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Division strategy of learning time formulation in blended learning based on prior knowledge on the ability to apply and analyze statistics courses

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Abstract: This study investigates the impact of various division strategies of learning time (DSLT) in a blended learning environment on students' ability to apply and analyze statistical concepts, considering their prior knowledge (PK) levels. A quasi-experimental 3 × 3 factorial design was employed, involving 125 students grouped based on high, medium, and low prior knowledge. Each group received one of three DSLT treatments, which combined online learning and face-to-face instruction in ratios of 40:60, 60:40, and 70:30. Data were collected via pre-tests and post-tests measuring application and analysis competencies in linear regression. Results from two-way MANOVA revealed significant main and interaction effects between DSLT and PK. The DSLT with a ratio of 70:30 was most effective for students with high PK, while the 60:40 ratio worked best for students with medium PK. Both 40:60 and 60:40 strategies showed similar effectiveness for students with low PK. The findings suggest that aligning instructional time distribution with students' prior knowledge enhances learning outcomes in statistical education.
Keywords: *Blended learning, DSLT, Prior knowledge.*

1. Introduction

Blended learning has emerged as one of the most transformative pedagogical innovations in higher education over the past two decades. Blended learning is a teaching method that utilizes both online and offline methods. It allows students to learn at their own pace and style while also having some interaction with teachers and peers. Blended learning helps students learn more deeply, manage their own learning, and become more independent [1-6]. However, despite its increasing adoption, the effectiveness of blended learning is highly contingent upon several pedagogical factors [7-10] among which time allocation strategies and students' prior knowledge play central roles. As indicated by recent research, the lack of alignment between instructional design and learner characteristics can result in reduced learning efficacy, especially in complex and cognitively demanding subjects such as statistics [11-15].

Prior knowledge has long been recognized as a major predictor of academic performance in higher education. Learners with strong foundational understanding are more likely to process new information meaningfully, engage in abstract thinking, and transfer knowledge across contexts. In the context of blended learning, this factor becomes even more critical. Students with higher prior knowledge levels are often more capable of navigating online content independently, whereas students with limited foundational understanding require greater levels of scaffolding and direct support [16-21]. Consequently, the interaction between prior knowledge and the division strategy of learning time (DSLT)—i.e., how instructional time is distributed between online and face-to-face formats—warrants closer investigation. There remains a paucity of empirical research exploring this interaction in structured higher education settings [22-24]. This research aims to fill this gap by looking at how different DSLT configurations (40:60, 60:40, 70:30) affect students' ability to apply and analyze

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statistical concepts in a blended learning, moderated by their prior knowledge levels. By employing a quasi-experimental factorial design, the study not only identifies which configurations yield optimal learning outcomes but also contributes to the theoretical framework of adaptive learning environments [5, 25-27]. Furthermore, it offers practical implications for curriculum designers, instructors, and educational policymakers striving to create more equitable and effective learning environments across diverse learner populations. The results of this research align with the broader educational shift toward student-centered instruction and the personalization of learning experiences through data-driven approaches.

2. Materials and Methods

This research employed a quasi-experimental factorial design (3×3) to explore how the Division Strategy of Learning Time (DSLT) in a blended learning setting influences students' ability to apply and analyze statistical concepts, moderated by their levels of prior knowledge. A total of 125 undergraduate colleger taking a Statistics course at a high school in Indonesia participated in the study. All participants had previously completed foundational mathematics coursework and were currently studying regression-based content, ensuring baseline competency across the sample.

2.1. Grouping Based on Prior Knowledge

To determine prior knowledge levels, students completed a validated algebra diagnostic test, adapted from publicly available standardized items (https://www.tests.com/practice/algebra-practice-test). Based on their test scores, students were divided into three categories:

1. High Prior Knowledge (n = 30; M = 82.37)
2. Medium Prior Knowledge (n = 69; M = 71.15)
3. Low Prior Knowledge (n = 26; M = 48.47)

This classification method aligns with established approaches in adaptive blended learning research, where initial student profiling informs instructional differentiation [28].

2.2. DSLT Configurations and Instructional Implementation

The main factor in this research was the Division Strategy of Learning Time (DSLT), which refers to how much of the instruction was online compared to in-person. Students were randomly assigned within their PK groups to one of three DSLT formats:

1. DSLT 40:60 (40% online, 60% face-to-face)
2. DSLT 60:40 (60% online, 40% face-to-face)
3. DSLT 70:30 (70% online, 30% face-to-face)

All students were taught the same learning content: linear regression, including topics on model formulation, interpretation of coefficients, and residual analysis. The course was delivered over a three-week period through a blended learning model integrating synchronous and asynchronous modalities via Moodle LMS and in-person instruction. The online components included video lectures, interactive quizzes, and simulations, while face-to-face sessions focused on collaborative problem-solving and instructor-led guidance. Such blended approaches have been widely validated in enhancing student learning outcomes and engagement [11, 29-32].

2.3. Instrumentation and Measurement

A pretest-posttest approach was used to assess student learning gains in two cognitive domains (1) application ability, measured through real-world statistical problems requiring the application of regression models and (2) analytical ability, measured through tasks involving interpretation of data, evaluating assumptions, and inferring statistical conclusions.

Both tests were checked by three experts to make sure they covered the rights topics. The test were also tested for validity and reliability using Cronbach's alpha, which was above 0,82. Instruments were delivered online and scored by two trained raters using a rubric-based protocol to minimize subjectivity.

2.4. Statistical Assumptions and Analysis

To analyze the effects of DSLT and prior knowledge on both dependent variables, the following statistical tests were applied (1) normality was checked using Shapiro-Wilk and Kolmogorov-Smirnov tests with p-values > .05 for all subgroups, (2) homogeneity of variance was tested with Levene's test ($p > .05$), and (3) equality of covariance matrices, evaluated using Box's M Test, which yielded nonsignificant results ($p = .067$), satisfying MANOVA assumptions.

Subsequently, a two-way MANOVA was conducted to assess the main effects of DSLT and Prior Knowledge (PK) and the interaction effect between DSLT and PK on application and analysis outcomes. All data analysis was performed using IBM SPSS Statistics v28. The MANOVA approach is recommended in factorial experimental research involving multiple dependent variables, especially in educational settings [33-35].

2.5. Connection to Results

This methodological framework enabled the study to determine the most pedagogically effective combination of DSLT and PK. As detailed in the Results section, significant main and interaction effects were found. Students with high PK benefited most from the DSLT 70:30 model, whereas medium PK students showed optimal performance under DSLT 60:40. For low PK students, the 40:60 and 60:40 configurations yielded nearly equivalent improvements. These results underscore the importance of adapting instructional design based on learner characteristics to enhance cognitive outcomes in blended learning environments.This study was designed using a quasi-experimental model due to constraints in fully randomizing selection of research subjects. This study employed a factorial design, incorporating three formulation of DSLT ratios of 40:60, 60:40, and 70:30 and examining their effects across three PK levels, which is high, medium, and low, resulting in a 3 x 3 factorial design. The experimental conditions included DSLT 40:60, 60:40, and 70:30 applied to students with high, medium, and low prior knowledge. The factorial design is summarized as follows:

Table 1.
Factorial Design Based on Student Prior Knowledge.

Factor	**Level**	**DSLT formulation**		
		60: 40 (Y_1)	**40: 60 (Y_2)**	**70: 30 (Y_3)**
Prior Knowledge (PK)	High (Z_1)	Z_1/Y_1	Z_1/Y_2	Z_1/Y_3
	Medium (Z_2)	Z_2/Y_1	Z_2/Y_2	Z_2/Y_3
	Low (Z_3)	Z_3/Y_1	Z_3/Y_2	Z_3/Y_3

Description:
Y = Treatment employing DSLT
Y_1 = DSLT 60:40
Y_2 = DSLT 40:60
Y_3 = DSLT 70:30
Z = Factorial
Z_1 = High Prior Knowledge (PKH)
Z_2 = Medium Prior Knowledge (PKM)
Z_3 = Low Prior Knowledge (PKL)

Research assessment tools include Mathematics test questions designed to determine students' prior knowledge (PK), and pretest-posttest questions in Statistics aimed at evaluating students' ability to apply and analyze based on the three components of DSLT. Data analysis in this study employs the two-way MANOVA statistical method. The null hypothesis (H_0) is tested at a significance level of 5% or $\alpha = 0.05$.

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3. Results and Discussion

3.1. Results

The results of the Kolmogorov-Smirnov and Shapiro-Wilk tests, both yielding significance levels greater than 0.05, indicate that the data on the ability scores for applying and analyzing Statistics based on the DSLT are normally distributed. The next step, after confirming normality, is to conduct a homogeneity of variances test for the ability scores across the three sample groups using Levene's test. Based on the calculations it is evident that the mean and median for the application variable have significance values greater than 0.05. This criterion also applies to the mean and median for the sample's analytical capability variable. Consequently, it can be concluded that the data originate from a population with homogeneous variances.

The Kolmogorov-Smirnov and Shapiro-Wilk tests were employed to assess the application and analysis of statistics based on PKH, PKM, and PKL, yielding significance values greater than 0.05. Consequently, it can be concluded that the data scores for applying and analyzing statistics according to PK follow a normal distribution. Therefore, homogeneity of variances was based it is evident that when applying statistics based on the mean, the significance level is 0.982, which exceeds the 0.05 threshold. Similarly, using the median as a measure yields a significance level of 0.914, also greater than 0.05.

The results of the normality and homogeneity distribution tests, based on DSLT and PK, confirm that all data follow a normal distribution and are homogeneous. Therefore, the next step involves conducting a covariance matrix equality test using Box's M test, with the following hypotheses:

a. *H_0 = The two dependent variables (application and analysis of statistics) have identical variance-covariance matrices in both DSLT and PK.*
b. *H_1 = The two dependent variables (application and analysis of statistics) have different variance-covariance matrices in both DSLT and PK.*

Using SPSS version 28, the analysis yielded results as shown in Table 2 below:

Table 2.
Assumption Test of Covariance Variance in the Dependent Variable.

Box's Test of Equality of Covariance Matrices[a]	
Box's M	18.517
F	2.074
df1	9
df2	78392.241
Sig.	0.067
Tests the null hypothesis that the observed covariance matrices of the dependent variables are equal across groups.	

Note: a. Design: Intercept + DSLT + PK + DSLT * PK.

The table above indicates that the Box'M value is 18.517 with a significance level of 0.067. Since the significance exceeds 0.05, the null hypothesis (H_0) is accepted, implying that the two dependent variables (application and analyzing statistics) share an identical variance-covariance matrix. Homogeneity tests for each variable, conducted using Levene's Test, yielded results as presented in Table 3.

Table 3.
Results of Homogeneity Tests for Each Dependent Variable.

Student's Ability	**F**	**df1**	**df2**	**Sig.**
APPLICATION	5.140	3	83	0.003
ANALYSIS	1.697	3	83	0.044
Tests the null hypothesis that the error variance of the dependent variable is equal across groups.				

Note: a. Design: Intercept + DSLT + PK + DSLT * PK.

From Table 3, it is evident that the significance value is below 0.05, indicating that the covariance matrix of variances across variables applied and analyzed statistically on an individual basis is homogeneous. Based on the calculations above, it can be concluded that the assumption of homogeneity of covariance matrices is satisfied; therefore, the analysis process using MANOVA can proceed.

In this study, hypothesis testing was conducted using MANOVA, with the results divided into three components: (1) the calculation outcomes indicating whether significant differences exist among the dependent variables, and (2) the results of the calculations used to assess the interaction effects of each variable.

Table 4.
Results of the MANOVA Analysis on the Effects of Division Strategy, Learning Time, and Prior Knowledge.

Multivariate Tests[b]						
Effect		**Value**	**F**	**Hypothesis df**	**Error df**	**Sig.**
Intercept	Pillai's Trace	0.969	1372.57[a]	3.00	82.0	0.000
	Wilks'Lambda	0.031	1372.57[a]	3.00	82.0	0.000
	Hotelling's Trace	31.038	1372.57[a]	3.00	82.0	0.000
	Roy's Largest Root	31.038	1372.57[a]	3.00	82.0	0.000
DSLT	Pillai's Trace	0.166	8.212[a]	3.00	82.0	0.002
	Wilks'Lambda	0.853	8.212[a]	3.00	82.0	0.002
	Hotelling's Trace	0.189	8.212[a]	3.00	82.0	0.002
	Roy's Largest Root	0.189	8.212[a]	3.00	82.0	0.002
PK	Pillai's Trace	0.455	47.872[a]	3.00	82.0	0.000
	Wilks'Lambda	0.546	47.872[a]	3.00	82.0	0.000
	Hotelling's Trace	1.294	47.872[a]	3.00	82.0	0.000
	Roy's Largest Root	1.294	47.872[a]	3.00	82.0	0.000
DSLT*PK	Pillai's Trace	0.048	1.739[a]	3.00	82.0	0.002
	Wilks'Lambda	0.972	1.739[a]	3.00	82.0	0.002
	Hotelling's Trace	0.040	1.739[a]	3.00	82.0	0.002
	Roy's Largest Root	0.040	1.739[a]	.00	82.0	0.002

Note: a. Exact statistic.
b. Design: Intercept +DSLT+PK+DSLT*PK.

With a significance level (α) of 5% and the acceptance of the alternative hypothesis when the significance value is less than 0.05, the data analysis results presented in Table 4 indicate a significance value of 0.002. This allows us to conclude that the learning strategy employing the DSLT model has a statistically significant effect on student performance (PK). Implicitly, based on the mean pretest and posttest scores for the variables of application and analysis skills, it is observed that for the high PK group, the most substantial improvement occurs with a 70:30 ratio of DSLT implementation, with pretest-posttest score differences of 7.91 for application skills and 4.83 for analytical skills. The moderate PK group exhibits the best score improvements when the DSLT strategy is applied with a 60:40 ratio, with score differences of 3.98 for application and an increase of 3.55 for analysis. Notably, in the low PK group, the pretest-posttest score differences are identical at 0.53 for both ratios of 40:60 and 60:40, suggesting that varied instructional approaches can be employed for this group, as detailed in Table 5.

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Table 5.
Results of MANOVA Analysis on the Effects of Division Strategy, Learning Time, and Prior Knowledge on Dependent Variables.

Tests of Between-Subjects Effects						
Source	**Dependent Variable**	**Type III Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**
Corrected Model	Application	317.754[a]	3	105.918	12.461	0.000
	Analysis	390.613[b]	3	130.204	29.421	0.000
Intercept	Application	14908.236	1	14908.236	1753.883	0.000
	Analysis	4528.195	1	4528.195	1023.201	0.000
DSLT	Application	136.353	1	136.353	16.041	0.000
	Analysis	4.054	1	4.054	0.916	0.041
PK	Application	172.142	1	172.142	20.252	0.000
	Analysis	376.080	1	376.080	84.980	0.000
DSLT * PK	Application	5.530	1	5.530	.651	0.022
	Analysis	10.792	1	10.792	2.439	0.012
Error	Application	705.511	83	8.500		
	Analysis	367.318	83	4.426		
Total	Application	15935.000	87			
	Analysis	5320.000	87			
Corrected Total	Application	1023.264	86			
	Analysis	757.931	86			

Note: a. R Squared = 0.311 (Adjusted R Squared = 0.286).
b. R Squared = 0.515 (Adjusted R Squared =0.498).

An analysis using MANOVA was conducted to examine the effects of DSLT and PK learning strategies on students' application and analysis skills. The results in table 5 revealed significance levels of 0.022 and 0.012 for application and analysis abilities, respectively ($p < \alpha$). These findings indicate that both DSLT and PK strategies significantly influence students' competencies in application and analyzing statistical concepts in the Statistics course.

Table 6.
Average pretest and posttest scores based on DSLT and PK for the application variable and analysis.

DSLT	**PK**	**APPLICATION**			**ANALYSIS**		
		PRETEST	**POSTEST**	**INCREASE**	**PRETEST**	**POSTEST**	**INCREASE**
BL 40:60	High	84.72	89.97	5.25	83.82	85.21	1.39
	Med	77.56	79.08	1.52	73.72	74.87	1.15
	Low	58.74	63.27	4.53	49.23	53.28	4.05
BL 60:40	High	85.73	91.76	6.03	88.45	89.72	1.27
	Med	74.27	78.25	3.98	72.31	75.86	3.55
	Low	57.23	61.23	4	55.04	58.89	3.85
BL 70:30	High	87.32	95.23	7.91	84.59	89.42	4.83
	Med	73.45	76.44	2.99	70.57	71.66	1.09
	Low	37.95	38.02	0.07	35.35	36.07	0.72

3.2. Discussions

The findings of this study provide understanding of how the Division Strategy of Learning Time (DSLT) interacts with students' prior knowledge to influence cognitive outcomes in a blended learning environment. Firstly, the significant differences found between the three DSLT groups (40:60, 60:40, and 70:30) in both application and analysis abilities reinforce the importance of instructional time design. These differences suggest that instructional time is not merely a logistical factor, but a pedagogical determinant that can enhance or inhibit students' ability to process, apply, and reflect on statistical content. The variation in outcomes across DSLT formats also aligns with recent research indicating that instructional strategies must be matched with task complexity and learner profile to yield optimal results [15].

Secondly, the significant variation in performance across students with high, medium, and low levels of prior knowledge underscores the role of cognitive readiness in determining academic success in blended environments. Prior knowledge acts as a scaffold upon which new concepts are built. Students with strong foundational knowledge were better able to engage with abstract statistical concepts and apply them effectively, particularly when instructional design allowed greater autonomy. This supports the theoretical perspective that learners' ability to integrate new material is contingent on the quality and accessibility of existing mental schemas. Importantly, the results also reveal that prior knowledge not only affects learning outcomes independently but also moderates the effectiveness of specific DSLT models.

The significant interaction between DSLT and prior knowledge across both learning outcomes—application and analysis—highlights the necessity of adaptive instruction. High-PK students performed well across all DSLT models, but their performance peaked under the 70:30 configuration, suggesting they thrive with greater opportunities for self-regulated and exploratory learning. The 7.91-point gain in application and 4.83-point gain in analysis among this group indicates that instructional autonomy does not hinder but rather enhances their academic development. In contrast, students with medium prior knowledge demonstrated highest gains under the 60:40 configuration, suggesting a balance of structure and independence is most effective for those who are moderately prepared. The improvement margins of 3.98 and 3.55, respectively, affirm that this group benefits from a steady transition from guided to independent learning.

Most revealing findings in this study are the limited progress observed among students with low prior knowledge, regardless of DSLT configuration. The marginal difference of only 0.53 points between the 40:60 and 60:40 groups indicates that time allocation adjustments alone are insufficient for student with weak foundational skills. These findings suggest that this cohort requires more than just proportionally increased face-to-face interaction; they may need entirely different pedagogical interventions such as remedial instruction, personalized mentoring, or scaffolding techniques that can break down complex statistical concepts into more digestible forms. Furthermore, the poor outcomes under the 70:30 model for low-PK students reinforce the risks of overexposing underprepared student to autonomous learning formats without adequate support.

Collectively, the data supports the adoption of differentiated DSLT models that align with students' initial competencies. Institutions seeking to implement or refine blended learning frameworks should not rely solely on uniform instructional models. Instead, diagnostic assessments should be employed early in the instructional process to determine students' cognitive readiness and inform the selection of DSLT configurations accordingly. These findings substantiate previous calls in the literature for more personalized and data-driven approaches in instructional design and contribute to a growing body of evidence that learning outcomes can be significantly improved through strategic, adaptive instructional planning in blended education settings.

4. Conclusion

The findings from this study provide strong empirical support for the strategic adaptation of blended learning time allocations based on students' prior knowledge levels. The results demonstrated that students with high prior knowledge benefitted most from the 70:30 configuration, characterized by more online, self-regulated learning, whereas students with medium prior knowledge achieved optimal outcomes under the 60:40 model. In contrast, students with low prior knowledge showed minimal gains across configurations, underscoring the need for greater instructional support beyond time division alone.

These outcomes reinforce the importance of differentiated instruction in blended learning contexts. As students enter higher education with increasingly diverse cognitive backgrounds, a uniform

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instructional model fails to adequately address individual learning needs. This study advocates for the implementation of diagnostic assessments at the beginning of courses to identify students' preparedness levels and adjust DSLT configurations accordingly. Furthermore, it calls attention to the role of instructional designers and faculty in ensuring that blended learning structures are pedagogically sound and aligned with empirical findings, rather than arbitrarily balanced for convenience or administrative purposes.

In line with recent theoretical frameworks on personalized learning and adaptive systems, this research contributes to a growing body of knowledge advocating for data-informed decision-making in educational settings. As emphasized by Dziuban, et al. [15]; Kyei-Akuoko, et al. [22] and Ali, et al. [24] the future of blended learning lies in its capacity to adapt—not only technologically but pedagogically—to the varied and evolving needs of learners. With these insights, institutions can move closer toward realizing the full potential of blended learning as a tool for inclusive, effective, and sustainable education.

Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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