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A Monetization Model for a Telemedicine Platform Based on Customer Segmentation using the K-Means Algorithm and Willingness-To-Pay

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Abstract

Telemedicine platforms in Indonesia face post-pandemic monetization challenges, where the freemium model has not been effective in converting free users into paying customers. This study aims to design a customer segmentation-based monetization model using the K-Means Clustering algorithm and Willingness-to-Pay (WTP) analysis in the suburban area of Kuningan Regency. Data were collected through a survey of 264 respondents and analyzed using K-Means with a Silhouette Score evaluation (0.42 at *k*=3) and the Kruskal-Wallis test for differences in WTP between segments. The clustering results identified three customer segments: the Digital Light Generation, Health Care Professionals, and Chronic Patients Needing Monitoring, with significantly different WTP ($p<0.001$). Revenue simulations recommended an optimal tiered subscription model: Basic Package Rp25,000/month, Premium Rp75,000/month, and Family Rp130,000/month. This model is able to maximize revenue while maintaining inclusiveness of service access, bridging business sustainability and affordability for suburban communities, and contributing to the Precision in Health Care approach in developing digital health businesses.

Keywords: *Telemedicine, Customer Segmentation, K-Means Clustering, Willingness-to-Pay, Monetization Model, Tiered Subscription*

1. Introduction

The global telemedicine market continues to show rapid growth. In 2024, the market value of online medical services reached USD 152.73 billion and is projected to reach USD 369.24 billion by 2033 with a compound annual growth rate (CAGR) of 10.6% [1]. This growth is driven by the convergence of increasing smartphone penetration, advances in cloud computing and artificial intelligence (AI) technology, and changing consumer preferences post-COVID-19 pandemic, which increasingly demand access to remote healthcare services. In Indonesia, the pandemic has been a major catalyst; the Ministry of Health recorded a 44% increase in new telemedicine users in the first six months of 2022. Local platforms such as Halodoc now control 46.5% of the market share, followed by Alodokter, KlikDokter, and Good Doctor [2]. Regulation through Minister of Health Regulation Number 20 of 2019 has provided a legal basis for the implementation of telemedicine, although details of financing and service rates still leave room for regulation that requires empirical study.

Despite their impressive growth, telemedicine platforms in Indonesia face serious challenges in monetization and business sustainability. Most platforms adopt a freemium model, offering basic services for free to build a large user base in the hope that some will convert to paid services. However, the effectiveness of this model has not been proven robust. A study of Teladoc, one of the largest global telemedicine platforms, showed that its revenue growth was heavily dependent on advertising spending; when advertising spending was reduced, revenue growth immediately slowed, indicating low organic conversion from free users to paying customers [3]. A systematic review of 23 telehealth business model studies by [4] confirmed that value proposition, revenue stream diversification, and adaptation to local contexts are key components determining business model success. These findings imply that a one-size-fits-all approach is inadequate, especially in a highly heterogeneous market like Indonesia.

Recognizing this heterogeneity, several studies have sought to understand the preferences and willingness-to-pay (WTP) of telemedicine consumers in Indonesia. [5] used choice-based conjoint analysis with 385 respondents in a metropolitan area and found that price, communication method, and doctor education level were the most important attributes in service selection. This study also identified three consumer segments with different marginal WTP, demonstrating heterogeneity in preferences. However, Lin's research stopped at estimating WTP per attribute and did not design a concrete subscription package. Meanwhile, a qualitative study [6] involving 24 stakeholders recommended a flat teleconsultation rate ranging from USD 0.05–2.54 per session. This recommendation met with resistance from platform managers who considered the rate too low to cover operational costs, indicating a tension between the social mission of affordability and business sustainability. Common weaknesses of these studies are: (a) focusing on metropolitan areas, which have different purchasing power and access to healthcare facilities than suburban areas; (b) not designing specific tiered subscription packages; and (c) not integrating data-driven segmentation techniques with income simulations to generate a quantitatively optimal pricing model.

This study selected Kuningan Regency, West Java, as the location. This choice is based on the unique characteristics of the region: according to data [7], the ratio of general practitioners in Kuningan is only 11.2 per 100,000 residents, far below that of DKI Jakarta (47.6). Conversely, internet penetration in this region reaches 78.3% [8]. The gap between limited physical access to healthcare facilities and high digital connectivity makes telemedicine a highly promising solution, but its success depends heavily on a thorough understanding of the purchasing power elasticity and preferences of local community segments. Without a precise pricing strategy, services risk being unaffordable for low-income segments or failing to generate sufficient revenue for the platform. Therefore, an approach is needed that not only identifies user segments but also quantifies their WTP (Welcome to Purchase) and simulates the impact of various pricing scenarios on total revenue.

To address this gap, this study integrates two analytical approaches: the K-Means Clustering algorithm for customer segmentation and the payment card method for WTP estimation. K-Means was chosen because of its ability to group individuals into homogeneous segments based on multi-attribute similarities in an unsupervised manner, without the need for initial labels. Meanwhile, WTP was measured for three hypothetical packages (Basic, Premium) to obtain a realistic picture of price preferences. This integration allows for simulation of total revenue at various price points, allowing for the determination of optimal pricing that maximizes revenue without sacrificing market coverage. Therefore, this study aims to design a precise customer segmentation-based monetization model, while also answering the following questions: (1) What is the profile of potential telemedicine user segments in suburban areas? (2) What is the WTP value of each segment for various service packages? (3) What is the optimal tiered subscription model in terms of package and price combinations?

The main contribution of this study is an empirically data-driven tiered subscription model ready for adoption by telemedicine platforms. Theoretically, this research enriches the literature on customer segmentation and pricing strategies in the digital health sector in developing countries. Practically, these findings provide operational guidance for product managers in designing competitive, inclusive, and sustainable service packages. This study also demonstrates that precision in the healthcare business—offering the right product to the right segment at the right price—is key to expanding healthcare access while ensuring the platform's economic viability.

2. Research Methodology

2.1. Research Design

This study used an exploratory quantitative approach with a cross-sectional survey design. A quantitative approach allows for numerical measurement of the phenomena under study, in this case customer segmentation and willingness to pay, through structured instruments that produce data that can be statistically analyzed [9]. The exploratory nature of this research means that this research does not test a strictly formulated hypothesis, but rather explores previously unknown segmentation patterns from the collected data. A cross-sectional design was chosen because it efficiently captures the characteristics and preferences of respondents at a single point in time, making it suitable for market segmentation research [10].

2.2. Population and Sample

The study population was all residents of Kuningan Regency, West Java, aged 18–55 who have internet access and use smartphones. Based on BPS data (2024), the population in this age range is estimated to be around 250,000 people. The population is defined as all elements from which research findings are generalized (Sekaran & Bougie, 2019). Since it is not possible to study the entire population, a sample was taken as a representative subset.

The sampling technique used non-probability purposive sampling, which involves selecting samples based on specific criteria set by the researcher, rather than randomly [11]. Inclusion criteria included: (1) being 18–55 years old, (2) residing in Kuningan Regency, (3) owning and actively using a smartphone, and (4) having searched for health information online or used a telemedicine application at least once in the past 12 months. These criteria ensured that respondents had exposure to the digital health services being studied.

The minimum sample size for clustering analysis follows the rule of thumb: at least 10 times the number of variables multiplied by the estimated number of clusters [12]. With five input variables and an estimate of three to four clusters, 150–200 respondents were required. In this study, 280 questionnaires were collected. After data cleaning—including the removal of duplicates, imputation of missing values using the median, and elimination of outliers with a Z-score threshold of > |3| [13]—264 valid respondents were analyzed.

2.3. Research Instrument

The instrument consisted of a structured questionnaire designed in five blocks [9]. The first block collected demographic data: age, gender, occupation, and monthly income (ordinal scale 1–5). The second block recorded the frequency of health consultations and experience using telemedicine. The third block was the Digital Literacy Scale, which measures an individual's ability to use digital technology to securely access, manage, and evaluate information [14]. This scale consists of five items with a Likert scale of 1–5 (1 = strongly disagree, 5 = strongly agree); it had good reliability, with a Cronbach's Alpha of 0.82, exceeding the recommended threshold of 0.70 [12]. The fourth block measured perceived severity of health conditions, a component of the Health Belief Model that reflects an individual's beliefs about the seriousness of their health condition [14]. Three items were measured on a Likert scale of 1–5, yielding a Cronbach's Alpha of 0.74. The fifth block measured preferences for four types of services (general consultation, specialist, routine monitoring, mental health) and WTP using the card payment method.

The payment card method presents a price range from Rp0 to Rp200,000 in Rp5,000 increments, plus an open-ended option ">Rp200,000, specify ____." This method is more intuitive for respondents and reduces non-response (Fifer et al., 2021). WTP was measured for three hypothetical packages: (a) Basic Package (2x/month general practitioner consultations via chat), (b) Premium Package (unlimited consultations + 1x/month specialist + regular monitoring), and (c) Family Package (Premium features + coverage for three family members).

2.4. Research Variables

Five variables were used as inputs to K-Means: age (numerical), monthly income (ordinal 1–5), frequency of consultations per year (numerical), digital literacy score (1–5 interval), and perceived severity score (1–5 interval). Service preference served as the post-cluster profiling variable, while WTP (in Rupiah) served as the dependent variable analyzed for differences between segments.

2.5. Data Analysis Procedure

Data analysis was performed in Python 3.x using the pandas, numpy, scikit-learn, scipy, matplotlib, and seaborn libraries [15]. The procedure consisted of seven stages.

1. **Data Preprocessing.** The five variables were normalized using Min-Max Scaling to the range [0,1] to prevent any single variable from dominating the Euclidean distance calculation. [13] Multicollinearity was checked using the Variance Inflation Factor (VIF); all variables had a VIF <3, indicating no significant correlation [12].
2. **Determining the Optimal Number of Clusters**. The number of clusters (*k*) was determined through a consensus of three methods. First, Method Elbow plots WCSS against *k* and finds the "elbow" point where the decrease in WCSS plateaus [16]. Second, the Silhouette Score measures internal cohesion and separation between clusters [17]; the *k* with the highest score is selected. Third, the Davies-Bouldin Index (DBI) measures the average similarity between clusters [18]; the lowest DBI value indicates the best separation.
3. **Application of K-Means Clustering**. K-Means is an unsupervised learning algorithm that groups data by minimizing intra-cluster variation [1]. The algorithm is initialized with k-means++ to avoid local optima [4]. The solution is iterated ten times with different initializations; the result with the lowest WCSS is selected. The stability of cluster membership is tested through 1,000 bootstrapping iterations on 80% of the data [22]; consistency above 85% is considered reliable.
4. **Segment Profile**. After clusters are formed, the data is returned to its original scale. The mean and standard deviation of each variable were calculated per cluster. Visualization was performed using Principal Component Analysis (PCA) to reduce the data dimensionality to two principal components [13].
5. **Willingness-to-Pay Analysis**. WTP is defined as the maximum amount a consumer is willing to pay, reflecting the perceived value of a service [6]. The average WTP for each segment was calculated for the three packages. Because the WTP data were not normally distributed (Shapiro-Wilk $p < 0.05$), differences between segments were tested using the Kruskal-Wallis H, a non-parametric test that compares the medians of three independent groups without assuming normality [25]. If significant, a Dunn's post-hoc test with Bonferroni correction was used to identify pairs of segments that differed [18].
6. **Revenue Simulation and Price Optimization**. An empirical demand curve is constructed by calculating the percentage of respondents in each segment whose WTP ≥ P is for various price points P. Total Revenue (TR) is calculated as:

$$TR(P) = \sum_{i=1}^{k} \mathrm{P \ x \ ni \ x \ fi(P)} \qquad (1)$$

   where *k* is the number of segments, n_i is the number of respondents in segment *i*, and f_i(P) is the proportion of segment *i* willing to pay at price P. Simulations were conducted in the range of IDR 0–IDR 200,000 with IDR 5,000 intervals. It was assumed that there was no cannibalization between packages.
7. **Monetization Model Formulation**. The resulting model is a tiered subscription, a tiered pricing strategy that allows consumers to choose packages with different features and prices according to their preferences and budget [19]. Each package is assigned an optimal price, a primary target segment, and a feature description.

3. Results and Discussion

3.1. Result

a. Respondent characteristics

A total of 264 valid respondents were included in the analysis. The demographic profile shows a fairly balanced gender distribution, with 55.3% female and 44.7% male. The age group was dominated by young adults: 37.1% aged 18–25, 31.1% aged 26–35, 20.5% aged 36–45, and 11.4% aged 46–55. In terms of occupation, the majority were students (27.3%) and private sector employees (25.8%), followed by entrepreneurs/traders (19.7%). 62.1% of respondents had a monthly income below Rp 3,000,000, indicating a relatively high price sensitivity. Interestingly, 54.5% of respondents had experience using telemedicine applications, with Halodoc being the most widely used platform (38%). The average frequency of health consultations per year was 3.4 times.

b. Evaluation of the Optimal Number of Clusters

Before running K-Means, the optimal number of clusters was determined using three evaluation metrics. The Elbow method showed that a kink point began to form at *k* = 3 and *k* = 4, although the transition was not very sharp. The Silhouette Score reached its highest value at *k* = 3 with a score of 0.42, which, according to Kaufman & Rousseeuw (1990) guidelines, falls into the fair category (moderately separable structure). The Davies-Bouldin Index (DBI) also had the lowest value at *k* = 3 with a value of 0.98. Based on this consensus, *k* = 3 was chosen as the optimal number of clusters. Further validation with 1,000 bootstrap iterations on 80% of the data showed an average membership consistency of 87%, indicating a statistically stable clustering solution.

c. Customer Segment Profile

After applying K-Means to *k* = 3, three segments with significantly different sizes and characteristics were formed. The mean and standard deviation of each variable in each segment are presented in Table 1.

Table 1: Profile of Three Potential Telemedicine Customer Segments (Mean ± SD)

Variabel	Segment 1: Digital Lite Generation (n=92)	Segment 2: Healthcare Professionals (n=104)	Segment 3: Chronic Patients Needing Monitoring (n=68)
Age (years)	22,4 ± 3,1	35,2 ± 5,4	42,8 ± 7,6
Income (score 1–5)	1,8 ± 0,6	3,2 ± 0,8	2,5 ± 0,7
Fr. Consultations/year	1,2 ± 0,5	4,5 ± 1,8	7,8 ± 2,3
Digital Literacy (score 1–5)	4,5 ± 0,4	3,8 ± 0,6	2,4 ± 0,8
Perceived Severity (score 1–5)	2,1 ± 0,7	3,4 ± 0,9	4,2 ± 0,6
Primary Preference	General Consultation	Specialist & Mental Health	Routine Monitoring

Segment 1: The Digitally Lite Generation (34.8%). This segment consists of young individuals (average age 22.4 years) with a relatively low income (score of 1.8) and very infrequent health consultations (1.2 times a year). They are highly digitally skilled (digital literacy 4.5) and perceive their health conditions as relatively mild (perceived severity score 2.1). Their primary preference is for general consultations via chat, rather than specialist services or intensive monitoring.

Segment 2: Healthcare Professionals (39.4%). This segment is a well-established, productive age group (average age 35.2 years) with a middle-to-upper income (score 3.2). They consult health care frequently (4.5 times a year), have good digital literacy (3.8), and perceive their health conditions as moderately serious (3.4). This segment highly values specialist and mental health services, making them a premium target for telemedicine platforms.

Segment 3: Chronic Patients Needing Monitoring (25.8%). This segment is dominated by middle-aged individuals (average age 42.8 years) with a middle income (score of 2.5) but a very high consultation frequency (7.8 times per year). They have the highest perceived disease severity (4.2), indicating a chronic condition requiring regular monitoring. Ironically, their digital literacy is the lowest (2.4), which is a barrier to adopting digital services despite their high medical need.

PCA (Principal Component Analysis) visualization, which reduces the five input variables into two principal components, shows that Segments 1 and 2 are quite well separated, while Segment 3 has little overlap with Segment 2 in the transition area. This finding is consistent with the Silhouette Score of 0.42, which indicates little natural overlap.

d. Willingness-to-Pay (WTP) Analysis per Segment

After segment formation, a WTP analysis was conducted for three hypothetical packages. The Shapiro-Wilk normality test showed that all WTP data were not normally distributed (*p* < 0.05), so the non-parametric Kruskal-Wallis H test was used. Table 2 presents the mean WTP and the results of the difference test.

Table 2: Mean Willingness-to-Pay per Segment (Rp/month) and Kruskal-Wallis Test Results

Package	Segment 1 (Rp)	Segment 2 (Rp)	Segment 3 (Rp)	*p*-value
Basic	22.500 ± 12.000	45.000 ± 18.000	35.000 ± 15.000	<0,001
Premium	42.000 ± 20.000	95.000 ± 30.000	68.000 ± 25.000	<0,001
Family	35.000 ± 18.000	130.000 ± 40.000	55.000 ± 22.000	<0,001

WTP values differed significantly between segments for all packages (*p* < 0.001). Dunn's post-hoc test with Bonferroni correction showed that Segment 2 (Healthcare Professionals) had a significantly different WTP than the other two segments (all *p* < 0.05). Meanwhile, the difference between Segments 1 and 3 was not significant for the Basic Package, but became significant for the Premium and Family Packages. This pattern indicates that the largest purchasing power gap occurs between the professional segment and the other two segments, especially for high-value-added services.

e. Revenue Simulation and Optimal Monetization Model

To determine the optimal price, Total Revenue (TR) simulations were conducted at various price points. Table 3 presents an example simulation for the Premium Package, which demonstrates the trade-off between price and absorption volume.

Table 3: Premium Package Revenue Simulation under Several Pricing Scenarios

Price (Rp)	% Segment 1	% Segment 2	% Segment 3	Total Revenue (Rp)
50	35%	90%	75%	8.850.000
75	20%	80%	60%	**10.650.000**
100	10%	65%	40%	10.400.000
125	5%	45%	25%	8.625.000

The optimal price for the Premium Package is IDR 75,000/month, which generates the highest total revenue (IDR 10,650,000) by capturing 80% of Segment 2 and 60% of Segment 3. A price increase to IDR 95,000 (the average WTP for Segment 2) actually reduces total revenue to around IDR 8,200,000 due to a significant drop in participation in Segment 3. This underscores the importance of considering the dropout effect of sensitive segments when setting prices.

Similar simulations were conducted for the Basic and Family Packages. The Basic Package achieved maximum revenue at IDR 25,000/month, while the Family Package at IDR 130,000/month. Table 4 summarizes the recommended tiered subscription models.

Table 4: Recommended Tiered Subscription Models

Package	Price/Month	Target Segment	Key Features
Basic	Rp25.000	Light Digital Generation	Unlimited general practitioner chats, access to premium articles
Premium	Rp75.000	Professionals & Chronic	Patients Chat with specialists 3 times per month, priority queue, medical record integration
Family	Rp130.000	Professionals with dependents	Access for 4 family members, regular monitoring, free medication delivery

3.2. Discussion

a. Segment Heterogeneity and Implications for Pricing Strategies
The findings of these three very different segments confirm the thesis that the telemedicine market in Indonesia, particularly in suburban areas, cannot be approached with a one-size-fits-all pricing strategy. The marked variations in income, digital literacy, and frequency of health consultations indicate that each segment has a unique demand curve and price elasticity. These results align with a study [5] that found heterogeneity in consumer preferences for teleconsultation, but this study goes further by translating these differences into concrete subscription packages.
The price-sensitive yet highly technology-adaptive Digital Generation segment represents a volume market. Pricing the Basic Package at IDR 25,000/month, equivalent to the cost of a single chat consultation on existing platforms (IDR 20,000–35,000), makes it a competitive entry point. This strategy is similar to a loss leader model, where low-cost packages are used to build a user base that can later be upgraded to higher packages as their age and medical needs increase.
The Healthcare Professionals segment is the most profitable (high-value) segment, with the highest WTP for all packages. The Rp75,000/month price for the Premium Package closely aligns with their average WTP of Rp95,000, providing sufficient consumer surplus to maintain retention. Furthermore, this price is still affordable for 60% of the Chronic Patients Segment, making it an inclusive solution. This finding bridges the classic tension between business sustainability and affordability highlighted by [6]. Platform managers who previously resisted low rates for margin reasons could adopt a cross-subsidization strategy, where revenue from the professionals segment covers the cost of services for the chronic segment in need.

b. Challenges of the Chronic Patient Segment: More Than Just Price
The Chronic Patients Needing Monitoring segment presents a paradox: the highest medical needs, adequate WTP, but low digital literacy. This implies that pricing is only one of a series of barriers. To serve this segment, platforms must provide a very simple user interface (UI)—for example, large icons, linear navigation, and a one-touch emergency call button—and include community-based onboarding programs, such as involving village health workers or midwives as facilitators. Without these non-price interventions, the segments most in need of healthcare services risk being excluded from the digital ecosystem. This approach aligns with recommendations [20], which emphasize the need for distinct operational strategies for each telehealth usage cluster.

c. Comparison with Market Prices and Previous Studies
The recommended tiered subscription model offers competitive value compared to current market practices. Large platforms like Halodoc and Alodokter charge general practitioners around IDR 20,000–IDR 35,000 per chat consultation. The Basic package of IDR 25,000/month, which includes unlimited consultations, is clearly more economically attractive for light users. The Premium package of IDR 75,000, which includes specialist access, is significantly lower than the cumulative cost of three separate specialist consultations, which can reach IDR 150,000–IDR 200,000. Meanwhile, the IDR 130,000 Family Package fills an under-explored market niche: subscription-based microhealth insurance for families.
Compared to previous WTP studies, the figures obtained in this study are slightly higher than the recommendation [6], which suggests a rate of USD 0.05–2.54 per session. This difference is understandable considering that the UI study used a qualitative approach from stakeholders, while this study directly measured consumers' WTP and packaged it in a monthly package that provides more value. Furthermore, the sample's location in a suburban area with limited physical access may have increased the perceived value of telemedicine, leading to a higher WTP.

d. Silhouette Score of 0.42
The Silhouette Score of 0.42 falls within the "fair" category (0.26–0.50) according to [21]. This indicates a reasonably good, though not perfect, cluster structure. The slight overlap between the Professional and Chronic Segments in the PCA visualization confirms that some individuals are in a transitional area—for example, professionals who are developing chronic illnesses, or chronic patients who are still actively working. The existence of this transition zone is not a weakness, but rather an opportunity for more personalized up-selling and cross-selling strategies. Platforms can design loyalty programs or free trials to move users from the transition zone to higher-tier packages.

e. Managerial Implications
This research produces several practical recommendations for telemedicine platform managers. First, implement a three-tiered subscription structure with prices as recommended. Second, use the Basic Package as a mass acquisition tool for the young segment through partnerships with campuses, student plan programs, or bundling with cellular operators. Third, position the Premium Plan as the default choice in the app interface with the label “Most Popular” or “Best Value” to take advantage of the anchoring effect and drive conversions. Fourth, for chronic segments with low literacy, invest in special UI designs (eg: simple/elderly mode) and recruit digital ambassadors from local health cadres. Fifth, consider collaborating with BPJS Health or local governments to subsidize part of the subscription costs for low-income chronic segments as part of the national health insurance program.

f. Theoretical Implications
From an academic perspective, this research contributes to the literature on customer segmentation and pricing strategies in the digital health sector by presenting a model that integrates unsupervised learning techniques and revenue simulation. This approach addresses the weaknesses of previous studies ([4]; [5]) which were descriptive in nature or only measured preferences without translating them into operational service packages. The integration of WTP into the Total Revenue simulation also adds a quantitative dimension that has been absent from telehealth business model research.

g. imitations and Future Research Agenda
This research has several limitations. First, the sample only comes from one district (Kuningan), so generalization to metropolitan or rural areas needs to be tested. Second, measuring WTP with payment cards is susceptible to anchoring bias in the range provided, even though an open option has been included to mitigate this. Third, the revenue simulation assumes no cannibalization between plans, which in practice may not be entirely true. Fourth, this research has not measured actual purchase behavior, only stated preference.

4. Conclusion

This study presents a novel approach to designing a telemedicine monetization model through the integration of the K-Means Clustering algorithm and Willingness-to-Pay (WTP) analysis—a method applied for the first time in the context of suburban Indonesia. The key novelty lies in transforming data segmentation and price preferences into quantitatively measured tiered subscription packages, going beyond the descriptive approaches dominant in previous literature. The remarkable finding is that the optimal price to maximize revenue lies not at the highest WTP value of the most affluent segment, but at a balance point that simultaneously maintains coverage of the price-sensitive segment—in this case, IDR 75,000 for the Premium Package. In other words, inclusivity and profitability can go hand in hand, not mutually beneficial. Furthermore, the discovery of a segment of chronic patients with high medical needs but low digital literacy confirms that effective monetization strategies must go beyond price to include adaptations in community interactions and support. The resulting tiered subscription model provides empirical evidence that machine learning-based segmentation can bridge the tension between visiting business platforms and healthcare affordability, particularly in areas with limited physical access but high digital penetration.

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