches standardized data structure and collaborative cloud data management.
AppSheet	No-code platform for building mobile applications used for standardized field data collection.	Enables environmental professionals to collect geo-tagged, structured data offline, ensuring data integrity at the source.
Google Apps Script	Automation layer used to write custom code for scheduled tasks and API integration.	Crucial for automatically pulling external data (e.g., historical weather from Open Weather API) directly into Google Sheets, eliminating manual downloads and ensuring data freshness.
Google Looker Studio	Data visualization platform used to connect directly to the Google Sheets back-end.	Allows students to build interactive, public-facing dashboards that translate complex environmental data into actionable insights for decision-makers.
Wokwi	Online IoT simulator for microcontrollers and sensors.	Provides a low-cost, hands-on environment to understand how IoT sensors generate raw data (e.g., temperature, humidity) and how that data is transmitted before being processed in the cloud.

2.4. Instrument and data collection

The evaluation instrument consisted of questions measured on a 5-point Likert scale (1 = strongly disagree/low understanding; 5 = strongly agree/high understanding). Questions were grouped into three quantitative domains: Knowledge (K), Behavioural Intent (B), and Confidence/Attitude (C). The survey was administered digitally immediately before and immediately after the module.Instrument validation: Reliability was established using Cronbach's alpha. A final pre-test was administered digitally immediately before the module, and the post-test was administered immediately after the module completion.

2.5. Statistical analysis

Pre- and post-intervention scores were matched by individual student ID. A paired samples t-test was performed on the mean scores of all survey items to assess statistical significance ($p < 0.05$). In addition to p-values, the **effect size (Cohen's d)** was calculated for all significant mean gains to determine the practical magnitude of the intervention's impact. Domain-level mean scores and overall mean gains were calculated by averaging the corresponding item scores.

2.6. Educational ethics and data integrity

This study was conducted strictly as an internal program assessment for curriculum refinement and was deemed exempt from formal Institutional Review Board (IRB) review under institutional policies concerning routine quality assurance of educational practices. To uphold ethical standards: 1) data was collected with the explicit assurance of anonymity, with student IDs used only for pairing and then delinked; and 2) students were guaranteed that participation was voluntary and would not influence their course grades, ensuring non-coercion and promoting candid self-assessment [5,7].

3. Results and discussion

3.1. Instrument reliability

The internal consistency for the instrument domains was assessed using Cronbach's alpha. The results showed strong reliability across all three domains: Knowledge (alpha = 0.89), Behavioural Intent (alpha = 0.81), and Confidence/Attitude (alpha = 0.85), indicating that the instrument provided stable and consistent measurements of the constructs.

3.2. Domain-level summary of mean gains

The analysis demonstrated highly significant and positive mean gains across all three assessed domains (Table 2 and Figure 1).

Table 2: Overall mean score gain by domain (pre vs. post, N=45)

Domain	Overall Mean Pre	Overall Mean Post	Overall Mean Gain	Cohen's d
Knowledge (K)	2.92	4.53	+1.61	Large
Behavioural Intent (B)	3.39	4.36	+0.96	Medium-Large
Confidence/Attitude (C)	3.65	4.10	+0.45	Medium

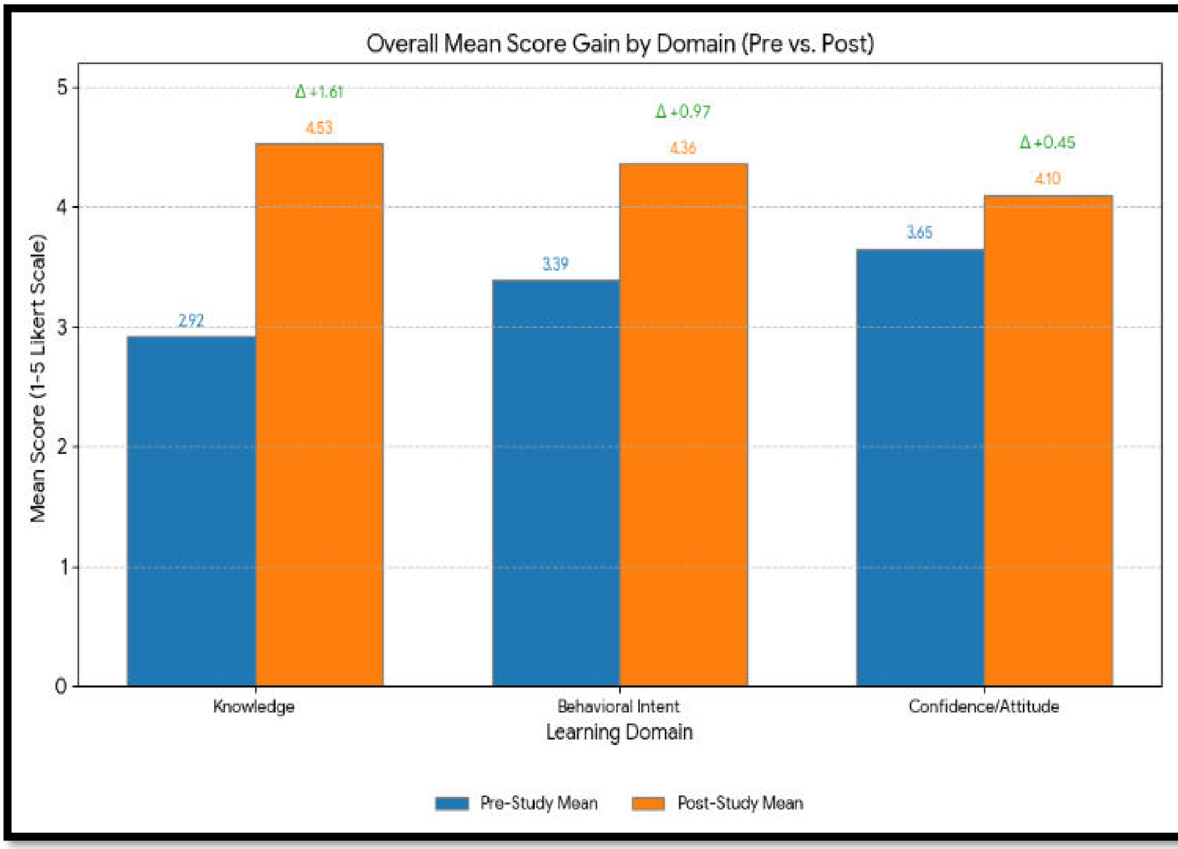

Figure 1. Comparison of mean score gains in knowledge, intent, and confidence

3.3. Detailed item analysis: Knowledge (K), behavioural intent (B) and confidence/attitude (C)

All eight items in the Knowledge domain showed highly statistically significant improvements (Table 3). The two concepts most central to the module's applied tools showed the largest gains. Intent to apply skills related to data workflow and technology integration showed significant gains (Table 4). Attitudinal items regarding the professional relevance and practicality of the new technologies improved significantly (Table 5).

The course evaluation successfully validated the pedagogical impact of integrating specific, applied cloud-based technologies into the environmental science curriculum. The +1.61 gain in knowledge is a powerful indicator of the successful transfer of digital literacy skills.

Table 3: Detailed results for knowledge domain (N=45)

Question Summary	Mean Pre	Mean Post	Mean Gain	Significance (p)
Purpose of "application programming interfaces" (APIs) in data retrieval?	2.50	4.50	+2.00	p=0.001
Main goal of creating a "dashboard" for data visualization?	2.62	4.62	+2.00	p=0.001
How can historical environmental data be used to predict future environmental hazards?	2.75	4.50	+1.75	p=0.004
What is "automation" in the context of data collection?	2.88	4.50	+1.62	p=0.003
What is the Internet of Things (IoT) and how can it be relevant to environmental monitoring?	3.50	4.50	+1.00	p=0.007

Table 4: Detailed results for behavioural intent domain (N=45)

Question Summary	Mean Pre	Mean Post	Mean Gain	Significance (p)
Attempt to automate repetitive tasks on a computer (e.g., using scripts, macros).	3.12	4.38	+1.25	p=0.028
Discuss with peers or instructors about new ways to use technology for environmental monitoring.	3.38	4.38	+1.00	p=0.033
Consider building a simple mobile app (e.g., using AppSheet) to streamline a data collection process.	3.25	4.25	+1.00	p=0.033

3.4. Critical linking tool use to quantified gains

The specific tools and exercises directly correlate with the most significant learning outcomes:

- **API knowledge (+2.00):** This most substantial gain is directly attributed to the task of using Google Apps script to write a script that successfully connected to the OpenWeather API. By writing the request and parsing the JSON response, students gained a functional understanding of how APIs enable automated access to critical open data—a skill far surpassing traditional data literacy.
- **Dashboard goals (+2.00):** This peak gain is the result of using Google Looker studio. Students moved beyond static charts (e.g., in Excel) to building dynamic, interactive dashboards that pulled data directly from their Google sheets back-end. This hands-on experience shifted their perception of visualization from reporting past events to creating tools for real-time risk communication [13, 14].
- **Automation intent (+1.25):** The high intent to automate is directly tied to the efficiency demonstrated by the Google Apps script automation. Witnessing the script automatically fetch data (API calls) or process repeated tasks (data cleaning) instilled a strong desire to apply this time-saving skill in their future environmental roles.
- **Mobile app intent/confidence (+1.00 & +0.62):** The significant increase in intent and confidence regarding mobile apps stems from the ease of building a functional, geo-tagged data collection app using the AppSheet no-code platform. This provided students with a tangible, deployable solution for a core environmental challenge: reliable field data collection.
- **IoT relevance (+1.00):** The demonstration using the Wokwi simulator provided the necessary conceptual bridge, allowing students to visualize the raw data output of an IoT sensor and understand its journey before it enters the structured environment of Google sheets and is visualized in Looker studio.

Table 5: Detailed results for confidence/ attitude domain (N=45)

Question Summary	Mean Pre	Mean Post	Mean Gain	Significance (p)
Learning to use open data analytics tools is important for my future career.	3.75	4.38	+0.62	p=0.011
Creating interactive dashboards is a valuable skill for communicating environmental information.	3.88	4.50	+0.62	p=0.049
Developing simple mobile apps is a practical skill for environmental professionals.	3.75	4.38	+0.62	p=0.011

I am open to exploring new computer tools and technologies for environmental monitoring.	3.88	4.38	+0.50	p=0.033
I feel overwhelmed by the technical aspects of using computer applications for data analysis. (Reverse coded)	2.12	1.75	-0.38	p=0.285 (NS)

3.5. Theoretical contributions and implications for educational theory

The findings align strongly with the Technology Acceptance Model (TAM), particularly regarding the increase in perceived usefulness (PU) and perceived ease of use (PEOU). The high gains in Knowledge and Intent suggest that the low-code, cloud-based tools successfully addressed the PEOU barrier, allowing students to immediately recognize the practical utility (PU) of the skills for their future EH careers. This shift in perception is evidenced by the significant gain in the belief that data analytics tools are "important for my future career" (Table 5).

Furthermore, the structure of the module provides evidence supporting the Kirkpatrick Model of Training Evaluation, Level 2 (Learning), definitively proving that the trainees acquired the intended knowledge and skills. Future research should target Level 3 (Behaviour) by tracking the longitudinal application of these tools in subsequent internships or professional practice.

3.6. Implications for environmental health pedagogy

This evaluation mandates the formal integration of low-code/ no-code application development (AppSheet), cloud-based visualization (Looker studio), and script-based automation (Apps script) into environmental health programs. These applied competencies shift the professional from a passive consumer of information to an active designer of data solutions, a vital step toward a proactive, technologically adept workforce (Figure 2).

3.7. Educational ethics and compliance

The study successfully quantified learning outcomes while strictly adhering to ethical principles (Section 2.5). The framing of the project as a course evaluation allowed for a rigorous paired-sample analysis to be conducted for quality improvement purposes, ensuring student privacy and voluntary participation were maintained without the necessity of formal IRB review. This approach provides a repeatable model for other institutions seeking to validate curriculum effectiveness through internal, data-driven assessment [10, 11, 12].

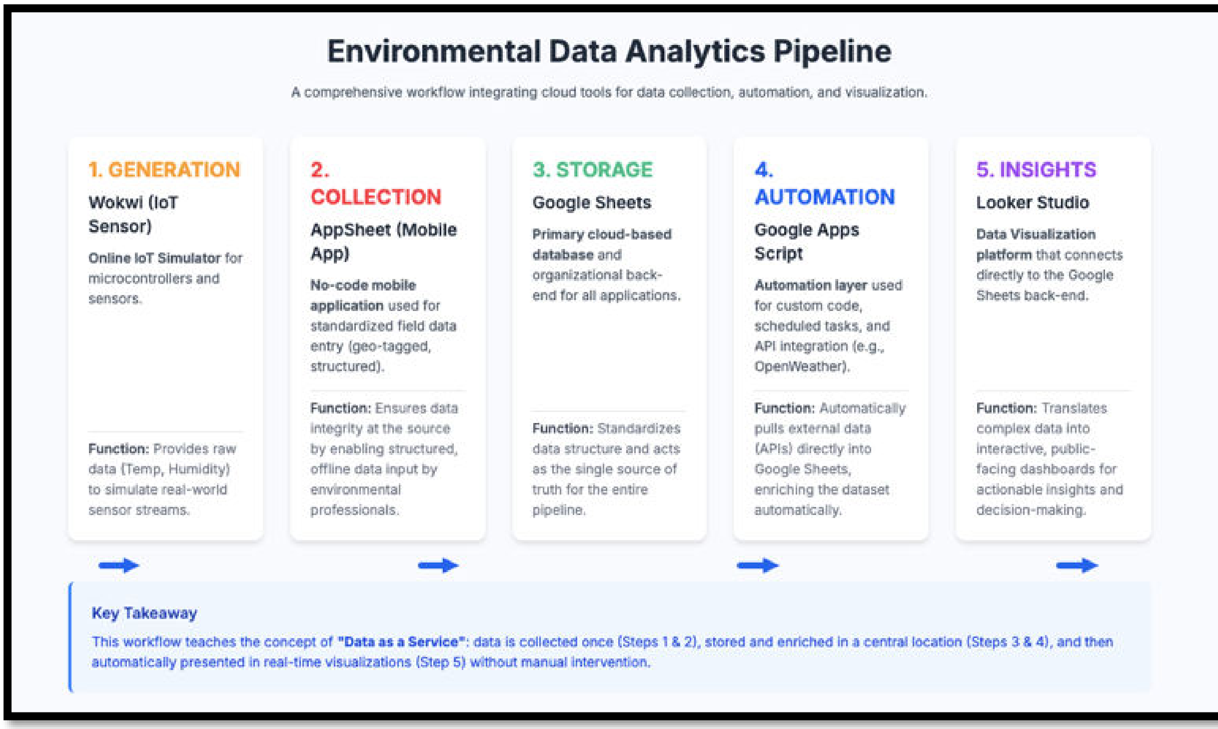

Figure 2: Environmental data analytics teaching flow

3.7. Limitations and future research

As a course evaluation, this study is inherently limited by its non-experimental, single-group design and its reliance on self-assessment. While the large effect sizes are compelling, future research must employ a control group or quasi-experimental design to establish stronger causal inference. Moreover, longitudinal follow-up, ideally six to twelve months post-intervention, would be essential to assess the long-term retention of technical skills and the translation of Behavioural Intent into actual professional Behaviour (Kirkpatrick Level 3), further validating the sustainability of this educational model.

4. Conclusion

The data confirms that the integration of practical, cloud-based tools—specifically AppSheet, Google Looker studio, Google Apps script, and Wokwi—resulted in substantial, statistically significant gains in the knowledge, behavioural intent, and confidence of environmental science students. This module is a successful model for modernizing environmental health education, equipping graduates with the digital literacy necessary to harness IoT and open data for proactive environmental management and public health protection.

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