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Statistical Evaluation of the Relationship between Bus dwell time and selected terminal-based factors

[1]Elufowoju, F.E., [2]Mohammed, H. and [3]Ayodele, A.L.

[1,2,3]Department of Civil Engineering, Obafemi Awolowo University, Ile-Ife, Nigeria

Corresponding Author: *efelufowoju@oauife.edu.ng*

Abstract: *Bus dwell time at terminals is a critical factor affecting public transportation efficiency, service reliability, and passenger satisfaction. This study examines the relationship between bus dwell time and selected terminal-based factors. The data collected at Terminal 3 of Oshodi Transport Interchange in Lagos State, Nigeria were used to derive headway - difference between consecutive bus arrival times; dwell time - difference between bus arrival and departure times; boarding time - difference between boarding start and end times, and the total number of passengers on board a bus at departure. Pearson correlation analysis indicated a significant relationship between dwell time, boarding time and headway ($p < 0.001$). Whereas headway has a negative relationship with dwell time($r = -0.193$), boarding time and number of passengers are positive ($r = 0.226$ and $r = 0.343$ respectively). Regression analysis indicates that boarding time and number of passengers jointly explains 16.4 % of dwell time variability, whereas headway does not have a significant influence in the model. The diagnostic tests indicate that the predictors show no problematic multicolinearity (VIF = 1.000, i.e. < 5.0). While, the linearity of the association between the predictors and dwell time was validated by ANOVA linearity test ($F = 48.05$, $p < 0.001$). Therefore, transit managers and planners seeking to improve operational efficiency and passenger satisfaction could consider shortening boarding time and improving passenger management.*

KEYWORDS: *headway, dwell time, boarding time, number of passengers, correlation, significan*

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1. INTRODUCTION

Urban mobility depends on effective public transit networks, but high wait times at bus terminals frequently impair operating efficiency. Headway, boarding time, and bus capacity are some of the variables that affect dwell time, which is the amount of time buses stay still at stops to for passengers to board and disembark. Passenger satisfaction, network efficiency, and overall service reliability are all directly impacted by these elements. In order to determine practical methods for reducing dwell periods, the current study explores the complex interactions between these variables. The primary aim of this research is to explore the influence of headway, boarding time, and bus capacity on dwell time at bus terminals. To achieve this, the study shall analyze the relationship between dwell time, headway, boarding time and bus capacity, and propose integrated strategies to mitigate dwell time by addressing the interplay among the identified factors.

The optimization of operational efficiency is a challenge facing public transportation networks around the world, and dwell time at bus terminals has emerged as a major bottleneck. In addition to causing schedule delays, extended dwell times also raise operating expenses and passenger discontent. Despite developments in transit technologies and operational methods, existing solutions generally fail to address the compounding consequences of headway inconsistencies, inefficient boarding processes, and inadequate bus capacity use. By methodically investigating the interrelated elements that affect dwell time and putting up comprehensive ideas to improve terminal operations, this study fills these gaps.

The urgent need to upgrade public transit networks in the face of rising urbanization and a growing dependence on environmentally friendly transit options serves as justification for this study. In line with more general sustainability objectives, shorter dwell periods can result in more dependable services, less fuel usage, and lower emissions. Furthermore, this study adds to the body of information needed for evidence-based decision-making in transit planning by addressing headway variability, boarding inefficiencies, and capacity restrictions. For transit operators, legislators, and urban planners looking to enhance passenger experiences and maximize bus terminal performance, the findings have real-world applications.

Enhancing the effectiveness of public transportation systems requires an understanding of the variables affecting dwell time at bus terminals. Headway, boarding time, and bus capacity are important factors that influence stay time, according to recent study, which uses a variety of approaches to measure their effects.

One crucial operational factor influencing dwell time is headway, or the amount of time that passes between successive buses on the same route. Increased passenger accumulation during stops is frequently linked to tight headways, which results in longer dwell durations. In their investigation of the connection between stay time and headway variability, Tirachini and Hensher (2021) discovered that erratic headways worsen terminal crowding, which lengthens the boarding and alighting procedures. In a similar vein, Gao *et al*. (2020) modelled the impact of headway on dwell time using real-time data from metropolitan bus systems and showed that lowering headway variability considerably shortens average dwell times. Some studies examined headway management approaches in order to reduce its influence. Delgado *et al.* (2019) suggested adaptive control techniques for headway stabilization, emphasizing how well they work to cut down on excessive dwell periods brought on by an unequal passenger distribution. This implies that resolving headway anomalies might improve service dependability and expedite terminal operations.

A number of variables, such as fare payment methods, passenger demographics, and the volume of passengers boarding, affect boarding time, which in turn affects dwell time. According to research by Liu *et al*. (2020), contactless payment methods result in lower dwell times by drastically cutting down on boarding time as compared to cash transactions. Their research showed that using smart card payment methods reduced boarding times by 15 % - 20 %. Another important factor is passenger conduct. In their investigation into the effects of passenger queuing systems, Ma *et al*. (2022) discovered that well-organized boarding techniques decreased boarding time by reducing passenger disputes. Additionally, Yu *et al*. (2021) noted that older and disabled passengers had higher boarding times, highlighting the impact of passenger age and mobility levels on boarding speed. These results highlight the necessity of effective boarding procedures and inclusive design at bus terminals.

The number of seats and standing spaces on a bus determines how quickly people can board and disembark, which in turn impacts dwell time. Due to higher passenger volumes, high-capacity buses frequently have longer dwell periods. In a simulation-based study, Wang *et al*. (2021) investigated the connection between dwell time and bus capacity and found that although larger buses can carry more passengers, they also experience longer delays during rush hours. On the other hand, methods to maximize capacity usage can lessen these delays. In order to increase efficiency, Zhang and Guo (2023) suggested implementing dynamic capacity allocation such as modifying bus schedules in response to current demand can reduce overcrowding and shorten dwell times while matching capacity with demand. According to Chen *et al.* (2020), bus layout has a crucial role in enabling effective passenger movement. Their research revealed that layouts that encourage unobstructed passageways and sufficient standing room reduce boarding and alighting delays, which in turn leads to shorter dwell durations.

Although headway, boarding time, and bus capacity all have an impact on dwell time on their own, they frequently compound one other's effects. In order to examine these interdependencies, studies are increasingly using integrated techniques. Sun *et al.* (2022) created a multivariate model to forecast dwell periods that included headway, boarding time, and bus capacity. Their results highlighted the combined impact of high passenger volumes and unpredictable headways on dwell time, especially during peak hours. In a similar vein, Lee et al.'s field tests from 2021 showed that coordinated interventions, like enhancing boarding systems and optimizing headway, resulted in larger stay time reductions than separate actions. Because dwell duration determinants are complex, these findings support the use of comprehensive approaches.

Technological developments provide new ways to address dwell time problems. To improve operations, artificial intelligence (AI) and Internet of Things (IoT) technologies are being used more and more. Kim et al. (2023), for instance, forecasted passenger demand using AI-driven predictive analytics, allowing for dynamic headway and capacity modifications. The average dwell times on all evaluated routes were reduced by 12% as a result of their strategy. According to Zhang *et al*. (2022), IoT-based technologies also make it easier to monitor boarding procedures in real time. These technologies give operators useful information that they can use to identify bottlenecks and modify schedules. Additionally, although their implementation is still in the experimental phase, autonomous buses with automatic boarding systems have the potential to decrease delays caused by people (Li *et al*., 2023).

Notwithstanding these developments, difficulties still exist. It takes a significant financial commitment and stakeholder collaboration to integrate new technology into current systems. Moreover, future research and implementation must continue to prioritize quality of service ensuring fairness in service improvements, especially for underprivileged communities.

II. METHODOLOGY

The passengers and buses data used in this study was collected at Terminal 3 of Oshodi Transport Interchange (OTI). The Terminal is situated on Latitude 6.55659° (6° 33' 24") North; and Longitude 3.35271° (3° 21' 10") East at the junction of Apapa-Oworonshoki expressway and Agege motor way in Oshodi, Lagos State Nigeria (Plate 1). The terminal is the most active of the three terminals situated at Oshodi Transport Interchange. A total of 481 records of bus arrival and departure times, boarding start and end times, number of on-board passengers were taken at the terminal during data collection on 21st - 30th August 2024, and 18th - 22nd November 2024 (Elufowoju, 2025).

The headway, boarding time and dwell time were derived from the data collected by finding the difference between consecutive bus arrival times (headway), the difference between boarding start and end times (boarding time), and the difference between bus arrival and departure times (dwell time). The total number of passengers on board every of the buses was also recorded at departure. Statistical analyses including Pearson correlation was used to establish the relationship between dwell time (dependent variable) and the independent variables (headway, boarding time and number of passengers). Regression analysis was used to further examine relationship between the dependent and independent variables in order to establish the level of influence of each independent variable on the dependent variable. Also, diagnostic tests (multicollinearity, linearity assumptions and homoscedasticity check) were performed on the outcome of the regression analysis in order validate it.

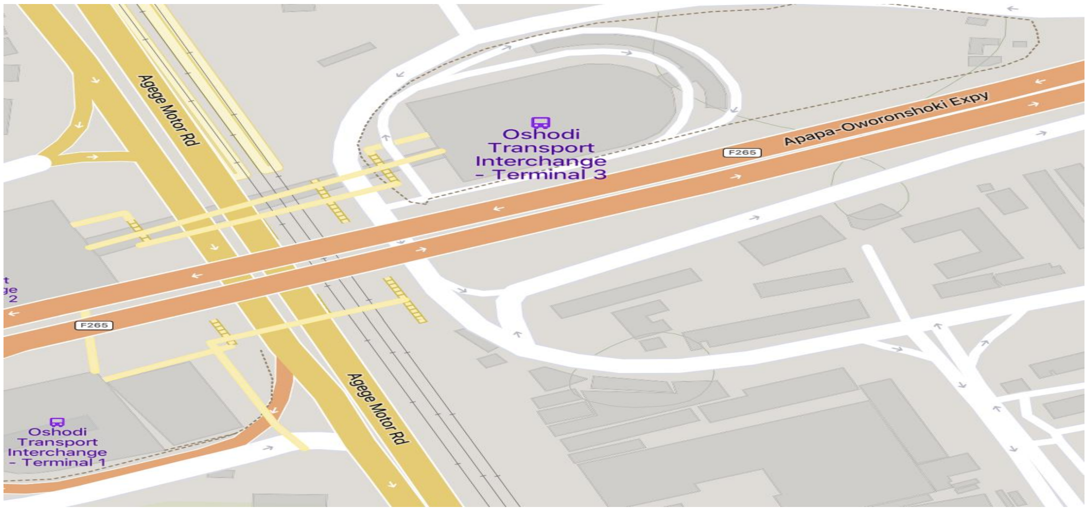

Plate 1, showing location of terminal 3, OTI

III. RESULT AND DISCUSSION

The sections presents the interpretation of the outcome of the statistical analyses which examined the relationships between the dependent variables (dwell time) and the independent variables (headway, boarding time and number of passengers).

A. DESCRIPTIVE STATISTICS

Table 1 presents the descriptive statistics of the data analyzed. The mean values and standard deviations indicate that buses experience substantial variation in stop durations, passenger volumes, and boarding times, which could impact overall bus operation efficiency (Furth & Day, 1985; Tirachini, 2012). Also, the high standard deviations suggest possible outliers or a non-normal distribution, which requires further investigation.

Table 1. Descriptive statistics of variables

Variables	Total No.	Mean	Standard Deviation
Dwell Time	480	67.8500	98.43374
Headway	480	11.2646	13.73652
No. of Passengers	480	48.9875	13.00104
Boarding Time	480	10.9792	12.34032

B. NORMALITY OF RESIDUALS

The result of the K-S test is presented in Table 2 which shows that all variables significantly deviate from a normal distribution ($p < 0.001$). The distribution of the data for each variable negates the assumption of normality (i.e., $p \geq 0.05$), confirming that the data does not follow a normal distribution (Razali & Wah, 2011). While normality is not a strict requirement for regression, large deviations could impact the accuracy of significance tests (Lumley et al., 2002). The large sample size ($N = 480$) mitigates the impact of non-normality, making the statistical inferences reliable.

Table 2: Result of Kolmogrov-Smirnov (K-S) test

Variable	K-S Statistics	p-value	Decision
Dwell Time	0.272	0.000	Not Normal
Headway	0.206	0.000	Not Normal
No. of Passengers	0.073	0.000	Not Normal
Boarding Time	0.263	0.000	Not Normal

Fig. 1, indicate that the histogram of standardized residuals shows slightly skewed distribution, but not severe enough to invalidate the regression model. Also, the Normal P-P plot of regression residuals (Fig. 2) suggests mild deviations from normality.

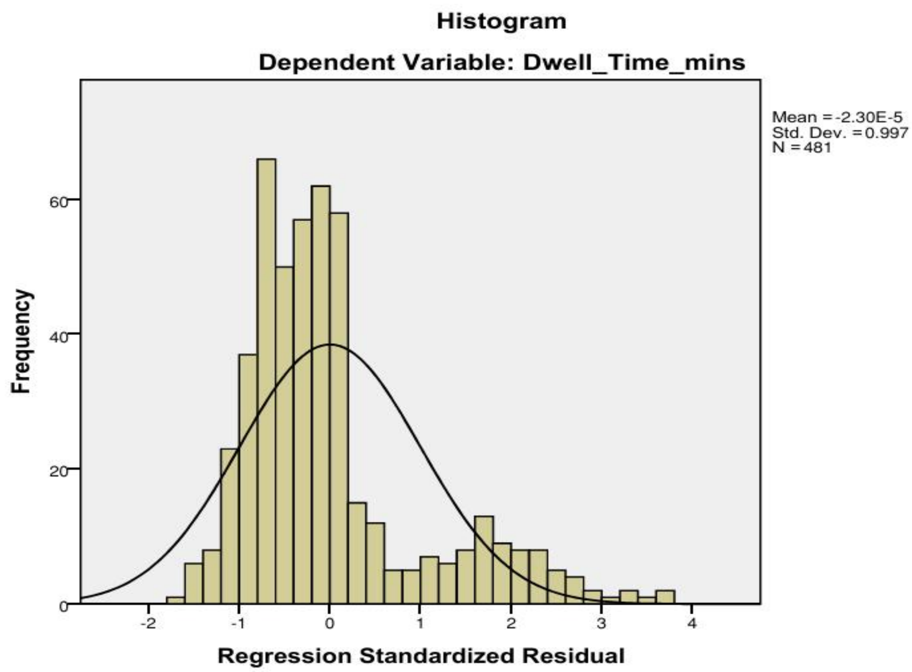

Fig. 1. Histogram of regression standard residuals

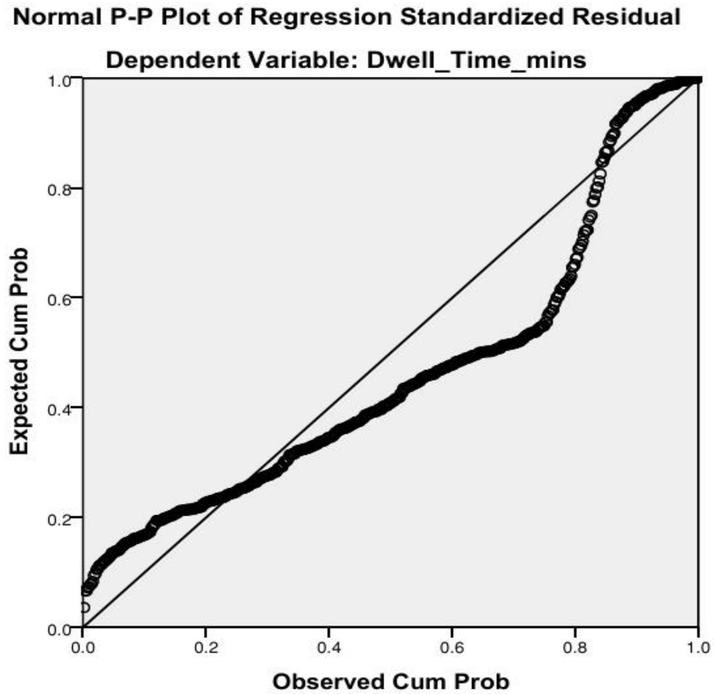

Fig. 2. Normal P-P plot of regression residuals

C. CORRELATION ANALYSIS

Table 3 below presents the outcome of the Pearson correlation analysis. The strength and direction of linear relationships among the variables are discussed in this section. The analysis showed that dwell time is significantly correlated with number of passengers ($r = 0.343$, $p < 0.001$) and boarding time ($r = 0.226$, $p < 0.001$). This suggests that higher passenger volumes, and prolonged boarding processes are associated with longer dwell times.

Table 3. Result of Pearson correlations and significance test

Test	Variables	Dwell Time	Headway	No. of Passengers	Boarding Time
Pearson	Dwell Time (mins)	1.000			
	Headway (mins)	-0.193	1.000		
	No. of Passengers	0.343	-0.361	1.000	
	Boarding Time (mins)	0.226	-0.071	0.005	1.000
Significance (1-tailed)	Dwell Time (mins)	-			
	Headway (mins)	0.000	-		
	No. of Passengers	0.000	0.000	-	
	Boarding Time (mins)	0.000	0.060	0.461	-
Data Size		480	480	480	480

Likewise, an increase in boarding passengers can lead to longer bus dwell times, affecting the overall schedule and efficiency of the bus service (Sun & Hickman, 2005). The statistical significance ($p < 0.001$) confirms that these relationships are not based on random variations but they reflect an inherent operational challenge in transit systems. In essence, higher passenger volumes lead to congestion during boarding and alighting, thereby prolonging bus dwell time.

Headway shows significant but negative correlation with dwell time ($r = -0.193$, $p < 0.001$) and number of boarding passengers ($r = -0.361$, $p < 0.001$). This implies that bus dwell time at terminals seems to be shorter when buses arriving frequently, i.e., when headway is shorter; more passengers could be encouraged to board, because they do not have to experience long waits thus improving passenger satisfaction and service reliability (UITP, 2023). Also, Gao *et al*. (2020), also reported that frequent bus arrivals lead to a more evenly distributed passenger load across multiple vehicles. This agrees with Soza-Parra *et al.* (2022) who identifies irregular dispatching at terminals as a primary contributor to headway irregularity which often result in congestion and increase in dwell time due to crowding of buses, this could be mitigated by effective management by transit agencies to balance headway optimization with demand fluctuations in order to avoid excessive passenger buildup. According to Sun *et al*. (2022), implementing dynamic headway control could help to address these issues by adjusting bus arrivals based on live passenger data. The statistical significance of this result underscores the operational trade-off that transit agencies must consider when reducing headways to improve service frequency. While shorter headway can enhance service reliability and reduce passenger waiting time, it can also contribute to terminal congestion, leading to increase in bus dwell time. Delgado *et al*. (2019) proposed that transit agencies could implement adaptive scheduling techniques that adjust bus arrivals based on real-time passenger demand.

The result of the correlation between boarding time and number of boarding passengers present an insignificant association between the two variables ($r = 0.005$, $p = 0.461$). This indicates that the number of boarding passengers alone does not significantly affect boarding time. The lack of a significant correlation suggests that other factors, such as fare payment methods, boarding practices, and passenger demographics, may play a more dominant role in influencing boarding time than passenger volume alone. Yu *et al*. (2021) emphasized that passenger age and mobility levels significantly affect boarding speeds, implying that transit agencies should consider inclusive design strategies that cater to different passenger needs.

While the correlation results provide preliminary information about the relationship among the variables; a further examination of their association through regression analysis is necessary to assess the relative influence of these variables on dwell time.

D. REGRESSION ANALYSIS

Multiple linear regression analysis was used to assess the influence of headway, number of boarding passengers, and boarding time on dwell time. The following inferences were drawn from the outcome of the regression analysis. Tables 4 and 5, shows the summary of regression analysis and the coefficients obtained in further examining the influence of the variables on dwell time.

Model 1 in Table 4 considered number of boarding passengers as the only predictor of dwell time. The adjusted R^2 is 0.116, indicating that 11.6 % of the variance in dwell time is explained by the number of boarding passengers. While model 2, considered both number of boarding passengers and boarding time as predictors. The adjusted R^2 obtained was 0.164; meaning that both variables jointly explain 16.4 % of the variability in dwell time; this is an improvement over model 1. Therefore, the number of boarding passengers and boarding time are significant predictors of dwell time, while headway was excluded due to insignificance ($p = 0.165$). The exclusion of headway suggests that bus arrival intervals alone do not significantly influence dwell time, contrary to some studies on bus bunching (Furth & Muller, 2000).

Table 4. Regression Analysis Summary[c]

del	R	R^2	Adjusted R^2	Standard Error of the Estimate	Change Statistics					Dubin-Watson
					R^2 Change	F Change	df	df2	Sig. F Change	
1				92.57231			1	478	0.000	-
2				4			1	477	0.000	

a. Predictors: (Constant), No. of Passengers

b. Predictors: (Constant), No. of Passengers, Boarding Time (mins)

c. Dependent Variable: Dwell time

D1. STATISTICAL SIGNIFICANCE OF RELATIONSHIPS

The results in Table 5 indicate that the unstandardized coefficients for number of boarding passengers (B = 2.586, $p < 0.001$) and boarding time (B = 1.790, $p < 0.001$) are statistically significant, demonstrating a strong association with dwell time. The significance levels (p-values) being less than 0.05 confirm the reliability of these findings, implying that the probability of these relationships occurring by chance is minimal (Field, 2018). However, headway did not exhibit statistical significance (p = 0.165), suggesting that variations in headway do not meaningfully influence dwell time in the observed dataset. The 95 % confidence intervals for the coefficients of number of boarding passengers (1.965 to 3.208) and boarding time (1.135 to 2.444) further validate the robustness of these relationships, as they do not include zero, reinforcing the presence of a genuine effect (Gujarati & Porter, 2009).

Table 5. Coefficients[a]

	Predictors	Unstandardized Coefficients		Standardized Coefficients			95 % Confidence Interval for B	
		B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound
1	(Constant)	-59.229	16.488		-.3,592	0.000	-91.628	-26.831
	No. of Passengers	2.594	0.325	0.343	7.974	0.000	1.955	3.233
2	(Constant)	-78.502	16.425		-4.780	0.000	-110.776	-46.229
	No. of Passengers	2.586	0.316	0.342	8.178	0.000	1.965	3.208
	Boarding Time	1.790	0.333	0.224	5.371	0.000	1.135	2.444

a. Dependent Variable: Dwell Time

D2. EFFECT SIZE AND RELATIONSHIP STRENGTH

Considering Table 5, the coefficients (i.e., B values) suggest that for each additional passenger, dwell time increases by 2.586 minutes, while for every additional minute of boarding time, dwell time rises by 1.790 minutes. The standardized coefficients (β values) indicate that number of boarding passengers (β = 0.342) has a stronger relative effect on dwell time compared to boarding time (β = 0.224). The adjusted R^2 value of 0.164 implies that the model explains 16.4 % of the variance in dwell time, which, while moderate, suggests that other unaccounted factors contribute to dwell time variability (Kutner *et al*., 2005). Despite the relatively low R^2, the statistical significance of the predictors indicates meaningful relationships rather than mere random associations.

E. DIAGNOSTIC CHECKS

Diagnostic checks were run on the regression equation (model) in order to ensure that the assumptions of the regression analysis are met. i.e., to identify any issues that could affect the validity and reliability of the model in accessing the relationship between the dependent variable and the independent variables. The diagnostic checks and the results are discussed on this section.

E1. MULTICOLLINEARITY ASSESSMENT

Multicollinearity among predictor variables can inflate standard errors, reducing the reliability of coefficient estimates (O'Brien, 2007). The Variance Inflation Factor (VIF) values for number of boarding passengers (1.000) and boarding time (1.000) indicate no problematic multicollinearity, Hair *et al*. (2014) stipulates that VIF values below 5.0 are generally considered acceptable. This suggests that the predictor variables in the model are sufficiently independent of one another. According to Kim (2019), condition indices above 30 generally signal severe multicollinearity, while values below 10 are considered moderate multicollinearity. The condition index for this study remains below critical thresholds, confirming that the variables are independent and do not distort the regression estimates. By ensuring low VIF values and an acceptable condition index, the regression model provides stable and unbiased parameter estimates, bringing about more reliable interpretations and predictions.

E2. LINEARITY ASSUMPTION CHECK

Linear regression assumes a linear relationship between predictor and dependent variables. An examination of the scatterplots reveals a moderate positive association between dwell time and number of passengers (Fig.s 3) and dwell time and boarding time (Fig.s 4), aligning with prior research on transit operations (Furth & Day, 1985). The residual vs. fitted plot indicates that residuals are randomly distributed around zero, supporting the assumption of linearity. The presence of a pattern in residual plots would have suggested model misspecification, but no such pattern is observed.

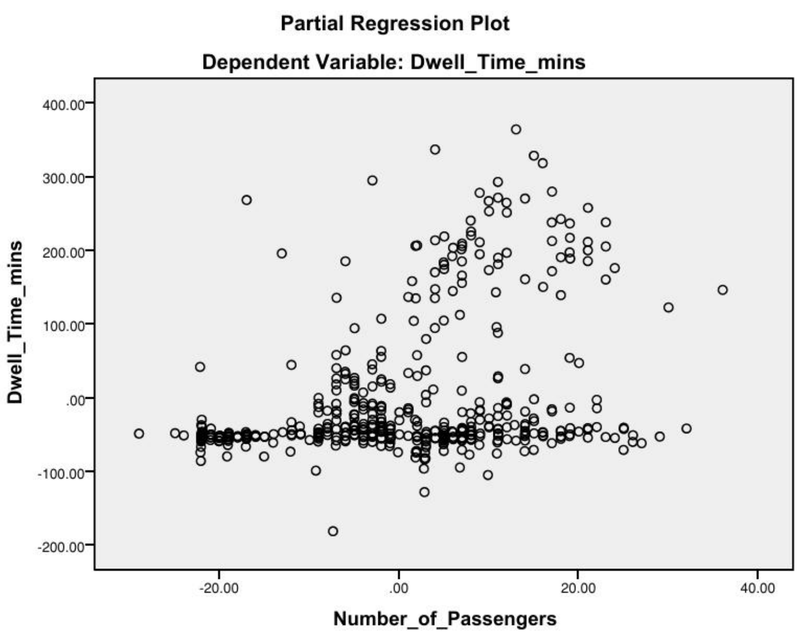

Fig. 3. Partial regression plot (dwell time vs. number of passengers)

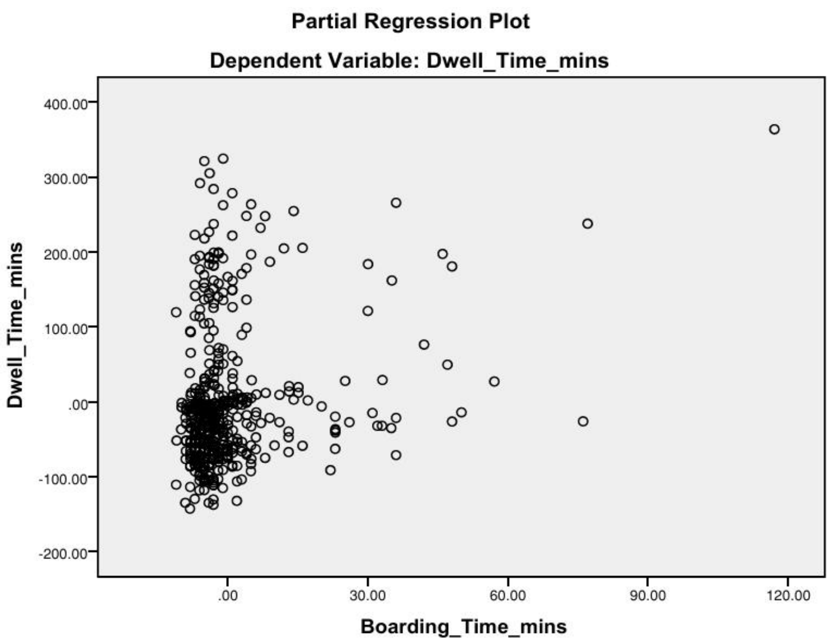

Fig. 4. Partial regression plot (dwell time vs. boarding time)

The ANOVA linearity test (Table 6) shows that F-value of the relationship between dwell time, boarding time and number of passengers is 48.05. This large value is corroborated by the statistical significance ($p < 0.001$), confirming a valid linear association. The partial regression plots (Fig.s 3 & 4) show a roughly linear relationship, supporting the appropriateness of the regression model.

Table 6. ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	544843.187	1	544843.187	63.578	0.000[b]
	Residual	4096284.013	478	8569.632		
	Total	4641127.200	479			
2	Regression	778453.597	2	389226.799	48.065	0.000[c]
	Residual	3862673.603	477	8097.848		
	Total	4641127.200	479			

a. Dependent Variable: Dwell Time
b. Predictors: (Constant), No. of Passengers
c. Predictors: (Constant), No. of Passengers, Boarding Time

E.3 HOMOSCEDASTICITY CHECK

It was observed that the residuals are evenly distributed in the scatterplots (Fig.s 3 & 4), thus indicating there is no significant heteroscedasticity. The absence of funnel-shaped patterns in the residual plots suggests that variance remains relatively constant across different levels of dwell time. This confirms that the regression model satisfies the homoscedasticity assumption, ensuring that the standard errors of estimates remain valid (Gujarati & Porter, 2009).

IV. CONCLUSION

The statistical analysis confirms that number of passengers and boarding time significantly influence dwell time, while headway does not exhibit a direct impact on dwell time. The findings align with existing research on bus dwell time determinants, emphasizing passenger-related factors as the primary contributors (Dueker *et al*., 2004; Tirachini, 2012). The model satisfies key regression assumptions, making the results statistically reliable despite the presence of some non-normality. Future studies may explore additional factors such as fare collection methods, alighting time, or route characteristics to enhance the explanatory power of the model.

Therefore, reducing bus boarding time and effective passenger management are very important considerations for transit managers and planners seeking to reduce bus dwell time as a way of improving operational efficiency and passenger satisfaction at stops and terminals.

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CONFLICT OF INTEREST

There is no conflict of interest associated with this work.

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