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Phase-Specific Perceived Difficulty and AI Scaffolding Demand in Design Thinking Final Year Projects: A Mixed-Methods Study of Diploma Electrical Engineering TVET Students at Politeknik Port Dickson

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ABSTRACT

The integration of Design Thinking (DT) into Final Year Projects (FYP) represents a promising pedagogical strategy within Technical and Vocational Education and Training (TVET) engineering programmes. However, diploma-level students may encounter phase-specific execution challenges when navigating the five DT phases of Empathise, Define, Ideate, Prototype, and Test, particularly within the ill-structured demands of FYP contexts. Concurrently, the emergence of artificial intelligence (AI) tools in educational settings raises important questions about which phases students identify as most challenging and what technology supports, they prefer. This study examined phase-specific perceived difficulty across all five DT phases and its association with preferred technology support features among Diploma Electrical Engineering students at Politeknik Port Dickson, Malaysia. A cross-sectional mixed-methods survey design was employed involving 139 students enrolled in FYP Part 1. Quantitative data were collected via Likert-scale items and multi-select instruments measuring DT satisfaction, phase-level perceived difficulty, and technology support preferences. Open-ended responses provided qualitative elaboration. Data were analysed using descriptive statistics, Cochran's Q test, chi-square tests of independence, and multivariable binary logistic regression. Findings revealed high overall satisfaction with DT implementation ($M = 4.243$), with Ideation (48.9%) and Prototyping (43.2%) most frequently identified as phase bottlenecks. AI Assistance (49.6%) and Mobile Application (46.0%) emerged as the most preferred support features. Logistic regression indicated that students who found Ideation and Prototyping challenging were approximately 2.5 times more likely to prefer AI Assistance, even after controlling for co-occurring phase difficulties. Mobile Application preference, by contrast, was broadly consistent across all phase-challenge profiles. These findings suggest that AI-enabled scaffolding holds particular promise for supporting students during cognitively demanding DT phases, while mobile platforms may serve as a universal delivery mechanism across all phases. Phase-level findings were further corroborated by convergent qualitative themes including idea generation difficulty, cognitive overload, and prototype execution challenges. Implications for TVET educators and DT support tool designers are discussed.

Keywords: Design Thinking; AI-Enhanced Scaffolding; TVET Engineering Education; Phase-Specific Perceived Difficulty; Technology Support Preferences

INTRODUCTION

The Education 4.0 paradigm emphasises digitally mediated innovation, interdisciplinary problem-solving, and industry-responsive competency development (Reyes et al., 2024). In Technical and Vocational Education and

Training (TVET) systems, this shift intensifies expectations that graduates demonstrate not only technical proficiency but also adaptive reasoning, creative ideation, and structured problem-solving capabilities.

Final Year Projects (FYPs) represent a culminating assessment mechanism in engineering diploma programmes. However, FYP contexts are inherently ill-structured, requiring students to navigate ambiguous problem definitions, generate alternative solutions, and translate abstract concepts into workable prototypes (Dringenberg & Wertz, 2016). For diploma-level learners who may possess developing domain schemas, such tasks impose substantial cognitive demands (Nolte & McComb, 2021).

Design Thinking (DT) has emerged as a structured pedagogical response to this challenge. Conceptualised as an iterative cycle—Empathise, Define, Ideate, Prototype, and Test—DT offers a scaffolded approach to navigating complex problem spaces. While empirical studies often report high levels of student satisfaction and engagement with DT, positive global perceptions can mask phase-specific execution difficulties. This divergence reflects an "execution gap" in Design Thinking: endorsement of the framework without operational fluency across its phases. In this study, perceived phase difficulty is operationalised as students' self-reported selection of the most challenging DT phase(s), serving as a proxy indicator of where difficulty is located across phases rather than a direct measure of cognitive load intensity.

Recent advances in artificial intelligence (AI) and mobile learning technologies offer potential mechanisms for adaptive, just-in-time scaffolding. Yet empirical investigations linking phase-specific difficulty to articulated demand for AI-supported scaffolding remain limited, particularly in diploma-level TVET contexts. Addressing this gap, this study contributes evidence from a diploma-level TVET engineering FYP setting by examining phase-specific perceived difficulty across DT phases and its association with preferred technology supports while accounting for multi-phase selections. This study therefore examines which DT phases students find most challenging, what technology supports they prefer, and whether phase-specific difficulty is associated with specific technology demand patterns during FYP implementation.

LITERATURE REVIEW

Design Thinking as Structured Innovation Pedagogy

Design Thinking (DT) has evolved from a professional design methodology into a widely adopted pedagogical framework in engineering and higher education. Commonly operationalised as an iterative cycle of Empathise, Define, Ideate, Prototype, and Test, DT promotes human-centred inquiry, divergent exploration, iterative experimentation, and reflective evaluation (Razzouk & Shute, 2012; Dorst, 2011). In contrast to traditional engineering approaches that prioritise convergent analytical reasoning, DT integrates creative ideation with systematic feasibility assessment (Dym et al., 2005; Cross, 2011).

Within engineering education, evidence syntheses and empirical studies generally report positive attitudinal and skill-based outcomes associated with DT integration, including improvements in creativity, collaboration, communication, and engagement with authentic design challenges (Henriksen et al., 2017; Deng & Liu, 2023). In capstone and FYP contexts, DT is valued for structuring early-stage ambiguity by decomposing complex problems into manageable yet iterative phases (Prince & Felder, 2006). However, broad appreciation of DT does not necessarily translate into seamless execution across all phases (Lake et al., 2021). Students frequently encounter difficulties during cognitively demanding stages such as Ideation and Prototyping (Kleinsmann & Valkenburg, 2008), suggesting a phase-level execution gap that warrants closer examination.

Phase-Specific Perceived Difficulty in Design Thinking

Although DT is presented as a coherent cycle, its phases do not impose uniform cognitive demands. Different stages require distinct forms of reasoning, information processing, and schema construction, particularly during early conceptual work and collaborative idea generation (Cramer-Petersen, 2019; Nolte & McComb, 2021). Ideation bottlenecks are consistent with design fixation, where novices prematurely anchor on early ideas or familiar solutions, limiting divergent exploration (Jansson & Smith, 1991). This pattern aligns with engineering concept generation research showing that novice designers benefit from structured heuristics to expand solution spaces (Daly et al., 2012).

Prototyping introduces a distinct challenge: translating abstract conceptual reasoning into tangible or functional representations (Cross, 2011), while integrating material constraints, cost considerations, technical validation, and iterative refinement (Kim et al., 2024). These phase-specific demands suggest that difficulty is not merely "general challenge," but may cluster around identifiable DT phases for novice learners working in ill-structured tasks.

Measurement Justification: Perceived Phase Difficulty vs. Cognitive Load

Because fine-grained cognitive load instrumentation is not used in this study, the focal construct is best framed as perceived phase difficulty or perceived bottlenecks rather than a direct intensity-based cognitive load measure. Nonetheless, the use of brief self-report indicators of task demand is well-established in cognitive load/workload research: single-item mental effort ratings have been used as proxies for invested cognitive effort (Paas, 1992), and subjective workload instruments such as NASA-TLX include perceived mental demand and effort dimensions to capture experienced task load (Hart & Staveland, 1988). Accordingly, this study's multi-select item ("Which DT phase(s) did you find most challenging?") is positioned as an efficient way to identify where students locate their primary bottlenecks (phase-level difficulty attribution), while recognising it does not quantify intensity or separate intrinsic/extraneous load components.

Diploma-Level TVET Context and Novice Design Cognition

The cognitive demands of DT phases may be particularly salient in diploma-level TVET settings, where students are often at earlier stages of cognitive and professional development and have limited experience navigating ill-structured, open-ended tasks. From a novice–expert perspective, experts rely on well-organised domain schemas that reduce working memory demands during complex problem solving, whereas novices process information in more fragmented ways (Nolte & McComb, 2021). In engineering design education, ambiguity is a known stressor for early-stage learners, particularly in open-ended design problem settings (Dringenberg & Wertz, 2016). Despite acknowledgement of Ideation and Prototyping challenges in broader engineering education literature, phase-specific investigations within diploma-level TVET FYP contexts remain comparatively limited, especially when linked to actionable support feature preferences.

AI and Mobile Scaffolding as Technology-Enhanced Support

Instructional scaffolding theory posits that learners perform optimally when adaptive support structures are provided during tasks that exceed their independent capability threshold (Wood et al., 1976). In STEM education, computer-based scaffolding has demonstrated positive effects across learning outcomes, with evidence suggesting that well-designed scaffolds can improve performance and understanding when aligned to task demands (Belland et al., 2017).

Mobile platforms extend scaffolding into authentic project settings by enabling timely prompts, resources, and guidance at the point of need. For example, mobile-supported scaffolding systems have been shown to support learners through context-sensitive guidance and "just-in-time" support structures (Chen et al., 2008). In vocational education and training, mobile/immersive approaches such as mobile augmented reality have also been examined as mechanisms to support skill development and situated learning (Bacca et al., 2015). Additionally, mobile learning environments can vary by scaffold source (e.g., teacher/peer e-scaffolding), influencing design skill outcomes and learner experiences (Al Mulhim & Zaky, 2022).

More recently, generative AI tools (including large language models) have been discussed as potential supports for idea generation, structured questioning, feedback, and iterative refinement—while also introducing risks such as overreliance, superficiality, and academic integrity concerns (Kasneci et al., 2023). Empirical work on student perceptions suggests learners often view LLMs as helpful for drafting, brainstorming, and improving clarity, though benefits vary by task and learner capability (Mogavi et al., 2024). In TVET systems undergoing digital transformation, AI-enabled tools are increasingly positioned as part of broader reskilling and training

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modernisation agendas (Leong, 2025). Taken together, these strands motivate examining whether students' support preferences (AI and/or mobile scaffolding features) vary depending on which DT phase(s) they identify as most challenging.

Synthesis and Research Gap

DT is widely valued in engineering and TVET education for structuring complex, innovation-oriented project work. Evidence indicates that phase difficulty can cluster around cognitively demanding stages, particularly Ideation (e.g., fixation, limited divergence) and Prototyping (e.g., abstract-to-concrete translation under constraints). Concurrently, computer-based, mobile, and emerging AI scaffolding approaches show theoretical and empirical promise for supporting complex learning tasks. However, empirical analyses linking phase-specific perceived difficulty to expressed demand for AI/mobile scaffolding features remain scarce, particularly in diploma-level TVET engineering FYP contexts. This study addresses that gap by examining phase-level perceived bottlenecks and their association with technology support preferences.

CONCEPTUAL FRAMEWORK AND RESEARCH QUESTIONS

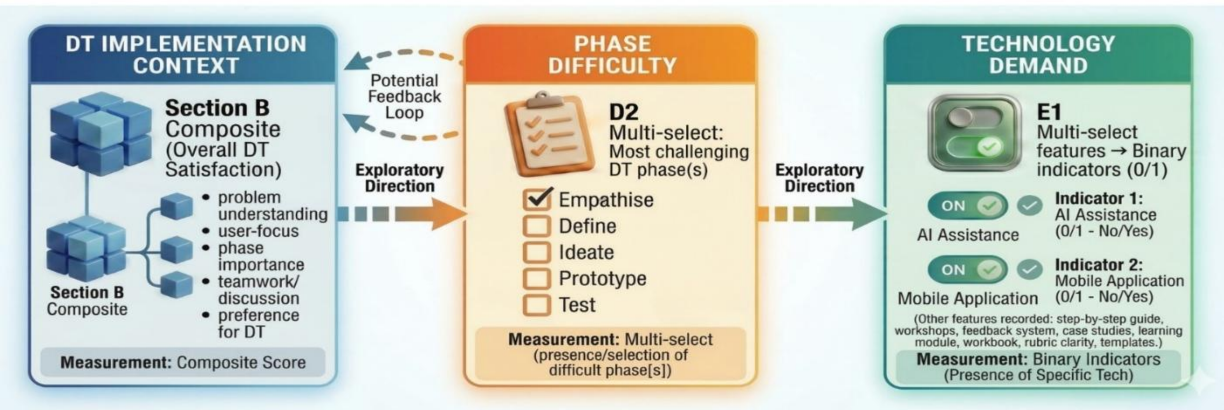
Theoretical Orientation

This study adopts an exploratory, cross-sectional survey design grounded in instructional scaffolding theory (Wood et al., 1976) and an exploratory technology-demand perspective, where learners' expressed support preferences are examined in relation to perceived task challenges. Phase-level difficulty is operationalised as perceived phase difficulty / perceived phase bottlenecks (i.e., the DT phase(s) students identify as most challenging) rather than an intensity-based cognitive load measure. This positioning aligns the construct with what the instrument captures, while remaining consistent with workload research that commonly uses brief subjective demand/effort indicators as proxies for experienced task demand. The growing intersection of AI-enhanced learning and design-based pedagogy has intensified interest in technology supports for complex iterative processes, yet empirical evidence specific to diploma-level TVET DT implementation remains limited.

Conceptual Model

An exploratory associative model is proposed mapping three constructs: (1) DT implementation context, operationalised through overall DT satisfaction (Section B composite); (2) perceived phase difficulty across the five DT phases (Empathise, Define, Ideate, Prototype, Test), captured via a multi-select phase-bottleneck item (D2); and (3) technology support demand, captured via binary indicators derived from a multi-select checklist (E1), with AI-assisted and mobile-based support treated as focal indicators for RQ4–RQ5 analyses. The model is presented in Figure 1.

Figure 1. Exploratory conceptual model linking DT satisfaction, perceived phase difficulty, and technology support demand.



Note. Arrows represent exploratory associations tested in this study; the model is associative and consistent with the cross-sectional design and therefore does not imply causality.

Research Questions

This study is guided by five research questions:

RQ1: What is the overall level of student satisfaction with Design Thinking implementation in the Diploma Electrical Engineering FYP programme?

RQ2: Which Design Thinking phase(s) do students most frequently identify as most challenging during FYP implementation?

RQ3: How does student-perceived phase difficulty vary across the five DT phases, and what qualitative factors do students attribute to their challenges?

RQ4: What technology support features do students who identify Ideation as most challenging prefer, and is this association statistically significant?

RQ5: What technology support features do students who identify Prototyping as most challenging prefer, and is this association statistically significant?

METHODOLOGY

Research Design

This study employed an exploratory cross-sectional survey design combining quantitative analyses with qualitative open-ended responses for contextual elaboration. A convergent mixed-methods approach was used: quantitative (Likert-scale and multi-select items) and qualitative (open-ended items) data were collected within the same instrument during the same timeframe, analysed separately, and integrated during interpretation through triangulation and narrative side-by-side comparison, and where relevant, linking quantitative patterns with qualitative themes (Fetters et al., 2013).

Research Context and Participants

The study was conducted at Politeknik Port Dickson, Malaysia, within the Diploma Electrical Engineering programme. Participants were Semester 4 students enrolled in Final Year Project Part 1, drawn from five programme tracks: DET (n = 44), DTK (n = 39), DEG (n = 22), DEQ (n = 19), and DEP (n = 15). Only responses from the Project Team Member (Student) role were included. A total of 139 students participated. Based on the eligible cohort size recorded at the time of data collection (N = 340), the response rate was 40.9%. The Google Form link was shared with students after completion of the programme session via the DT FYP Telegram group for Session 2 (2025/2026); participation was voluntary and anonymous.

Nonresponse bias note: Because individual-level data were not available for non-respondents, nonresponse bias cannot be ruled out; however, the distribution of respondents across programme tracks is reported in Table 1 to support transparency of sample composition.

Table 1. Demographic Profile of Participants (N = 139)

Variable	Category	n	%
Gender	Male	107	77.0
	Female	32	23.0
Age	20–24 years	124	89.2
	Below 20 years	15	10.8

Programme	DET	44	31.7
	DTK	39	28.1
	DEG	22	15.8
	DEQ	19	13.7
	DEP	15	10.8

Note. Programme codes: DET = Diploma Electrical Engineering (Technology); DTK = Diploma Electronic Engineering (Computer); DEG = Diploma Electrical Engineering (Green Energy); DEQ = Diploma Electrical Engineering (Energy Efficiency); DEP = Diploma Electronic Engineering (Communications).

Section B: Overall Design Thinking Satisfaction

Overall satisfaction with DT was measured using five Likert-scale items (1 = Strongly Disagree, 5 = Strongly Agree) covering problem understanding (B1), user-focus (B2), phase importance (B3), teamwork (B4), and preference for DT (B5). Reliability analysis confirmed excellent internal consistency (Cronbach's $\alpha = .949$). Item-total correlations (Spearman ρ with rest-of-scale) ranged from $\rho = .784$ (B5) to $\rho = .862$ (B2), all $p < .001$, exceeding the $\rho \geq .30$ retention criterion (Field, 2018). Mean inter-item correlation was .749, indicating strong scale homogeneity. Because very high α values can reflect strong consistency but also potential item redundancy, the scale is interpreted as internally consistent for this exploratory study; future refinement may include item reduction guided by content validity and reporting ω (omega) alongside α where appropriate (Tavakol & Dennick, 2011).

Section C: Phase-Specific Experience

Ten Likert-scale items (C1–C10, two per phase) assessed students' experience within each DT phase. Cronbach's $\alpha = .969$. Item-total correlations ranged from $\rho = .794$ (C6) to $\rho = .898$ (C4). Mean inter-item correlation was .741. Section B and C composites were strongly correlated (Spearman $\rho = .817$, $p < .001$), confirming convergent validity across scale sections. Given the high mean inter-item correlations, the instrument is treated as an internally consistent exploratory measure; future studies may assess dimensionality (e.g., EFA/CFA) and report ω to strengthen measurement evidence (Tavakol & Dennick, 2011).

D2: Perceived Phase-Level Difficulty

Students were asked: "Which Design Thinking phase(s) did you find most challenging during FYP Part 1?" using a multi-select format (Empathise, Define, Ideate, Prototype, Test). Students could select one or more phases. Of 139 respondents, 83 (59.7%) selected a single phase, 53 (38.1%) selected two or more phases, and 3 (2.2%) did not respond. This item is operationalised as perceived phase difficulty / perceived phase bottlenecks (i.e., the location of difficulty across phases) rather than an intensity-based cognitive load or strain measure. Binary flags (0/1) were created for each phase for inferential analyses. As an enhancement for future work, phase-specific difficulty/effort ratings (e.g., a 1–5 mental effort rating) may be added (Paas, 1992), and/or a workload instrument such as NASA-TLX may be used to quantify perceived demand more directly (Hart & Staveland, 1988).

E1: Technology Support Demand

Students selected all technology or programme features they would like added or improved, from a multi-select checklist of 10 options including Mobile Application, AI Assistance, Step-by-Step Guide, Workshop Sessions, Feedback System, EE-Specific Case Studies, Learning Module, Workbook, Rubric Clarity, and Report Templates. Binary demand indicators (0/1) were derived for each feature for regression analysis.

Qualitative Component

Open-ended items (D1, D3, F1) invited students to describe valuable lessons learned, reasons for phase challenges, and how DT helped their FYP. Responses were analysed using inductive open coding (Strauss & Corbin, 1998). Codes were non-mutually exclusive: a single response could receive multiple codes. Two researchers independently coded all D3 responses (n = 110); discrepancies were resolved through consensus discussion. Initial proportion-of-agreement was 85.2%. Qualitative theme percentages reflect the proportion of coded responses receiving each theme and do not sum to 100% due to non-exclusive coding.

Missing Data

Missing data were minimal for Likert items (0.7–2.2% per item, n = 1–3), handled via listwise deletion for composite computation. D2 had 3 missing responses (2.2%), excluded from phase-challenge analyses. D3 had 29 missing responses (20.9%), consistent with optional open-ended completion rates.

Data Analysis Strategy

Quantitative analyses: (1) Cronbach's α and item-total correlations for scale reliability; (2) descriptive statistics with 95% confidence intervals; (3) one-sample t-test and Wilcoxon Signed-Rank test for RQ1; (4) Cochran's Q test to evaluate whether the proportion of students selecting each DT phase as challenging differs across the five phases (RQ2–RQ3), followed by McNemar tests for planned pairwise phase comparisons with Holm–Bonferroni correction; (5) chi-square tests of independence with Phi (φ) effect size for exploratory bivariate phase × feature patterns; (6) multivariable binary logistic regression for RQ4/5 with all phase-challenge indicators, programme, and gender entered simultaneously; (7) Kruskal–Wallis H with Bonferroni-corrected Mann–Whitney U post-hoc for programme comparison. Bonferroni correction applied to all multiple-comparison analyses. Significance threshold $\alpha = .05$. Qualitative analysis: inductive thematic coding of open-ended responses. All quantitative analyses conducted using IBM SPSS Statistics.

Ethical Considerations

Participation was voluntary, informed consent was secured, and responses were anonymised. Ethical approval was obtained from the institutional research ethics committee.

RESULTS

RQ1: Overall Satisfaction with Design Thinking

Students reported high overall satisfaction with DT implementation (M = 4.243, SD = 0.820, 95% CI [4.106, 4.381]; scale 1–5; Cronbach's α = .949). A one-sample t-test confirmed that mean satisfaction significantly exceeded the scale midpoint of 3.0, $t(138) = 17.88$, $p < .001$, Cohen's $d = 1.52$ (very large effect). A Wilcoxon Signed-Rank test provided non-parametric corroboration, $W = 240$, $p < .001$, $r = .778$ (large effect), confirming the robustness of this finding for ordinal Likert data. A majority endorsed continuation of DT in FYP projects (Yes: 73.4%, n = 102; Maybe: 22.3%, n = 31; No: 2.9%, n = 4) and recommended DT for real engineering problems (79.1%, n = 110).

Table 2. Descriptive Statistics for Section B Overall DT Satisfaction Items (N = 139)

Item	Statement	M	SD	Item-Total r
B1	The DT process helped me understand the real problem clearly.	4.217	0.886	.851
B2	DT made the project more user-focused, not just technical.	4.245	0.892	.862
B3	Each DT phase was important in shaping the final prototype.	4.268	0.892	.825

B4	DT helped improve teamwork and discussion.	4.353	0.908	.811
B5	I prefer DT compared to directly jumping into a solution.	4.122	0.920	.784
Scale	**Composite**	**4.243**	**0.820**	**α = .949**

Note. Scale: 1 = Strongly Disagree, 5 = Strongly Agree. Item-Total r = Spearman ρ with rest-of-scale composite, all $p < .001$. Mean inter-item correlation = .749. N = 138–139 (1 missing B1; 1 missing B3).

RQ2 & RQ3: Distribution of Phase-Specific Difficulty

Students selected one or more DT phases they found most challenging (multi-select). Table 3 reports phase-mention frequencies descriptively (i.e., the proportion of students citing each phase, regardless of other selections).

Table 3. Phase-Mention Frequency: Most Challenging DT Phase(s) (N = 139, multi-select)

Design Thinking Phase	Mentions (n)	% of Students	Rank
Ideation	**68**	**48.9%**	**#1**
Prototyping	**60**	**43.2%**	**#2**
Define	39	28.1%	#3
Testing	36	25.9%	#4
Empathy	33	23.7%	#5
Students selecting multiple phases	53	38.1%	—
D2 missing / no response	3	2.2%	—

Note. Percentages reflect the proportion of N = 139 students citing each phase. Total exceeds 100% due to multi-select design. 53 students (38.1%) selected two or more phases simultaneously.

Table 4. Perceived Phase Difficulty Across Design Thinking Phases (RQ2–RQ3)

Phase	Multi-select: % citing phase as challenging	Single-primary subgroup (n = 83): n	Single-primary subgroup (n = 83): %
Empathy	23.7	9	10.8
Define	28.1	7	8.4
Ideation	**48.9**	**32**	**38.6**
Prototype	**43.2**	**25**	**30.1**
Testing	25.9	10	12.0

Note. Multi-select percentages reflect the proportion of participants who selected each phase as challenging (percentages do not sum to 100). A Cochran's Q test on the five within-student phase-challenge indicators tested whether the proportion of students identifying each phase as challenging differed across phases. Pairwise McNemar tests with Holm–Bonferroni correction were used for post-hoc comparisons.

Table 5. Convergent Evidence from Section C Phase Composites (Experience Scores)

Phase (Composite)	M	95% CI for M
Define	4.065	[3.919, 4.211]
Ideation	4.129	[3.985, 4.274]
Prototype	4.149	[4.005, 4.292]
Testing	4.169	[4.026, 4.312]
Empathy	4.205	[4.064, 4.346]

Note. Table ranked lowest to highest M (lowest score = comparatively weaker reported phase experience, i.e., comparatively greater perceived difficulty). Lower composite scores provide convergent support for the multi-select difficulty pattern (D2).

Table 6. Open Coding Themes from D3: Why Students Found Phases Challenging (n = 110, multi-code)

Theme	N	% of D3	Representative Quote
1. Idea generation difficulty	16	14.5%	“Brainstorming was challenging just unrefined thoughts”
2. Social / interview difficulty	11	10.0%	“At interview cause I’m so introvert”
3. Cognitive overload	11	10.0%	“Too many thinking required at once”
4. User perspective-taking	8	7.3%	“Hard to see the problem from the user’s view”
5. Creativity–feasibility tension	7	6.4%	“Balance creativity with what is actually possible”
6. Time constraints	7	6.4%	“Time consuming and need to create from scratch”
7. Problem statement narrowing	6	5.5%	“Hard to clearly narrow down the real problem”
8. Prototype execution difficulty	6	5.5%	“Turning ideas into something that works technically”

Note. Codes are non-mutually exclusive; a single response may be assigned multiple codes. Percentages represent the proportion of n = 110 D3 responses receiving each code and do not sum to 100%. Two researchers independently coded all responses; initial proportion-of-agreement = 85.2%.

RQ4 & RQ5: Technology Support Demand and Phase-Challenge Association

Table 7. Student-Preferred Technology Support Features Ranked by Frequency (N = 139, multi-select)

Support Feature	n	% of Students
AI Assistance	69	49.6%
Mobile Application	64	46.0%
Step-by-Step Guide	44	31.7%

Workshop / Training Sessions	41	29.5%
User Testing & Feedback System	40	28.8%
EE-Specific Case Studies	39	28.1%
Learning Module / Content	30	21.6%
Workbook	24	17.3%
Assessment & Rubric Clarity	24	17.3%
Documentation & Report Templates	22	15.8%

Note. Multi-select format; percentages do not sum to 100%.

Bivariate Chi-Square Tests of Independence (Bonferroni-Corrected)

Ten exploratory bivariate chi-square tests were conducted across all five phase-challenge flags × AI and Mobile demand indicators. Because phase-challenge groups overlapped (38.1% selected multiple phases), these bivariate comparisons are interpreted as descriptive screening rather than independent subgroup tests. After Bonferroni correction ($\alpha = .005$), all ten comparisons were non-significant (range: $\chi^2(1) = 0.000–2.609$, $p = .106–1.000$, $\varphi = .000–.137$). Accordingly, the primary inference for RQ4/RQ5 is based on the multivariable logistic regression models that control for co-occurring phase challenges.

Table 8. Bivariate Chi-Square Independence Tests: Phase Challenge × Technology Demand (Bonferroni-Corrected, $\alpha = .005$)

Phase (D2)	Feature (E1)	$\chi^2(1)$	p	Φ	Challenged %	Sig.
Empathy	AI Demand	0.199	.656	.038	54.5%	ns
Empathy	Mobile Demand	0.000	1.000	.000	45.5%	ns
Define	AI Demand	2.444	.118	.133	61.5%	ns
Define	Mobile Demand	0.042	.837	.017	48.7%	ns
Ideation	**AI Demand**	2.593	.107	.137	57.4%	ns
Ideation	Mobile Demand	0.556	.456	.063	50.0%	ns
Prototype	**AI Demand**	2.609	.106	.137	58.3%	ns
Prototype	Mobile Demand	0.002	.965	.004	45.0%	ns
Testing	AI Demand	1.037	.309	.086	58.3%	ns
Testing	Mobile Demand	0.000	1.000	.000	47.2%	ns

Note. Bonferroni-corrected $\alpha = .005$ (10 tests). φ = Phi coefficient. 'Challenged %' = percentage of students in the challenged group who selected that feature. ns = not significant after correction.

Multivariable Binary Logistic Regression

To address multi-select overlap across phase-challenge flags, multivariable binary logistic regression was conducted with all five phase-challenge indicators entered simultaneously as predictors, controlling for programme (dummy-coded, reference = DEG) and gender. This analysis is the primary test for RQ4 and RQ5 as it controls for co-occurring challenges that attenuated bivariate associations.

For AI Assistance demand, identifying Ideation as challenging (OR = 2.486, 95% CI [1.075, 5.748], $p = .033$) and identifying Prototyping as challenging (OR = 2.535, 95% CI [1.159, 5.545], $p = .020$) were significant positive predictors. Empathy (OR = 0.761, $p = .594$), Define (OR = 1.930, $p = .166$), and Testing (OR = 1.347, $p = .508$) were not significant. Programme and gender were not significant predictors of AI demand (all $p > .40$).

For Mobile Application demand, no phase-challenge indicator was a significant predictor (all $p > .30$). This divergence indicates that AI Assistance specifically responds to Ideation and Prototyping challenges when co-occurring difficulty is controlled, whereas Mobile Application demand is broadly uniform across all phase-challenge profiles.

Table 9. Multivariable Binary Logistic Regression: Phase-Challenge Indicators Predicting AI Assistance Demand (N = 139)

Predictor	B	SE	Wald	p	OR	95% CI
Intercept	−1.260	0.625	4.067	.044	0.284	[0.083, 0.975]
CH_Ideation ✓	**0.911**	0.428	4.527	**.033***	**2.486**	**[1.075, 5.748]**
CH_Prototype ✓	**0.930**	0.398	5.459	**.020***	**2.535**	**[1.159, 5.545]**
CH_Empathy	−0.273	0.512	0.284	.594	0.761	[0.279, 2.075]
CH_Define	0.658	0.473	1.937	.164	1.930	[0.761, 4.893]
CH_Testing	0.298	0.452	0.435	.508	1.347	[0.557, 3.254]
Programme dummies (ref = DEG)	—	—	—	all ns	—	—
Gender (Male = 1)	0.357	0.444	0.647	.421	1.429	[0.597, 3.418]

Note. Dependent variable = AI Assistance demand (0 = not selected, 1 = selected). Predictors entered simultaneously (Enter method): five phase-challenge flags (0/1), programme (dummy-coded; reference = DEG), and gender (Male = 1). OR = odds ratio; CI = 95% confidence interval. ✓ = significant predictor ($p < .05$). Programme dummies (DEP, DEQ, DET, DTK vs. DEG) all non-significant ($p > .40$). For Mobile Application demand, all phase-challenge predictors were non-significant (all $p > .30$; results not tabled).

Model Fit and Diagnostics

Model fit statistics were examined for each logistic regression model. For the AI Assistance demand model, the omnibus likelihood-ratio test indicated that the full model did not significantly improve fit over the intercept-only model at $\alpha = .05$, $\chi^2(10) = 15.771$, $p = .106$; accordingly, the overall model-level improvement should be interpreted cautiously, even though individual phase-challenge predictors reached significance. Model description indices: −2 Log Likelihood = 176.916; Nagelkerke $R^2 = .143$. The Hosmer–Lemeshow test indicated no evidence of lack of fit, $\chi^2(8) = 7.420$, $p = .492$. Discrimination was assessed using the ROC curve, yielding AUC = .686, indicating acceptable discrimination above chance. Multicollinearity among predictors was examined using variance inflation factors (VIF) and inter-predictor correlations; all VIF values were low (max VIF = 1.322) and the maximum inter-predictor correlation was $r = .442$, indicating no evidence of problematic multicollinearity. For the Mobile Application demand model, the omnibus likelihood-ratio test was non-significant, $\chi^2(10) = 2.157$, $p = .995$, with −2 Log Likelihood = 189.666 and Nagelkerke $R^2 = .021$, confirming that the predictor set as a whole did not explain variance in Mobile demand. The Hosmer–Lemeshow test indicated adequate fit, $\chi^2(8) = 6.477$, $p = .594$, and the ROC AUC = .565, consistent with near-chance discrimination and supporting the interpretation that Mobile Application demand is uniformly distributed regardless of phase-challenge profile.

Programme Comparison

A Kruskal–Wallis H test comparing Section B satisfaction across programmes revealed a statistically significant difference, $H(4) = 12.212$, $p = .016$, with a small-to-moderate effect size ($\varepsilon^2 = .061$). Bonferroni-corrected post-hoc Mann–Whitney U tests ($\alpha = .005$, 10 pairs) indicated that DEP students ($M = 4.733$, 95% CI [4.427, 5.040]) reported significantly higher satisfaction than DEQ ($p = .003$, $r = .59$) and DET ($p = .003$, $r = .50$). The DEP vs. DTK comparison was not significant after Bonferroni correction ($p = .008$, $r = .45$). Given the small DEP subgroup size ($n = 15$), programme differences should be interpreted cautiously.

DISCUSSION

The findings confirm an execution gap in DT implementation among diploma-level engineering students: high overall satisfaction ($M = 4.243$, $d = 1.52$) coexists with concentrated perceived phase difficulty at Ideation (48.9%) and Prototyping (43.2%). This pattern aligns with design cognition literature on novice fixation during divergent ideation (Daly et al., 2012) and abstract-to-concrete translation challenges during prototyping (Cross, 2011). A key contribution of this study concerns the structure of technology support demand. Exploratory bivariate screening suggested that AI and Mobile Application demand was broadly similar across phase-challenge profiles; however, these comparisons should be interpreted cautiously because phase-challenge groups overlapped (38.1% selected multiple phases).

When overlap was appropriately controlled using multivariable logistic regression, identifying Ideation as challenging ($OR = 2.486$, $p = .033$) and identifying Prototyping as challenging ($OR = 2.535$, $p = .020$) were associated with higher odds of selecting AI Assistance. In contrast, Mobile Application demand remained non-differentiated by phase challenge. This divergence suggests that learners who struggle in Ideation and Prototyping are especially likely to seek AI-enabled support, whereas mobile delivery appears to represent a broadly preferred access mode across students.

Qualitative Insights into Phase-Specific Challenges

The quantitative pattern of phase-level difficulty at Ideation and Prototyping was further substantiated by students' open-ended responses, which revealed rich, contextually grounded accounts of their challenges. Idea generation difficulty emerged as the most frequently coded theme (14.5%), with students describing brainstorming as cognitively taxing and unproductive without structured support. As one student noted, "Brainstorming was challenging just unrefined thoughts," reflecting the well-documented phenomenon of design fixation among novice designers (Jansson & Smith, 1991), wherein early anchoring on familiar ideas limits divergent exploration. Cognitive overload was equally prominent (10.0%), with students reporting that "too many thinking required at once" during phases that demanded simultaneous reasoning across multiple constraints. This aligns with cognitive load theory's recognition that ill-structured tasks impose high intrinsic load on learners with limited domain schemas (Nolte & McComb, 2021).

Beyond ideation, prototype execution difficulty (5.5%) captured the abstract-to-concrete translation challenge inherent in the Prototyping phase, with students articulating the difficulty of "turning ideas into something that works technically." This resonates with Cross's (2011) characterisation of prototyping as a cognitively distinct challenge requiring integration of material constraints, feasibility reasoning, and iterative refinement. The creativity–feasibility tension theme (6.4%) further highlighted students' struggles to "balance creativity with what is actually possible," suggesting that diploma-level learners may require scaffolded frameworks that simultaneously support creative divergence and practical constraint navigation. Time constraints (6.4%) and problem statement narrowing (5.5%) additionally underscore that phase difficulty is not purely cognitive but also structural and pedagogical in nature, pointing to the need for multi-layered support interventions rather than purely AI-driven solutions.

Taken together, these qualitative themes do not merely corroborate the quantitative phase-difficulty pattern they illuminate the specific cognitive and social mechanisms underlying it, providing a more granular basis for designing targeted AI and mobile scaffolding features in future interventions.

AI-Supported Ideation Guidance

The association between Ideation difficulty and AI Assistance demand is consistent with the need for structured prompting and alternative perspective generation during early concept development. In scaffolding terms, AI features may be designed to support brainstorming breadth, guided questioning, and structured comparison of alternatives (Wood et al., 1976; Belland et al., 2017). Importantly, these findings do not establish that AI causes improvement; the observed demand may also reflect alternative influences such as prior AI familiarity, supervisor encouragement, or differences in students' self-efficacy and digital literacy. Accordingly, AI-enabled ideation support should be treated as a design direction to be evaluated empirically rather than as a guaranteed solution.

Specific AI Tools and a Proposed DT Mobile Scaffolding Framework

Building on the demand signals identified in this study, a comprehensive AI-powered mobile scaffolding application is proposed as a practical intervention framework for diploma-level TVET FYP implementation. The proposed platform provisionally termed a DT Scaffold Companion would deliver phase-specific support across all five DT phases through six integrated feature sets.

For the Ideation phase, where students reported the highest difficulty (48.9%), the application would deploy large language model (LLM)-powered brainstorming prompts drawing on tools such as ChatGPT (OpenAI), Gemini (Google), and Claude (Anthropic) to support divergent idea generation, structured concept comparison, and feasibility checking. These AI prompts directly address the idea generation difficulty and design fixation patterns identified in qualitative responses (Jansson & Smith, 1991; Mogavi et al., 2024). For the Prototyping phase (43.2%), AI-assisted constraint prompts and iterative refinement coaches analogous to CAD-assistive AI features available in platforms such as Autodesk Fusion 360 and Tinkercad would scaffold the abstract-to-concrete translation process (Cross, 2011; Kim et al., 2024).

Across all five phases, the proposed application would integrate a step-by-step exploration guide with quick-fact input fields, phase-by-phase template familiarisation, and milestone checklists, directly addressing the structured process support demand identified in this study. A dedicated AI coach feature would provide Socratic questioning, real-time phase-specific feedback, and improvement suggestions tailored to each student's documented progress. A documentation hub would capture phase outcomes, checklist completions, AI feedback logs, and iterative improvement records supporting both student reflection and supervisor oversight.

The supervisor portal component would enable phase-by-phase review, annotation, and approval workflows, addressing the institutional accountability requirements inherent in TVET FYP assessment contexts. Finally, integrated output generators including a complete report compiler and a slide deck generator would convert documented phase outcomes into submission-ready FYP reports and presentation decks, reducing the administrative burden on students during final project completion. Consistent with the mobile application preference observed across all phase-challenge profiles in this study (46.0%), the platform's mobile-first design would ensure just-in-time scaffolding at the point of need (Chen et al., 2008; Wood et al., 1976). These design proposals are offered as empirically motivated hypotheses warranting prototype development and rigorous evaluation including pre–post and comparison-group designs rather than as validated solutions (Kasneci et al., 2023).

Mobile Scaffolding for Prototyping Execution

Although Mobile Application demand did not vary by phase-challenge profile, qualitative responses indicate practical barriers consistent with a need for structured process support (e.g., time constraints, cognitive overload, and difficulties translating ideas into workable prototypes). This supports the interpretation that mobile platforms may function as a universal delivery layer for checklists, milestones, and guidance resources across phases, rather than as a phase-specific preference signal. The regression finding that Prototyping difficulty is also associated with AI demand suggests that students may view AI not only as an ideation tool but also as a support for prototyping decisions (e.g., feasibility checking prompts, constraint clarification, iterative refinement suggestions). These implications are best framed as hypotheses for future tool design and evaluation.

Programme Differences

The programme difference in satisfaction ($H(4) = 12.212$, $p = .016$), with DEP scoring higher than DET and DEQ, warrants further investigation. Possible explanations include variation in supervision practices, cohort dynamics, or programme culture. A targeted qualitative follow-up (e.g., supervisor interviews or focus groups) could clarify which contextual factors contribute to higher satisfaction and whether they are transferable.

Policy Implications

Beyond immediate pedagogical applications, the findings of this study carry several implications for policy development within Malaysian TVET systems and broader vocational education governance frameworks. First, the high overall satisfaction with DT implementation ($M = 4.243$) alongside concentrated phase-level difficulty at Ideation and Prototyping provides empirical justification for institutionalising structured DT support mechanisms within TVET FYP policy frameworks rather than treating DT implementation as an informal pedagogical choice left to individual supervisors. Policy directives from the Department of Polytechnic and Community College Education (DPCC) under the Ministry of Higher Education Malaysia could formally mandate the provision of phase-specific scaffolding resources as part of standardised FYP supervision guidelines, ensuring equitable access to structured support across all polytechnic institutions nationwide.

Second, the finding that AI Assistance emerged as the most preferred technology support feature (49.6%) and was specifically associated with higher demand among students who found Ideation and Prototyping challenging signals a readiness among TVET learners to engage with AI-enabled learning tools. This aligns with Malaysia's broader digital transformation agenda under the MyDIGITAL Blueprint and the Education 4.0 imperatives outlined in the Malaysian Education Development Plan (PPPM) 2015–2025, both of which emphasise the integration of emerging technologies into vocational training pathways (Leong, 2025; Reyes et al., 2024). Policymakers should therefore consider allocating dedicated funding streams for the development, piloting, and institutional deployment of AI-powered scaffolding tools within TVET FYP programmes prioritising platforms that address the Ideation and Prototyping bottlenecks empirically identified in this study.

Third, the programme-level satisfaction differences observed with DEP students reporting significantly higher satisfaction than DET and DEQ counterparts suggest that supervision quality and pedagogical culture vary meaningfully across programme tracks within the same institution. This finding points to a need for standardised DT facilitator training and quality assurance mechanisms at the institutional and national policy levels. Professional development programmes equipping TVET supervisors with structured DT facilitation competencies including familiarity with AI scaffolding tools and phase-specific coaching strategies should be incorporated into continuing professional development (CPD) requirements for polytechnic academic staff. Such policy measures would help reduce inter-programme variability in student experience and ensure more consistent DT implementation quality across the TVET sector.

Finally, the mobile application preference observed broadly across all phase-challenge profiles (46.0%) reinforces the strategic value of mobile-first educational technology infrastructure investment within TVET institutions. Given that diploma-level students are predominantly mobile-native learners, national TVET digital infrastructure policies should prioritise mobile-accessible learning platforms that deliver just-in-time scaffolding, supervisor communication, and automated documentation support consistent with the comprehensive DT scaffolding application framework proposed in this study.

Boundary Conditions

Given the cross-sectional design, all findings should be interpreted as associations rather than causal effects. The D2 measure captures perceived phase difficulty (phase bottlenecks) rather than difficulty intensity or validated cognitive load components. The models also did not include covariates such as prior AI familiarity, digital literacy, academic performance, or self-efficacy, which may shape technology preferences independently of perceived phase difficulty.

CONCLUSION AND FUTURE DIRECTIONS

This study provides empirical evidence that Ideation (48.9%) and Prototyping (43.2%) are the primary perceived bottlenecks in Design Thinking (DT) Final Year Project (FYP) implementation among Diploma Electrical Engineering students ($N = 139$), even against a backdrop of high overall satisfaction ($M = 4.243$, $d = 1.52$). AI Assistance (49.6%) and Mobile Application (46.0%) emerged as the most preferred support features. Multivariable logistic regression further showed that identifying Ideation and Prototyping as challenging was associated with higher odds of selecting AI Assistance ($OR \approx 2.5$, $p < .05$) when controlling for co-occurring phase challenges, whereas Mobile Application demand appeared broadly consistent across phase-challenge profiles.

Practical Recommendations

Based on the observed demand patterns, the following design implications are proposed for future DT support tools and should be tested empirically:

- AI-supported ideation assistance may be incorporated to support idea generation and concept comparison (e.g., structured prompts, guided questioning, and justification of concept selection criteria).
- AI-supported prototyping guidance may be explored to assist feasibility reasoning and iterative refinement (e.g., constraint prompts and structured diagnostic questions).
- A mobile platform may function as a universal delivery layer across all five DT phases (e.g., step-by-step guides, milestone checklists, and feedback channels), rather than as a phase-specific preference signal.
- The higher satisfaction observed in the DEP subgroup warrants follow-up investigation to identify potentially transferable pedagogical or supervisory practices.

Limitations and Future Research Agenda

Several limitations of the present study should be acknowledged before outlining directions for future investigation. First, the D2 phase-challenge measure captures perceived phase difficulty as a location indicator rather than an intensity-based cognitive load measure; future studies should incorporate rating-scale difficulty and effort measures such as a 1–5 mental effort rating per phase (Paas, 1992) or validated workload instruments such as the NASA-TLX (Hart & Staveland, 1988) to strengthen measurement precision and enable direct comparison across phases. Second, the single-site design at Politeknik Port Dickson limits the generalisability of findings; multi-site studies spanning diverse TVET institutions, engineering disciplines, and geographical regions are strongly recommended to establish the external validity of the phase-difficulty and technology-demand patterns observed here. Third, the cross-sectional design precludes causal inference; all associations reported should be interpreted as exploratory and directional rather than definitive.

Building on these limitations, a structured future research agenda is proposed across three progressive stages.

Stage 1 Prototype Development and Usability Testing. The first and most immediate research priority is the development and usability evaluation of the AI-powered DT mobile scaffolding application proposed in this study. A design-based research approach (DBR) is recommended, wherein the application is iteratively designed, implemented, and refined in authentic TVET FYP settings. Initial usability studies should assess student and supervisor perceptions of the platform's phase-specific features including the AI coach, step-by-step exploration guide, template library, documentation hub, and output generators using validated usability instruments such as the System Usability Scale (SUS). This stage would also provide an opportunity to incorporate direct cognitive load measurement instruments, addressing the primary measurement limitation of the present study.

Stage 2 Quasi-Experimental Efficacy Evaluation. Following usability refinement, a quasi-experimental pre–post or comparison-group study is recommended to evaluate the efficacy of AI scaffolding features on measurable FYP outcomes. Outcome variables should include DT process quality assessed via rubric-based scoring, prototype quality evaluated by panels of academic and industry assessors, process metrics such as number of design iterations and time-on-task per phase, and student workload ratings during Ideation and Prototyping. A comparison group receiving standard FYP supervision without AI scaffolding support would enable effect size estimation and provide evidence for or against the technology-demand associations observed in the present study.

Stage 3 Longitudinal and Policy-Level Investigation. To establish sustained efficacy and scalability, longitudinal studies tracking student DT competency development across multiple semesters are recommended. Such designs would clarify whether AI scaffolding produces durable improvements in design thinking fluency or merely provides temporary performance support. Multi-level modelling incorporating team and supervisor clustering effects omitted from the present study due to sample size constraints would also strengthen the analytical framework. Additionally, future models should incorporate covariates identified as potential confounders in this study, including prior AI familiarity, digital literacy, academic performance, and self-efficacy, to disentangle technology-demand signals from individual difference factors. For qualitative components in future studies, reporting chance-corrected inter-rater reliability using Cohen's κ at the theme and category level is recommended to strengthen the rigour of thematic coding procedures (Strauss & Corbin, 1998).

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