

T-DASH: INTEGRATING TASK-BASED TRAINING AND AN INTERACTIVE DATA-DRIVEN LEARNING ENVIRONMENT FOR DATA VISUALIZATION AND DASHBOARD COMPETENCY DEVELOPMENT

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ABSTRACT

This study developed and preliminarily evaluated T-DASH, a five-stage task-based training model supported by an Interactive Data-Driven Learning Environment for data visualization and dashboard competency development. The three-phase research-and-development process comprised conceptual synthesis; development and expert review of task-based training activities, assessment instruments, and the interactive environment; and field implementation using a one-group pretest-posttest design. The T-DASH architecture links a staged data-to-decision workflow, five competency domains, and an evidence-to-feedback cycle supported by eight environment functions: website access, interactive media, multimedia, learning resources, analytics, assessment, communication, and online activities. Five experts evaluated the model and supporting components. Twenty-five support personnel at Chulabhorn Royal Academy completed a 30-hour program, and one external assessor scored parallel pretest and posttest performance tasks and completed dashboards using analytic rubrics. Expert ratings were high for the model ($M = 4.41$, $SD = 0.57$), activity plans ($M = 4.40$, $SD = 0.59$), and interactive environment ($M = 4.28$, $SD = 0.60$). Overall competency increased from pretest ($M = 2.79$, $SD = 0.39$) to posttest ($M = 4.13$, $SD = 0.29$), $t(24) = 12.96$, $p < .001$, Cohen's $d_z = 2.59$. Completed-dashboard quality ($M = 4.18$, $SD = 0.31$) and participant satisfaction ($M = 4.33$, $SD = 0.35$) were high. The study contributes an operational training architecture that connects authentic whole-task performance, explicit competency criteria, and actionable learning evidence within one dashboard-development workflow. The findings support the feasibility of T-DASH in the study context and document substantial within-group change; however, the one-group design does not establish a causal effect.

Keywords: *Task-Based Training, Data Visualization, Dashboard Development, Data-Driven Learning Environment, Professional Competency, Learning Analytics*

1. INTRODUCTION

Organizations increasingly rely on data to monitor services, allocate resources, evaluate performance, and support managerial decisions. Access to data and self-service business intelligence software, however, does not by itself produce useful evidence. Staff members must be able to prepare reliable data, select appropriate analyses, design interpretable visualizations, construct functional dashboards, and explain findings in relation to organizational questions [1]-[6]. These requirements are particularly relevant to support personnel whose responsibilities connect administrative operations, reporting, service delivery, and institutional decision-making.

Data visualization and dashboards can condense complex information into coordinated displays for monitoring, exploration, explanation, and action [4]-[11]. Effective dashboard development nevertheless requires more than assembling charts. Developers must define the decision problem, understand users and information needs, inspect data quality, establish valid measures, choose appropriate visual encodings, organize information hierarchically, design meaningful interactions, test usability, and communicate implications without misleading the audience [5]-[15]. Weakness at any stage can produce a dashboard that is visually appealing yet analytically unreliable, difficult to interpret, or poorly aligned with the decision task.

When dashboard instruction is organized primarily around software commands or isolated features, learners may practice importing a spreadsheet, creating a chart, or applying a filter without coordinating the full data-to-decision workflow. This creates a practical competency gap: learners may execute individual software operations yet remain unable to integrate them into a defensible, decision-oriented dashboard workflow. Authentic performance, by contrast, requires the integration of technical procedures, analytical judgment, visual design, communication, and revision. Whole-task and task-centered approaches are relevant to this problem because they organize instruction around meaningful performances and provide supporting knowledge, procedural guidance, practice, and feedback in relation to the complete task [16]-[20].

Experiential learning adds a cycle of action, reflection, conceptualization, and renewed application [21]-[23]. In dashboard training, learners need opportunities to inspect data, test interpretations, compare alternative visualizations, receive feedback, revise products, and explain design decisions. Authentic learning perspectives further emphasize realistic tasks, professional tools, meaningful outputs, and social interaction that resembles the context of later performance [22]-[25].

Competency-based training provides a complementary assessment logic. Expected outcomes are expressed as observable performance and are judged against explicit criteria rather than attendance or software exposure alone [23], [26]-[28]. For dashboard development, relevant evidence includes the quality of data preparation, analysis, visual representation, dashboard construction, and communication. Analytic rubrics can make these expectations visible and provide a common basis for practice, feedback, and assessment.

A learning environment should do more than store files or report activity counts. To support complex performance, it should enable learners to examine demonstrations, manipulate examples, complete online activities, submit evidence, communicate with trainers and peers, receive assessment information, and use progress data to guide revision. Learning analytics can organize activity records, formative checks, rubric results, and feedback histories, but their instructional value depends on whether learners can interpret the evidence and act on it [12], [29]-[41]. Recent work therefore emphasizes analytics and dashboards that support feedback, self-regulation, and subsequent action rather than passive monitoring [12], [31]-[43].

Across these strands of literature, the central design problem is the separation of capabilities that

must be coordinated in professional dashboard work. Research provides guidance on whole-task learning, authentic assessment, visualization design, dashboard usability, and learning analytics, yet these elements do not by themselves specify how learners can move from an organizational decision problem to prepared data, validated analysis, an interactive dashboard, and a defensible recommendation within one coherent training architecture [4]-[20], [23]-[43]. T-DASH was developed to address this integration problem by combining authentic tasks, an iterative five-stage training process, explicit competency criteria, and an Interactive Data-Driven Learning Environment. The key scientific contribution of the study is an operational architecture that links the data-to-decision workflow with evidence capture, feedback, revision, and performance assessment rather than treating software operation, visualization, and learning analytics as separate instructional components. The study examined the design and expert evaluation of this architecture and documented preliminary implementation outcomes among organizational support personnel.

The study was guided by three research questions:

RQ1. What components and operating relationships characterize T-DASH as an integrated task-based training model for data visualization and dashboard competency development?

RQ2. How do experts evaluate the alignment, feasibility, and quality of the T-DASH model, its task-based training activity plans, and its Interactive Data-Driven Learning Environment, and does the environment function as intended during implementation?

RQ3. What pretest-posttest competency changes, completed-dashboard quality outcomes, and participant satisfaction are observed following implementation of T-DASH in the study cohort?

2. LITERATURE REVIEW

2.1 Task-Based Training for Complex Data Work

Task-based training organizes learning around performances that resemble the work learners are expected to complete after training. Whole-task designs introduce an authentic problem or product and connect demonstrations, supporting information, procedural guidance, practice, and feedback to that task [16]-[20]. Learners therefore encounter the relationships among decisions rather than studying each software feature in isolation.

Dashboard development is suitable for this approach because a complete task begins with a decision need and proceeds through data access, cleaning, transformation, analysis, visualization, interaction design, validation, and communication. Later decisions depend on earlier ones: inaccurate preparation affects analysis, unsuitable analysis affects visual meaning, and unclear communication reduces the value of an otherwise functional dashboard. A task sequence can make these dependencies visible while moving learners from structured examples to more independent performance.

2.2 Experiential and Competency-Based Development

Experiential learning describes learning as a recurring movement among concrete experience, reflection, conceptual interpretation, and active experimentation [21]-[23]. Applied to dashboard development, the cycle occurs when learners build a product, compare it with user needs and criteria, identify limitations, revise the design, and apply the revised approach to a new dataset or problem. Feedback is useful when it clarifies the goal, the current state of performance, and the next action [24]-[25], [42]-[43].

Competency-based training specifies what learners should be able to do and aligns learning tasks, practice, evidence, and assessment with those outcomes [23], [26]-[28]. T-DASH defines five competency domains: Data Preparation, Data Analysis, Data Visualization, Dashboard Development, and Data Communication and Decision-Making. The domains represent the complete progression from raw data to an interpretable product and an actionable explanation.

2.3 Data Visualization and Dashboard Development

Visualization design requires alignment among data characteristics, analytical questions, visual encodings, interaction techniques, and audience tasks [6]-[13]. Visualization literacy includes the ability to read, interpret, critique, and construct visual representations [8]-[9], [12]. Training should therefore address both production and judgment, including the identification of misleading scales, unnecessary decoration, weak hierarchy, and unsupported conclusions.

Dashboards combine indicators, charts, annotations, and controls within a coordinated interface. Their purpose may emphasize monitoring, analysis, communication, or decision support [4]-[6], [10]-[11]. Effective designs manage screen

space, visual consistency, information hierarchy, interaction, usability, and cognitive demand. General patterns can guide design, but developers must still make context-sensitive decisions about users, tasks, data, and actionability [5]-[6], [12]-[15].

2.4 Interactive Data-Driven Learning Environments

Learning analytics involves the collection, analysis, and use of data about learners and learning contexts to understand and support learning [29]-[30]. Learning dashboards are a common interface for presenting such evidence [12], [31]-[41]. Reviews have shown considerable variation in data sources, design principles, theoretical grounding, and evaluation methods. Recent work emphasizes dashboards that are connected to self-regulation, feedback, and learner action rather than passive monitoring [12], [32]-[41].

An Interactive Data-Driven Learning Environment extends learning analytics beyond a dashboard display. In T-DASH, learners access sequenced tasks through a website, use interactive examples and multimedia demonstrations, retrieve digital resources, complete formative and summative assessments, communicate with the trainer and peers, submit work, and review progress information. Evidence generated through these activities is returned as feedback for revision, making the environment both a learning workspace and an instructional evidence system.

2.5 Research Gap and Design Principles

The literature reviewed above establishes several strong but largely distinct design strands: authentic whole-task performance, experiential revision, competency standards, visualization and dashboard design, and evidence-informed feedback [4]-[43]. What remains insufficiently specified across these strands is an applied training architecture that coordinates the complete dashboard workflow with learning resources, assessment, communication, analytics, feedback, and required revision. The research gap is therefore not the absence of individual technologies or instructional techniques. It is the limited integration of these elements into a structured performance process in which learners must connect data preparation, analysis, visualization, dashboard construction, and decision communication while using learning evidence to improve the same task. Recent reviews of learning analytics dashboards and technology-supported feedback environments reinforce the importance of guidance, actionability, and learner response to feedback [12], [31]-[43].

On this basis, T-DASH was designed around five principles: use authentic decision tasks; coordinate the complete data-to-decision workflow; define observable competency outcomes; make practice, feedback, and revision iterative; and connect learning evidence to a specific next action. These principles translate the literature into an operational training design rather than adding another standalone dashboard or software tutorial. Table 1 summarizes how each theoretical and applied foundation informed the model.

Table 1: Literature-Based Design Principles for T-DASH

Foundation	Instructional contribution	T-DASH design response
Task-based and whole-task instruction [16]-[20]	Authentic performance, integration, scaffolding, transfer	Five-stage workflow centered on complete dashboard tasks
Experiential and authentic learning [21]-[25]	Action, reflection, revision, contextualized practice	Repeated creation, critique, improvement, and workplace application
Competency-based training and authentic assessment [23], [26]-[28]	Observable standards and performance evidence	Five competency domains aligned with analytic rubrics
Visualization and dashboard design [4]-[15]	Analytical validity, visual judgment, usability, communication	Professional content from data preparation to decision communication
Learning analytics and feedback [12], [24], [29]-[43]	Progress evidence, self-regulation, actionable feedback	Evidence-to-feedback cycle embedded across online activities

Drawing on the literature and the identified design principles, the conceptual framework for T-DASH links five foundations—task-based and whole-task instructional principles, experiential learning, data visualization and dashboard design, competency-based training, and learning analytics with data-driven feedback—to the training process, the Interactive Data-Driven Learning Environment, and the five competency domains. These foundations are operationalized through the five-stage task-based workflow and the evidence-to-feedback cycle. The conceptual contribution lies in mapping established instructional, assessment, visualization, and analytics foundations onto one professional data-to-decision workflow, while the design contribution lies in making the relationships among performance evidence, feedback, and revision explicit within that workflow. Figure 1 presents this framework.

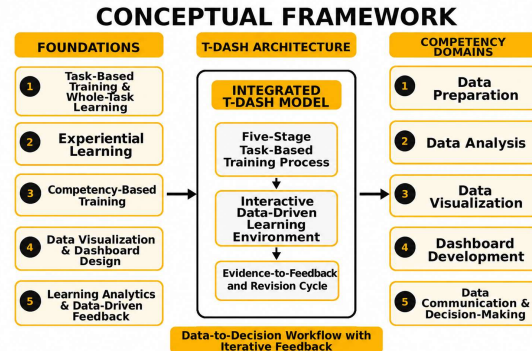


Figure 1: Conceptual framework linking the theoretical foundations, T-DASH architecture, and competency domains

3. RESEARCH OBJECTIVES

- 3.1 To develop the T-DASH model as an integrated task-based training architecture with an Interactive Data-Driven Learning Environment for data visualization and dashboard competency development.
- 3.2 To develop and evaluate the task-based training activity plans and the Interactive Data-Driven Learning Environment through expert review and functional verification.
- 3.3 To examine observed pretest-posttest competency change, the quality of completed dashboards, and participant satisfaction following implementation of T-DASH.

4. RESEARCH METHODOLOGY

4.1 Research Design and Context

The study employed a three-phase research-and-development design. Phase 1 synthesized the conceptual model and competency framework. Phase 2 developed and expert-reviewed the task-based training activity plans, assessment instruments, and Interactive Data-Driven Learning Environment. Phase 3 implemented the integrated system in a one-group pretest-posttest field study. The phases were aligned with the research objectives, training tasks, evidence sources, and intended outcomes. Development drew on established instructional-design and rapid-prototyping practices [20].

The field implementation was conducted with support personnel at Chulabhorn Royal Academy. The training addressed administrative and support work in which participants were expected to interpret data, prepare reports, or communicate evidence for operational decisions. Microsoft Power BI Desktop was used as the dashboard-authoring tool, while the web environment organized learning

access, resources, activities, communication, submission, assessment, and progress information.

4.2 Participants

Twenty-five support personnel participated voluntarily. Eligibility required current administrative, operational, service, planning, or reporting responsibilities involving data; basic spreadsheet and computer skills; and availability to complete the training and all assessment tasks. The participants formed a single organizational cohort; the sample was not intended to be statistically representative of all support personnel.

All 25 participants completed the scheduled training and all study measures. The analyses therefore included complete pretest, posttest, dashboard, and satisfaction data. Results are presented at the group level without identifying individual participants or organizational units.

4.3 Development of the T-DASH Model

Model development began with an analysis of workplace reporting tasks, the data-to-dashboard workflow, participant needs, and the competencies

required for acceptable performance. The conceptual synthesis integrated task-based and whole-task instructional principles, Experiential Learning, Data Visualization and Dashboard Design, Competency-Based Training, and Learning Analytics with Data-Driven Feedback. Figure 1 presents the resulting framework.

The five competency domains were translated into observable criteria covering data preparation, analysis, visual representation, dashboard construction, and communication for decision-making. The training process was then organized as five linked stages whose initials form T-DASH: T, D, A, S, and H. Although the stages provide a clear sequence, learners can return to an earlier stage when feedback reveals a data-quality problem, an unsupported interpretation, a weak visual choice, or an unmet user need.

Figure 2 presents the overall architecture of the T-DASH model. It integrates five conceptual foundations, the five-stage task-based training process, a learning analytics and data-driven feedback loop, and five competency domains for data visualization and dashboard development.



Figure 2: The T-DASH Model

4.4 Interactive Data-Driven Learning Environment

The supporting environment was developed as a web-accessible learning workspace linked to Power BI Desktop for dashboard production. Interactivity was operationalized through eight connected functions: website navigation, interactive media, multimedia demonstrations, learning resources, analytics, assessment, communication, and online activities. Learners could move among T-DASH stages, access resources, complete and submit tasks, receive feedback, and review progress information through an evidence-to-feedback loop. The design followed recommendations emphasizing explicit planning, user-centered design, implementation checks, and evaluation [31]-[32], [39]-[40].

The platform provided digital books, multimedia lessons, instructional videos, interactive demonstrations, downloadable datasets, Power BI practice files, dashboard templates, reference materials, and step-by-step tutorials. It also included quizzes, educational games, case-based activities, guided practice, self-assessment, and authentic dashboard development tasks. Each resource and activity was aligned with a T-DASH stage and competency domain to support progressive development and iterative revision [20], [25].

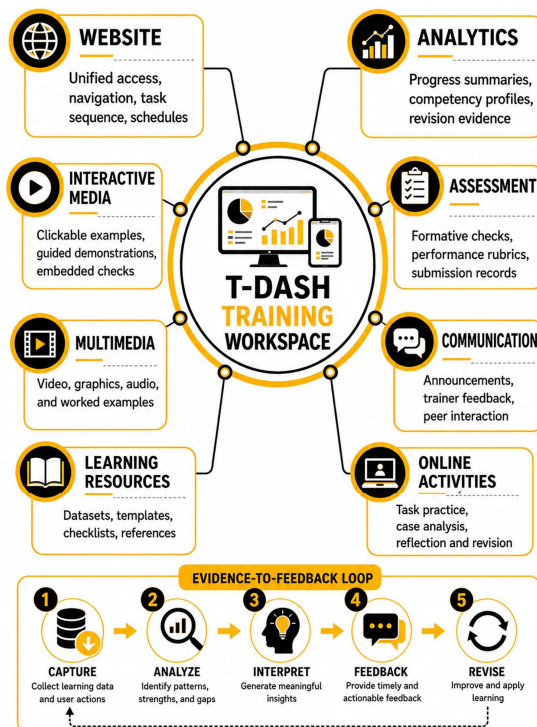


Figure 3: Functional architecture of the Interactive Data-Driven Learning Environment

The data-driven component used task-completion records, formative checks, submitted files, rubric evidence, feedback, and revision histories. Trainer-facing summaries helped identify common difficulties and feedback priorities, whereas learner-facing information highlighted current progress, competency areas requiring attention, and the next task or revision. Training relied on anonymized or synthetic datasets, and the resulting analytics were used for learning support rather than personnel evaluation [12], [31]-[41]. These system-generated analytics were not analyzed as formal research outcome measures.

Assessment, communication, and analytics were integrated within the same instructional workflow. Participants submitted assignments, received rubric-based feedback, reviewed progress, communicated with the trainer, and revised their work. Online activity and assessment evidence supported reflection and targeted feedback, consistent with recommendations that analytics should lead to understandable and actionable learning decisions [12], [25], [31]-[41].



Figure 4: Interactive Data-Driven Learning Environment

4.4.1 Evidence-to-Feedback Operation

The environment was designed so that each interaction could produce evidence relevant to a learning decision. Completion records indicated whether a learner had reached an activity, while formative checks showed whether essential concepts

were understood. Submitted task files and rubric scores provided direct performance evidence. Feedback messages, reflections, and revision histories showed how learners responded after receiving guidance. The evidence types were selected to support formative feedback, self-regulation, and iterative improvement [24]-[25], [39], [42]-[43].

The trainer reviewed evidence at both individual and group levels. Individual profiles were used to identify a learner's next step, whereas group summaries were used to decide whether an additional demonstration, example, or class discussion was needed. The environment did not treat all low scores in the same way. A data-preparation error led to a different response from a weak visual hierarchy or an unsupported recommendation.

Learners were expected to act on feedback. A feedback cycle was considered complete only when the learner reviewed the message, returned to the relevant resource or criterion, revised the task, and submitted new evidence. Table 2 summarizes the operational rules connecting evidence, interpretation, feedback, and learner action. Requiring a visible response to feedback is consistent with feedback-as-action and self-regulated learning perspectives [24]-[25], [42]-[43].

Table 2: Evidence-to-Feedback Rules in the Interactive Environment

Evidence source	Interpretive question	Feedback action	Learner response
Website records	Task completed?	Clarify next steps.	Complete the task.
Formative checks	Understanding achieved?	Explain key concepts.	Review and retry.
Datasets	Data valid?	Identify data errors.	Revise and resubmit.
Dashboard drafts	Design appropriate?	Suggest revisions.	Revise the dashboard.
Presentation	Insights actionable?	Clarify actions.	Revise the presentation.
Reflection	Feedback applied?	Confirm progress.	Submit final revision.

4.5 Training Program and T-DASH Stages

The training comprised five six-hour modules, for a total of 30 hours. Each module focused on one primary T-DASH stage while retaining links to earlier and later decisions. Participants used realistic task scenarios and datasets related to organizational support work. Demonstrations and guided practice preceded increasingly independent task performance, and each module included checkpoints, feedback, reflection, and revision.

The five stages form a structured but iterative cycle:

a) T – Task Orientation and Problem Definition: Learners analyze the context, stakeholders, decision needs, key questions, objectives, success criteria, and required data.

b) D – Data Understanding and Preparation: Learners collect or access data, profile data quality, clean and transform values, integrate sources, establish relationships, and prepare data for analysis.

c) A – Analyze and Visualize: Learners define metrics, conduct descriptive and comparative analyses, identify patterns, select suitable visual representations, and validate findings.

d) S – Synthesize and Develop the Dashboard: Learners organize findings into a coherent information structure, develop interactive views, apply filters and navigation, and test usability and performance.

e) H – Highlight Insights, Evaluate, and Transfer: Learners communicate key findings and recommendations, evaluate dashboard quality and task-level decision implications, revise the solution, and transfer learning to another work task.

Learners may return to earlier stages when new evidence reveals a data-quality problem, an invalid analytical assumption, an ineffective visualization, or an unmet user requirement. Figure 5 illustrates the iterative T-DASH process and the continuous improvement cycle. References to impact, action, and performance in Figures 2 and 5 denote task-level training goals or application within the training cycle rather than measured organizational effects.

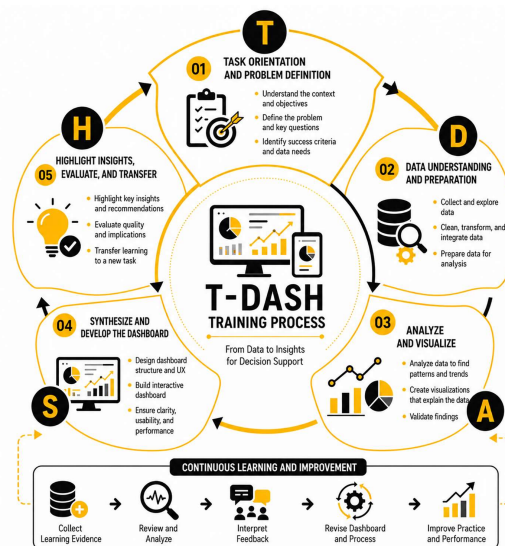


Figure 5: Five-stage T-DASH training process and continuous improvement cycle

4.5.1 Competency Framework and Assessment Alignment

The competency framework served as the link between the training process and assessment. Each domain was associated with one or more T-DASH stages, but assessment required integration across the full task. For example, an analytically correct measure could not receive a high overall judgment if the underlying data were inaccurate or if the result was communicated through a misleading chart. Table 3 summarizes the assessment focus.

Table 3: Competency Domains and Assessment Evidence

Competency domain	T-DASH stage	Observable performance	Evidence
Data Preparation	T-D	Prepares and validates data.	Dataset, data model, and quality checks
Data Analysis	D-A	Analyzes data and validates findings.	Measures, calculations, and findings
Data Visualization	A-S	Creates clear and accurate visualizations.	Visuals and design rationale
Dashboard Development	S	Builds and tests an interactive dashboard.	Dashboard and usability evidence
Data Communication and Decision-Making	H	Communicates findings and recommendations.	Presentation, recommendations, and reflection

4.6 Research Instruments

The study used six instrument sets: the T-DASH model evaluation form; the task-based training activity plan evaluation form; the Interactive Data-Driven Learning Environment evaluation form with a functional checklist; a 25-criterion Data Visualization and Dashboard Development Competency Rubric; a Completed Dashboard Quality Rubric; and a Participant Satisfaction Questionnaire.

Five experts in educational technology, instructional design, data analytics, data visualization, and organizational training examined the alignment, clarity, relevance, feasibility, and coverage of the model, activity plans, environment, and assessment instruments. Their comments informed revisions to task scope, rubric wording, navigation labels, analytics displays, feedback procedures, and the allocation of time for data preparation and revision.

The competency rubric contained five domains with five criteria per domain and five performance levels, consistent with competency-based and authentic-assessment principles [23], [26]-[28]. The completed dashboard rubric assessed problem alignment, data integrity, analytical validity, visual

appropriateness, information architecture, interactivity and usability, insight communication, and technical functionality. The satisfaction questionnaire covered the training process and task-based activities, the interactive environment, and perceived outcomes and transfer.

Table 4 summarizes the six research instruments, the evidence generated by each instrument, and its role in the study.

Table 4: Instruments and Evidence Used in the Study

Instrument	Primary evidence	Use
Model evaluation form	Expert ratings and comments	Evaluate and refine the model
Activity-plan evaluation form	Expert ratings and comments	Evaluate task design and feasibility
Environment evaluation and checklist	Expert ratings and functional checks	Evaluate usability and system functions
Competency rubric	Pretest and posttest scores	Assess five competency domains
Completed-dashboard rubric	Product-quality scores	Assess dashboard quality
Satisfaction questionnaire	Post-training ratings	Assess satisfaction and perceived transfer

4.7 Data Collection and Scoring

Before receiving access to training modules, demonstrations, or formative feedback, participants completed an individual baseline task requiring data preparation, analysis, visualization, dashboard construction, and communication of recommendations. After the 30-hour program, they completed a parallel task based on a different scenario and dataset but the same competency structure. The two tasks were designed to be comparable in scope and competency coverage and used the same software conditions, submission requirements, and rubric criteria. No instructional assistance was provided during either assessment.

A single external assessor with experience in data analytics and dashboard development scored the coded pretest, posttest, and completed-dashboard files. For the pretest and posttest competency tasks, the assessor used the same competency rubric and performance-level descriptors; the completed dashboard was scored with the separate Completed Dashboard Quality Rubric. Scores were recorded separately for each assessment source. This standardized procedure was used to maintain consistency across scoring occasions.

After the posttest and dashboard submission, participants completed the satisfaction questionnaire. Functional records and trainer observations were used to confirm that the learning resources, online activities, evidence capture,

analytics displays, feedback, and submission procedures operated as intended during implementation.

4.8 Implementation Controls and Data Management

The baseline task was completed before orientation, access to demonstrations, or formative feedback. The posttest used a different scenario and dataset but retained the same five competency domains and comparable dashboard requirements. Assessment tasks were separated from practice activities, and no instructional support was available during either assessment.

All participants used the same dashboard-authoring software, written instructions, submission procedures, and analytic rubric structure. The external assessor received coded files organized by assessment source and applied the designated rubric and fixed performance-level descriptors consistently within each assessment source. These controls reduced avoidable variation in task administration and scoring.

Training datasets were anonymized or synthetically constructed to avoid disclosure of organizational information. The website used participant access controls, and files were stored according to the training procedures established before implementation. Analytics summaries were used for learning support and group-level reporting rather than personnel appraisal.

The final analysis included all 25 participants who completed the required measures. No imputation was required because the dataset contained complete pretest, posttest, dashboard, and satisfaction records. Table 5 summarizes the principal controls applied during implementation.

Table 5: Implementation and Data-Quality Controls

Control area	Procedure	Purpose
Baseline timing	Pretest before training and feedback	Preserve the baseline
Parallel tasks	Parallel scenarios with standardized task conditions	Support comparability across assessment occasions
Assessment support	No assistance during testing	Separate testing from training
Scoring	One external assessor using standardized rubrics	Standardize application of scoring criteria
Training data	Anonymized or synthetic datasets	Protect confidentiality
Environment access	Controlled access and file management	Ensure secure data handling
Analytics	Progress data for learning support	Support learning, not evaluation
Analysis dataset	Complete data from 25 participants	Ensure transparent reporting

5. DATA ANALYSIS

Qualitative information from the needs analysis, expert comments, functional verification, and training observations was examined through content analysis and used to refine the model and environment. Quantitative results were summarized using means and standard deviations. For all five-point scales, mean scores were interpreted as follows: 4.51-5.00 = Very High, 3.51-4.50 = High, 2.51-3.50 = Moderate, 1.51-2.50 = Low, and 1.00-1.50 = Very Low.

A paired-samples t-test compared the overall pretest and posttest competency scores. Cohen's *d* quantified the standardized within-participant difference, and a 95% confidence interval was calculated for the mean difference [44]. Competency domain results, dashboard quality, and satisfaction were summarized descriptively. Correlation analysis was not performed because the competency and completed-dashboard rubrics shared several performance criteria and did not represent independent constructs.

6. RESULTS

6.1 Specification of the T-DASH Model

The development process produced an integrated model with four connected parts: a conceptual framework, the five-stage T-DASH training process, the Interactive Data-Driven Learning Environment, and five competency domains. The model positions dashboard development as a professional problem-solving process rather than a sequence of software commands. The environment supplies resources and interaction across the stages, while the evidence-to-feedback loop supports revision.

The five competency domains were defined as follows. Data Preparation concerns the collection, profiling, cleaning, transformation, integration, organization, and quality assurance of data. Data Analysis concerns the definition of metrics, exploration of patterns and trends, application of suitable descriptive or comparative techniques, validation, and derivation of defensible insights. Data Visualization concerns chart selection, visual encoding, hierarchy, clarity, consistency, and storytelling. Dashboard Development concerns information architecture, coordinated views, interactivity, navigation, usability, accessibility, functionality, and performance. Data Communication and Decision-Making concerns accurate explanation, linkage to stakeholder questions, feasible recommendations, responsible

communication of limitations, and support for action.

6.2 Expert Evaluation and Design Revision

Expert ratings were used to examine the alignment, feasibility, and overall quality of the model and its supporting components. Table 6 presents the evaluation results.

Table 6: Expert Evaluation of the T-DASH Model and Supporting Components

Development output	M	SD	Level
Conceptual framework	4.40	0.58	High
Five-stage training process	4.44	0.58	High
Competency domains	4.40	0.58	High
T-DASH model overall	4.41	0.57	High
Task-based training activity plans overall	4.40	0.59	High
Interactive Data-Driven Learning Environment overall	4.28	0.60	High

Five experts rated the T-DASH model at a high level overall ($M = 4.41$, $SD = 0.57$). The five-stage training process received the highest component mean ($M = 4.44$, $SD = 0.58$), while the conceptual framework and competency domains each received $M = 4.40$ ($SD = 0.58$). These ratings indicated favorable judgments of alignment among the foundations, performance stages, and intended outcomes.

The task-based training activity plans were also rated high ($M = 4.40$, $SD = 0.59$). Experts particularly valued coverage of the complete data-to-decision workflow and alignment between task activities and competency criteria. Comments led to clearer time allocation for data preparation, more explicit revision checkpoints, and additional guidance for participants with limited prior dashboard experience.

The Interactive Data-Driven Learning Environment received a high overall rating ($M = 4.28$, $SD = 0.60$). Expert comments focused on simplifying navigation, clarifying the meaning of progress indicators, strengthening instructions for submission and revision, and specifying procedures for access to training data. The environment was revised before field implementation.

6.3 Functional Verification of the Environment

The environment was functionally verified before and during implementation to confirm that its major components operated as intended. Table 7 summarizes the grouped verification areas and their final status.

Table 7: Functional Verification of the Interactive Environment

Verification area	Verification criterion	Final status
User access and navigation	Website access, resources, and stage navigation function correctly.	Verified after minor revision
Resource delivery	Datasets, media, templates, checklists, and rubrics open correctly.	Verified
Interactive media	Interactive examples and embedded checks function as intended.	Verified
Online activities and submission	Activities and revised work can be submitted and retrieved.	Verified
Evidence captures and analytics	Learning records, scores, feedback, and revisions are stored and summarized.	Verified after minor revision
Assessment support	Assessment files can be coded and organized for scoring.	Verified
Communication and feedback	Announcements, feedback, and interaction tools function correctly.	Verified
Data access and protection	Permissions, storage, and anonymized data are applied consistently.	Verified after minor revision

All verification criteria were satisfied in the final version. The checklist grouped related environment functions for testing and included a cross-cutting data-access and protection check. Resource delivery, interactive media, online activities, submission, assessment support, and communication operated without substantive changes. Minor revisions were made to navigation labels, the presentation of analytics information, and explanations of data-access procedures.

During implementation, the environment supported movement among the five stages rather than requiring learners to follow a fixed linear path. Participants could return to examples, review criteria, examine feedback, revise files, and resubmit evidence. This interaction pattern was consistent with the iterative design of the T-DASH process.

6.4 Pretest–Posttest Competency Results

Table 8 presents the pretest and posttest scores for the five competency domains and the overall competency measure.

Table 8: Pretest and Posttest Competency Scores

Competency	Pretest M (SD)	Posttest M (SD)	Mean difference
Data Preparation	3.02 (0.48)	4.18 (0.34)	1.16
Data Analysis	2.74 (0.55)	4.04 (0.45)	1.30
Data Visualization	2.88 (0.46)	4.29 (0.35)	1.41
Dashboard Development	2.62 (0.61)	4.20 (0.37)	1.58

Data Communication and Decision-Making	2.70 (0.39)	3.96 (0.39)	1.26
Overall	2.79 (0.39)	4.13 (0.29)	1.34

Overall competency was higher at posttest ($M = 4.13$, $SD = 0.29$) than at pretest ($M = 2.79$, $SD = 0.39$). The mean within-participant difference was 1.34 points, 95% CI [1.13, 1.56], $t(24) = 12.96$, $p < .001$, with a large standardized change (Cohen's $d_z = 2.59$). Given the one-group design, this result represents within-group change rather than a causal estimate of the model's effect.

All five domains had higher descriptive means at posttest. Dashboard Development showed the largest difference (1.58), followed by Data Visualization (1.41) and Data Analysis (1.30). Data Communication and Decision-Making had the lowest posttest mean ($M = 3.96$, $SD = 0.39$), although it remained within the high interpretation range. This pattern suggests that participants performed more strongly in constructing visual and interactive products than in communicating limitations and translating evidence into organizational recommendations.

6.5 Posttest Competency Profile

To examine the posttest performance pattern in greater detail, scores were summarized for all 25 rubric criteria. Table 9 presents the criterion-level competency profile.

Table 9: Posttest Profile of Data Visualization and Dashboard Development Competencies

Competency criterion	M	SD	Level
1. Data Preparation			
1.1 Accesses data from appropriate and reliable sources	4.18	0.35	High
1.2 Profiles data structure, completeness, and quality before analysis	4.16	0.40	High
1.3 Cleans missing, inconsistent, duplicate, and invalid values appropriately	4.20	0.43	High
1.4 Transforms and integrates data while preserving meaning and traceability	4.08	0.34	High
1.5 Organizes the data model and verifies data quality for dashboard use	4.28	0.46	High
Data Preparation mean	4.18	0.34	High
2. Data Analysis			
2.1 Defines relevant metrics and analytical questions	4.06	0.46	High
2.2 Explores distributions, comparisons, relationships, and trends	4.04	0.52	High
2.3 Applies appropriate descriptive or comparative techniques	4.12	0.51	High
2.4 Validates calculations, assumptions, and interpretations	3.94	0.51	High

Competency criterion	M	SD	Level
2.5 Derives defensible insights linked to the task problem	4.04	0.61	High
Data Analysis mean	4.04	0.45	High
3. Data Visualization			
3.1 Selects visual representations appropriate to the data, audience, and purpose	4.32	0.38	High
3.2 Applies accurate and effective visual encodings	4.28	0.43	High
3.3 Establishes visual hierarchy, consistency, and readability	4.28	0.43	High
3.4 Avoids misleading scales, visual clutter, and unnecessary decoration	4.34	0.43	High
3.5 Uses annotations and data storytelling to support understanding	4.24	0.54	High
Data Visualization mean	4.29	0.35	High
4. Dashboard Development			
4.1 Organizes the layout around user tasks and priority information	4.28	0.43	High
4.2 Builds accurate key indicators, charts, and coordinated views	4.36	0.40	High
4.3 Implements useful filters, navigation, drill-down functions, or tooltips	4.18	0.41	High
4.4 Ensures usability, accessibility, consistency, and appropriate viewing	4.04	0.48	High
4.5 Tests functionality and optimizes dashboard performance	4.14	0.40	High
Dashboard Development mean	4.20	0.37	High
5. Data Communication and Decision-Making			
5.1 Explains key findings accurately and clearly	4.04	0.38	High
5.2 Relates insights to stakeholder questions and the operational context	3.98	0.53	High
5.3 Translates evidence into feasible recommendations or actions	3.98	0.53	High
5.4 Communicates limitations, uncertainty, and responsible data use	3.84	0.45	High
5.5 Evaluates task implications and identifies opportunities for improvement	3.96	0.43	High
Data Communication and Decision-Making mean	3.96	0.39	High
Overall posttest competency	4.13	0.29	High

The detailed posttest profile showed consistently high performance across the 25 criteria. The highest scores concerned accurate key indicators and coordinated views ($M = 4.36$, $SD = 0.40$) and the avoidance of misleading scales and visual clutter ($M = 4.34$, $SD = 0.43$). The lowest score concerned communication of limitations, uncertainty, and responsible data use ($M = 3.84$, $SD = 0.45$). These results reinforce the distinction between producing a technically sound dashboard and communicating the boundaries of its evidence.

6.6 Quality of Completed Dashboards

The completed dashboards were evaluated separately to describe the quality of the final

products across analytical, visual, functional, and communication criteria. Table 10 presents these results.

Table 10: Quality of Completed Dashboards

Assessment criterion	M	SD	Level
Alignment with the problem, stakeholders, and decision requirements	4.20	0.43	High
Data accuracy, preparation quality, and model integrity	4.24	0.39	High
Validity of analysis, calculations, and performance indicators	4.16	0.46	High
Appropriateness, accuracy, and clarity of visual representations	4.32	0.36	High
Information architecture, layout, hierarchy, and consistency	4.22	0.41	High
Interactivity, navigation, usability, and accessibility	4.02	0.49	High
Insights, recommendations, limitations, and decision implications	3.96	0.53	High
Technical functionality, performance, reliability, and completeness	4.30	0.38	High
Overall	4.18	0.31	High

The completed dashboards were rated high overall ($M = 4.18$, $SD = 0.31$). Visual appropriateness and clarity received the highest criterion mean ($M = 4.32$, $SD = 0.36$), followed by technical functionality and completeness ($M = 4.30$, $SD = 0.38$). Data accuracy and model integrity were also strong ($M = 4.24$, $SD = 0.39$).

The lowest criterion was the communication of insights, recommendations, limitations, and decision implications ($M = 3.96$, $SD = 0.53$). Interactivity, navigation, usability, and accessibility were also comparatively lower ($M = 4.02$, $SD = 0.49$). The scores remained high, but they identified two areas for further practice: designing for a wider range of users and connecting dashboard evidence to precise and responsible recommendations.

6.7 Participant Satisfaction

Participant satisfaction was examined across the training process, the Interactive Data-Driven Learning Environment, and perceived outcomes and transfer. Table 11 presents the item-level and aspect-level ratings.

Table 11: Participant Satisfaction with the T-DASH Model

Satisfaction aspect and item	M	SD	Level
1. Training Process and Task-Based Activities			
1.1 Training objectives, tasks, and expected outcomes were clear	4.40	0.65	High
1.2 Task scenarios were relevant to organizational work	4.28	0.68	High
1.3 The five T-DASH stages were systematic and easy to follow	4.36	0.70	High

Satisfaction aspect and item	M	SD	Level
1.4 Activities supported active problem solving and hands-on practice	4.52	0.59	Very High
1.5 Feedback and revision opportunities supported improvement	4.44	0.65	High
Aspect mean	4.40	0.47	High
2. Interactive Data-Driven Learning Environment			
2.1 Learning resources, datasets, and examples were useful and accessible	4.32	0.69	High
2.2 Interface and navigation were clear and practical	4.08	0.70	High
2.3 Progress information clarified performance and areas for improvement	4.04	0.68	High
2.4 Feedback mechanisms supported timely revision and improvement	4.24	0.72	High
2.5 The environment supported data visualization and dashboard development	4.32	0.69	High
Aspect mean	4.20	0.40	High
3. Perceived Outcomes and Transfer			
3.1 I can prepare and analyze data more systematically	4.36	0.70	High
3.2 I can design clearer and more effective visualizations and dashboards	4.52	0.59	Very High
3.3 I can communicate insights and recommendations more effectively	4.20	0.71	High
3.4 I can apply the T-DASH process to relevant organizational tasks	4.32	0.69	High
3.5 Overall, I was satisfied with the T-DASH model	4.56	0.58	Very High
Aspect mean	4.39	0.39	High
Overall satisfaction	4.33	0.35	High

Overall satisfaction was high ($M = 4.33$, $SD = 0.35$). The training process and task-based activities received the highest aspect mean ($M = 4.40$, $SD = 0.47$), followed closely by perceived outcomes and transfer ($M = 4.39$, $SD = 0.39$). The highest individual rating was overall satisfaction with the T-DASH model ($M = 4.56$, $SD = 0.58$); hands-on problem solving and the ability to design clearer and more effective visualizations and dashboards were also rated very high (both $M = 4.52$, $SD = 0.59$).

7. DISCUSSION

7.1 T-DASH Model Development

The first research question concerned the components and operating relationships of T-DASH. The resulting model integrates five conceptual foundations, a five-stage task-based training process, an Interactive Data-Driven Learning Environment, a learning-analytics and data-driven feedback loop, and five competency domains. This architecture frames dashboard development as a complete

professional problem-solving process rather than as a sequence of isolated software operations.

The model connects authentic tasks, experiential revision, explicit performance criteria, and evidence-informed feedback. In contrast to tool-centered instruction, the T-DASH stages preserve dependencies across problem definition, data preparation, analysis, visualization, dashboard construction, insight communication, evaluation, and transfer. This structure is consistent with whole-task and authentic-learning perspectives, which emphasize coordination of interdependent decisions rather than fragmented practice [16]-[25]. The option to return to earlier stages also reflects professional data work, where new evidence may require revision of the data, analysis, visual encoding, or recommendation.

Expert ratings supported the alignment, coherence, and feasibility of the model, with the five-stage training process receiving the highest component mean. A key scientific contribution is the explicit coupling of the professional dashboard workflow with five competency domains and an evidence-to-feedback cycle. Existing research describes task-centered instruction, authentic assessment, visualization literacy, dashboard design, and learning analytics as important elements [4]-[43]; T-DASH operationalizes their relationships within a single training architecture. The present evidence supports the coherence and feasibility of that integration, but it should not be interpreted as evidence that the model is superior to alternative training designs.

7.2 Task-Based Training Activity Plans and Interactive Data-Driven Learning Environment

The second research question addressed the quality and operation of the task-based training activity plans and the Interactive Data-Driven Learning Environment. The plans connected each T-DASH stage with realistic organizational tasks, learning resources, guided practice, formative checks, feedback, revision, and performance evidence. Experts rated the plans highly and recommended clearer time allocation for data preparation, explicit revision checkpoints, and additional guidance for participants with limited dashboard experience.

The environment extended beyond a content repository by integrating website access, interactive media, multimedia, learning resources, analytics, assessment, communication, and online activities. These functions were connected through an evidence-to-feedback cycle in which task records,

rubric evidence, feedback, and revision histories informed the next learning action. This relationship is important because recent learning-analytics research cautions that dashboards have limited instructional value when they merely display data without supporting interpretation, self-regulation, feedback, and action [12], [31]-[43]. T-DASH therefore treats analytics as part of a revision process rather than as an endpoint.

Expert evaluation and functional verification indicated that the environment operated as intended after minor revisions to navigation labels, analytics displays, and data-access procedures. However, participant ratings were comparatively lower for interface navigation and progress information. This convergence between expert feedback and user ratings suggests that technically functional analytics are not necessarily self-explanatory. Further usability testing should examine whether learners can correctly interpret progress information, identify the reason for a performance gap, and select an appropriate follow-up action.

7.3 Competency, Dashboard Quality, and Participant Satisfaction

The third research question examined observed competency change, completed-dashboard quality, and participant satisfaction. Overall and domain-level competency scores were higher at posttest, with the largest descriptive differences in Dashboard Development and Data Visualization. These domains were repeatedly practiced through product creation, testing, feedback, and revision. The pattern is compatible with whole-task learning, in which learners coordinate procedures and judgments that are often taught separately [16]-[25], [42]-[43]. Because the field phase used a one-group design, the observed improvement cannot be attributed uniquely to T-DASH.

Data Communication and Decision-Making had the lowest posttest domain mean, and criterion-level scores were comparatively lower for communicating limitations, uncertainty, recommendations, and decision implications. This pattern is important because a technically functional dashboard does not automatically constitute sound decision support. From a training-design perspective, it indicates that software fluency and visual quality should not be treated as sufficient proxies for data reasoning. Future iterations should provide more deliberate practice in distinguishing observation from inference, expressing uncertainty, qualifying claims, and translating evidence into feasible organizational action [6]-[15].

The completed dashboards were rated high overall, with particularly strong results for visual appropriateness, clarity, technical functionality, and data integrity. Interactivity, accessibility, and decision communication were comparatively weaker, identifying priorities for further development. Because the competency and dashboard-quality rubrics shared several criteria, the latter was used as a complementary description of final product quality rather than as an independent construct.

Participant satisfaction was high, particularly for hands-on problem solving, revision opportunities, clearer dashboard design, and overall satisfaction with T-DASH. Lower ratings for navigation and progress information were consistent with expert feedback and identify a concrete design priority: analytics should communicate not only status but also a comprehensible next action. Taken together, the competency, product-quality, and satisfaction results support the feasibility and practical relevance of T-DASH in this cohort while remaining preliminary evidence from a single implementation.

A broader critique emerging from the results concerns software-centered dashboard training. If successful completion is defined mainly by a functioning and visually polished dashboard, learners may receive insufficient practice in questioning data quality, communicating uncertainty, and defending the link between evidence and action. Dashboard value depends on analytical validity, usability, and actionability as well as visual presentation [4]-[15]. Training designs should therefore assess the reasoning behind the product and the responsible communication of its limitations, not only the product itself.

7.4 Practical Implications

T-DASH may guide professional development for administrative, planning, service, quality-assurance, technical-support, and other roles that require staff to convert data into decision-oriented dashboards. Implementation should begin with a realistic decision problem and relevant data rather than a list of software features. Trainers should make competency criteria visible, model analytical reasoning as well as procedures, require independent performance, and reserve sufficient time for feedback and revision. This structure can help align training activities with the integrated technical, analytical, visual, and communication demands of professional dashboard work.

The eight environment functions can be implemented through different technical platforms.

The essential requirement is a coherent flow among task access, resources, interaction, evidence capture, assessment, communication, feedback, and revision. Organizations with limited infrastructure may begin with a simple website, shared resources, embedded media, structured online forms, and progress summaries, whereas more advanced systems may automate analytics and personalized feedback. The architecture is therefore conceptually adaptable across software stacks, although its implementation and outcomes should be re-evaluated whenever the platform, learner population, or professional context changes.

The five stages can also be adapted to other data domains by changing datasets, indicators, stakeholder questions, and dashboard purposes while preserving the data-to-decision sequence. Such adaptation should involve domain specialists because valid metrics and responsible interpretations depend on context. For business-intelligence and workforce-development settings, T-DASH may provide a framework for structured upskilling or reskilling in which participants work through authentic reporting and decision tasks. However, the present study did not test comparative effectiveness in an external industry setting; these professional and industry applications should therefore be treated as plausible uses requiring further validation. Clear documentation of task instructions, datasets, rubrics, environment functions, and feedback rules can improve reproducibility [2]-[3], [40], [45].

7.5 Limitations and Future Research

The study involved one volunteer cohort from a single organization, used a one-group pretest-posttest design, and relied on one external assessor. These conditions limit causal interpretation, generalizability, and evaluation of scoring consistency across assessors. The posttest was administered immediately after training, so the study also does not establish long-term retention or sustained workplace transfer. Future research should compare T-DASH with alternative training conditions, include larger and more heterogeneous samples across multiple organizations, use multiple independent assessors, and incorporate delayed performance measures.

Beyond these methodological limitations, several open issues remain. It is not yet known how the model performs with learners who differ substantially in prior data literacy, how well the environment scales to larger cohorts, whether the five-stage training process transfers across different visualization platforms and professional domains, or how authentic organizational datasets affect

performance and data-governance requirements. Other unresolved questions concern collaborative dashboard development, accessibility for diverse users, and the appropriate role of automated or AI-assisted feedback within the evidence-to-feedback cycle. These issues define a research agenda for testing which components are essential, which can be adapted, and under what conditions the model supports durable professional performance.

8. CONCLUSION

This study developed T-DASH, a five-stage task-based training model supported by an Interactive Data-Driven Learning Environment for data visualization and dashboard competency development. Its principal contribution is a training architecture that connects a data-to-decision process, five observable competency domains, and an evidence-to-feedback cycle so that task performance, assessment, feedback, and revision operate within the same professional workflow.

Expert evaluations indicated high alignment and feasibility for the model, task-based training activity plans, and the Interactive Data-Driven Learning Environment. In the field implementation, participants showed substantial within-group increases from pretest to posttest, completed dashboards were rated highly, and satisfaction was high. At the same time, decision communication, expression of limitations and uncertainty, navigation, and accessibility were comparatively weaker than visual and technical performance. This pattern suggests that dashboard training should not stop at producing a functional artifact; it should also require learners to justify analytical choices and communicate what the evidence can and cannot support.

For educational and professional practice, T-DASH offers a structured way to organize authentic data tasks, visible competency criteria, iterative feedback, and revision. The architecture may be useful for workforce upskilling in administrative, business-intelligence, reporting, and related contexts where technical dashboard production must be integrated with data reasoning and decision communication. These applications are potential extensions of the model rather than demonstrated industry effects, and implementation should be adapted to the domain, users, data-governance requirements, and available technology.

The findings should be interpreted within the boundaries of a single volunteer cohort, a one-group design, immediate post-training measurement, and scoring by one external assessor. Open issues include long-term retention and workplace transfer,

scalability, cross-platform adaptation, collaborative use, accessibility, and the role of automated or AI-assisted feedback. Addressing these questions through comparative, multi-site, and longitudinal studies will be necessary to determine the conditions under which T-DASH remains feasible and transferable across contexts. Within the present evidence, the model provides a coherent and testable foundation for further research on integrated data visualization and dashboard training.

CONFLICT OF INTEREST

The authors declare no financial or non-financial conflicts of interest that could have influenced the research, authorship, or publication of this article.

AUTHOR CONTRIBUTIONS

Parwapun Kamtab contributed to conceptualization, model and instrument design, research methodology, coordination of expert evaluation, participant recruitment, training implementation, data collection, formal analysis, interpretation of the findings, preparation of figures and tables, project administration, and drafting and revision of the manuscript.

Nopparat Sabaykan contributed to the technical design, development, testing, implementation, and revision of the Interactive Data-Driven Learning Environment and to the preparation of related technical and visual materials.

Both authors reviewed and approved the final version of the manuscript and agreed to be accountable for all aspects of the work, ensuring the accuracy and integrity of the research.

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