JTH: Journal of Technology and Health *ISSN 3025-1168*
Vol. 4, No. 1, 2026, pp. 875 ~ 891
Open Acces: *https://doi.org/10.61677/jth.v4i1.861*

ANALYSIS OF COMPOUNDED MEDICATION WAITING TIME IN OUTPATIENT SERVICES AT NENE MALLOMO REGIONAL GENERAL HOSPITAL, SIDENRENG RAPPANG REGENCY, 2026

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Received June 6, 2026; Revised July 21, 2026; Accepted July 25, 2026; Published July 27, 2026

ABSTRACT

Timeliness of compounded medication dispensing is an important indicator of outpatient pharmacy quality. The 2024 Internal Quality Report of Nene Mallomo Regional General Hospital showed that only 47% of compounded prescriptions met the hospital target, while the national maximum waiting-time standard is 60 minutes. This study examined the association of service hours and prescription volume with compounded medication waiting time in the hospital's outpatient pharmacy. An analytical observational study with a cross-sectional design used total sampling of 290 compounded-prescription visits recorded from January to March 2026. Secondary data were obtained from pharmacy service reports and the Hospital Management Information System. Univariate analysis, bivariate regression, classical-assumption testing, and multiple linear regression were performed; skewed prescription-volume and waiting-time data were transformed using natural logarithms for the adjusted model. In bivariate analysis, service hours were associated with waiting time ($p = 0.040$), and high prescription volume was associated with longer waiting time ($p = 0.023$). In the adjusted model, prescription volume remained significantly associated with waiting time ($B = 0.132$; $p = 0.023$), whereas service hours did not ($B = -0.110$; $p = 0.051$). The model was significant overall ($p = 0.012$) but explained only 3.0% of waiting-time variation. Prescription volume was therefore the only significant predictor in the adjusted model. Workload-based staffing, a dedicated compounded-prescription flow, advance preparation of frequently used materials, and HMIS-based monitoring are recommended, while other operational determinants should be examined in future studies.

Keywords: *Compounded medication waiting time, outpatient pharmacy services, prescription volume, service hours, pharmacy service quality.*

INTRODUCTION

Healthcare services are a fundamental component of global development aimed at improving the health status of the community. The World Health Organization (WHO) emphasizes that access to quality healthcare services must include aspects of availability, affordability, and timeliness of services. Timeliness of service is an important indicator in assessing the overall performance of the health system. Delays in service can directly affect patients' quality of life as well as the effectiveness of the therapy provided (World Health Organization, 2022, 2025).

The issue of waiting time in healthcare services remains a global concern, including in developed countries such as the United Kingdom. NHS England data show that approximately 7.3 million patient cases were still on the waiting list to begin treatment by the end of 2025. In Indonesia, the national service target expects most patients to receive services within less than 18 weeks; however, actual achievement has remained below the expected target. This gap shows that waiting time is not merely an administrative delay but a quality-of-care problem because it can reduce service responsiveness, prolong patient flow, increase dissatisfaction, and weaken public trust in healthcare services (British Medical Association, 2026; NHS England, 2026; Wood et al., 2025).

The healthcare service system in Indonesia has expanded substantially since the implementation of the National Health Insurance program (Jaminan Kesehatan Nasional/JKN), managed by BPJS Kesehatan. By 30 June 2024, JKN membership had reached 273.5 million people, equivalent to 96.8% of Indonesia's population. This high coverage increases service utilization and the operational burden on healthcare facilities. Hospitals therefore require service systems that are not only accessible but also efficient, timely, and responsive to outpatient needs (BPJS Kesehatan, 2024; Purba & Ediyono, 2025; Putri et al., 2025).

Along with the increasing number of patient visits, waiting time has become a common problem in various healthcare facilities in Indonesia. Long waiting times remain a major complaint among patients, both in hospitals and other healthcare facilities. This condition indicates an imbalance between the number of patients and the available service capacity. In outpatient pharmacy services, prolonged waiting time may delay medication use, increase patient crowding, disrupt service flow, and reduce the perceived quality of pharmaceutical care (Rebecawati et al., 2024; Supriyati & Kusumaningsih, 2023; Zulaika et al., 2022).

The pharmacy installation is one of the units in hospital services that plays an important role in supporting the patient recovery process. Pharmacy services not only focus on the provision of medicines but also serve as an indicator of the overall quality of healthcare services. One indicator used to assess the quality of pharmacy services is medication service waiting time. Excessively long waiting times can lead to patient dissatisfaction and reduce the quality of hospital services (Maahury & Basabih, 2025; Pasaribu et al., 2020; Yoseva & Andriani, 2025).

Indonesia has established quality standards for pharmacy services through the Decree of the Minister of Health of the Republic of Indonesia Number 129/Menkes/SK/II/2008 concerning Minimum Hospital Service Standards, which regulates a maximum waiting time of 30 minutes for non-compounded prescriptions and 60 minutes for compounded prescriptions (Ministry of Health of the Republic of Indonesia, 2008). However, in practice, many hospitals are still unable to achieve these standards. This indicates a gap between service standards and actual conditions in the field (Afqary et al., 2023; Arini et al., 2020; Lasaib et al., 2025; Shulihah, 2024).

Pharmacy service waiting time has also been proven to have a close relationship with patient satisfaction levels. Studies show that the longer the waiting time, the lower the level of patient satisfaction with the services provided. Conversely, fast and efficient services can increase patients' trust and loyalty toward the hospital. Therefore, controlling waiting time is very important in improving the quality of healthcare services (Arfania et al., 2022; Halomoan et al., 2025; Sulo, 2020).

The problem of waiting time for medication services in Indonesia is influenced by various factors, both internal and external. Internal factors include the limited number of pharmacy personnel, suboptimal service flow, and limited facilities and infrastructure. Meanwhile, external factors include the high number of patients and the daily prescription workload that must be served. The combination of these factors leads to increased waiting time in pharmacy services (Mumtaz et al., 2025; Utami & Dhamanti, 2025).

A study by Pasaribu et al. (2020) stated that the number of pharmacy personnel is one of the main factors, where an imbalance between the number of personnel and workload can increase waiting time to more than 60 minutes. Furthermore, Yustina et al. (2025) found that prescription type also affects waiting time, with compounded prescriptions having a longer average waiting time of around 65 minutes compared to ready-made medicines, which only take around 30 minutes. A study by Meila et al. (2020) stated that service hours also affect waiting time, where during peak hours (11:00 a.m.–2:00 p.m.) there is an increase in the number of prescriptions received simultaneously, resulting in queue buildup and service delays (Nurhaliza et al., 2025; Yulianti & Lakoan, 2023).

Theoretically, pharmacy service waiting time can be explained through Donabedian's quality-of-care theory, which states that quality is influenced by structure, process, and outcome. In this study, service hours and the number of prescriptions are included in the structural components that affect the pharmacy service process, from prescription reception to medication compounding, thereby producing an outcome in the form of waiting time. In addition, WHO, through the Quality of Care Framework, emphasizes that timeliness is an important indicator in assessing healthcare service quality. Therefore, compounded medication waiting time can be used to assess service quality while also reflecting the condition of the service being delivered (Donabedian, 1980; Phommachanh et al., 2019).

The 2024 Quality Report of Nene Mallomo Regional General Hospital, as one of the main referral hospitals in Sidenreng Rappang Regency, shows that the waiting time for compounded prescription services still has not met the standard, especially during peak service periods (Nene Mallomo Regional General Hospital, 2024). Based on data from the Pharmacy Installation, the hospital set an internal target for compounded medication waiting time of 39.25 minutes, which is stricter than the national standard. However, actual achievement showed that only 47% of compounded prescriptions were completed according to the target. This discrepancy indicates a gap between service capacity and daily workload, particularly when the volume of compounded prescriptions increases. Therefore, this study aimed to analyze the association of service hours and prescription volume with compounded medication waiting time in outpatient services at Nene Mallomo Regional General Hospital, Sidenreng Rappang Regency, in 2026.

The novelty of this study lies in isolating compounded prescriptions as a distinct outpatient workflow and examining whether service-hour patterns remain associated with waiting time after prescription volume is taken into account. Recent Indonesian studies have mainly evaluated overall prescription waiting time, patient satisfaction, prescription type, or broad service-flow problems (Runggandini et al., 2021; Aisyah et al., 2023; Rahmi et al., 2024; Mumtaz et al., 2025; Pinem et al., 2025). In contrast, this study uses HMIS-based records from a regional public hospital to distinguish the unadjusted association of peak service periods from the adjusted contribution of prescription volume. Its practical contribution is a workload-triggered improvement approach in which hourly prescription volume informs staff allocation, dedicated compounded-prescription flow, advance preparation of frequently used materials, and continuous waiting-time monitoring.

RESEARCH METHOD

This study employed a quantitative analytical observational design with a cross-sectional approach. Service-hour category and prescription volume were treated as predictor variables, while compounded medication waiting time was the outcome variable. All variables were derived from records within the same service period; therefore, the findings were interpreted as associations rather than causal effects.

The research was conducted at the Outpatient Pharmacy Installation of Nene Mallomo Regional General Hospital, Sidenreng Rappang Regency. The study focused on outpatient pharmacy services, particularly patients who received compounded medications during the research period. The population in this study consisted of all outpatient visits that received compounded medication services at the Pharmacy Installation of Nene Mallomo Regional General Hospital from January to March 2026. The total population was 290 outpatient visits. The sampling technique used in this study was total sampling. All outpatient visits that met the inclusion criteria and did not fall under the exclusion criteria were included as research samples. Therefore, the total sample in this study was 290 outpatient visits.

The inclusion criteria were outpatient visits during January–March 2026 that received compounded medication services and had complete records in the pharmacy report and HMIS, including date of service, service-hour category, number of prescriptions, prescription receipt time, medication completion time, and waiting-time status. The exclusion criteria were incomplete or duplicate records, cancelled prescriptions, inpatient or emergency prescriptions, prescriptions without compounded medications, and records with unclear service-time documentation.

The data used in this study were secondary data obtained through documentation studies. Data were collected from compounded prescription service documents, pharmacy service reports, monthly quality reports, and the Hospital Management Information System at Nene Mallomo Regional General Hospital.

The data extraction instrument was a documentation checklist prepared according to the study variables. It included an anonymized visit code, service date, service-hour category, number of compounded prescriptions, prescription receipt time, medication completion time, total waiting time, and on-time service status. Service hours were coded as peak hours = 0 and regular hours = 1. For descriptive presentation, prescription volume was grouped as low load (≤5 prescriptions) and high load (>5 prescriptions); the continuous prescription count was retained for the adjusted regression model. Data accuracy was verified by cross-checking pharmacy service documents with HMIS records and monthly quality reports, removing duplicate entries, and confirming unclear records with the pharmacy service administrator before analysis.

Data analysis included univariate, bivariate, and multivariate procedures. Bivariate associations were examined using simple regression with the coded service-hour and prescription-load categories. Before the adjusted model was interpreted, residual normality, multicollinearity, and heteroscedasticity were assessed. Because the initial residuals were not normally distributed, natural-logarithm transformation was applied to the continuous prescription count and waiting-time variables. Multiple linear regression was then used to estimate the adjusted associations of service hours and prescription volume with compounded medication waiting time. A two-sided p value <0.05 was considered statistically significant.

RESULTS AND DISCUSSION

Results

Univariate Analysis

Univariate analysis was conducted to describe service hours, prescription volume, and compounded medication waiting time. The frequency distribution of compounded prescription services according to service hours is presented in Table 1.

Table 1. Frequency Distribution of Service Hours

Service Hours	Frequency	Percentage (%)
Peak hours	118	40.7
Regular hours	172	59.3
Total	290	100

Source: Secondary Data, 2026

Table 1 shows the results of the univariate analysis of the service hours variable. Of the total 290 compounded prescription services, most services were provided during regular hours, namely 172 services (59.3%), while 118 services (40.7%) were provided during peak hours. These results indicate that compounded prescription services in the outpatient pharmacy installation occurred more frequently during regular hours than during peak hours. Nevertheless, the proportion of services during peak hours was still relatively high, accounting for nearly half of the total services. This condition indicates that pharmacy service activities remained quite busy at certain times, which could potentially affect the service process and the waiting time for compounded medications.

Table 2. Statistical Distribution of Number of Prescriptions

Number of Prescriptions	Frequency	Percentage (%)
Low load (≤5 prescriptions)	101	34.8

High load (>5 prescriptions)	189	65.2
Total	290	100

Source: Secondary Data, 2026

Table 2 shows that of the total 290 compounded prescription services, most were included in the high prescription load category (>5 prescriptions), namely 189 services (65.2%), while 101 services (34.8%) were included in the low prescription load category (≤5 prescriptions). These results indicate that outpatient pharmacy services at Nene Mallomo Regional General Hospital were dominated by a relatively high prescription volume. This condition indicates a considerable service burden in the pharmacy installation, which could potentially affect the efficiency of the service process and the length of waiting time for compounded medications.

Table 3. Frequency Distribution of Compounded Medication Waiting Time

Waiting Time	Frequency	Percentage (%)
On time	170	58.6
Not on time	120	41.4
Total	290	100

Source: Secondary Data, 2026

Based on Table 3, the frequency distribution of the waiting time variable shows that of the total 290 compounded prescription services, 120 services (41.4%) were not completed on time. Meanwhile, 170 services (58.6%) were completed on time. These results indicate that although most services were completed on time, the proportion of services that were not completed on time was still quite high and therefore requires attention in efforts to improve the quality of outpatient pharmacy services.

Table 4. Statistical Distribution of Waiting Time Variable

Variable	N	Minimum	Maximum	Mean	Std. Deviation
Waiting Time	290	9	140	58.14	26.089

Source: Secondary Data, 2026

Based on Table 4, the average waiting time for compounded medications in outpatient services at Nene Mallomo Regional General Hospital was 58.14 minutes, with a standard deviation of 26.09 minutes. This indicates that, in general, the waiting time for compounded medication services was close to the minimum hospital service standard limit of ≤60 minutes. However, there was still considerable variation in waiting time among patients. The shortest waiting time recorded was 9 minutes, while the longest waiting time reached 140 minutes. This difference in waiting time indicates that the compounded medication service process had not been carried out consistently in every service period. Variations in waiting time may be influenced by several factors, such as the high number of prescriptions received, service density at certain hours, the complexity of medication compounding, and the workload of pharmacy personnel in providing services to outpatients.

Classical Assumption Test

Normality Test

Table 5. Results of the One-Sample Kolmogorov-Smirnov Normality Test

Unstandardized Residual	Value
Kolmogorov-Smirnov Z	0.082
Asymp. Sig. (2-tailed)	0.000

Source: Secondary Data, 2026

Based on Table 5, the Kolmogorov-Smirnov test produced a residual significance value of 0.000 ($p < 0.05$), indicating that the initial residuals were not normally distributed. Natural-logarithm transformation was therefore applied to the continuous prescription-count and waiting-time variables before multiple linear regression analysis.

Table 6. Normality Test after Transformation

Unstandardized Residual	Value
Kolmogorov-Smirnov Z	0.053
Asymp. Sig. (2-tailed)	0.051

Source: Secondary Data, 2026

Table 6 shows that after transformation, the normality test produced an Asymp. Sig. (2-tailed) value of 0.051. Since this value was greater than the significance level of 0.05, the residual data were normally distributed. Thus, the data met the normality assumption and could be used for multiple linear regression analysis.

Multicollinearity Test

Table 7. Results of the Multicollinearity Test Coefficients

Model	Tolerance	VIF
Service hours	1.000	1.000
Number of prescriptions	1.000	1.000

Source: Secondary Data, 2026

Based on the results of the multicollinearity test in Table 7, the service hours and number of prescriptions variables each had a tolerance value of 1.000 and a Variance Inflation Factor (VIF) value of 1.000. These results indicate that there was no multicollinearity, as tolerance >0.10 and VIF <10. Therefore, the service hours and number of prescriptions variables were suitable for use in the regression model for further analysis.

Table 8. Results of Heteroscedasticity Test Using the Glejser Test

Variable	Sig.
Constant	0.000

Service hours	0.425
Number of prescriptions	0.590

Source: Secondary Data, 2026

Based on the results of the heteroscedasticity test in Table 8, the significance value of the service hours variable was 0.425, and the number of prescriptions variable was 0.590. Since all significance values were >0.05, the regression model did not experience heteroscedasticity. Thus, after the normality, multicollinearity, and heteroscedasticity tests were presented, the residual variance was homogeneous, and the regression model met the classical assumptions required for further regression analysis.

Bivariate Analysis

Association between Service Hours and Waiting Time

Table 9. Bivariate Association between Service Hours and Waiting Time

Variable	Coefficients	Std. Error	T	Sig.
Constant	68.324	5.170	13.215	0.000
Service hours	-6.392	3.101	-2.061	0.040

Source: Secondary Data, 2026

Table 9 shows a significant bivariate association between service-hour category and compounded medication waiting time ($B = -6.392$; $t = -2.061$; $p = 0.040$). Because peak hours were coded 0 and regular hours were coded 1, the negative coefficient indicates that services during regular hours had an estimated waiting time 6.392 minutes shorter than services during peak hours. Thus, compounded prescriptions processed during peak hours tended to require more time.

Association between Prescription Load and Waiting Time

Table 10. Bivariate Association between Prescription Load and Waiting Time

Variable	Coefficients	Std. Error	T	Sig.
Constant	46.090	5.488	8.398	0.000
Number of prescriptions	7.296	3.192	2.286	0.023

Source: Secondary Data, 2026

Table 10 shows a significant bivariate association between prescription-load category and compounded medication waiting time ($B = 7.296$; $t = 2.286$; $p = 0.023$). The positive coefficient indicates that the high-load category had an estimated waiting time 7.296 minutes longer than the low-load category.

Multivariate Analysis
Multiple Linear Regression

Table 11. Multiple Linear Regression Coefficients

Model	B	Std. Error
Constant	3.915	0.133
Service hours	-0.110	0.056
Ln number of prescriptions	0.132	0.058

Source: Secondary Data, 2026

As presented in Table 11, the adjusted regression model used the natural logarithm of waiting time as the outcome and the natural logarithm of continuous prescription volume together with service-hour category as predictors. The constant was 3.915. The service-hours coefficient was -0.110, indicating that regular hours tended to have a lower adjusted waiting time than peak hours. The coefficient for Ln prescription volume was 0.132, indicating that higher prescription volume was associated with longer waiting time after service hours were controlled.

Because both prescription volume and waiting time were log-transformed, the coefficient for prescription volume can be interpreted approximately as an elasticity: a 1% increase in prescription volume was associated with a 0.132% increase in waiting time, holding service hours constant. This interpretation is more appropriate than describing the coefficient as a fixed increase in minutes.

Table 12. Results of Partial t-Test

Variable	Coefficient (B)	t-value	Sig.
Constant	3.915	29.409	0.000
Service hours	-0.110	-1.956	0.051
Number of prescriptions	0.132	2.281	0.023

Source: Secondary Data, 2026

In Table 12, service hours were not statistically significant after adjustment for prescription volume ($B = -0.110$; $t = -1.956$; $p = 0.051$), although the direction remained consistent with shorter waiting times during regular hours. Ln prescription volume remained significantly and positively associated with Ln waiting time ($B = 0.132$; $t = 2.281$; $p = 0.023$). Prescription volume was therefore the only statistically significant predictor in the adjusted model.

Table 13. Results of Simultaneous Test Calculation (F-Test)

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	1.971	2	0.985	4.457	0.012
Residual	63.452	287	0.221		
Total	65.423	289			

Source: Secondary Data, 2026

Based on the results of the simultaneous test (F-test) in Table 13, the calculated F-value was 4.457, with a significance value of 0.012. Since the significance value was less than 0.05 (0.012 < 0.05), it can be concluded that the service hours and number of prescriptions variables simultaneously had a significant association with waiting time for compounded medication services. Thus, the regression model used in this study was appropriate for explaining the relationship between the independent and dependent variables.

Table 14. Coefficient of Determination (R^2)

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	0.174	0.030	0.023	0.470

Source: Secondary Data, 2026

As shown in Table 14, the model had an R^2 of 0.030 and an adjusted R^2 of 0.023, indicating that service hours and prescription volume explained only 3.0% of the observed variation in compounded medication waiting time. Although the overall model was statistically significant, its explanatory power was low. The findings should therefore be interpreted cautiously, and important unmeasured determinants may include staffing levels, prescription complexity, availability of compounding materials, queue management, facility layout, and HMIS performance.

Discussion

Association between Service Hours and Compounded Medication Waiting Time

The results of the study showed that compounded prescription services occurred more frequently during regular hours than during peak hours. Nevertheless, services during peak hours still accounted for a relatively high proportion, reflecting service congestion at certain times. This condition indicates that the outpatient pharmacy installation experiences periods of service with a higher intensity of patient visits compared to other service times. Descriptive statistical analysis of the waiting time variable also showed variations in service time among patients, indicating that the service process had not been carried out consistently in every service period.

Bivariate regression showed that service-hour category was significantly associated with compounded medication waiting time. Prescriptions processed during peak hours tended to have longer waiting times than those processed during regular hours. During peak periods, patients and prescriptions arrive within a narrower time window, increasing queue density and the simultaneous workload handled by pharmacy personnel.

Compounded prescription services have more complex stages compared to non-compounded medication services. These stages include prescription screening, preparation of ingredients, mixing, and packaging before the medication is handed over to the patient. This complexity makes compounded prescription services highly influenced by service congestion at certain hours. The higher the number of patients arriving at the same time, the greater the possibility of service delays.

In the adjusted multiple linear regression model, service-hour category was no longer statistically significant after prescription volume was included ($p = 0.051$). The attenuation of the association suggests that the longer waits observed during peak hours may be explained largely by the concentration of prescriptions during those periods. The significant F-test indicates that the predictors jointly contributed to the model, although the low R^2 shows that their practical explanatory power was limited.

The coefficient of determination showed that the ability of the variables to explain variations in waiting time was still relatively low. This condition indicates that there are likely other factors outside this study that may also influence service waiting time, such as the number of pharmacy personnel, the complexity of compounded medications, medication availability, and the queuing system. These factors may affect service speed and the efficiency of the dispensing process in the outpatient pharmacy installation.

This phenomenon is consistent with the condition found at Nene Mallomo Regional General Hospital based on the 2024 Quality Report, which showed that compounded prescription services had not optimally achieved the service time target, especially during service periods with high prescription volume (Nene Mallomo Regional General Hospital, 2024). The hospital set an internal waiting time target that was stricter than the national standard, but the achievement of on-time services remained low. This condition illustrates that the efficiency of outpatient pharmacy services still faces several obstacles, especially when there is an increase in the number of patients at certain times.

Within Donabedian's structure-process-outcome framework, peak-hour demand represents an organizational context that places pressure on service capacity and the dispensing process, while waiting time is an outcome indicator. The WHO Quality of Care Framework similarly identifies timeliness and efficiency as central dimensions of service quality. The present findings suggest that peak-hour congestion may influence waiting time primarily through the workload generated during those periods rather than through clock time itself.

The findings of this study are in line with recent studies from the last five years. Rahmi et al. (2024) found that outpatient medication waiting time increased when patient queues accumulated during certain service periods. Nurhaliza et al. (2025) also reported that prescription-service waiting time was influenced by service-flow factors, prescription type, and workload conditions at the pharmacy unit. Yustina et al. (2025) further showed that prescription arrival time and the number of human resources were associated with waiting-time noncompliance in outpatient pharmacy services. These studies support the finding that peak service periods can create queue buildup and slow down the compounded medication service process.

However, the findings of this study are not fully consistent with Amiruddin et al. (2023), who stated that service hours did not have a significant effect on prescription waiting time. Halomoan et al. (2025) also found that the number of prescriptions was not correlated with waiting time when service layout, stock control, and service responsiveness were properly managed. Walujo et al. (2024) showed that the division of work among pharmacy personnel could maintain waiting-time stability despite an increase in service activity. These differences indicate that service hours may affect waiting time only when peak-hour congestion is not supported by adequate staffing, workflow control, and queue management.

Association between Prescription Volume and Compounded Medication Waiting Time

The results of the study showed that most services were included in the high prescription load category. This condition reflects that the outpatient pharmacy installation has a relatively large prescription service volume each day. The high number of prescriptions that must be served indicates that pharmacy personnel have a heavy workload in providing services to outpatients.

Descriptive statistical analysis of the waiting time variable also showed considerable variation in service time among patients, indicating that the high number of prescriptions can affect the length of the pharmacy service process. The greater the number of prescriptions received, the more service stages must be completed by pharmacy personnel at the same time.

Bivariate regression showed that high prescription load was significantly associated with longer compounded medication waiting time. When more prescriptions must be processed concurrently, pharmacy personnel complete a larger number of screening, preparation, compounding, checking, and packaging activities, which can lengthen queues and service time.

Compounded prescription services have more complex stages compared to non-compounded medication services. These stages include prescription review, preparation of medication ingredients, weighing, mixing, and packaging before the medication is handed over to the patient. The high number of prescriptions requires pharmacy personnel to handle many service processes simultaneously, resulting in longer queues and increased patient waiting time. This condition shows that an increased service burden can affect the efficiency of outpatient pharmacy services.

In the adjusted multiple linear regression model, prescription volume remained significantly associated with compounded medication waiting time ($p = 0.023$), whereas service-hour category did not. Prescription volume was therefore the only significant predictor in the adjusted model. However, the low coefficient of determination indicates that this variable explains only a small part of waiting-time variation and should be interpreted together with other operational determinants.

The coefficient of determination showed that the variables in this study were only able to explain a small portion of the variation in service waiting time. This condition indicates that there are likely other factors outside this study that may also influence service delays, such as the number of pharmacy personnel, the complexity of compounded prescriptions, medication availability, and the service queuing system. These factors can affect service speed and the efficiency of the dispensing process in the outpatient pharmacy installation.

This phenomenon is consistent with the findings in the 2024 Quality Report of Nene Mallomo Regional General Hospital, which showed that compounded prescription services had not yet achieved the service time target set by the hospital (Nene Mallomo Regional General Hospital, 2024). The high volume of outpatient services requires the pharmacy installation to handle many prescriptions every day, increasing the service workload and slowing down the medication dispensing process. This condition shows that the number of prescriptions is one of the main factors affecting the efficiency of outpatient pharmacy services at Nene Mallomo Regional General Hospital.

Within Donabedian's framework, prescription volume reflects demand placed on available structural capacity, including personnel, workspace, equipment, and information systems. When demand exceeds operational capacity, dispensing processes become less efficient and waiting-time outcomes worsen. The WHO Quality of Care Framework likewise emphasizes that timely care depends on an appropriate match between service demand and the resources used to deliver care.

The practical benefit of these findings is the use of prescription volume as an operational trigger for capacity planning. Daily and hourly HMIS trends can support workload-based staff scheduling, a dedicated or prioritized flow for compounded prescriptions, advance preparation of frequently used compounding materials, and real-time monitoring of waiting-time performance. These measures are consistent with recent evidence showing that workload control, task allocation, queue redesign, stock readiness, and lean workflow interventions can reduce delays and stabilize outpatient pharmacy services (Runggandini et al., 2021; Rahmi et al., 2024; Walujo et al., 2024; Mumtaz et al., 2025; Pinem et al., 2025; Yoseva & Andriani, 2025). At the managerial level, the results can inform shift planning and quality-improvement targets; at the service level, they may reduce crowding and improve patient experience; and at the policy level, they support the use of routinely collected HMIS data for evidence-based pharmacy governance.

The findings of this study are in line with Aisyah et al. (2023), who found that compounded prescriptions required longer service time than non-compounded prescriptions. Pinem et al. (2025) also showed that high prescription volume and service-flow problems increased outpatient pharmacy waiting time. Huvaid et al. (2023) reported that high prescription volume combined with limited human resources contributed to delays in medication services. Mumtaz et al. (2025) similarly emphasized that prescription waiting time is an important quality indicator in outpatient pharmacy services and may be affected by prescription characteristics and operational workload.

The findings of this study are not in line with Pionita et al. (2024), who showed that variations in the number of medication items in prescriptions did not significantly increase service waiting time. Ekadipta et al. (2022) also found that an increase in the number of prescriptions does not always cause service delays when supported by an effective service system. Runggandini et al. (2021) showed that service management and the division of duties among pharmacy personnel may have a greater influence on waiting time than the number of incoming prescriptions. Therefore, the effect of prescription volume should be interpreted together with operational capacity, pharmacy workflow, and the quality of service management.

Taken together, the study's principal novelty is not merely the confirmation that busy pharmacy services are associated with longer waits. Rather, it shows that prescription volume remained significant after adjustment, whereas service-hour category became marginally non-significant ($p = 0.051$). This distinction suggests that peak hours may function mainly as a proxy for workload and that prescription volume is a more actionable operational indicator. The study therefore extends recent Indonesian evidence by focusing specifically on compounded prescriptions, using routine HMIS data, and translating the adjusted result into a workload-triggered service model. Nevertheless, the low R^2 indicates that the proposed model should complement—not replace—assessment of staffing, prescription complexity, material availability, queue design, and information-system performance.

CONCLUSION

Service hours and prescription load were significantly associated with compounded medication waiting time in the bivariate analyses ($p = 0.040$ and $p = 0.023$, respectively). In the adjusted multiple linear regression model, prescription volume remained significantly associated with waiting time ($B = 0.132$; $p = 0.023$), whereas service hours did not reach statistical significance ($B = -0.110$; $p = 0.051$). The model was significant overall ($p = 0.012$) but explained only 3.0% of waiting-time variation. Prescription volume was therefore the only significant predictor in the adjusted model, but it should not be considered a comprehensive explanation of waiting time. Improving compounded medication services requires workload-based capacity planning together with attention to staffing, prescription complexity, workflow, queue management, stock readiness, facility layout, and HMIS support.

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