e-ISSN : 2597-6052

MPPKI MEDIA PUBLIKASI PROMOSI KESEHATAN INDONESIA

Research Articles

Open Access

Behavioral Drivers of First-Time Blood Donor Retention in Yogyakarta, Indonesia

Mohammad Adam Jerusalem[1]*, Kartika Ratna Pertiwi[2], Agung Wijaya Subiantoro[3], Ummi Fakhriyah Jayatri[4], Dyantika Putry Mahmud[5]

[1]Bachelor Program of Industrial Engineering, Faculty of Engineering, Universitas Negeri Yogyakarta, Yogyakarta, Indonesia
[2]Faculty of Medicine, Universitas Negeri Yogyakarta, Yogyakarta, Indonesia
[3]Faculty of Mathematics and Natural Sciences, Universitas Negeri Yogyakarta, Yogyakarta, Indonesia, Indonesia
[4]Bachelor Program of Industrial Engineering, Faculty of Engineering, Universitas Negeri Yogyakarta, Yogyakarta, Indonesia
[5]Bachelor Program of Industrial Engineering, Faculty of Engineering, Universitas Negeri Yogyakarta, Yogyakarta, Indonesia

***Corresponding Author**: E-mail: adam_jerusalem@uny.ac.id

ARTICLE INFO

Manuscript Received: 30 Nov, 2025
Revised: 20 Mar, 2026
Accepted: 30 Apr, 2026
Date of Publication: 06 May, 2026
Volume: 9
Issue: 5
DOI: 10.56338/mppki.v9i5.9414

KEYWORDS

Blood Supply Chain;
Donor Retention;
Clustering Analysis;
Blood Donation Behavior

ABSTRACT

Introduction: Voluntary blood donor retention is still challenging in blood stock issue, specifically in decentralization system like in Indonesia. Most of previous research has focused on logistic or survey-based study, hence it cannot explain the dynamics of actual donor behavior from time to time. Further, there is a lack of understanding of donor retention as a behavioral process that develops longitudinally. This research aims to identify the first-time donor retention pattern and also demographic characteristics and relevant service context as basis for developing more effective health promotion strategies.
Methods: This research implemented a retrospective longitudinal cohort design based on routine blood donor registration data of 26,170 first-time donors from five Blood Transfusion Units in the Province of Special Region of Yogyakarta during the period 2021–2024. Donor visit trajectories were analyzed using a sequence analysis approach with the optimal matching method and then grouped using the Partition Around Medoids algorithm. Cluster validity was determined using the silhouette and Dunn indeces and further analyzed descriptively and statistically to examine differences in characteristics among groups.
Results: The study found three main donor patterns, i.e. one-time donors, regular donors, and donors who have temporarily stopped donating. City of Yogyakarta has highest retention rate, while Gunung Kidul is dominated by donors-once. Male donors tend to dominant among regular donors, on the contrary female donors are more represented in temporarily stopped donating. The vital finding points out the first 6–12 months engagement after initial donation is strongly associated with donor behavioral intentions.
Conclusion: Blood donor retention is dynamic process that is influenced by demographic characteristics and service context. A limitation of this study is the lack of consideration of psychosocial as a variable. However, the use of actual longitudinal data is a major strength of this study. The managerial implication of this study is that segmentation-based strategies, strengthening interventions in the early phase, and gender-sensitive and community-based approaches are needed to increase donor retention in a sustainable manner.

Publisher: Fakultas Kesehatan Masyarakat Universitas Muhammadiyah Palu

INTRODUCTION

As a prosocial behavior in the health sector, blood donation plays a vital role in health service system. It has direct contribution in saving lives and improving the quality of life of patients both acute and chronic conditions (1). At variance from other medical resources, blood cannot be synthetically produced and is entirely dependent on voluntary public participation. Consequently, blood stock sustainability is absolutely influenced by donors' behavior. Hence, the capacity of the health system to retain regular donors has become crucial.

Some countries, particularly middle-low-income countries, face significant challenges related to the gap between demand and availability of blood, where the need often exceeds the stockpile (2). Its challenge is further exacerbated because of the perishable nature of blood and the complete dependence on voluntary donations as the sole source of supply (3,4). The situation worsened during the COVID-19 pandemic, which caused significant severance on blood donors rate in various countries include Saudi Arabia, Canada, and Malaysia (5). This condition shows that blood supply system is still vulnerable to crisis. remains highly vulnerable to crises. Therefore, ongoing system strengthening efforts are needed both in emergency and normal conditions (6,7). In this context, there are two important factors in ensuring stable and reliable blood availability i.e. the effectiveness of blood supply chain management and the existence of a donor base that can be maintained sustainably (8,9).

In Indonesia, blood donor management is decentralized and handled by Indonesia Red Cross (IRC), involving three main stakeholders, namely donors, Blood Transfusion Units (BTUs), and hospitals (4,10). BTUs are responsible for collecting, processing, and distributing blood to hospitals. Two top collecting mechanisms are services at BTU's building and mobile blood donation units. The main problems are the uncertainty of blood availability due to the low frequency of repeat donations and inconsistent of donor pattern (11). Therefore, donor retention strategies are needed to develop a more stable and sustainable blood donation system, specifically in Province of Special Region of Yogyakarta.

The Blood Supply Chain (BSC) operates through four echelons: collection, production, inventory, and distribution (11). Research has extensively explored supply chain network design and inventory policies to address cost optimization, service levels, and sustainability (12). Jabbarzadeh et al (13) and Haghjoo et al (14) developed models for minimizing total costs and optimizing blood center locations under various disruption scenarios, while Altunoglu & Batur Sir (15) focused on integrating fixed and mobile blood centers for timely delivery. Inventory studies by Gunpinar & Centeno (16), Dillon et al (17), and Shokouhifar et al (18) examined cost reduction, service levels, and balancing shortages with wastage. However, these efforts heavily rely on the stability of the collection process, which underpins the entire BSC.

Donor retention, a crucial component of the collection echelon, directly influences donor arrival policies and collection strategies (11). Most studies on donor retention rely on survey-based methods. For example, Romero-Domínguez et al (19) segmented Spanish donors into clusters based on donation barriers, while Germain et al (20) examined sociodemographic and motivational differences between current, lapsed, first-time, and repeat donors. Godin et al (21) explored factors affecting return intentions, and studies by Mauka et al (22) and Schlumpf et al (23) used regression analyses to identify predictors of repeat donations. Nguyen et al. (24) highlighted the link between donor satisfaction and future intent, and Ling et al (25) examined sociodemographic influences on donation behavior in Malaysia.

An advanced analytical approach complements survey-based study in which focus on donors profile modelling and predictive analysis. In Indonesia, Soedarmono (26) identified donor characteristic. he did not investigate blood donation patterns or the dynamics of retention behavior. Therefore, gaps remain in the formulation of context-specific strategies. Several studies have employed statistics and machine learning methods for predict donor retention. Alkahtani & Jilani (27) modeled the likelihood of repeat donations, focusing on aggregate population data, while individual consideration was not considered. This approach was further developed by Kauten et al. (28), who predicted the probability of a donor returning within a certain time frame. Meanwhile, Chan et al. (29) classified donors in Hong Kong using the Poisson-Geometric Process model, and Jagirdar et al. (30) analyzed donor return times using Kaplan–Meier curves and the Cox proportional hazards model.

Fundamentally, blood donation can be positioned as a form of prosocial health behavior that develop from the adoption to the maintenance step. Conceptually, health behavior explains that the transformation from initial to repetitive action is highly determined by habit forming process, reinforcement mechanism, as well as social environment support. In the blood donation context, initial experience, perception on social value, and interaction quality with institution act as reinforcers that influence sustainability of donor participation. Therefore, donor retention is more accurately understood as behavior process that is dynamic and sustained, not just a momentary decision.

Donors' retention, especially for first time donors, is a crucial issue in public health promotion. This group is in the initial phase of habit formation in which the decision of repeat donation reflects success of health behavior adoption process. Several research show initial experience, perceived benefits, satisfaction level, and social support are vital determinant factors in differentiating between first time donors that convert to routine donors and donate only once. Hence, factors identification that encourage and barriers its transition are significant foundation in designing health promotion intervention that is more effective. However, most studies are still focused on logistics, system management, or survey approach in identifying donor motivation and barriers. Even if it gives significant contribution, these approaches are not yet fully capable of capturing the dynamics of donor behavior over time, especially on first time donors in decentralization and community-based system. Therefore, comprehension on donor behavior patterns that are based on longitudinal data becomes significant need for creating health promotion strategies that are more focused and sustainable.

The Province of Special Region of Yogyakarta has heterogeneity in demography and vary in local context, so that it potential to develop a distinct of donor behavior pattern. Its condition relates to the gaps in this research. Analysis of donor visit patterns, and demographic characteristics can provide important insights into the behavioral drivers underlying blood donor retention, as well as identify groups requiring more intensive health promotion and community empowerment approaches. Despite previous efforts, a gap remains in analyzing donor visitation patterns and return behaviors using real-world data. In the Province of Special Region of Yogyakarta, research on first time blood donor behaviors across BTUs is limited. This study uses IRC data via the SIMDONDAR system (9) to segment donors based on visitation trajectories. The findings of this study are expected to provide an empirical basis for the development of health promotion strategies, behavior change interventions, and community empowerment approaches that are more effective in encouraging voluntary blood donor participation on a sustainable basis as part of efforts to improve public health.

METHOD

Study Design

This study is a retrospective longitudinal cohort study on the blood donation data. The study tracks first-time blood donors from their initial donation (as the baseline) throughout their consecutive visit over a 3.5-year period (from January 2021 to June 2024), to identify patterns of donation continuity or discontinuity.

Study population and data collection

Data utilized in this study is a trajectory data from 26,170 first-time blood donors collected from five Blood Transfusion Units (BTUs) across Yogyakarta Province: they are Bantul, Gunung Kidul, City of Yogyakarta, and Sleman. First-time donors were defined as individuals who made their first donation without prior donation history in the respective BTUs database. Donors were distinctly identified to avoid duplicate records using a combination of donor ID, name, and date of donation. Any records with missing or inconsistent identifiers were marked out and manually verified.

The data observation period range over 3,5 years from January, 1 2021 to June, 30 2024, then is divided into seven consecutive half-year periods (T1: Jan-Jun 2021; T2: Jul-Dec 2021; T3: Jan-Jun 2022; T4: Jul-Dec 2022; T5: Jan-Jun 2023; T6: Jul-Dec 2023; T7: Jan-Jun 2024). The first half-year period is defined as the baseline (T1: January-June 2021).

Donors who made multiple donations within the baseline (T1), only the first donation was recorded as the baseline, the subsequent donations within T1 were not counted in the analysis. The behavioral tracking commenced from T2 onwards, to ensure that donation patterns analyzed reflect post-initial donation behavior across comparable time windows.

Donation patterns were categorized by visitation frequency within each half-year period: "none" (no visits), "once (single visit), or "multiple" (two or more visits) as shown in Table 1. Clustering method for trajectory donation data is utilized to analyze the demographic factors including age, gender, and donation location to identify key influences on return behavior.

Table 1. State encoding of number of visitation number

State	Donation frequency	Code	Behavioral interpretation
None	0	N	No donation within the period
One-time	1	O	Single visitation (minimum commitment)
Multiple time	> 2	M	Repeats visitation within the period (continuous commitment)

The state encoding (None, Once, Multiple) depicts the distinct donation behaviors suitable for trajectory clustering. The threshold of ≥2 is used because the Indonesian blood donation guidelines only permits whole blood donation every 2 to 3 months, hence it allows maximum 2-3 donations per half-year period. The categorical state encode emphasizing on the behavioral state transition instead of the exact counts of visitation aligns with health behavior stage that envision change as qualitative state transition.

Inclusion and Exclusion Criteria

The inclusion criteria for the data are individuals whose their first blood donation was made at any of the five BTUs in Yogyakarta between January to June 2021, with complete demographic data (age, gender, recruitment location) and identification records (donor ID, name, and date of donation).

Meanwhile, donors record were excluded if they have made donation previously prior to the January 2021, donation record have incomplete or missing demographic information, and duplicate records that could not be adjusted through manual verification. The inclusion and exclusion criteria were applied to ensure that the data analyzed only consist of first-time donors with complete trajectory and demographic data necessary.

Data pre-processing and Quality Control

The raw donation records (*n* = 26,170) underwent systematic cleaning procedures to ensure data quality and analytical reliability. First, records were screened for duplicates using donor ID, name, and date of donation; identified duplicate entries were merged to maintain unique donor identifiers. Second, records with missing demographic variables were examined and excluded from the analysis.

First, donation records were filtered for duplicates based on the donor ID, name, and date of donation; the duplicate entries were then merged. Second, the incomplete donation records with missing demographic variable were screened and excluded from the analysis.

Study Limitations

This study has several methodological limitations that should be noted. First, the trajectory was restrained by the baseline period structure. There were 415 individuals (1.6%) out of 26,170 donations who made multiple donations within the baseline period (T1). For their donors, only their first donation was recorded, their consecutive donation within T1 were eliminated to ensure the standardized measurement of post-initial donation behavior (the analysis commenced from T2) across comparable time windows but it may diminish early repeat donation intensity.

Second, the cut-off period for the donation record before 2021 prevent complete verification of first-time donor status. While donors were examined against the BTU historical records, individuals with donation history at other BTUs outside Yogyakarta or before the digitization of donation records could not be identified, hence there are potential of including some repeat donors in the cohort.

Third, the cut-off period at T7 (after June 2024) might represent behavioral patterns during the observation window rather than lifetime donation behavior. “Lapsed” donors may resume their donation beyond the study period.

Fourth, the heterogeneity exists as the five BTUs serve populations with varying demographic and socioeconomic characteristics across Yogyakarta province. The heterogeneity was examined in the demographic analysis (Table 5).

Last, the baseline cohort was formed during COVID-19 pandemic, which may have influenced both who become first-time donors and subsequent donation patterns in 2021-2022. Pandemic effects were recognized in interpreting the result but were not modeled as separate variables.

Ethical Considerations

This study used anonymized administrative donor registry data and did not involve any direct contact or intervention with human subjects. The study protocol was reviewed and approved by the Indonesian Red Cross as the data custodial authority. Given that the data were fully de-identified and analyzed retrospectively, a formal ethics review and individual informed consent were waived in accordance with applicable institutional guidelines. All data were handled in compliance with data protection and confidentiality standards. The study complied with relevant ethical standards for research using secondary administrative data.

Forming the visitation data into trajectory data

Donation trajectories were developed to represent sequences of donor participation over time. The trajectories capture whether individuals maintain, discontinue, or temporarily engage in blood donation. Sequential data in donation trajectories represents unit with dynamic behaviors and time constraint (29,30). It is often used to analyze movement or behavior, enabling cluster analysis based on similarities in path, properties, or movement (31). Within the context of social science, sequence data allows the meaningful interpretations of the complex trajectories (32). This research used *N* trajectories *T,* where N represent individual donors.

Statistical Analysis

Distance Calculation and Cost Structure

The dissimilarities between donor trajectories were calculated using Optimal Matching (OM), an algorithm to analyze the sequence data implemented through the TraMineR package in R (33). Since all the donor trajectories spanned across T1 to T7 with complete data, hence the length adjustment were not required, which ensure the direct comparability across all donor.

The Optimal Matching algorithm requires the parameter values of substitution cost that quantify the dissimilarity between behavioral states. The cost matrix reflecting the theoretically-grounded assumption about behavioral transition is shown in Table 2.

Table 2. Cost matrix of the Optimal Matching used in this research

	N	**O**	**M**
N	0	1	4
O	1	0	1
M	4	1	0

Note: N represents no donation, O indicates a single donation, and M denotes multiple donations within a period.

The cost structure conceptualizes health behavior theory by giving lower cost (cost=1) of a transition from non-participation to minimal engagement (N↔O) and from minimal to repeat engagement (O↔M). Furthermore, direct transition between non-participation to repeat engagement cost higher cost (cost=4), depicting the theoretical implausibility of sudden behavioral shifts without intermediate stages. This specification counts for the identification of gradual behavioral changes over the sudden or discontinuous changes.

The insertion-deletion cost was set to 20, this value ensure that the algorithm rely on state-to-state substitution rather than sequence length manipulations.

Conducting the clustering using Partition around Medoid

Trajectory clustering was used to identify behaviorally distinct donor profiles, which enables the interpretation of retention pattern. These trajectories capture whether individuals maintain, discontinue, and occasionally engage in blood donation, which can be interpreted as different patterns of health behavior dropout.

After the dissimilarity measure had been calculated, Partition Around Medoids (PAM) clustering algorithm are used to analyze the trajectory data. Similar to K-means, PAM uses medoinds instead of means to represent the center of each group. The algorithm iteratively selects initial medoids, assigns data point to the closes medoid, and stops when optimal condition is met (32).

The final decision of *k* cluster number was based on the multiple validity criteria. Number from k=2 to k=5 was examined separately for each of BTU using the average silhouette width, which quantifies within cluster homogeneity relative to between-cluster separation, and the Dunn index, which assesses the ration of minimum inter-cluster distance to maximum intra-cluster distance. After the comparison, the k=3 solution shown to be optimal number of clusters across all five BTUs, consistently resulted in the superior or near-superior performance on the metrics (Table 3). Following cluster identification, the validation of the cost structure was assessed through sensitivity analysis

Conceptual Framework: Donor Retention and Behavioral Trajectories

Donor retention is visualized in this study as the continuation of donation following initial participation. This viewpoint acknowledges that retention manifest through varying behavioral donation pattern over time, ranging from sustained engagement to occasional participation. Rather than put a prior group of donation, we employ an exploratory clustering approach that allows distinct trajectory patterns to emerge empirically from observed donor.

The clustering algorithm identifies group with similar pattern across the T1 to T7. The empirically-derived clusters are characterized through the temporal patterns of engagement and interpreted different donor retention profiles. The profiles may include, for example, donors who immediately shows up after their first donation, one-time participants who do not return following their initial donation, or early-lapsing donors who exhibit initial re-engagement followed by discontinuation.

To validate the identified cluster, represent behaviorally meaningful distinction rather that only statistically good, we utilized two complementary approaches. First, we examine demographic profiles to asses whether the trajectory data differ systematically in their composition. Second, we compare objectively the retention group, for example the proportion of donors returning within defined time windows, to confirm that different clusters shows distinct retention.

RESULTS

BTUs in Yogyakarta province comprises of Yogyakarta City, Bantul, Kulon Progo, Gunung Kidul, and Sleman. Table 3 shows the sociodemographic profile of first-time donors from each BTUs. As it is shown, most first-time donors across all BTUs are within the active working age group (20 to 44 years old), with this age group constituting 73% in Bantul, 74% in Gunung Kidul (GK), 69% in Yogyakarta City, 66% in Kulon Progo, and 68% in Sleman. This reflects a consistence pattern across regions, even though the highest percentage is observed in GK and the lowest in KP. Gender proportion also consistent, with male donors represents the majority in all BTUs. This finding mirrors findings in other studies such as conducted by (34). Contrarily, recruitment places show significant variations between BTUs. Mobile units (MU) dominate in Bantul (54%), while IB (inside building) is recorded more. The significant differences underscore the tailored approached employed by each BTU, reflecting the regional priorities and constraint.

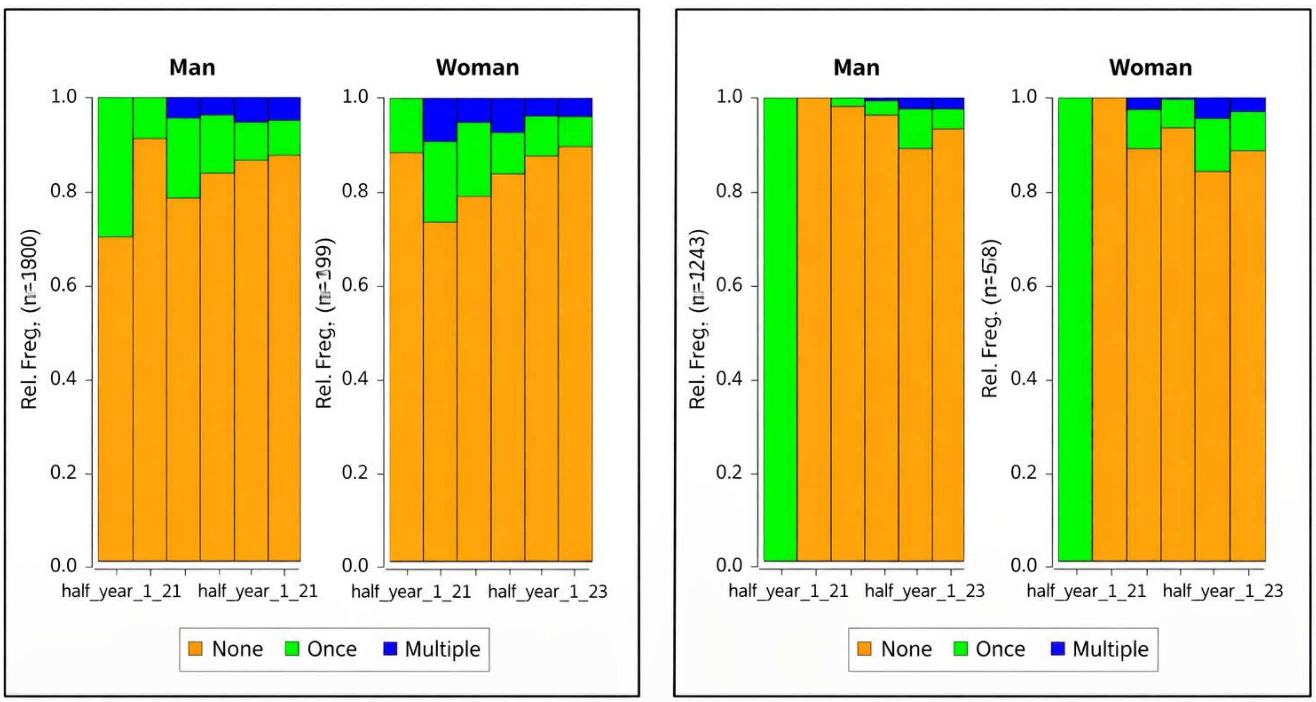
Table 3. Sociodemographic profile of first-time donors

Criteria	Bantul		Gunung Kidul		City of Yogyakarta		Kulon Progo		Sleman	
Age:	*%*	*n*	*%*	*n*	*%*	*n*	*%*	*n*	*%*	*n*
20-44	73%	1,197	74%	1,545	69%	11,087	66%	1,647	68%	2,604
45-59	18%	292	18%	376	24%	3,831	28%	689	25%	965
15-19	8%	134	6%	129	5%	793	5%	119	6%	217
>60	0%	8	0%	4	2%	399	1%	32	2%	59
Under 15	0%	3	1%	23	0%	3	0%	3	0%	1
Gender:										
Female	15%	243	22%	458	22%	3.475	18%	456	21%	815
Male	85%	1,391	78%	1,619	78%	12.638	82%	2,034	79%	3,041

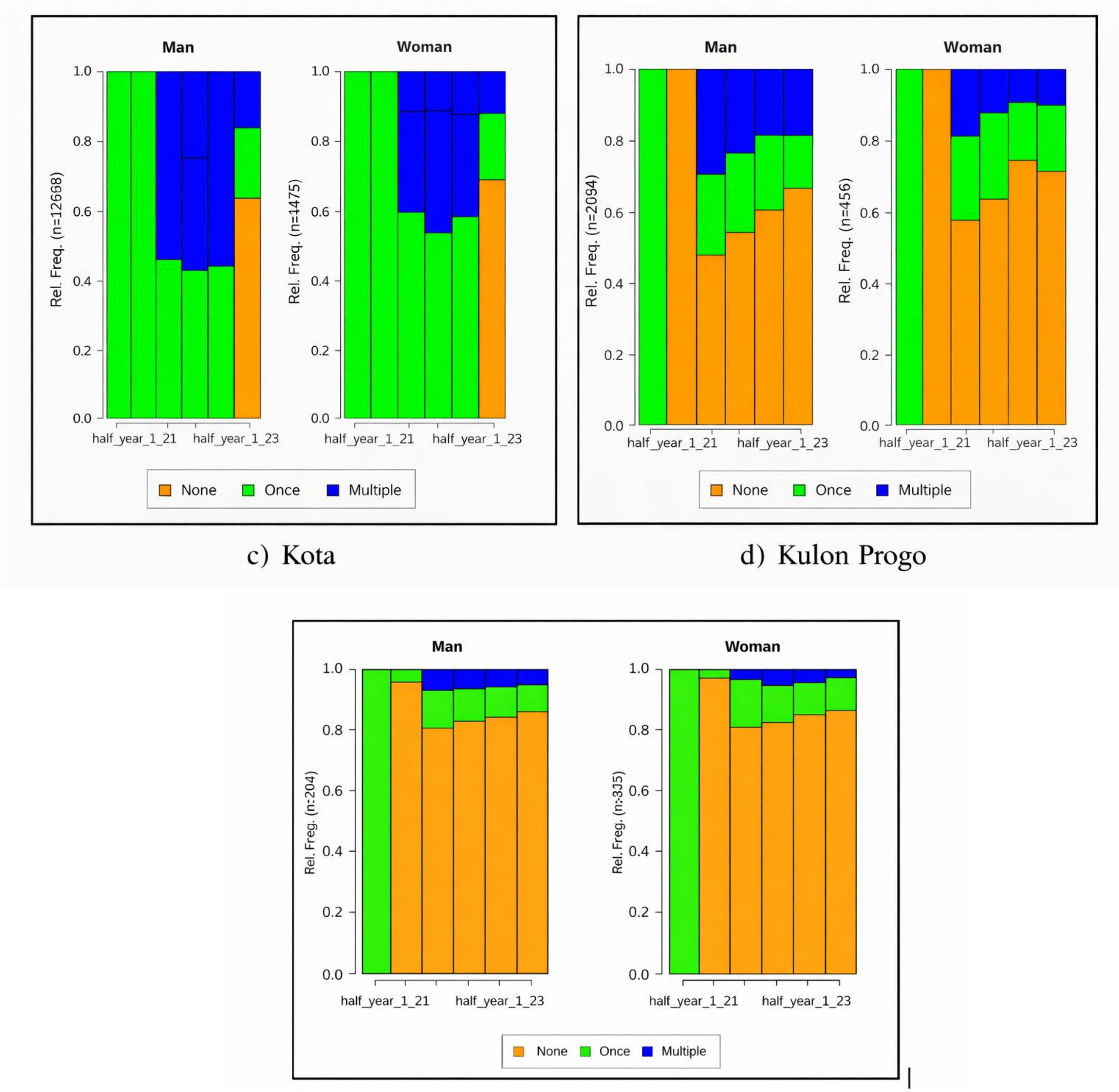
Criteria	Bantul		Gunung Kidul		City of Yogyakarta		Kulon Progo		Sleman	
Age:	*%*	*n*	*%*	*n*	*%*	*n*	*%*	*n*	*%*	*n*
Recruitment Place:										
IB	46%	746	100%	2,077	83%	13,299	82%	2.038	40%	1,543
MU	54%	888	0	0	17%	2,814	18%	452	60%	2,313

Notation:
IB: Inside Building
MU: Mobile Units

Figure 1 shows the gender-based donation pattern for each BTUs. Donors categorized as "multiple donations" (blue colored) only if after an initial donation within the first six period, this indicate that repeat donor often requires at least one follow-up. City of Yogyakarta's BTU shows the highest retention, of which 100% of first-time donors at least have made one donation in the subsequent window (green segment), and 60% have donated multiple times. On contrary, Gunung Kidul has the highest dropout rate, whom most of the first-time donors drop-out after the first donation (orange segment). Male donors dominate the multiple donations across all BTUs, while Bantul shows slightly better retention rates for females as compared to Sleman.



a) Bantul b) Gunungkidul



e) Sleman

Figure 1. Donation trajectory patterns of first-time blood donors by gender across Blood Transfusion Units (BTUs) in the Special Region of Yogyakarta

Segmenting first-time donors

For each 26,170 trajectories data, the dissimilarity is measured using optimal matching analysis as it is suitable for sequence data (35). The clustering step using Partition Around Medoid is then conducted for each BTUs. Cluster validity index (Silhouette Index, Dunn Index) as explained by (36–38) is used as the standard to choose optimum *k* cluster. It is apparent from cluster validity index show in Table 4, that cluster with k = 3 is the optimum segment group for all BTUs.

Table 4. Cluster validity index

Cluster	Bantul		Gunung Kidul		City of Yogyakarta		Kulon Progo		Sleman	
k	SI	DI	SI	DI	SI	DI	SI	DI	SI	DI
2	0.74	0.24	0.84	0.25	0.62	0.22	0.62	0.22	0.73	0.22
3	0.70	0.24	0.82	0.25	0.56	0.22	0.56	0.22	0.70	0.24
4	0.65	0.24	0.82	0.25	0.50	0.22	0.50	0.22	0.65	0.22
5	0.65	0.24	0.82	0.27	0.50	0.22	0.50	0.22	0.65	0.22

Notation:
SI: Silhouette Index
DI: The Dunn Index

Sensitivity Analysis

To evaluate the robustness of the three-cluster solution to the cost matrix, sensitivity analysis were conducted for each BTU separately. There were two alternative of cost structure that were tested: (1) uniform cost with all state transition set to 2 and indel 1, representing neutral baseline, and (2) high asymmetry cost with none to one-time (N↔O)=2, one-time to multiple (O↔M)=2, and none to multiple (N↔M) =6, and indel=20, urging stronger penalization of sudden transition.

For this evaluation using alternative cost structure, distance matrices were recalculated and PAM clustering was repeated using k=3. The stability of cluster was then examined using the Adjusted Rand Index (ARI). ARI quantifies agreement between clustering solutions (shown in Table 5) (39). Value of ARI ranges between 0 (random agreement) to 1 (perfect agreement), values indicating >0.75 indicates substantial agreement (40).

Table 5. Cluster Stability Across Cost Structures (Adjusted Rand Index)

BTU	n	High Asymmetry
Bantul	1,634	0.486
Gunung Kidul	2,077	0.975
City of Yogyakarta	16,113*	0.754
Kulon Progo	2,490	0.415
Sleman	3,856	0.455
Range		0.415 – 0.975

Note: Due to computational constraint, City of Yogyakarta were analyzed based on random sample of 3.000 donors.

Gunung Kidul demonstrated excellent stability with ARI equals to 0.975, indicating robust behavioral patterns that emerge regardless of the cost specification. City of Yogyakarta shows substantial value of ARI with 0.754, which still exceed the threshold for stability. Bantul (ARI=0.486), Kulon Progo (ARI = 0.415), and Sleman (ARI = 0.455) exhibited moderate agreement. This regional variation of ARI reflects differing degrees of behavioral pattern certainty across BTUs. Region with lower ARI shows more nuanced trajectory patterns where the gradual progression (N→O→M) is distinct to the abrupt transition (N→M) and have meaningfull affects on the cluster composition. On the other hand, regions with higher ARI values shows more noticeable behavioral difference where distinct patterns emerge even without theoretical weighting. Crucially, three cluster group structure remained conceptually stable across all BTUs, with switch mainly occurs at cluster boundaries. This can be defined that while theoretical costs refine cluster precision in some context.

Characteristics of the segment

Cluster 1 ("one-time donors") are the majority from all BTUs, in which characterized by a single donation followed by no donation at all (orange). Cluster 2 ("regular donors") are donors who consistently visit donation centers. BTUs in City of Yogyakarta are mainly consist of this cluster. Cluster 3 ("lapsed donors") shows more varied but less consistent behavior, defined by a lapse of two or more years since the last donation (41) . These findings align with prior studies, highlighting regional variations, such as multi-time donations in City of Yogyakarta, which offer insights for tailored donor engagement strategies.

Table 6. Composition of blood donor segment from each BTUs

Cluster	Bantul		Gunung Kidul		City of Yogyakarta		Kulon Progo		Sleman	
	%	*n*	%	*n*	%	*n*	%	*n*	%	*n*
RD	84%	1,372	10%	217	67%	10,853	14%	348	87%	3,349
OTD	5%	87	82%	1,711	19%	3,088	56%	1,400	3%	132
LD	11%	175	7%	149	13%	2,172	30%	742	10%	375

Notation:
RD: regular donor
OTD: one-time donor
LD: lapsed donor

Developing tailored strategies requires understanding the profiles and donation behaviors of each cluster in the BTUs.

Table 7. Sociodemographic profile based on segment donation from each BTUs

Region	Variable	Category	One-time	Regular	Lapsed	Chi-Square	p-value
Gunung Kidul	Age	20-44	75%	70%	76%	34.04	0.00039
		45-59	19%	16%	17%		
City of Yogyakarta	Age	20-44	67%	72%	56%	456.24	<0.0001
		45-59	27%	20%	36%		
Kulon Progo	Age	20-44	68%	68%	62%	19.38	0.01296
		45-59	25%	28%	32%		
Sleman	Age	20-44	57%	69%	61%	23.03	0.00333
		45-59	36%	24%	32%		
Gunung Kidul	Gender	Female	13%	30%	27%	11.88	0.00262
		Male	87%	70%	73%		
City of Yogyakarta	Gender	Female	23%	23%	10%	183.37	<0.0001
		Male	77%	77%	90%		
Kulon Progo	Gender	Female	21%	9%	18%	28.33	0.0007
		Male	79%	91%	82%		
Bantul	Recruitment Place	IB	76%	42%	63%	18.14	0.00011
		MU	24%	58%	37%		
Gunung Kidul	Recruitment Place	IB	100%	100%	100%	2251.06	< 2.2e-1
City Of Yogyakarta	Recruitment Place	IB	90%	77%	99%	743.96	< 2.2e-1
		MU	10%	23%	1%		
Kulon Progo		IB	75%	97%	89%	124.93	< 2.2e-1

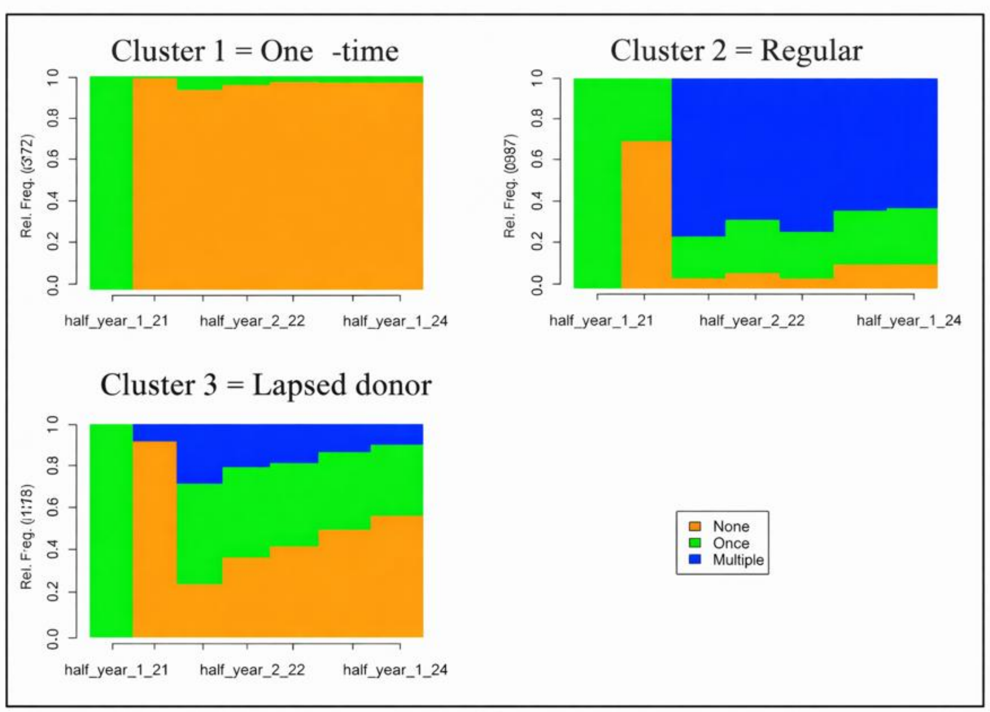
Region	Variable	Category	One-time	Regular	Lapsed	Chi-Square	p-value
	Recruitment Place	MU	25%	3%	11%		
Sleman	Recruitment Place	IB	52%	40%	33%	14.963	0.00056
		MU	48%	60%	67%		

Note: Bantul showed no significant differences by age (χ^2 = 10,287, p = 0.245) or gender (χ^2 = 1,078, p = 0.58) and is excluded. Other age groups (15-19, >60, Under 15) comprised <10% across all segments. Complete data in Supplementary Table S1.

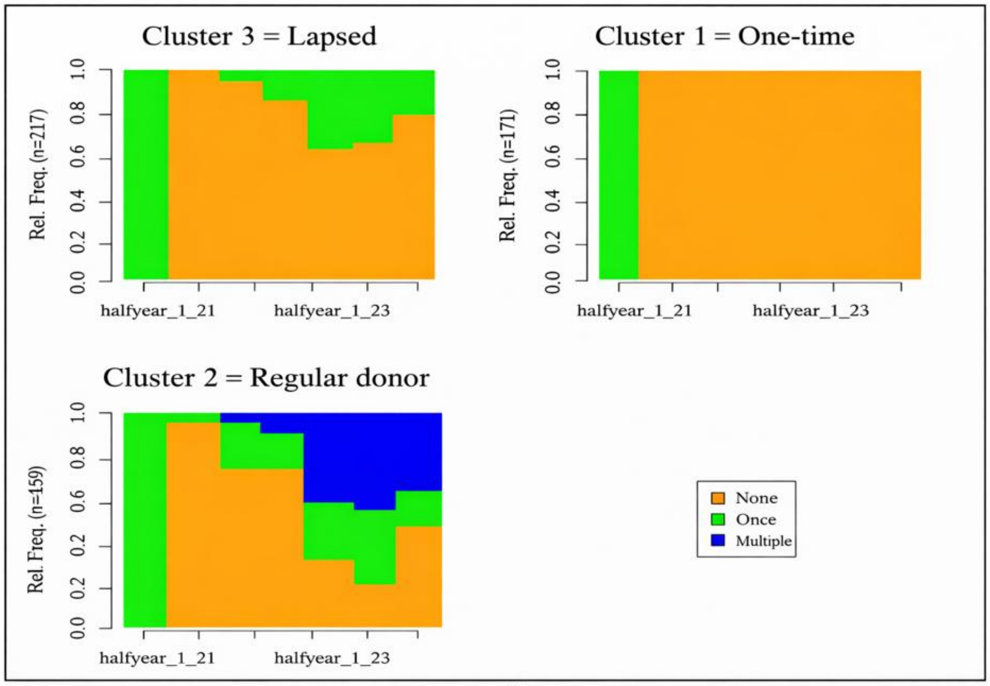
Chi-Square test results highlight significant regional variations in donor distributions by age and gender. In terms of age, no significant differences were found in Bantul (χ^2 = 10,287, $p - value$ = 0.245), while significant patterns emerged in other regions.

In contrast, age-based patterns emerged clearly in other regions (all p < 0.05). Regular donors mainly consist of the 20–44 age group across BTU in Gunung Kidul (70%), City of Yogyakarta (72%), and Sleman (69%). Meanwhile, lapsed donors show a major shift toward 45-59 years old category, notably in City of Yogyakarta. This finding suggest that age-related influence requires targeted retention strategies.

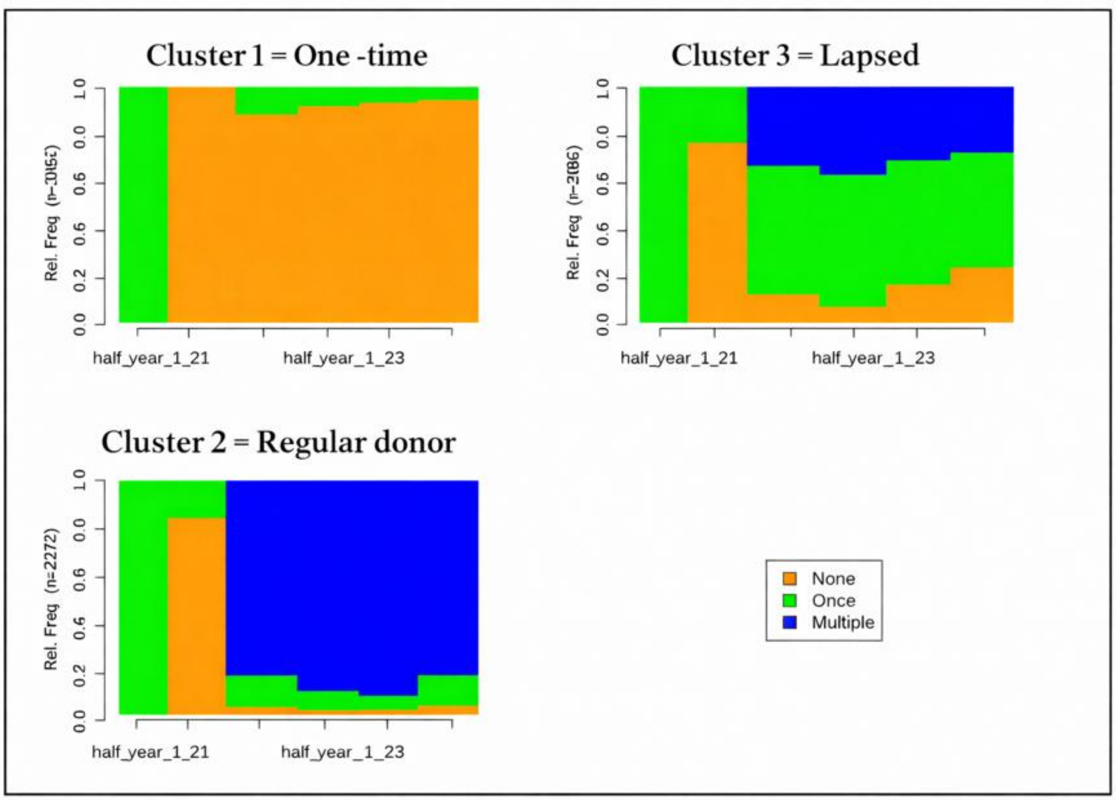
Gender differences between cluster group are even more notable. Male dominate regular donation across almost all BTUs: Gunung Kidul (70%), City of Yogyakarta (77%), Kulon Progo (91%), and Sleman (79%). Meanwhile, female donors increases in lapsed categories, particularly in Kulon Progo (18%). These finding highlight two strategic priorities: maintain engagement with younger cohort (20-44 years old) as they are more likely to become repeat donors, and design gender-specific retention programs to address disproportionate female attrition.



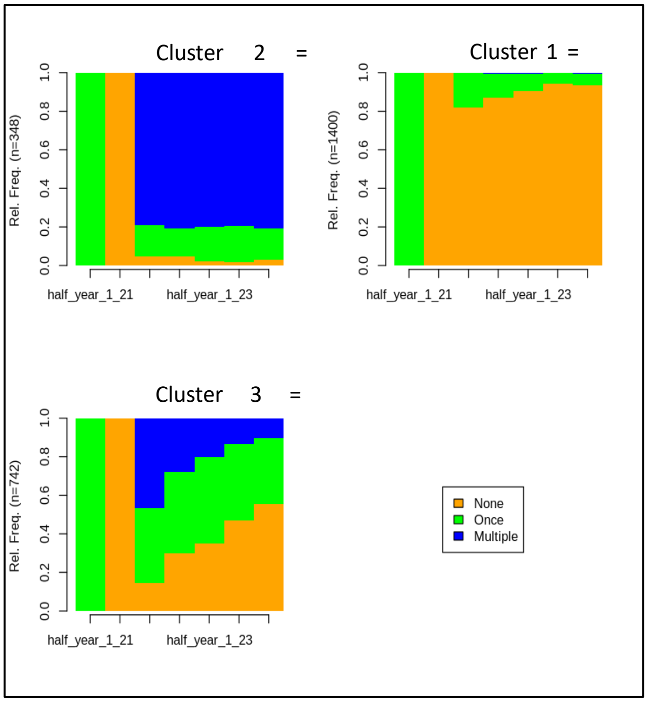
(a)


Cluster 3 = Lapsed
Rel. Freq. (n=217)
0.0 0.2 0.4 0.6 0.8 1.0
halfyear_1_21 halfyear_1_23
Cluster 1 = One-time
Rel. Freq. (n=171)
0.0 0.2 0.4 0.6 0.8 1.0
halfyear_1_21 halfyear_1_23
Cluster 2 = Regular donor
Rel. Freq. (n=159)
0.0 0.2 0.2 0.6 0.8 1.0
halfyear_1_21 halfyear_1_23
None
Once
Multiple

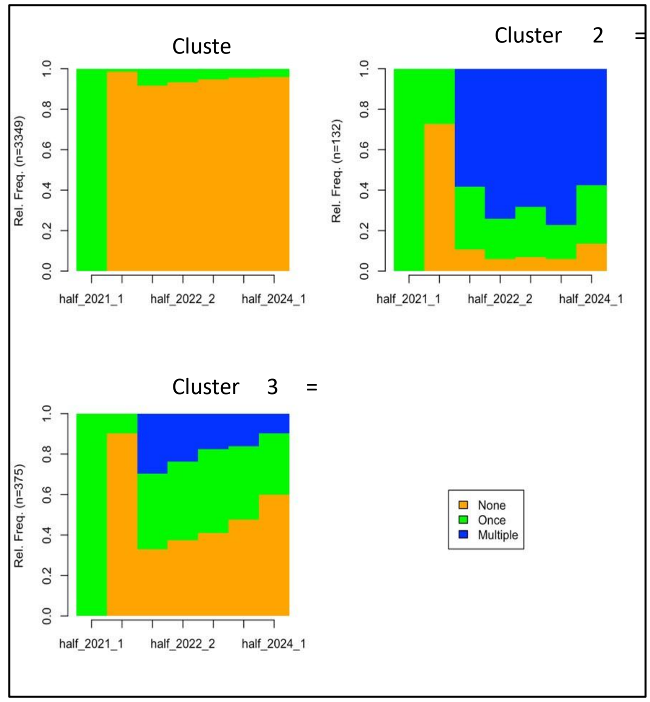
(b)


Cluster 1 = One -time
Rel. Freq
half_year_1_21 half_year_1_23
Cluster 3 = Lapsed
Rel. Freq
half_year_1_21 half_year_1_23
Cluster 2 = Regular donor
Rel. Freq (n=2272)
half_year_1_21 half_year_1_23
None
Once
Multiple

(c)



(d)



(e)

Figure 2 Visitation pattern for each segment in BTUs: a) Bantul, b) Gunung Kidul, c) City of Yogyakarta, d) Kulon Progo, e) Sleman.

DISCUSSION

This study helps us to understand how to profile and retain donors by examining real donation trends over time and using administrative data rather than just survey-based research. The results show that demographic and contextual factors have an impact on donor retention in the Special Region of Yogyakarta.

The findings provide an empirical foundation for understanding how retention trajectories vary across demographic regions, which can help shape the design of focused engagement strategies. This approach provides a clearer behavior-oriented framework for comprehending how first-time donors become regular donors or stop donating. This research highlight donation patterns rather than direct causal linkages, it views donor retention as a dynamic process, evolving over time as giving trends shift.

One of the key findings is that first-time donations are very important in shaping their blood donation behavior. As shown in Figure 1, people who donate again within the subsequent time (T2-T3) after their first donation are more likely to form a retention pattern. This pattern aligns with the idea that initial reinforcement and positive experiences are crucial in determining whether a behavior becomes a habit or stops. Therefore, the retention program focusing on post-donation is better developed to keep donors committed, such as BTUs can do follow-up with their first-time donors.

From Table 7, the domination of people aged 20 to 44 years in the regular donors group, highlighting that they are more consistent in maintaining their blood donation behavior rather than other age groups. In line with the results, young adults generally have higher levels of social mobility, health literacy, and exposure to the health promotion messages, making them more responsive to the blood donation campaign. Therefore, BTUs can give focused-health promotion strategies to this demographic by giving a tailored messages and tailored media campaign to recruit them more.

Gender also plays a significant role in blood donor retention. The predominance of male donors in the regular donors group, as well as the higher proportion of female donors in the group of donors who have ceased or experienced a prolonged hiatus, suggests gender-based barriers to maintaining donor behavior. The findings align with global research, emphasizing male donor dominance (42,43). Health concerns, social roles, and variations in health risk perceptions between man and woman influence the blood donation pattern as shown in Figure 1. Therefore, a gender-sensitive health promotion approach, including more targeted health education and greater convenience in accessing services, is crucial to increasing female donor participation and retention.

Variations in retention rates across regions demonstrate the strong influence of community context on the blood donation behavior. The high retention rate in City of Yogyakarta compared to other regions suggests that the social environment and the easier access to services can reinforce positive social norms regarding blood donation. Conversely, the high proportion of one-time donors in areas like Gunung Kidul indicates the need for a more intensive and contextualized community empowerment approach, such as involving local leaders, strengthening social networks, and organizing community-based donor activities.

From a health promotion perspective, the findings of this study emphasize the importance of shifting strategies from a general approach to more targeted and behavior-based interventions. Efforts to retain first-time blood donors should focus on strengthening the initial donor experience, consistent follow-up communication, and leveraging social and community support as behavioral reinforcers. This approach not only has the potential to increase the number of regular donors but also strengthens the community's sense of ownership and collective responsibility for blood availability.

This study contributes to the health behavior literature by demonstrating that recorded blood donation data can be used to understand the dynamics of donor behavior in a realistic manner. This approach complements survey based studies by providing a snapshot of actual donor behavior within the context of public health services. The findings also broaden understanding of the importance of integrating behavior analysis and community-based health promotion strategies within a voluntary blood donation system.

Future research is recommended to combine behavioral analysis based on service data with a qualitative approach to gain more thorough understanding of the factors influencing blood donor retention.

CONCLUSION

Through this research, donor retention patterns can be modeled using trajectory data. From trajectory data, it can be revealed that differences across the five BTUs in the Special Region of Yogyakarta in terms of gender, age, and recruitment methods. Routinely donors who return for frequent donations are predominantly male and young, aged within 20 to 44 years old. However, recruitment methods differ due to geographic influences. Based on these patterns, recommendations are provided for each PMI regarding strategies to increase the number of repeat donors who regularly donate blood. Strategies for maintaining donor retention differ due to demographic and geographic differences. Future research can improve these findings with more qualitative approaches to obtain better results and improve blood donation services.

AUTHOR CONTRIBUTION STATEMENT

Mohammad Adam Jerusalem: Conceptualization; study design; supervision; interpretation of behavioral findings; manuscript drafting and revisions. Kartika Ratna Pertiwi: Health behavior and health promotion framing; interpretation of health-related implications; validation of behavioral analyses. Agung Wijaya Subiantoro: Data curation; sequence data preparation; statistical validation; visualization. Ummi Fakhriyah Jayatri: Data processing; donor behavior classification; preparation of results and tables. Dyantika Putry Mahmud: Literature review; supporting analysis; manuscript editing. All authors reviewed and approved the final manuscript.

CONFLICT OF INTEREST

The authors declare no conflicts of interest. This research was conducted in accordance with ethical guidelines and received approval from the relevant institutional ethics committee. The funders had no role in the design of the study, the collection, analysis, or interpretation of data, the writing of the manuscript, or in the decision to publish the results.

DECLARATION OF GENERATIVE AI AND AI-ASSISTED TECHNOLOGIES IN THE WRITING PROCESS

The authors used generative AI tools to enhance the structural clarity and grammatical quality of the manuscript, and to assist in developing and refining analytical scripts for data processing. All AI-generated suggestions were critically reviewed, verified, and substantially edited by the authors. The authors take full responsibility for the content of this publication and affirm that the research design, data interpretation, and intellectual contributions are solely their own.

SOURCE OF FUNDING STATEMENTS

This research was supported by BIMA Research Grant (collaboration between the Directorate of Research, Technology, and Community Service of the Directorate General of Higher Education, Research, and Technology of the Ministry of Education, Culture, Research and Technology with Universitas Negeri Yogyakarta) with the Grant Number: T/105.1.27 /UN34.9/PT.01.03/2024.

The funding agency had no involvement in the design of the study, data collection, analysis, interpretation, or manuscript writing. The authors remain solely responsible for all research content.

ACKNOWLEDGMENTS

The authors express sincere gratitude to the Indonesian Red Cross (PMI) Yogyakarta for providing access to donor data via the SIMDONDAR system, and to the Yogyakarta Blood Transfusion Units for their collaboration. The authors also thank the Universitas Negeri Yogyakarta for institutional support throughout the project.

BIBLIOGRAPHY

1. World Health Organization. Towards 100% voluntary blood donation: a global framework for action. WHO. 2010
2. Raykar NP, Makin J, Khajanchi M, et al. Assessing the global burden of hemorrhage: The global blood supply, deficits, and potential solutions. Sage Open Med. 2021;9. https://doi.org/10.1177/20503121211054995
3. Fallahi A, Pourghazi A, Mokhtari H. A multi-product humanitarian supply chain network design problem: A fuzzy multi-objective and robust optimization approach. Int J Eng. 2024;37(5):941–958. https://doi.org/10.5829/ije.2024.37.05b.12
4. Mansur A, Vanany I, Arvitrida NI. Horizontal collaboration in a decentralised system: Indonesian blood supply chain. Supply Chain Forum Int J. 2023;24(4):334–350. https://doi.org/10.1080/16258312.2022.2161287
5. Loua A, Kasilo OMJ, Nikiema JB, Sougou AS, Kniazkov S, Annan EA. Impact of the COVID-19 pandemic on blood supply and demand in the WHO African region. Vox Sang. 2021;116(7):774–784. https://doi.org/10.1111/vox.13071
6. Gammon RR, Rosenbaum L, Cooke R, Friedman M, Rockwood L, Nichols T, et al. Maintaining adequate donations and a sustainable blood supply: Lessons learned. Transfusion. 2021;61(1):294–302. https://doi.org/10.1111/trf.16145
7. Stanworth SJ, New HV, Apelseth TO, Brunskill S, Cardigan R, Doree C, et al. Effects of the COVID-19 pandemic on supply and use of blood for transfusion. Lancet Haematol. 2020;7(10):e756–e764. https://doi.org/10.1016/S2352-3026(20)30186-1
8. Delabranche X, Kientz D, Tacquard C, Bertrand F, Roche A, Tran Ba Loc P, et al. Impact of COVID-19 and lockdown regarding blood transfusion. Transfusion. 2021;61(8):2327–2335. https://doi.org/10.1111/trf.16422
9. Pandey HC, Coshic P, CS C, Arcot PJ, Kumar K. Blood supply management in times of SARS-CoV-2 pandemic: Challenges, strategies adopted, and lessons learned from a hospital-based blood centre. Vox Sang. 2021;116(5):497–503. https://doi.org/10.1111/vox.13019
10. Vanany I, Maryani A, Amaliah B, Rinaldy F, Muhammad F. Blood traceability system for Indonesian blood supply chain. Procedia Manuf. 2015;4:535–542. https://doi.org/10.1016/j.promfg.2015.11.073
11. Mansur A, Vanany I, Arvitrida NI. Blood supply chain challenges: Evidence from Indonesia [Internet]. Thailand: IEOM Society; 2019 [cited 2024 Jun 23]. Available from: https://index.ieomsociety.org/index.cfm/article/view/ID/2045

12. Osorio AF, Brailsford SC, Smith HK. A structured review of quantitative models in the blood supply chain: A taxonomic framework for decision-making. Int J Prod Res. 2015;53(24):7191–7212. https://doi.org/10.1080/00207543.2015.1005766
13. Jabbarzadeh A, Fahimnia B, Seuring S. Dynamic supply chain network design for the supply of blood in disasters: A robust model with real world application. Transp Res E Logist Transp Rev. 2014;70:225–244. https://doi.org/10.1016/j.tre.2014.06.003
14. Haghjoo N, Tavakkoli-Moghaddam R, Shahmoradi-Moghadam H, Rahimi Y. Reliable blood supply chain network design with facility disruption: A real-world application. Eng Appl Artif Intell. 2020;90:103493. https://doi.org/10.1016/j.engappai.2020.103493
15. Altunoglu B, Batur Sir GD. Multi-objective location-distribution optimization in blood supply chain: An application in Turkiye. BMC Public Health. 2024;24(1):3181. https://doi.org/10.1186/s12889-024-20647-x
16. Gunpinar S, Centeno G. Stochastic integer programming models for reducing wastages and shortages of blood products at hospitals. Comput Oper Res. 2015;54:129–141. https://doi.org/10.1016/j.cor.2014.08.017
17. Dillon M, Oliveira F, Abbasi B. A two-stage stochastic programming model for inventory management in the blood supply chain. Int J Prod Econ. 2017;187:27–41. https://doi.org/10.1016/j.ijpe.2017.02.006
18. Shokouhifar M, Sabbaghi MM, Pilevari N. Inventory management in blood supply chain considering fuzzy supply/demand uncertainties and lateral transshipment. Transfusion and Apheresis Science. 2021;60(3):103103. https://doi.org/10.1016/j.transci.2021.103103
19. Romero-Domínguez L, Martín-Santana JD, Beerli-Palacio A. Segmenting Active Blood Donors According to Their Barriers to Develop Retention Programs. Transfus Med Rev. 2019;33(3):176–82. https://doi.org/10.1016/j.tmrv.2019.06.004
20. Germain M, Glynn SA, Schreiber GB, Gélinas S, King M, Jones M, Bethel J, Tu Y. Determinants of return behavior: a comparison of current and lapsed donors. Transfusion. 2007 Oct;47(10):1862-70. https://doi.org/10.1111/j.1537-2995.2007.01409.x
21. Godin G, Conner M, Sheeran P, Bélanger-Gravel A, Germain M. Determinants of repeated blood donation among new and experienced blood donors. Transfusion. 2007;47(9):1607–1615. https://doi.org/10.1111/j.1537-2995.2007.01331.x
22. Mauka WI, Mahande MJ, Msuya SE, Philemon RN. Factors associated with repeat blood donation at the Northern Zone Blood Transfusion Centre in Tanzania. J Blood Transfus. 2015;2015:717653. https://doi.org/10.1155/2015/717653
23. Schlumpf KS, Glynn SA, Schreiber GB, Wright DJ, Steele WR, Tu Y, et al. Factors influencing donor return. Transfusion. 2008;48(2):264–272. https://doi.org/10.1111/j.1537-2995.2007.01519.x
24. Nguyen DD, DeVita DA, Hirschler NV, Murphy EL. Blood donor satisfaction and intention of future donation. Transfusion. 2008;48(4):742–748. https://doi.org/10.1111/j.1537-2995.2007.01600.x
25. Ling LM, Hui TS, Tan AKG, Ling GS. Determinants of blood donation status in Malaysia: Profiling non-donors, occasional donors and regular donors. Kajian Malaysia. 2018;36(1):1–27..
26. Soedarmono YSM. Donor issues in Indonesia: A developing country in Southeast Asia. Biologicals. 2010;38(1):43–46. https://doi.org/10.1016/j.biologicals.2010.02.001
27. Alkahtani AS, Jilani M. Predicting return donor and analyzing blood donation time series using data mining techniques. Int J Adv Comput Sci Appl. 2019;10(8):1–8. https://doi.org/10.14569/IJACSA.2019.0100816
28. Kauten C, Gupta A, Qin X, Richey G. Predicting blood donors using machine learning techniques. Inf Syst Front. 2022;24(6):1–16. https://doi.org/10.1007/s10796-021-10149-1
29. Chan JSK, Wan WY, Yu PLH. A Poisson geometric process approach for predicting drop-out and committed first-time blood donors. J Appl Stat. 2014;41(7):1486–1503. https://doi.org/10.1080/02664763.2014.881781
30. Jagirdar H, Nwobi NH, Swanevelder R, Cockeran R, Bruhn R, Kaidarova Z, et al. Blood donor return behavior in South Africa and the United States before and during the COVID-19 pandemic. Transfusion. 2024;64(8):1492–1502. https://doi.org/10.1111/trf.17934
31. Gusfield D. Algorithms on strings, trees and sequences. Cambridge: Cambridge University Press; 1997. https://doi.org/10.1017/CBO9780511574931

32. Liao TW. Clustering of time series data: A survey. Pattern Recognit. 2005;38(11):1857–1874. https://doi.org/10.1016/j.patcog.2005.01.025
33. Ghassempour S, Girosi F, Maeder A. Clustering multivariate time series using hidden Markov models. Int J Environ Res Public Health. 2014;11(3):2741–2763. https://doi.org/10.3390/ijerph110302741
34. Aassve A, Billari FC, Piccarreta R. Strings of adulthood: A sequence analysis of young British women's work-family trajectories. Eur J Popul. 2007;23(3–4):369–388. https://doi.org/10.1007/s10680-007-9134-6
35. Gabadinho A, Ritschard G, Müller NS, Studer M. Analyzing and visualizing state sequences in R with TraMineR. J Stat Softw. 2011;40(4):1–37. https://doi.org/10.18637/jss.v040.i04
36. Sun R, Giles CL, editors. Sequence learning: Paradigms, algorithms, and applications. Berlin: Springer; 2001. https://doi.org/10.1007/3-540-44565-X
37. Wong GBK, Joseph D. Embracing a cluster perspective: Optimal matching analysis tutorial and tool demonstration. In: Proceedings of the Computers and People Research Conference. New York: ACM; 2024. p. 1–8. https://doi.org/10.1145/3632634.3655871
38. Dunn JC. Well-separated clusters and optimal fuzzy partitions. J Cybern. 1974;4(1):95–104. https://doi.org/10.1080/01969727408546059
39. Rousseeuw PJ. Silhouettes: A graphical aid to the interpretation and validation of cluster analysis. J Comput Appl Math. 1987;20:53–65. https://doi.org/10.1016/0377-0427(87)90125-7
40. Liu Y, Li Z, Xiong H, Gao X, Wu J. Understanding of internal clustering validation measures. In: Proceedings of the IEEE International Conference on Data Mining. IEEE; 2010. p. 911–916. https://doi.org/10.1109/ICDM.2010.35
41. Hubert L, Arabie P. Comparing partitions. J Classif. 1985;2(1):193–218. https://doi.org/10.1007/BF01908075
42. Brusco MJ, Singh R, Cradit JD, Steinley D. Cluster analysis in empirical OM research: Survey and recommendations. Int J Oper Prod Manag. 2017;37(3):300–320. https://doi.org/10.1108/IJOPM-08-2015-0493
43. Boenigk S, Leipnitz S. Acquiring potential blood donors in large cities: A preference-based donor segmentation study. J Nonprofit Public Sect Mark. 2016;28(4):364–393. https://doi.org/10.1080/10495142.2016.1238330
44. Martín-Santana JD, Beerli-Palacio A, Romero-Domínguez L. Recruitment strategies: Non-donor segmentation based on intrinsic and extrinsic stimuli. Vox Sang. 2020;115(1):47–59. https://doi.org/10.1111/vox.12858
45. Jansen P, Sümnig A, Esefeld M, Greffin K, Kaderali L, Greinacher A. Well-being and return rate of first-time whole blood donors. Vox Sang. 2019;114(2):154–161. https://doi.org/10.1111/vox.12752
46. Schreiber GB, Sharma UK, Wright DJ, Glynn SA, Ownby HE, Tu Y, et al. First-year donation patterns predict long-term commitment for first-time donors. Vox Sang. 2005;88(2):114–121. https://doi.org/10.1111/j.1423-0410.2005.00593.x