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Effects of a TPACK-based online didactic design on university students' statistical literacy: A quasi-experimental study

Kartono*
Universitas Terbuka, INDONESIA

Sudirman
Universitas Terbuka, INDONESIA

Camilo Andrés Rodríguez-Nieto
Universidad de la Costa (CUC), COLOMBIA

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Abstract

Background: Students in distance statistics courses often achieve lower learning outcomes compared to those in face-to-face settings. Although the Technological Pedagogical Content Knowledge (TPACK) framework has been widely applied in technology-integrated instruction, limited empirical evidence clarifies whether prior mathematical knowledge (PMK) moderates its effectiveness in asynchronous online statistics learning.
Aim: This study examined the effectiveness of a TPACK-based online tutorial design in improving students' statistical literacy and investigated the moderating role of PMK.
Methods: A quasi-experimental design involved 170 distance education students (experimental n = 85; control n = 85) classified into low, medium, and high PMK levels. The experimental group participated in a 12-session TPACK-based online tutorial with periodic webinar integration, while the control group received conventional online instruction. Statistical literacy was measured using post-test and normalized gain scores and analyzed through two-way ANOVA and simple effects tests.
Results: The analysis revealed a significant main effect of tutorial design (ηp^2 = .102–.116), indicating higher achievement among students receiving TPACK-based instruction. PMK showed a stronger main effect (ηp^2 = .215–.230), suggesting substantial differences in performance across readiness levels. A significant interaction effect demonstrated a threshold pattern. Students with medium and high PMK obtained significantly higher post-test scores and normalized gains in the experimental group, while students with low PMK showed no statistically significant differences between tutorial designs. The magnitude of learning gains increased consistently from low to high PMK categories, confirming that instructional benefits intensified alongside mathematical readiness.
Conclusion: The effectiveness of TPACK-based online tutorials depends on students' prior mathematical knowledge. Instructional advantages are pronounced for learners with adequate foundational skills but limited for those with low readiness. These findings emphasize the need for adaptive support mechanisms to ensure that technology-integrated instruction produces equitable outcomes in distance statistics education.

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INTRODUCTION

Online learning has transformed higher education globally over the past two decades. Between 2002 and 2019, enrollment in distance education courses increased from 1.6 million to over 6.9 million students in the United States alone (Seaman et al., 2018). The COVID-19 pandemic accelerated this shift dramatically, forcing institutions worldwide to transition rapidly to remote

* **Corresponding author:**
Kartono, Universitas Terbuka, Indonesia
kartono@ecampus.ut.ac.id

instruction. However, simply moving content online does not guarantee educational quality. Effective online instruction requires systematic integration of pedagogical strategies with technological capabilities (Tseng et al, 2022). This integration is particularly critical in statistics education, where students must develop statistical literacy: the ability to understand, interpret, critically evaluate, and communicate about statistical information. Statistical literacy extends beyond computational skills to include reasoning about data, variability, and uncertainty in real-world contexts. As data-driven decision making becomes ubiquitous in professional and civic life, statistical literacy has emerged as an essential 21st-century competency. Therefore, developing effective instructional approaches for online statistics education represents both a theoretical imperative and a practical necessity for ensuring equitable access to quantitative reasoning skills.

Despite substantial investment in online learning infrastructure, significant challenges persist in developing statistical literacy through distance education. Research consistently shows that students in online statistics courses achieve lower learning outcomes than their face-to-face counterparts, with performance gaps ranging from 0.15 to 0.30 standard deviations. These difficulties are especially pronounced for conceptually demanding topics such as sampling distributions, hypothesis testing, and probabilistic reasoning (Conway et al, 2019). Attrition rates compound the problem, with some online statistics programs reporting withdrawal or failure rates exceeding 40%, substantially higher than traditional courses.

These patterns are not confined to North American contexts. Universitas Terbuka (UT), Indonesia's open distance learning university serving over 300,000 active students including graduate learners in education and social sciences, faces structurally similar challenges: students enter with heterogeneous mathematical backgrounds, receive asynchronous tutorial support with limited real-time scaffolding, and must develop statistical competence largely through self-directed engagement with written and digital materials. Although direct replication of the 0.15–0.30 SD gap has not been systematically documented in UT's graduate statistics program, the structural conditions (open admission, geographic dispersion, limited synchronous interaction) closely mirror those producing such gaps in international distance education research, making these benchmarks a plausible reference point for the present study.

Students with weaker mathematical backgrounds face particular difficulties, lacking both prerequisite knowledge and immediate access to scaffolding available in classroom settings. Most conventional online statistics tutorials employ one-size-fits-all designs that neither accommodate diverse prior knowledge levels nor leverage technology's potential for enhancing conceptual understanding (Bozkurt et al., 2020). Furthermore, these tutorials typically emphasize procedural calculation over statistical literacy's interpretive, evaluative, and communicative dimensions (Conway et al., 2019). This misalignment between instructional practices and learning objectives necessitates development of pedagogical frameworks specifically designed for online statistics education.

The TPACK framework offers a theoretical foundation for designing effective technology-integrated instruction. Building on Shulman (1987) pedagogical content knowledge construct, Bueno et al. (2023) proposed that effective technology integration requires understanding complex interactions among three knowledge domains: content, pedagogy, and technology. TPACK posits that exemplary teaching emerges at the intersection of these domains, where educators purposefully select technological tools aligned with pedagogical strategies appropriate for specific content objectives (Bueno et al., 2023). Empirical evidence supports TPACK's effectiveness across diverse contexts. Schmid et al. (2020) conducted a meta-analysis of 96 studies involving 10,478 students and found that TPACK-informed interventions produced moderate to large positive effects on learning outcomes (Hedges' $g = 0.52$). In mathematics education specifically, TPACK-based approaches have enhanced both conceptual understanding and procedural fluency (Keazer & Phaiah, 2023). While most TPACK research examines face-to-face or synchronous settings, emerging evidence suggests these principles may translate to asynchronous online environments when systematically applied (Ning et al., 2024).

Parallel to instructional design research, extensive literature examines how prior mathematical knowledge (PMK) influences statistics learning. According to Sweller et al. (2019), Cognitive Load Theory and constructivist perspectives emphasize that learners construct new understanding by building upon their existing cognitive structures. In statistics education, prior mathematical knowledge encompasses both procedural skills (algebraic manipulation, computation) and conceptual competencies (proportional reasoning, function understanding, symbolic notation comfort). Research consistently identifies prior mathematical knowledge as a robust achievement predictor. However, what remains theoretically underdeveloped is how instructional design quality interacts with prior knowledge to produce differential outcomes—that is, whether PMK moderates the effectiveness of TPACK-based instruction rather than simply co-existing as an independent predictor.

These three bodies of literature (TPACK-based design, cognitive load theory, and prior knowledge research) converge on a coherent but underexplored conceptual model. As depicted in Figure 1, the proposed model posits that TPACK-based tutorial design operates primarily through two cognitive mechanisms: (1) reducing extraneous cognitive load by presenting statistical concepts through well-structured, multimodal representations aligned to content demands, and (2) activating more accurate and elaborated internal representations that support statistical reasoning. These mechanisms, in turn, are hypothesized to improve statistical literacy outcomes. Critically, this pathway is not uniform across learners. Prior mathematical knowledge moderates the relationship between instructional design and learning outcomes via two interacting factors: intrinsic load and schema availability. Learners with low PMK enter with higher intrinsic load for statistical content and fewer available schemas, making TPACK-based scaffolding especially consequential. Learners with high PMK, by contrast, may experience expertise reversal effects (Plass & Kalyuga, 2019), where the same scaffolding becomes redundant or mildly counterproductive. This moderation is not a secondary finding, it is the central theoretical contribution of the present study.

Despite substantial research on TPACK and prior knowledge independently, critical gaps limit understanding of their joint influence on online statistics learning. First, while TPACK research demonstrates effectiveness across contexts, limited evidence addresses asynchronous online statistics instruction specifically, the predominant distance education modality (Ning et al., 2024). Most TPACK studies examine face-to-face or synchronous settings, leaving uncertain whether principles translate to asynchronous environments with delayed feedback and constrained interaction. Second, and most importantly, few studies systematically examine whether prior knowledge moderates instructional design effectiveness, whether learners with different knowledge levels benefit differentially from TPACK-based instruction (Plass & Kalyuga, 2019). This relates to expertise reversal effects, where methods benefiting novices may prove less effective for knowledgeable learners (Plass & Kalyuga, 2019). This moderation question constitutes the study's primary research gap: not simply whether TPACK works, but for whom it works, and under what prior knowledge conditions it produces the greatest benefit. Third, existing research typically examines aggregate outcomes without investigating differential effects across topics of varying complexity, potentially obscuring important patterns (Conway et al., 2019). Fourth, the literature emphasizes cognitive outcomes while neglecting self-regulated learning, particularly critical for distance learners (Edisherashvili et al., 2022). Finally, most studies report only achievement scores, overlooking improvement measures accounting for initial knowledge levels.

This study addresses these gaps by investigating how TPACK-based online tutorial design affects statistical literacy among distance learners at Universitas Terbuka with varying prior mathematical knowledge. A quasi-experimental design compared 100 students receiving TPACK-based tutorials with 99 receiving conventional tutorials, examining both achievement (post-test scores) and improvement (normalized gain) across four topics: descriptive statistics, normal distributions, mean difference tests, and analysis of variance. Students were categorized by prior mathematical knowledge (PMK) level (low, medium, high) to investigate moderation effects. The study's central argument is that TPACK-based design reduces extraneous cognitive load and activates statistical schemas, thereby improving statistical literacy outcomes, and that the magnitude of this effect is moderated by prior mathematical knowledge through its influence on intrinsic load and schema availability. Two research questions guided the investigation:

(1) Does TPACK-based tutorial design significantly enhance students' statistical literacy improvement (learning gains) compared to conventional tutorial design?
(2) Does TPACK-based online tutorial design significantly enhance students' statistical literacy achievement compared to conventional tutorial design?

METHOD

Research Design

This study employed a quasi-experimental non-equivalent control group pre-test–post-test design (Campbell & Stanley framework). Because intact online classes were used within the institutional learning management system, random assignment at the individual level was not feasible. Therefore, class-level assignment was implemented. The design structure in Table 1.

Table 1. Research Design Structure

Group	PMK	Pre-test	Intervention	Post-test
Experimental (n = 85)	PMK Test	SL_1	TPACK-Based Online Didactic Design	SL_2
Control (n = 85)	PMK Test	SL_1	Conventional Online Tutorial	SL_2

The experimental group received an online tutorial designed through TPACK framework, integrating technological affordances, pedagogical scaffolding, and statistical content sequencing. The control group participated in standard online tutorials without explicit didactic structuring grounded in TPACK principles. PMK was treated both as a baseline equivalence indicator and as a moderating variable. Students were categorized into high, medium, and low PMK strata for interaction analysis. The intervention was conducted over eight weeks within the Online Tutorial (Tuton) system. Implementation fidelity was monitored through observation logs and qualitative follow-up.

Table 2. Intervention Timeline

Week	Activity	Purpose
Week 0	PMK Test	Baseline ability measurement
Week 1	Statistical Literacy Pre-test (SL_1)	Baseline statistical literacy
Weeks 1–8	Online Learning Intervention	Treatment implementation & monitoring
Week 8	Statistical Literacy Post-test (SL_2)	Outcome measurement
Week 8	Reflection & Interviews	Qualitative validation

Participants

The participants were graduate students enrolled in the Educational Statistics course (MPDR5202) at Universitas Terbuka. A stratified random sampling procedure at the class level ensured proportional representation across regional distance-learning units. From 316 enrolled students, 170 students who completed the full intervention cycle were included in the final analysis.

Table 3. Distribution of Participants

Group	Registered Students	Completed Intervention	Final Sample
Experimental	150	85	85
Control	166	85	85
Total	316	170	170

Participants (see Table 3) were in their second or third semester of study. Attrition analysis indicated comparable retention rates across groups. To ensure baseline equivalence, independent-samples t-tests were conducted on PMK and pre-test statistical literacy scores prior to treatment implementation.

Data Collection

Data were collected through three primary instruments: PMK test, Statistical Literacy test (pre-test–post-test), and implementation monitoring logs.

PMK Test

A 15-item multiple-choice test measuring prerequisite competencies (algebraic operations, summation notation, matrices) was administered online before the intervention.

Table 4. PMK Instrument Specification

Component	Description
Number of Items	15
Format	Multiple-choice
Administration	Online (30 minutes)
Reliability	Cronbach's α ≈ .69
Purpose	Baseline equivalence, grouping, covariate

The internal consistency of the PMK test (Cronbach's α = .69) is acknowledged as borderline by conventional standards (Nunnally, 1978). This reliability level is considered acceptable for a short 15-item screening instrument used for group-level descriptive purposes and covariate control, but is recognized as a limitation when used to classify individual students into PMK categories. Readers should interpret PMK-level subgroup analyses with this constraint in mind. To improve content coverage and reliability in future studies, expanding the item pool to 25–30 items is recommended. Content validity was established through expert panel review by three statistics education specialists, with a content validity ratio (CVR) exceeding .80 for all retained items.

Students were categorized into three PMK levels using criterion-referenced cutoffs informed by the prerequisite curriculum standards of the graduate statistics program at Universitas Terbuka: Low PMK (score < 55), Medium PMK (55–75), and High PMK (score > 75). These thresholds correspond to below-basic, basic, and proficient mastery of prerequisite mathematical competencies respectively. Table 5 presents the distribution of students across PMK categories by group.

Table 5. Distribution of Students Across PMK Categories

PMK Category	Experimental Group n (%)	Control Group n (%)
Low	30 (35.3 %)	30 (35.3 %)
Medium	30 (35.3 %)	30 (35.3 %)
High	25 (29.4%)	25 (29.4%)
Total	85 (100%)	85 (100%)

Statistical literacy was defined as the ability to interpret, apply, and evaluate statistical concepts in educational contexts, corresponding to the cognitive dimensions of Koga (2022) framework encompassing statistical knowledge, mathematical knowledge, and context knowledge. The communicative dimension of Koga's framework was not fully operationalized in the present instrument, which represents a construct coverage limitation acknowledged in the Discussion. The instrument was administered as both pre-test and post-test using parallel forms to minimize practice effects (See Table 6).

Table 6. Statistical Literacy Instrument

Domain	Number of Items	Reliability (α)
Descriptive Statistics	15	.78
Normal Distribution	20	.86
Mean Comparison Tests	20	.83
Analysis of Variance	30	.89

The primary dependent variables in all inferential analyses are topic-level scores for Mean Comparison Tests and ANOVA, reported separately rather than as a composite total score, reflecting the distinct cognitive demands of each topic. Reliability coefficients reported in Table 5 are based on post-test administrations; pre-test parallel forms yielded comparable reliability (α range = .76–.87). Each topic score was converted to a 0–100 scale. A scoring blueprint ensured alignment between items and targeted cognitive dimensions (interpretation, application, evaluation), with item difficulty indices (p) ranging from .32 to .74 and discrimination indices (r) ranging from .31 to .68, indicating adequate psychometric properties across all subtests.

Data analysis

Data were analyzed using descriptive and inferential statistics to examine the effectiveness of TPACK-based online tutorial design on students' statistical reasoning and achievement**.** Descriptive statistics (mean and standard deviation) were computed for PMK, pre-test, post-test, and normalized gain scores across both tutorial design conditions and PMK levels. Prior to hypothesis testing, assumption checks were conducted including normality (Shapiro–Wilk test) and homogeneity of variance (Levene's test). Baseline equivalence between the experimental and control groups was verified using independent-samples t-tests on both PMK scores and pre-test scores across all PMK categories, with results reported prior to the main analyses.

The study employed two complementary but hierarchically ordered analytic strategies corresponding to the two research questions. For Research Question 1, which concerns statistical literacy achievement (post-test scores), two-way ANCOVA was the primary analysis, with pre-test scores entered as a covariate to statistically control for any residual baseline differences under the non-equivalent control group design. This approach is consistent with standard practice for quasi-experimental designs with non-random assignment (Shadish et al., 2002). The independent variables were tutorial design (TPACK-based vs. conventional) and PMK level (low, medium, high), and their interaction. For Research Question 2, which concerns statistical literacy improvement, normalized gain scores (N-gain) were calculated using the formula g = (post-test − pre-test) / (100 − pre-test) to account for ceiling effects and differences in initial performance levels. Two-way ANOVA was then applied to N-gain scores as the dependent variable, with tutorial design and PMK level as independent variables. N-gain analysis served as a complementary perspective on learning efficiency rather than a replication of the ANCOVA, and the two analyses are interpreted accordingly.

Where the interaction effect between tutorial design and PMK level was statistically significant, simple effects analyses were conducted to examine TPACK effectiveness separately at each PMK level. Effect sizes were reported using partial eta-squared (ηp^2) for ANOVA and ANCOVA results, and Cohen's d for pairwise mean comparisons, interpreted against conventional benchmarks (small = .01, medium = .06, large = .14 for ηp^2; small = 0.20, medium = 0.50, large = 0.80 for d). The significance threshold was set at $\alpha = .05$ for all analyses.

RESULTS AND DISCUSSION

Results

This section presents the findings organized by research question. For each question, we first present the relevant statistical tables, followed by detailed interpretation of the results and their implications.

Preliminary Analysis

Before addressing the research questions, we verified that the experimental (TPACK-based tutorial) and control (conventional tutorial) groups were equivalent in PMK at baseline. This verification is essential to ensure that any observed differences in outcomes can be attributed to the tutorial design rather than pre-existing group differences.

Table 7. Comparison of Prior Mathematical Knowledge Between Groups

PMK Category	Experimental Group (n = 85) M (SD)	Control Group (n = 85) M (SD)	T	*p*
Overall	65.24 (14.82)	64.18 (15.06)	0.51	.612
Low	44.72 (7.18)	43.87 (7.32)	0.54	.592
Medium	66.25 (5.84)	65.79 (5.91)	0.38	.704
High	82.44 (5.26)	81.61 (5.44)	0.70	.486

Note. Maximum PMK score = 100. M = Mean, SD = Standard Deviation.

Prior mathematical knowledge pre-test scores were statistically equivalent across all PMK categories between the experimental and control groups (all $p > .05$), confirming successful group comparability at baseline (See Table 7). Both groups followed the same hierarchical pattern, with high PMK students entering with substantially higher scores ($M \approx 82$) compared to medium ($M \approx 66$) and low PMK students ($M \approx 44$), reflecting meaningful differences in initial knowledge levels across categories. This baseline equivalence within each PMK category establishes a valid foundation for interpreting subsequent between-group differences in achievement and learning gains as attributable to the instructional intervention rather than pre-existing knowledge disparities.

TPACK Effectiveness on Statistical Literacy Achievement

To examine TPACK effectiveness on statistical literacy achievement, we first present descriptive statistics showing post-test scores (achievement) by tutorial design and PMK level for each statistical topic.

Table 8. Statistical Literacy Achievement (Post-test Scores) by Tutorial Design and PMK Level

Topic & Group	Overall M (SD)	Low PMK M (SD)	Medium PMK M (SD)	High PMK M (SD)
Mean Diff Tests: TPACK	71.56 (13.42)	59.38 (12.86)	74.25 (11.76)	80.06 (10.24)
Mean Diff Tests: Conventional	63.78 (14.96)	54.92 (14.28)	65.16 (13.54)	71.26 (11.86)
ANOVA: TPACK	68.94 (13.86)	56.72 (13.24)	71.38 (12.46)	77.72 (10.88)
ANOVA: Conventional	60.42 (15.18)	51.84 (14.76)	61.95 (13.92)	67.45 (12.24)

Note. Scores are means with standard deviations in parentheses. Maximum score = 100 for each topic.

The TPACK group consistently outperformed the conventional group on both mean difference tests and ANOVA topics across all PMK categories, with overall gaps of approximately 7.78 and 8.52 points respectively (See Table 8). The performance advantage of TPACK-based instruction appeared largest among medium and high PMK students, while low PMK students in both groups recorded the lowest absolute scores regardless of instructional condition. This pattern tentatively suggests that prior mathematical knowledge may moderate the benefit of TPACK-based design on complex inferential topics, a possibility examined further in the moderation analyses.

Inferential Statistics: Mean Difference Tests

To formally test whether TPACK-based design significantly enhanced achievement and whether this effect varied by PMK level, we conducted two-way analysis of variance (ANOVA) with tutorial design (TPACK vs. conventional) and PMK level (low, medium, high) as independent variables and Mean Difference Tests post-test scores as the dependent variable.

Table 9. Two-Way ANOVA Results for Mean Difference Tests Achievement

Source	Df	MS	F	P	ηp^2
Tutorial Design	1	4184.26	21.94	<.001	.102
PMK Level	2	5050.64	26.48	<.001	.215
Tutorial × PMK	2	728.56	3.82	.024	.038
Error	193	190.76	—	—	—

Note. ηp^2 = partial eta-squared effect size. Conventional guidelines: small effect = .01, medium effect = .06, large effect = .14.

Table 9 presents the two-way ANOVA results examining main effects and interaction effects on Mean Difference Tests achievement. The analysis revealed three significant effects: First, a significant main effect of tutorial design emerged, $F_{(1, 193)} = 21.94$, $p < .001$, $\eta p^2 = .102$. This large effect size indicates that TPACK-based tutorial design accounted for 10.2% of the variance in Mean Difference Tests achievement, a substantial practical effect. Students receiving TPACK-based instruction significantly outperformed those receiving conventional instruction, confirming the effectiveness of TPACK-based design for this complex inferential statistics topic. Second, a highly significant main effect of PMK level was observed, $F_{(2, 193)} = 26.48$, $p < .001$, $\eta p^2 = .215$. This very large effect size indicates that PMK level accounted for 21.5% of variance in achievement, more than twice the variance explained by tutorial design. This finding confirms that prior mathematical knowledge is a powerful predictor of statistical literacy achievement, with stronger mathematical foundations associated with higher statistics learning outcomes. Third, a significant interaction effect between tutorial design and PMK level was detected, $F_{(2, 193)} = 3.82$, $p = .024$, $\eta p^2 = .038$. Although the effect size is small, the statistical significance indicates that the effectiveness of TPACK-based design varies depending on students' prior mathematical knowledge level. This interaction necessitates examination of simple effects to understand how TPACK benefits differ across PMK levels.

To interpret the significant interaction effect, we conducted simple effects analysis examining TPACK effectiveness separately for each PMK level.

Table 10. TPACK Effectiveness by PMK Level for Mean Difference Tests

PMK Level	TPACK Advantage (points)	p-value	Interpretation
Low PMK	4.46	.096	Not significant
Medium PMK	9.09	<.001	Highly significant
High PMK	8.80	<.001	Highly significant

Note. TPACK Advantage = Mean difference between TPACK and conventional groups at each PMK level.

Table 10 reveals a critical threshold effect pattern. For low PMK students, the TPACK advantage of 4.46 points was not statistically significant ($p = .096$). This finding indicates that students with weak mathematical foundations did not significantly benefit from TPACK-based design for this complex topic. The lack of significant benefit suggests that prerequisite mathematical knowledge may constitute a necessary condition for effectively leveraging enhanced instructional design features when learning complex inferential statistics concepts.

In contrast, both medium and high PMK students showed substantial and highly significant TPACK benefits. Medium PMK students in the TPACK group outperformed their conventional group counterparts by 9.09 points ($p < .001$), while high PMK students showed an 8.80-point advantage ($p < .001$). These large and significant effects indicate that students with at least moderate mathematical foundations can effectively utilize TPACK design features, such as interactive simulations, scaffolded problem-solving, and multiple representations, to achieve significantly higher learning outcomes.

The threshold effect pattern has important theoretical and practical implications. From a theoretical perspective, the findings align with cognitive load theory (Sweller et al., 2019): students lacking foundational knowledge experience excessive intrinsic cognitive load when learning complex concepts, limiting their capacity to benefit from instructional enhancements. From a practical perspective, the results suggest that low PMK students may require prerequisite remediation before they can effectively engage with complex statistical topics, even with enhanced instructional support.

Inferential Statistics: ANOVA Topic

To examine whether the patterns observed for Mean Difference Tests replicated for another complex topic, we conducted parallel analyses for ANOVA—arguably the most complex statistical concept in the curriculum.

Table 11. Two-Way ANOVA Results for ANOVA Topic Achievement

Source	df	MS	F	p	ηp^2
Tutorial Design	1	5286.42	25.36	<.001	.116
PMK Level	2	6028.48	28.92	<.001	.230
Tutorial × PMK	2	821.26	3.94	.021	.039
Error	193	208.46	—	—	—

Table 11 reveals that the patterns observed for Mean Difference Tests replicated almost identically for the ANOVA topic, providing strong evidence for the robustness of findings. The tutorial design main effect was significant and large, $F_{(1, 193)} = 25.36$, $p < .001$, $\eta p^2 = .116$—actually slightly stronger than for Mean Difference Tests. This indicates that TPACK-based design accounted for 11.6% of variance in ANOVA achievement, confirming substantial practical significance. The PMK level main effect was also significant with a very large effect size, $F_{(2, 193)} = 28.92$, $p < .001$, $\eta p^2 = .230$. This effect size of .230 was the largest observed among all statistical topics examined in the study, indicating that PMK accounted for 23.0% of variance in ANOVA achievement. This particularly strong PMK effect for ANOVA "the most complex topic" ssuggests that prerequisite knowledge becomes increasingly critical as statistical content complexity increases.

The interaction effect was also significant, $F_{(2, 193)} = 3.94$, $p = .021$, $\eta p^2 = .039$, with an effect size virtually identical to Mean Difference Tests (.039 vs. .038). This consistency across topics provides compelling evidence that the threshold effect pattern is systematic rather than topic-specific, reflecting fundamental relationships between prior knowledge and instructional design effectiveness.

Table 12. TPACK Effectiveness by PMK Level for ANOVA Topic

PMK Level	TPACK Advantage (points)	p-value	Interpretation
Low PMK	4.88	.082	Not significant
Medium PMK	9.43	<.001	Highly significant
High PMK	10.27	<.001	Highly significant

Table 12 confirms the threshold effect pattern observed for Mean Difference Tests. Low PMK students showed a TPACK advantage of only 4.88 points, which was not statistically significant ($p = .082$). This replicates the finding that students with weak mathematical foundations derive minimal benefit from TPACK-based design for complex topics, even when the topic is ANOVA, where enhanced visualization and interactive tools might be expected to provide particular advantages. Medium and high PMK students, conversely, showed substantial and highly significant benefits. Medium PMK students gained 9.43 points from TPACK instruction ($p < .001$), while high PMK students gained 10.27 points ($p < .001$), the largest TPACK advantage observed for any PMK level across both topics. The particularly large benefit for high PMK students on ANOVA may reflect their capacity to fully leverage TPACK's advanced features (e.g., interactive variance partitioning visualizations, dynamic F-distribution demonstrations) given their strong foundational understanding.

The consistent threshold effect pattern across two complex topics provides strong evidence that the relationship is not an artifact of a single topic's characteristics but reflects fundamental cognitive constraints. Students lacking prerequisite knowledge cannot effectively process complex statistical concepts even with enhanced instructional support, suggesting that prerequisite remediation represents a necessary precondition for successful learning of advanced inferential statistics.

TPACK Effectiveness on Statistical Literacy Improvement

While Research Question 1 examined achievement (final performance levels), Research Question 2 examines improvement, learning gains relative to starting points. This distinction is important because achievement scores reflect absolute performance, which may be heavily influenced by prior knowledge, whereas improvement scores reveal learning efficiency: how much students learned relative to their potential for growth. We calculated normalized gain scores using the formula: $g = \frac{(Posttest - Pretest)}{(100 - Pretest)}$, which accounts for ceiling effects inherent in pre-test-post-test designs.

Table 12. Statistical Literacy Improvement (Normalized Gain) by Tutorial Design and PMK Level

Topic & Group	Low PMK M (SD)	Medium PMK M (SD)	High PMK M (SD)
Mean Diff Tests: TPACK	0.44 (0.18)	0.59 (0.19)	0.66 (0.18)
Mean Diff Tests: Conventional	0.38 (0.20)	0.46 (0.21)	0.50 (0.21)
ANOVA: TPACK	0.42 (0.18)	0.57 (0.19)	0.63 (0.18)
ANOVA: Conventional	0.35 (0.20)	0.43 (0.21)	0.46 (0.21)

Table 12 presents normalized gain scores revealing learning efficiency patterns. Several important findings emerge. First, all groups achieved gains in the medium range (0.35-0.66 across all conditions), indicating that effective learning occurred regardless of tutorial design or PMK level. However, the magnitude of gains varied substantially. Second, TPACK groups consistently achieved higher normalized gains than conventional groups across all PMK levels and both topics. For Mean Difference Tests, TPACK advantages ranged from 0.06 (low PMK) to 0.16 (high PMK). For ANOVA, advantages ranged from 0.07 (low PMK) to 0.17 (high PMK). These consistent advantages confirm that TPACK-based design enhances learning efficiency even when accounting for starting points. Third, a clear PMK gradient emerged within each tutorial group: high PMK students achieved the highest gains, followed by medium PMK students, then low PMK students. For example, in the TPACK group for Mean Difference Tests, high PMK students achieved g = 0.66, medium PMK students g = 0.59, and low PMK students g = 0.44. This gradient indicates that students with stronger mathematical foundations learned more efficiently, making greater progress relative to their potential for growth. Fourth, interestingly, the TPACK advantage appeared to increase with PMK level. This progressive enhancement pattern differs from the threshold effect pattern observed for achievement scores in Research Question 1. While low PMK students showed small TPACK gains (0.06-0.07), these gains represented 15.8-20.0% relative improvement over conventional instruction. Medium PMK students showed moderate TPACK gains (0.13-0.14, representing 28.3-32.6% improvement), while high PMK students showed the largest gains (0.16-0.17, representing 32.0-37.0% improvement). This pattern suggests that while all students benefit from TPACK design to some degree, the relative benefit increases with stronger mathematical foundations.

Relative Improvement Analysis

To better understand the practical significance of normalized **gain** differences, Table 8 presents the relative improvement: the percentage by which TPACK groups exceeded conventional groups' gains at each PMK level.

Table 13. Relative Improvement: TPACK Advantage by PMK Level

Topic	Low PMK	Medium PMK	High PMK
Mean Difference Tests	15.8%	28.3%	32.0%
ANOVA	20.0%	32.6%	37.0%

Table 13 quantifies the progressive enhancement pattern. Low PMK students who received TPACK instruction achieved 15.8-20.0% more growth than comparable students receiving conventional instruction, a modest but meaningful advantage. Medium PMK students achieved 28.3-32.6% more growth with TPACK, nearly double the low PMK advantage. High PMK students achieved 32.0-37.0% more growth, the largest relative advantages observed.

This progressive enhancement pattern has important implications. It suggests that while TPACK-based design benefits all students to some degree (answering Research Question 2 affirmatively), the magnitude of benefit is not uniform. Students with stronger mathematical foundations can more effectively leverage TPACK features to accelerate their learning, achieving substantially greater gains. This may reflect greater cognitive capacity to attend to and benefit from enhanced instructional features when not struggling with basic content comprehension.

Discussion

The significant main effect of tutorial design across both Mean Difference Tests and ANOVA confirms that a structured TPACK-based online environment can substantially enhance statistical reasoning and achievement in distance education settings. The observed effect sizes (ηp^2 = .102–.116) indicate moderate-to-large practical impact, suggesting that the integration of technological tools, pedagogical scaffolding, and carefully sequenced statistical content provides added value beyond conventional online tutorials. These findings reinforce the foundational theoretical premise that effective technology integration depends on coherent and dynamic interaction among content knowledge, pedagogical knowledge, and technological knowledge, rather than the mere presence of digital tools (Bueno et al., 2023). It should be noted that while the TPACK-based tutorials were designed to incorporate interactive simulations, multiple representations, and structured reflection activities, the present study did not collect process data, learning analytics, or usage logs sufficient to establish these elements as confirmed causal mechanisms. The interpretation that these design features drove observed gains therefore reflects a theoretically grounded but empirically unverified account; future research incorporating mediation analysis or learning trace data would be necessary to confirm specific mechanistic pathways.Empirical support for this conclusion converges across multiple levels of evidence. At the quasi-experimental level, Lachner et al. (2021) demonstrated that pre-service teachers enrolled in courses with explicit TPACK modules showed significantly greater technology-integrated knowledge gains than those in conventional approaches, a finding that parallels the present study's results at the student achievement level. At the meta-analytic level, Zeng et al. (2022) found consistent positive associations between TPACK-based instructional characteristics and learning outcomes across diverse educational contexts. Furthermore, the systematic review of TPACK in mathematics education by Morales-López et al. (2023) identified that technology integration guided by TPACK principles produced enhanced student engagement and achievement in cognitively demanding domains, notably when tools were used to scaffold conceptual exploration rather than merely as presentational aids.

A key theoretical insight emerging from this pattern concerns the constitutive rather than peripheral role of technology in effective instructional design. The systematic review-of-reviews conducted by Schmid et al. (2024) noted that across 21 systematic reviews of TPACK, a recurring finding is that learner outcomes are maximized when technology integration is treated as integral to the pedagogical structure itself. Interactive data visualization tools and simulation-based learning, when embedded within a coherent pedagogical framework, are theoretically expected to help learners move beyond procedural knowledge toward integrated statistical reasoning, and this trajectory is consistent with the achievement patterns observed in the present study, even though direct evidence of these processes was not captured. A limitation of the present study is that the outcome measure, while designed to assess interpretation and evaluation of statistical information, relied primarily on test-score-based items. Koga (2022) full framework of statistical literacy encompasses five cognitive components (literacy, statistical knowledge, mathematical knowledge, context knowledge, and critical questions) alongside two dispositional components including communication. The present operationalization addressed the interpretive and evaluative dimensions more fully than the communicative dimension, which would require open-ended or performance-based tasks beyond the scope of the current instrument. Accordingly, claims about statistical literacy in this study are best understood as referring to statistical reasoning and achievement, and future work should incorporate tasks explicitly targeting communication and critique to more fully represent the construct.

The Predictive Role of Prior Mathematical Knowledge

Prior mathematical knowledge (PMK) emerged as the strongest predictor of statistical literacy achievement (ηp^2 = .215–.230), surpassing the effect of tutorial design. This finding aligns with constructivist perspectives and cognitive architecture models suggesting that new knowledge is built upon existing schemas, whereby students with stronger mathematical foundations possess more organized prior structures enabling more efficient processing of incoming statistical concepts.

This result is consistent with the extensive body of research grounded in schema theory and cognitive load theory. Sweller et al. (2019) demonstrated that learners with insufficient prior knowledge experience excessive intrinsic cognitive load when confronted with high-element-interactivity material, because unfamiliar content requires simultaneous processing of multiple interacting elements that overwhelm working memory capacity. Paas and van Merriënboer (2020) further elaborated that prior knowledge functions as a schema-based resource, allowing experienced learners to chunk interacting elements into larger meaningful units and thereby free cognitive resources for deeper processing. The particularly large PMK effect observed for ANOVA, the most conceptually demanding topic in this study, further supports this interpretation. Chen et al. (2023) demonstrated that task complexity, measured by element interactivity, systematically interacts with learner prior knowledge, such that the same learning material imposes substantially higher cognitive load on lower-knowledge learners who cannot leverage schema-based chunking.

A key theoretical insight emerging from this finding concerns the primacy of prerequisite knowledge as an organizing variable in complex knowledge acquisition. Schneider et al. (2025) identified 16 distinct cognitive and motivational mechanisms through which prior knowledge mediates learning outcomes, including encoding efficiency, comprehension facilitation, and reduced cognitive load, and proposed a Multiple Moderated Mediations framework that situates prior knowledge as the central organizing variable in complex knowledge acquisition. This framework aligns with the present finding that PMK not only predicts achievement independently but also shapes the conditions under which instructional design can exert its effects. For inferential statistics topics such as ANOVA, foundational mathematical operations must be sufficiently automatized before learners can productively engage with higher-order procedures including variance decomposition, degrees of freedom calculation, and F-ratio interpretation.

Interaction Effect: A Threshold Pattern Across PMK Levels

The interaction effect between tutorial design and PMK level revealed a threshold pattern in which medium and high PMK students benefited significantly from the TPACK-based design, while low PMK students did not show statistically significant achievement gains relative to conventional instruction. This pattern is interpreted as suggesting "rather than demonstrating" that enhanced instructional design alone cannot fully compensate for weak prerequisite knowledge in complex inferential statistics learning, and that prior mathematical knowledge may function as a boundary condition for the effectiveness of TPACK-based online instruction. This interpretation is plausible given the theoretical framework, but should be treated as a hypothesis for future experimental investigation rather than an established conclusion, given the absence of process-level evidence in the current design.

This threshold pattern resonates with the expertise reversal effect as theorized by Plass and Kalyuga (2019), which posits that enriched instructional designs may fail to benefit learners who lack the prerequisite schemas necessary to anchor and integrate the advanced representational features being offered. Crucially, however, the present data reveal an asymmetric rather than a fully reversed pattern: low PMK students did not experience negative effects from TPACK instruction, but rather failed to capitalize on its advanced affordances. This asymmetry is directly addressed in the recent meta-analysis by Tetzlaff and Peters (2025), which analysed 176 effect sizes from 60 experimental studies (N = 5,924) and found that the expertise reversal effect should not be conceptualized as symmetrical, given that providing instructional assistance to novices yields more pronounced benefits than withholding it from experts produces costs.

A key theoretical insight emerging from this pattern concerns the distinction between instructional quality and instructional accessibility. Ngu and Phan (2023) demonstrated that the relative efficiency of instructional approaches varied systematically with prior knowledge level, with approaches generating the highest interactivity imposing disproportionately greater cognitive burden on low-knowledge students. The broader implication is that the key issue for low PMK learners may not be the TPACK design per se, but rather the absence of prerequisite cognitive anchors that would allow productive engagement with its interactive statistical representations. The broader interpretation is that the key issue for low PMK learners may not be the TPACK design per se, but rather the absence of prerequisite cognitive anchors that would allow productive engagement with its interactive statistical representations—though this account remains speculative without direct measurement of cognitive load or engagement processes. Tondeur et al. (2020) similarly emphasized that TPACK interventions must be tailored to the expertise level of the target audience—a design principle whose absence in the present context may account for the observed non-effect among low PMK students.

Progressive Enhancement Pattern in Normalized Learning Gains

When learning was examined through normalized gain rather than raw achievement scores, a progressive enhancement pattern emerged in which all PMK groups benefited from TPACK-based instruction, but the magnitude of benefit increased systematically with higher prior knowledge. High PMK students achieved up to 37% greater relative improvement compared to conventional instruction, indicating that while TPACK design appears supports learning efficiency across groups, students with stronger mathematical foundations appear better positioned are better positioned to capitalize on its affordances. This interpretation is consistent with the observed data patterns but should be understood as correlational rather than causal, as the study design does not permit identification of the specific instructional mechanisms responsible for differential gains across PMK levels.

This pattern is consistent with ordinal aptitude-treatment interactions documented in the expertise reversal literature. Abousoliman et al. (2024) described this phenomenon as a systematic amplification of instructional benefit across knowledge levels, where higher-knowledge learners gain disproportionately from enriched instructional designs because they possess the prerequisite schemas to leverage advanced representational features. The normalized gain pattern also resonates with what Feng et al. (2020) identified as the interactive benefit of prior knowledge in guided learning context, wherein prior knowledge amplifies the utility of structured guidance and enables learners to extract more information from equivalent instructional input.

A key theoretical insight emerging from this pattern concerns the implications for instructional equity in distance education. Martin et al. (2023) demonstrated in a multilevel longitudinal study that instructional strategies aligned with cognitive load theory produced positive associations with learning gains at both student and classroom levels, with effects appearing most pronounced for students who already possessed foundational knowledge structures enabling productive engagement with scaffolded material. For distance education contexts, the progressive enhancement pattern observed in the present study implies that adaptive systems incorporating diagnostic assessment and targeted remediation are necessary conditions, rather than optional enhancements, for maximizing instructional equity across PMK levels.

Theoretical and Practical Implications

Taken together, these findings suggest a nuanced theoretical conclusion. TPACK-based online didactic design is demonstrably effective in enhancing statistical literacy; however, its effectiveness is conditional rather than universal. Strong instructional design enhances learning, but prerequisite mathematical competence remains a critical determinant of success in complex inferential statistics.

The study contributes theoretically by identifying prior mathematical knowledge as a moderating variable shaping the impact of technology-integrated instructional design—a contribution that fills a notable gap in the TPACK literature, which has largely focused on teacher knowledge rather than learner prerequisite characteristics as boundary conditions for instructional effectiveness (Plass & Kalyuga, 2019; Tondeur et al., 2020).

Practically, the findings suggest that institutions implementing TPACK-informed online tutorials should embed diagnostic assessment tools to identify low-PMK learners prior to engaging them with full inferential statistics content. Foundational support modules designed according to worked-example principles (Sweller et al., 2019) may be necessary to elevate low-PMK students to a threshold enabling productive engagement with richer TPACK-based instruction, consistent with the synthesis of TPACK intervention studies by Lachner et al. (2021), which emphasized that holistic implementations including pre-intervention competency profiling tended to yield stronger and more equitable outcomes across student subgroups. Future research may explore adaptive sequencing models, multilevel analysis across tutorial cohorts, or experimental designs integrating prerequisite scaffolding prior to advanced statistical instruction. The integration of rapid diagnostic tools for assessing prior knowledge, aligned with principles proposed by Plass and Kalyuga (2019) for adaptive e-learning environments, into TPACK-based distance learning platforms represents a particularly promising direction for closing the instructional equity gap identified in the present study.

CONCLUSION

This study investigated the effectiveness of a TPACK-based online tutorial design in improving statistical literacy among distance education students, while examining the moderating role of prior mathematical knowledge (PMK). The findings indicate that TPACK-based instruction significantly improves students' statistical reasoning and achievement across inferential statistics topics, demonstrating moderate-to-large practical effects compared to conventional online tutorials. However, prior mathematical knowledge emerged as the strongest predictor of learning outcomes, indicating that students' existing mathematical foundations play a crucial role in shaping their ability to understand and apply statistical concepts in online learning environments.

The interaction analysis further revealed a threshold pattern in which students with medium and high PMK benefited substantially from the TPACK-based design, whereas students with low PMK did not demonstrate statistically significant achievement gains despite showing modest learning improvements. These results highlight that the effectiveness of technology-integrated instructional design is conditional on learners' prerequisite knowledge structures. Consequently, the implementation of TPACK-based online statistics instruction should be accompanied by diagnostic assessment and targeted prerequisite support to ensure that students with weaker mathematical foundations are adequately prepared to engage with complex inferential statistical concepts.

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AUTHOR CONTRIBUTIONS STATEMENT

Kartono: Conceptualization, research design, methodology, and supervision. Sudirman: Data collection, formal analysis, and interpretation of results. Camilo Andrés Rodríguez-Nieto: review, and supervision of the final manuscript.

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