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# Identifying community pharmacists' preferences for attributes of public health interventions in Kenya: a discrete choice experiment

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## Abstract

**Community pharmacies are increasingly recognized as access points for public health interventions (PHIs) such as vaccination, family planning services, and disease screening. In Kenya, evidence suggests the feasibility of pharmacy-delivered PHIs; however, the uptake remains inconsistent. This is partly attributed to poor programme design without taking pharmacy providers preferences into consideration. We employed a discrete choice experiment (DCE) to investigate community pharmacists' preferences for attributes of PHIs delivered in community pharmacies in Kenya. We constructed a Bayesian efficient design and conducted a DCE survey among 663 community pharmacy providers in Makueni, Nairobi, and Kisumu counties in Kenya from January 2025 to March 2025. Panel multinomial mixed logit, generalized multinomial logit, and latent class models were used in the analysis. We also estimated willingness to pay (WTP) and willingness to accept (WTA) estimates using cost and profit margins as the monetary estimates, respectively. We found that community pharmacists were willing to offer PHIs with a low preference for opting out ($\beta = -3.5723$, $P < 0.01$). Preferences for PHIs significantly increased with higher profit margins ($\beta = 0.028$, $P < 0.01$) and decreased with higher cost of equipment ($\beta = -0.00023$, $P < 0.01$). There were higher preferences for PHIs that require moderate training ($\beta = 0.266$, $P < 0.01$) and extensive training ($\beta = 0.141$, $P < 0.05$) compared to no additional training and lower preferences for PHIs with complex interventions compared to simple interventions ($\beta = -0.323$, $P < 0.01$). The WTP estimates showed that providers were willing to pay Khs. 11 738 (USD 90) for moderate training and Kshs. 7327 (USD 56) for extensive training. Moreover, the WTA estimates showed that providers were willing to accept a 10.9% increase in profit margin in order to deliver complex interventions. In addition to this, a three-class latent class model revealed preference heterogeneity among the respondents. These findings can be used to inform the design of PHIs to enhance uptake and acceptability among providers.**

**Keywords** community pharmacy, discrete choice experiment, public health interventions, extended role, preferences, attributes

### Key messages

- Community pharmacies in Kenya are well-positioned to deliver public health interventions (PHIs); however, there is a gap in evidence on what makes such interventions acceptable to the providers.
- Community pharmacists strongly prefer PHIs that generate a high profit margin, are simple in nature, and are associated with moderate training. High equipment cost is a barrier to participation, while government support does not influence preferences for PHIs.

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- There is a variation in preferences, indicating a need for tailored strategies for programme design.
- To increase uptake and acceptability of PHIs among community pharmacists, it is important that programme design is aligned with providers' preferences.

# Introduction

Many low- and middle-income countries (LMICs) health systems continue to face challenges of health care accessibility and affordability (Chan 2018, World Health Organization and World Bank Group 2018). Community pharmacies are well placed to address some of these challenges given their convenient locations, flexibility, and perceived affordability (Miller and Goodman 2016, Kitutu et al. 2017, Mayora et al. 2018). Community pharmacies complement resource-limited public health systems and are viewed as key access points for minor ailments, particularly in LMICs (Akutey et al. 2018, Gentilini et al. 2025).

The role of community pharmacies has expanded extensively to encompass the delivery of public health interventions (PHIs) in many countries globally, and Kenya is not an exception. PHIs refer to interventions aimed at health promotion and disease prevention. Evidence shows that community pharmacies are feasible channels for PHIs such as vaccination, screening for non-communicable diseases, health education, weight management services, and smoking cessation services (Brown et al. 2015, Agomo et al. 2018). In Kenya, community pharmacies have demonstrated feasibility in delivering PHIs. For instance, pilot programmes have successfully integrated HIV self-testing kits into pharmacy services, enhancing access to HIV prevention strategies (Mugo et al. 2017, Ortblad et al. 2023). Similarly, initiatives have shown that pharmacies can effectively provide family planning commodities, contributing to broader reproductive health goals (Corroon et al. 2016, Aloo et al. 2023), and are avenues for point-of-care testing services (Abuya et al. 2007, Bigogo et al. 2010, Mugo et al. 2015). The accessibility and wide distribution of community pharmacies position them as strategic avenues for enhancing PHI delivery in Kenya aimed at improving public health outcomes.

The delivery of these interventions through community pharmacies aligns with national health priorities that are outlined in key policy documents, including Kenya Health Policy 2014–2030, which recognizes the importance of participation of the private sector in the delivery of health care (Ministry of Health 2014). Additionally, national guidelines increasingly recognize pharmacies as avenues to increase access to PHIs. For instance, the National Aids and STIs Control Programme guidelines and National Family Planning Guidelines for Service providers recognize community pharmacies as avenues of HIV self-tests and family planning commodities, respectively (Ministry of Health 2010, National AIDS and STI Control Programme 2017).

Despite this demonstrated feasibility, the uptake of PHIs by community pharmacy providers in Kenya remains inconsistent. This can be attributed to the fact that the community pharmacies are largely missing from national health strategies and policies. This leads to unclear roles, limited institutional support, and missed opportunities for leveraging their full potential in expanding access to PHIs in Kenya (Aloo et al. 2023). Additionally, there is misalignment between PHI programme design and the providers' realities. For instance, some PHIs require pharmacies to have a dedicated private room for consultation, data reporting system, and additional staff, which are often absent in the practice (Mugo et al. 2022, Nakambale et al. 2023). Given these challenges, it is crucial to understand provider preferences for the characteristics of PHI to gain insights into how programmes can be designed in a manner that aligns with their motivations, capacities, and business realities.

Stated preference methods such as discrete choice experiments (DCEs) are useful for preference elicitation (Louviere et al. 2000). A DCE assumes that goods or services can be described by their characteristics (attributes) and that individuals' decisions regarding goods or services are influenced by their preference for the attributes of the goods or services (Ryan et al. 2012). Unlike traditional surveys, DCEs force individuals' to make choices and trade-offs, thereby revealing and quantifying their underlying preferences for different attributes (Mangham et al. 2009, van Helvoort-Postulart et al. 2009). Second, it allows for different attributes to be compared against each other simultaneously (Lagarde and Blaauw 2009). Finally, a DCE can be applied to evaluate preferences in areas where markets for goods do not exist (Mangham et al. 2009).

There is a growing application of DCEs in community pharmacy studies to assess consumer preferences for pharmacy-delivered services (Feehan et al. 2017, van de Pol et al. 2021, Chua et al. 2022) and providers' preferences (Grindrod et al. 2010, Raghunandan et al. 2021). However, the majority of these studies have been conducted in high-income countries, and few studies have focused on preferences for PHIs. In LMICs, the method has been applied to understand client preferences for services delivered through community pharmacies. For instance, DCE has been applied to assess the preferences of pregnant women for an HIV prevention service delivery in community pharmacies in Kenya (Mugambi et al. 2024). However, despite the utility of DCEs in understanding preferences, none of the studies have assessed the preferences of community pharmacy providers in Kenya.

To bridge this gap, we conducted a DCE to identify community pharmacists' preferences for attributes of PHIs delivered in community pharmacies. In addition to this, we aimed to quantify the relative importance placed on the attributes and determine the trade-offs providers would be willing to make. Understanding these is crucial for designing PHIs that are both acceptable to pharmacists and effective in achieving public health objectives.

# Methodology

## Study setting

Kenya is classified as a lower middle-income country (LMIC) with an estimated population of 47.5 million in 2019 (Kenya National Bureau of Statistics 2019a). In 2013, Kenya adopted a decentralized system of governance with a national government and 47 semi-autonomous county governments. The provision of health services is pluralistic, consisting of equal service provision by both public and private health facilities (Ministry of Health Republic of Kenya 2011, Ministry of Health 2024). In Kenya, community pharmacies are registered by a government regulatory agency known as the Pharmacy and Poisons Board (PPB) (National Council for Law 2012). There are approximately 8000 registered pharmacies, which are operated by pharmacists

holding a Bachelor of Pharmacy (BPharm) or pharmaceutical technologists holding a diploma in pharmacy (Pharmacy and Poisons Board 2025). The pharmacy market is divided between individual and chain pharmacies, operating independently as private for-profit businesses (Pharmacy and Poisons Board 2024).

We conducted the study in three counties in Kenya namely, Nairobi, Kisumu, and Makueni Counties. These counties were selected purposively to represent the number of pharmacies and the poverty level in the country. Nairobi and Kisumu counties were selected, as they have the highest number of pharmacies and representatives of the main urban areas in Kenya. Makueni County was selected as a representative of the counties with a high multidimensional poverty index (Kenya National Bureau of Statistics 2019b, Table 1).

## Study design

This study applied the DCE methodology. In a DCE, goods or services are described by their attributes (characteristics), which are described by a defined number of dimensions called levels (Louviere et al. 2011). The attributes and their levels are combined in an experimental design to generate hypothetical alternatives, and respondents are then presented with the hypothetical choices and asked to select the ones that they prefer (De Bekker-Grob et al. 2012, Johnson et al. 2013). The respondents' choice indicates the utility that is attached to a good or service's characteristics (Lancsar and Louviere 2008). We followed the recommended guidelines on conducting a DCE (Bridges et al. 2011).

## Deriving attributes and attribute levels

We followed the Helter and Boehler four-stage process to derive the attribute and their levels namely: raw data collection, data reduction, removal of inappropriate attributes, and wording of attributes (Helter and Boehler 2016). Raw data collection and reduction entailed conducting a literature review to identify conceptual attributes, followed by a qualitative study to identify contextual attributes. We identified six attributes from the literature review that influence community pharmacists' decision to offer PHIs (Mumbi et al. 2024). We then conducted in-depth interviews (IDIs) with 26 community pharmacy providers across the three study counties and identified eight contextual attributes. The attributes from the interviews aligned conceptually with those from the literature review; however, there were notable differences in the attribute levels mainly because most of the studies identified in the review were conducted in high-income settings. In the literature, financial compensation was mainly through reimbursement structures such as fee for services and dispensing fees while from the IDIs it was through a profit margin. Secondly, the levels for the training attribute in literature were mainly on the modes of training while from IDIs it was on the training duration.

The third and fourth steps entailed a validation process of the attributes by researchers who agreed on an interim list of attributes and levels to be included in the pilot study. Attributes to be included were selected based on relevance, plausibility, and capability of being traded (Coast and Horrocks 2007). This process resulted in a total of five attributes and levels indicated in Table 2.

**Table 1** Characteristics of study counties.

| County | Population size (2019) | No of registered pharmacies | Poverty incidence |
|---|---|---|---|
| Nairobi | 4 397 073 | 1400 | 16.5% |
| Kisumu | 1 155 574 | 250 | 36.3% |
| Makueni | 987 653 | 100 | 39.7% |

## Experimental design and construction of choice tasks

### Initial design and piloting

For the pilot, we generated an orthogonal experimental design using Ngene software version 1.2.0 (Ngene). Given that we had no prior information on preferences, the initial DCE design was generated using zero priors. We generated an unlabelled

**Table 2** List of attributes and attribute levels.

| Attributes | Definition | Attribute levels |
|---|---|---|
| 1. Nature of intervention | Complexity of the PHI to be offered in community pharmacies in terms of time and resources needed | a. Simple intervention[a]<br>b. Complex intervention[b] |
| 2. Training requirements | The extent of training required by community pharmacy providers to successfully offer PHI | a. No additional training required<br>b. Moderate training (1–2 days)<br>c. Extensive training (Up to 1 week) |
| 3. Government support | The type and extent of support provided by the government to community pharmacies to facilitate the uptake of PHI delivery | a. Financial support<br>b. Regulatory support |
| 4. Cost of the equipment | Financial investment needed to purchase the equipment needed to offer PHI | a. Kshs. 0<br>b. Kshs, 4000<br>c. Kshs. 8000<br>d. Kshs. 12 000 |
| 5. Profit margin | The expected gain generated by offering the PHI | a. 0%<br>b. 15%<br>c. 30%<br>d. 45% |

[a]Simple interventions: Interventions that can be provided within normal pharmacy workflow and require minimal additional resources, time, or specialised equipment. E.g. Blood pressure screening, weight management services.
[b]Complex interventions: Interventions that require multiple steps, longer client engagement, additional resources. For example: HIV testing, vaccination services.

experiment with two alternatives (PHI 1, PHI 2) and an opt-out option, with 12 choice sets. This design was piloted among 36 respondents with similar characteristics as the target population, selected from a non-study county. We conducted the pilot for several reasons: (1) to generate prior parameters for the final design and (2) to ensure that the questionnaire was comprehensive and clear and that the attribute levels were consistent with the range of preferences, and the choices were reasonable. Based on the pilot, 12 choice sets were deemed to be easily handled by the respondents without any cognitive burden (Bridges et al. 2011).

### Final experimental design

Using the parameters obtained from the pilot, we generated a Bayesian D efficient design for the main study. We selected a Bayesian design over a D efficient design because it generates smaller standard errors and provides reliable parameters using smaller sample sizes (Bliemer et al. 2008). Additionally, a Bayesian design is less sensitive to misspecification of errors compared to a D-efficient design (Bliemer and Collins 2016). The D error for our final design was 0.02246.

## Questionnaire development

We developed a questionnaire that contained five main sections (Supplementary file S1). Section A contained general information about the study area. Section B collected basic demographic information about the respondent. Section C covered basic information about the pharmacy and the PHIs offered. Section D introduced the DCE hypothetical scenario and an explanation of the different attributes and levels. Section E contained the 12 choice sets. An example of a choice set is shown in Fig. 1. Section F asked for supplementary information, whereby respondents were asked whether they were satisfied with the attributes measured in the study.

## Sampling and data collection

Data were collected by a team of trained field workers across the three study counties. Prior to data collection, the data collectors underwent a 3-day training which covered the study objectives, ethical considerations, and DCE methodology and tool. This training aimed to standardize data collection procedures across the study counties and enhance the reliability of the findings.

The sampling frame was obtained from a list of pharmacies registered by the PPB. The minimum sample size for this study was calculated based on the S error estimate of 583 derived from the experimental design. In order to account for potential refusals and low response rate, we increased the sample size by 20% resulting in a sample size of 700 pharmacies. However, since the number of pharmacies across the three counties was unbalanced with Nairobi County having up to six times more pharmacies than the other study counties, the number of

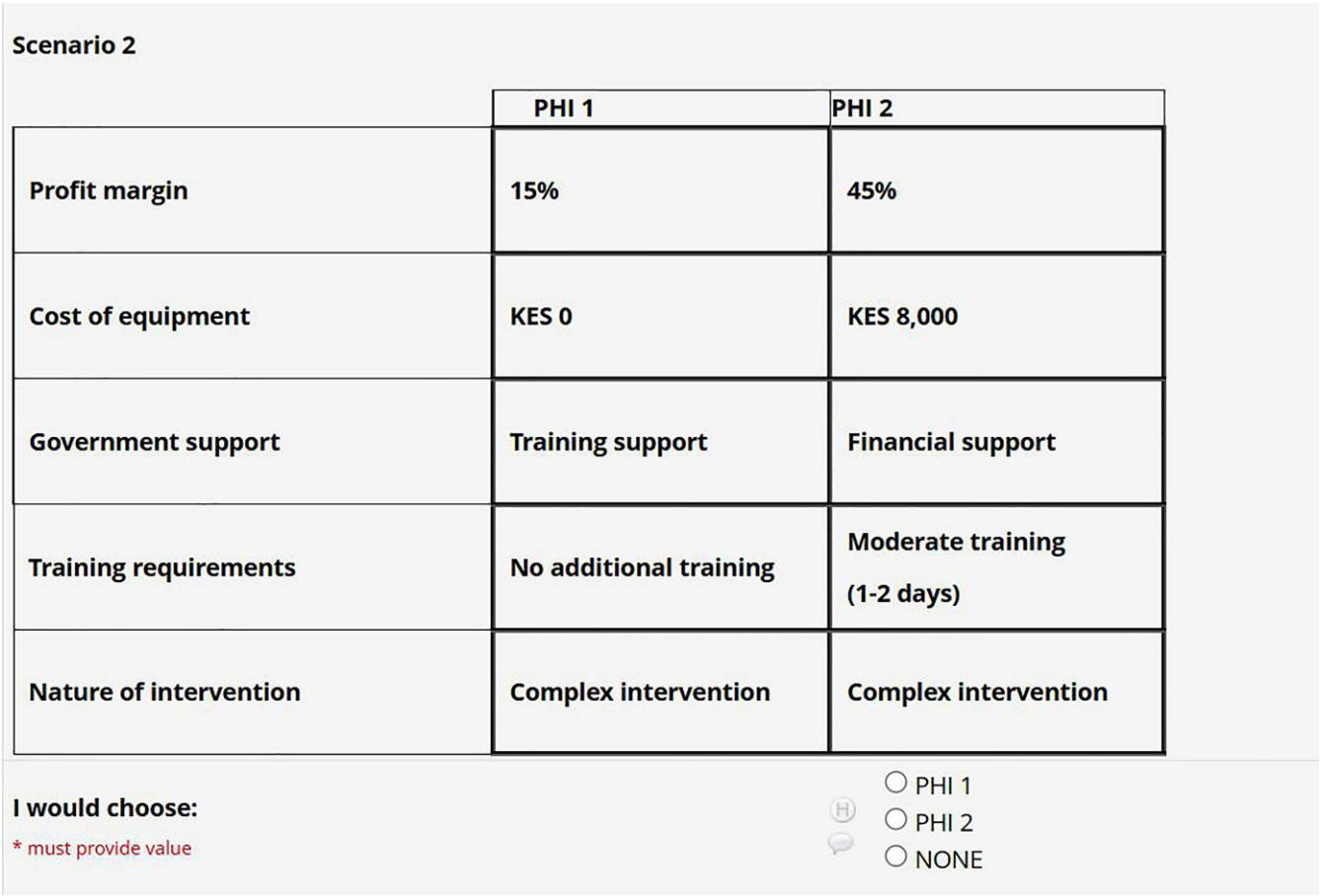


**Figure 1** Example of a choice set.

pharmacies sampled in each county was determined using power allocation with power value set at α 0.5 (Bankier 1988). The questionnaire was interviewer-administered using Research Electronic Data Capture (REDCap) (Harris et al. 2019).

## Statistical analysis

The analysis of DCE data is based on random utility theory. This theory proposes that the individuals *i* utility for an alternative *j* in a choice set *s* can be broken down into two components: a systematic and a random component (Louviere et al. 2002);

$$U_{ijs} = V_{ijs} + \varepsilon_{ijs}$$

$V_{ijs}$ is the systematic, observable (explainable) component of utility that is used to quantify the importance of attributes and trade-offs, and $\epsilon_{ijs}$ is the random, unobservable (unexplainable) component of utility that represents researchers' inability to ever fully observe or understand (McFadden 1973, Louviere et al. 2002). The key assumption therefore is that individuals *i* will choose alternative *j* if it is the alternative that maximizes their utility among *J* alternatives included in a choice set $C_s$ (Ryan et al. 2007, Hensher et al. 2015).

Based on the attributes presented in Table 2, the utility function for this DCE work was defined as

$$\begin{aligned} U_{ijs} = {} & \beta_0 + \beta_1 \text{profit margin}_{ijs} + \beta_2 \text{Cost}_{ijs} \\ & + \beta_3 \text{Government support}_{ijs} + \beta_4 \text{Training requirements}_{ijs} \\ & + \beta_5 \text{Nature of intervention}_{ijs} + \varepsilon_{ijs} \end{aligned}$$

where $\beta_0$ was the alternative specific constant for the opt-out option, $\beta_1$ to $\beta_5$ were the parameters to be estimated, and $\epsilon_{ijs}$ were the error terms. Cost and profit margin were continuous variables and were therefore modelled linearly. The other categorical variables were dummy coded.

The 'workhorse' of DCE analysis is the conditional logit model (De Bekker-Grob et al. 2012, Hensher et al. 2015). However, this model assumes that the random component $\epsilon^{ijs}$ to be independently and identically distributed (IID) across individuals and alternatives, following a Gumbel (extreme value type I) distribution (Hensher et al. 2015). This assumption leads to Independence of irrelevant alternatives, which states that for a given individual, the ratio of choice probabilities of any two alternatives is unaffected by any other alternatives, which implies that the choice probabilities would change in the same proportion once a new alternative is introduced or once an existing alternative is deleted (Ryan et al. 2007). However, this does not account for heterogeneity in preferences among respondents resulting from both observable and unobservable factors (Hole 2008). For this reason, we opted for a mixed multinomial logit model (MMNL) for our analysis for two reasons: (1) it accounts for heterogeneity in preferences, and (2) it relaxes the IIA assumption (McFadden and Train 2000, Hensher and Greene 2003). We used 1000 Halton draws for all MMNL panel models.

Following the MMNL above, we estimated the relative importance that community pharmacy providers placed on the different attributes of PHIs. We derived this using the partial log likelihood procedure, which entails calculating the contribution of each attribute to the overall log likelihood of the model (Lancsar et al. 2007).

In addition to this, we computed WTP and WTAbased on the MMNL model in the WTP space (Scarpa and Alberini 2005), using the cost and profit margin attributes as the monetary attributes, respectively. The MMNL does not account for scale heterogeneity; for this reason, we fitted a generalized multinomial logit model (GMNL) to assess for scale heterogeneity. Scale heterogeneity implies that the choice behaviour of respondents is more random for some individuals than for others (Fiebig et al. 2010). We used 500 random draws with a gamma restricted to zero due to computational efficiency (Gu et al. 2013).

To further explore how individual characteristics influence preferences, we included interaction terms based on the literature (Grindrod et al. 2010, Munger et al. 2017). These included the level of education with nature of intervention and the training requirements. However, given the novelty of the research, there was little relevant literature, so we proposed our own hypothesis. For instance, we hypothesized that community pharmacists with structural capacity (consultation rooms) could handle complex interventions, and we therefore tested for interactions between the availability of a consultation room the nature of interventions. We also tested interactions between years of experience and profit margin, nature of intervention and level of education, profit margin and number of years worked, level of education and government support, and number of years worked and government support. The full list of interaction terms is shown in supplementary file S2.

Only the variables with significant SD in the MMNL panel were deemed to be associated with preference heterogeneity.

Finally, we fitted a latent class model to observe for unobserved heterogeneity. A latent class analysis fits a group of respondents into a prespecified number of segments (classes) and allows estimation of class-specific preferences. Class membership is latent (unobserved) as the respondents belong to each class based on a modelled probability and not deterministically assigned. The preferences are assumed to be homogeneous within the classes but heterogeneous between classes (McFadden 1986, Hess 2024). To determine the optimal number of classes, we estimated a series of models with an increasing number of classes from 2 to 5 (Supplementary file S4). We then used the log likelihood, Akaike Information Criteria (AIC), and Bayesian information Criteria (BIC) to determine the number of classes to be retained, with a lower value implying a better fit (Louviere et al. 2000, Lanza and Rhoades 2013). It is essential to avoid groups that are either too large or too small to ensure interpretability of the differences in utility coefficients (Khan et al. 2021).

# Results

## Descriptive statistics

A total of 663 community pharmacists participated in the study, representing a 94.7% response rate. The baseline characteristics for the respondents are shown in Table 3. Of the participants, 51% were female. In terms of educational qualification, 77% of the respondents were diploma holders, 18% were degree holders, 3% were certificate holders, and 1% had a master's as the highest educational qualification. Additionally, the surveyed pharmacies had an average of 3

**Table 3** Socio-demographic and pharmacy characteristics.

| Category | Variable | *N* (%)/Mean (SD) |
|---|---|---|
| Respondent characteristics | Age (years) | 32.87 (7.86) |
| | Gender | |
| | Male | 339 (51%) |
| | Female | 324 (49%) |
| | Highest education level achieved | |
| | Masters level | 7 (1%) |
| | Bachelor of Pharmacy | 121 (18%) |
| | Diploma in Pharmacy | 511 (71%) |
| | Certificate in pharmacy | 24 (4%) |
| | Years of experience (years) | 6 |
| Pharmacy characteristics | Number of staff | 3 (2.76) |
| | Number of days open | 6 (0.49) |
| | Number of hours open | 13 (3.83) |
| | Consultation room available | 28.05 (186) |

**Table 4** Characteristics of PHIs offered.

| PHI offered | *N* (%) | Average fee in KES (USD) |
|---|---|---|
| Blood sugar testing | 399 (60.2) | 120 ($0.93) |
| Blood pressure measurement | 440 (66.4) | 50 ($0.39) |
| Vaccination services | 22 (3.3) | 950 ($7.34) |
| Weight management | 226 (34.1) | 0 |
| HIV testing | 354 (53.2) | 200 ($1.55) |
| Malaria testing | 262 (39.5) | 170 ($1.31) |
| Pregnancy testing | 387 (58.4) | 120 ($0.93) |
| None | 134 (20.2) | |
| Charge fees for PHIs | | |
| Yes | 493 (92.5) | |
| No | 40 (7.5) | |

members of staff and opened for an average of 6 days per week for 13 hours a day. Approximately 28% of pharmacies had a consultation room.

## Characteristics of PHIs offered

Eighty percent of the community pharmacies sampled reported to offer certain PHIs. The type of PHIs and the average fee charged are illustrated in Table 4.

## Model estimates for preferences for attributes and attribute levels

Table 5 reports the estimates of the MMNL. The estimated coefficients of the means of the attributes were all statistically significant, with the exception of government support and extensive training.

The alternative specific constant was statistically significant with a high negative coefficient, showing that community pharmacy providers place high importance on offering PHIs as opposed to opting out of PHI delivery ($\beta = -3.57$ $P < 0.01$). Our findings revealed that the preferences of community pharmacy providers for PHIs significantly increased with higher profit margins ($\beta = 0.028$, $P < 0.01$). Cost of equipment was associated with a decreased preference for PHI ($\beta = -0.00023$, $P < 0.01$). In terms of government support, community pharmacy providers had lower preferences for financial support ($\beta = -0.003$, $P < 0.01$). However, overall government support was not statistically significant ($P > 0.01$). In terms of training, community pharmacists generally preferred PHIs that require moderate training of 1–2 days ($\beta = 0.266$, $P < 0.01$) or extensive training of up to 1 week ($\beta = 0.141$, $P < 0.05$) compared to those that do not require additional training at all. Finally, as expected, community pharmacists had lower preferences for complex interventions ($\beta = -0.323$, $P < 0.01$).

## Marginal WTP and WTA estimates

Using cost as the price attribute, the marginal WTP estimates indicated that community pharmacy providers were willing to pay Ksh. 1165 ($9) for a 1% profit margin. Second, providers were willing to pay Kshs. 11 738 ($90) to offer PHIs that require moderate training, as opposed to those that have no additional training and up to Kshs. 7328 ($56) to offer PHIs that require extensive training. The negative WTP estimates of complex intervention indicate that community pharmacy providers need to be compensated Kshs. 12 300 ($94.8) to offer complex interventions, indicating a disutility for complex interventions. Finally, community pharmacy providers had a strong preference to offer PHIs and would need to be compensated KES 224 000 ($1726) to not offer PHI services in their pharmacies.

Using profit margin as the monetary price attribute, we found that providers were willing to accept up to a 10.9% increase in profit margin to offer complex interventions, indicating that they do not prefer complex interventions due to perceived effort and resource demand. The WTA for opting out from PHI delivery was over 400% of profit margin, indicating a high preference for offering PHIs.

A negative WTA indicates that, for our entire sample for those attributes, the providers would be willing to forego any monetary compensation as they are highly valued. The full findings of WTA and WTP estimates are in Table 6.

## Partial log likelihood estimation of relative importance

Figure 2 shows the relative importance of the different attributes of PHIs. Profit margin was the most important attribute to community pharmacy providers, which is not surprising as community pharmacy providers in Kenya operate in for-profit private health sector with the aim of maximizing profit (74.12%). This was followed by the nature of interventions (12.45%), training

**Table 5** Main effects MMNL model preference weights.

| Attributes | Preference estimates | | | Standard deviation | | |
|---|---|---|---|---|---|---|
| | Coefficient | 95% CI | *P* Value | Coefficient | 95% CI | *P* value |
| Proft margin | 0.0283 | 0.025 to 0.032 | <0.001*** | 0.033 | 0.029 to 0.036 | <0.001*** |
| Cost | −0.00023 | −0.000 to −0.000 | <0.001*** | −0.0004 | −0.000 to −0.000 | |
| Government support | | | | | | |
| Regulatory support | Ref (0) | | | | | |
| Financial support | −0.0026 | −0.082 to 0.077 | 0.949 | 0.530 | 0.393 to 0.667 | <0.001*** |
| Training requirements | | | | | | |
| No additional training | Ref (0) | | | | | |
| Moderate training | 0.266 | 0.177 to 0.355 | <0.001*** | 0.229 | −0.005 to 0.462 | 0.045 |
| Extensive training | 0.141 | 0.024 to 0.258 | 0.018** | 0.619 | 0.474 to 0.764 | 0.060 |
| Nature of intervention | | | | | | |
| Simple intervention | Ref (0) | | | | | |
| Complex intervention | −0.323 | −0.401 to −0.245 | <0.001*** | 0.572 | 0.454 to 0.690 | 0.040 |
| None (Opt out) | −3.572 | −4.028 to −3.115 | <0.001*** | 2.216 | 1.844 to 2.588 | 0.233 |
| Model fit statistics | | | | | | |
| Log likelihood | −5885.996 | | | | | |
| Number of observations | 23 868 | | | | | |
| Number of decision makers | 663 | | | | | |
| Draws (Halton) | 1000 | | | | | |

*** $P < 0.001$, ** $P < 0.05$.

requirements (6.02%), and cost of equipment (5.59%), and the least important attribute for the providers was government support (1.82%), highlighting that the decision to offer PHIs is rarely influenced by either financial or regulatory support from the government (supplementary file S3). This was not surprising as government support was not statistically significant.

## Preference heterogeneity

Based on the GMNL model, the value of scale heterogeneity was $\beta = 0.952$, $P < 0.01$, indicating a considerable scale heterogeneity among the respondents, which might constitute an additional source of heterogeneity associated with respondents' preferences. Additionally, the standard deviations from the MMNL model were statistically significant, indicating that there was heterogeneity in preferences. To explore the factors driving taste heterogeneity, we included interaction terms in the MMNL model.

The interaction terms between the number of years worked and extensive training suggested that community pharmacy providers with more years of experience had a higher preference for extensive training compared to no training. However, having a consultation room does not change the preferences for the nature of intervention. Other interactions with socio-demographic characteristics were not statistically significant, indicating that the variation in the preferences is not influenced by those observed socio-demographic characteristics. The full model is presented in supplementary file S2.

## Latent class analysis

Based on the information criteria, a three-class model was used in the latent class analysis, as model statistics showed minimal gains from more classes. The model diagnostics for the different classes are presented in supplementary information (Supplementary file S4). With an increase in the number of classes, there was a decrease in the AIC and BIC. However, when the number of classes was increased to 5, there was an issue of excessively small classes, with one of the classes having 1% of respondents. Taking these into account, we determined 3 to be the optimal number of classes for the analysis.

Table 7 summarizes the findings of the latent class model estimates. Preference heterogeneity was observed across three latent classes. Community pharmacy in class 1, accounting for 15%, had a strong disutility for extensive training ($\beta = -0.382$, $P < 0.001$). However, their preferences for other attributes were not statistically significant, indicating that their preferences were shaped by other factors. Class 2, which had a membership probability of 29.5%, was profit-driven, with a strong preference for higher profit margins ($\beta = 0.0667$, $P < 0.01$). Finally, class 3 with the largest membership probability of 55.4% was capacity development-oriented with strong preferences for both moderate and extensive training ($\beta = 0.312$ and 0.333, respectively, with $P < 0.01$). The opt-out option was negative and statistically significant in all classes, indicating that none of the respondents in all classes were in favour of not providing PHIs.

# Discussion

We found that community pharmacy providers in Kenya have a strong preference for offering PHIs in general. This shows that the extended role of PHI delivery is widely accepted by the providers. These findings are similar to studies conducted in LMICs such as Nigeria (Boniface et al. 2023), Sudan (Mohamed et al. 2013), and Ethiopia (Ayenew et al. 2022), which have indicated providers' willingness to offer PHIs. This is a crucial insight given

**Table 6** Marginal WTP and WTA estimates.

| Attributes | Marginal WTP estimates | | | Marginal WTA estimates | | |
|---|---|---|---|---|---|---|
| | Coefficient | 95% CI | *P* value | Coefficients | 95% CI | *P* value |
| Profit margin | 1165.315 | 752.694 to 1577.937 | <0.001*** | WTA denominator | | |
| Cost | WTP denominator | | | 0.001 | −0.001 to −0.000 | <0.001*** |
| Government support | | | | | | |
| Regulatory support | Ref (0) | | | | | |
| Financial support | −21.147 | −3184.756 to 3142.462 | 0.990 | 1.806 | −3.948 to 0.336 | 0.098 |
| Training requirements | | | | | | |
| No additional training | Ref (0) | | | | | |
| Moderate training | 11 738.470 | 6337.751 −17 139.190 | <0.001*** | −9.118 | 6.026 to 12.209 | <0.001*** |
| Extensive training | 7327.973 | 1519.925 to 13 136.020 | 0.013* | −4.714 | 0.231 to 9.197 | 0.039* |
| Nature of intervention | | | | | | |
| Simple intervention | Ref (0) | | | | | |
| Complex intervention | −12 306 | −1.74304 to 7217.711 | <0.001*** | 10.946 | −13.526 to 8.366 | <0.001*** |
| None (opt out) | −224 000 | | <0.001*** | 411.864 | −510.836 to −312.892 | <0.001*** |
| Model fit logistics | | | | | | |
| Log likelihood | −5878.4137 | | | −5933.6078 | | |
| Number of observations | 23 868 | | | 23 868 | | |
| Number of decision makers | 663 | | | 663 | | |
| Halton Draws | 1000 | | | 1000 | | |

*$P < 0.05$, **$P < 0.01$, ***$P < 0.001$.

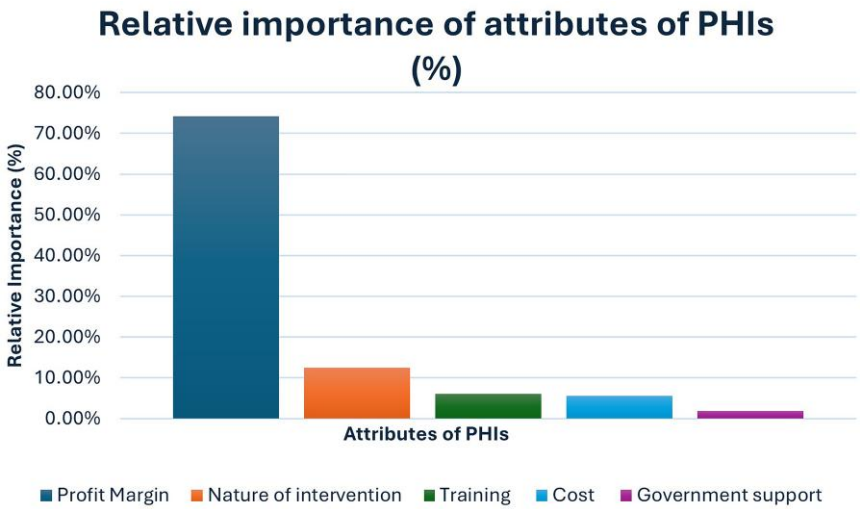


**Figure 2** Relative importance of attributes.

Kenya's interest to leverage the private sector to deliver essential health services.

As expected, profit margin was the most preferred attribute. This is not surprising as community pharmacy providers in Kenya operate as private providers, and their aim is profit maximization for their business. These findings align with previous research, which finds financial incentive to be an important attribute with pharmacists having a higher preference for

**Table 7** Latent class model preference estimates.

| Attributes | Class 1 (15%) | | | Class 2 (29.5%) | | | Class 3 (55.4%) | | |
|---|---|---|---|---|---|---|---|---|---|
| | Coefficient | SE | *P* value | Coefficient | SE | *P* value | Coefficient | SE | *P* value |
| Optout | −0.4849 | 0.1624 | 0.003 | −2.099 | 0.3021 | <0.001 | −4.0389 | 0.3637 | <0.01 |
| Profit margin | 0.00413 | 0.0027 | 0.129 | 0.0666 | 0.0050 | <0.001 | 0.0087 | 0.00156 | <0.001 |
| Cost | −0.0015 | 0.0009 | 0.096 | −0.0023 | 0.0011 | 0.827 | −0.00243 | −0.4333 | <0.001 |
| Government support | | | | | | | | | |
| Regulatory support | Ref (0) | | | Ref (0) | | | Ref (0) | | |
| Financial support | −0.0508 | 0.0923 | 0.582 | −0.2872 | 0.1093 | 0.009 | 0.0872 | 0.0447 | 0.051 |
| Training requirements | | | | | | | | | |
| No additional training | Ref (0) | | | Ref (0) | | | Ref (0) | | |
| Moderate training | −0.1157 | 0.1014 | 0.254 | 0.2459 | 0.1164 | 0.035 | 0.3121 | 0.0519 | <0.001 |
| Extensive training | −0.3819 | 0.1165 | <0.001 | −0.0061 | 0.1712 | 0.972 | 0.3333 | 0.0643 | <0.001 |
| Nature of intervention | | | | | | | | | |
| Simple intervention | Ref (0) | | | Ref (0) | | | Ref (0) | | |
| Complex intervention | −0.1493 | 0.0911 | 0.101 | −0.3607 | 0.0976 | <0.001 | −0.2709 | 0.4046 | <0.001 |
| BIC | 13 204.93 | | | | | | | | |
| AIC | 13 114.994 | | | | | | | | |
| Log likelihood | −6537.4971 | | | | | | | | |

services that will generate an additional income in their business settings (Scott et al. 2007, Grindrod et al. 2010, Wang et al. 2011, Raghunandan et al. 2021, Waters et al. 2024). Policy makers should therefore design PHIs that include financial-based incentives in order to enhance scale-up of PHIs in community pharmacies in Kenya.

Providers preferred simple interventions over complex interventions. These findings are further augmented by WTP estimates, whereby community pharmacists would have to be compensated at Kshs. 12 306 ($94.85) for them to accept complex interventions. These results echo findings from a previous study (Waters et al. 2024), in which community pharmacists reported that they preferred screening services that were simple to understand and easy to explain to the clients on how to use them. This can be attributed to the fact that simple interventions increase providers' self-efficacy and are easy to integrate into existing workflow without the need for additional resources. Negative utility towards complex interventions has also been reported elsewhere. For instance, Doucette et al. reported that pharmacy technicians were not willing to take up interventions that constituted a high workload and impacted their working hours in USA and Australia (Doucette and Schommer 2018, Taylor et al. 2022). It is therefore important that PHIs be designed in a manner that is compatible with existing environment of community pharmacies workflow and values in order to enhance uptake.

However, as pharmacy-based PHIs become more complex and multifaceted, training of providers should be a priority. This is essential to ensure that providers are equipped with the necessary skills and knowledge to provide high-quality care. Community pharmacy providers in this study indicated significantly higher preferences for PHIs with provisions for capacity development through additional training (moderate and extensive) compared to no training. However, their preference for moderate training was relatively higher than that of extensive training. This is expected as extensive training periods may disrupt business continuity, particularly for busy pharmacists. Therefore, community pharmacists are willing to build their capacity in PHI delivery however not at the expense of their time. This is consistent with findings from a study conducted in Malaysia (Ang et al. 2022), Ghana (Marfo and Owusu-Daaku 2017), and Nigeria (Ilesanmi et al. 2021), where providers reported a 1–2-day training as adequate. These findings imply that community pharmacists acknowledge the need for enhancing knowledge for PHI delivery and therefore training should be tailored in a manner that does not disrupt the providers' workflow. Additionally, we found that community pharmacy providers with over 10 years' experience preferred extensive training. These findings are similar to those of a study conducted in Canada (Schindel et al. 2019), where providers with more experience reported the need for additional training for most skills. In Australia, the need for training has also been reported to be influenced by the number of years in practice (Hoti et al. 2014). Taking on new roles of PHI delivery may be associated with a steep learning curve, especially for providers whose role has primarily focused on the traditional role of dispensing medication. Therefore, as the roles of community pharmacies continue to advance, training for ongoing changes in practice is needed. This suggests that community pharmacists who have practised in traditional dispensing roles for many years may require additional training to support the changes to take on newer roles of PHI delivery.

Community pharmacy providers indicated a disutility for PHIs that were associated with high costs, implying that the financial burden associated with the purchase of equipment may deter the providers from taking up additional roles of PHI delivery. This is expected as most of the providers in our study charged a relatively low fees for PHIs, with some offering PHIs free of charge. For instance, weight management services such as offering basic lifestyle and dietary advice were offered for free. This was mainly used as a means of building the client's trust and loyalty. On the other hand, vaccination services were charged a higher fee. This is due to the procurement cost of the vaccines, cold chain requirements, and the requirement for additional staff who are trained on the vaccinology, which increases the operational costs for

the community pharmacy providers. It is therefore reasonable that they would avoid incurring high costs of equipment, especially without direct financial returns. This is consistent with findings among community pharmacists in other contexts, where direct costs associated with equipment and supplies have been reported as a significant barrier to adoption of services by community pharmacy providers (Garcia-Cardenas et al. 2017, Martínez et al. 2023, Martínez et al. 2024). In high-income countries, structured reimbursement models and supportive policy mechanisms have been applied to mitigate financial barriers for providers (Dixon et al. 2023). For instance, pharmacists-led interventions for blood pressure control have been deemed successful in the USA due to the well-established reimbursement frameworks for the providers (Dixon et al. 2023). Therefore, policy interventions that offer financial support or subsidize initial investments could be pivotal in encouraging the adoption of comprehensive PHIs by community pharmacies in Kenya.

However, despite the disutility of the high cost of equipment, government support, which entailed financial subsidies, had the least influence in decision-making of providers to offer PHIs. This was surprising as previous studies have highlighted the importance of government support in enhancing the uptake PHIs. For instance, government support has been deemed important to enhance the uptake of vaccine delivery in Ethiopia (Erku and Mersha 2017, Gelayee et al. 2017). The low preference for government support reported in this study could be attributed to scepticism towards government involvement. Currently, the collaboration between the government and community pharmacists for PHI delivery is weak, as community pharmacists are often left out of the national public health strategies. Furthermore, the absence of clear policies on the role of community pharmacy in PHI delivery over the years has led providers to feel that their role is not recognized or valued by the government sector. Providers therefore prefer autonomy when it comes to taking extended roles of PHI delivery. However, these findings should not be interpreted to mean that government support is not important, but rather implies that there is a need to rethink the role that the government can play in enhancing the delivery of PHIs through community pharmacies beyond financial subsidies and regulatory support. For instance, more collaborative approaches such as public–private partnerships may be more effective in developing trust and sustainable relationships with the providers.

This study has several strengths; first, we used a DCE, which allowed us to evaluate alternatives and attribute characteristics that do not exist yet. Second, the findings contribute to the limited evidence of preferences of community pharmacy providers for attributes of PHIs in LMIC settings. Third, this study identified trade-offs that community pharmacy providers were willing to make, which offers insights into the design of PHI programmes.

One limitation of the study is hypothetical bias, which is typical of the DCE methodology. Second, given the limited number of statistically significant interactions in our MMNL model, there is a possibility that heterogeneity of preferences was influenced by other variables not captured in our study. Nevertheless, this study provides a valuable insight into the community pharmacists' preferences for attributes of PHIs that could be used to inform the design of PHIs to be delivered through community pharmacies in Kenya and similar LMIC settings.

# Conclusion

This study revealed that there is a high acceptance of the role of PHI delivery among community pharmacists in Kenya. Providers value PHIs that generate a profit margin, indicating the importance of financial viability. They also value simple interventions that are easy to implement in their practice. Additionally, they have a higher preference for PHIs that require moderate training that does not interfere with their day-to-day practice, highlighting the importance of capacity development. Finally, providers prefer PHIs that are associated with minimal equipment costs for initial setup. Government support, in the form of financial or regulatory support, was the least important attribute and did not have an influence on decision-making for community pharmacists. Therefore, as Kenya accelerates efforts to achieve universal health coverage, community pharmacies are a viable channel to increase access to PHIs. However, it is important that public health programmes be designed in a manner that aligns with the providers' preferences and operational realities to enhance acceptability and uptake.

Findings from this study offer several policy implications in Kenya. First, it is important that the structure of PHIs ensures that providers are not financially disadvantaged by participating. Generating profit is central to providers, and ignoring this in programme design risks alienating a large portion of providers from participation. Second, complex interventions were associated with high disutility; therefore, policy makers should prioritize PHIs that are straightforward and easy to adopt to existing practice while ensuring that there are training opportunities available and designed in a manner that does not disrupt providers from their daily practice. Third, the cost of equipment is reported to be a barrier to providers. While financial subsidies from the government were not considered to be important, it is crucial that other measures be employed to offset the costs associated with the initial setup. This is particularly important for smaller pharmacies that may lack the capital to invest in PHI delivery.

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# Author contributions

A.M., G.A., J.K., J.N., and E.B. contributed to the conception and design of the work. A.M. contributed to data collection. A.M., G.A., and J.K. contributed to the data analysis and interpretation. A.M. drafted the initial manuscript. A.M., G.A., J.K., J.N., and E.B. contributed to the critical revision of the manuscript. All authors approved the submission of the final manuscript.

# Supplementary files

Supplementary material is available at *Health Policy and Planning* online.

Supplementary file S1 Study questionnaire.
Supplementary file S2 MMNL interaction results.

Supplementary file S3 Partial log likelihood.
Supplementary file S4 Model diagnostics for 2 to 5 classes.

## Conflicts of interest

None declared.

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## Reflexivity statement

The research was conducted jointly by a team comprising two females and three males, all hailing from low- and middle-income settings, with varying research seniority levels, academic backgrounds, and qualifications. Four of the authors are Kenyan-based researchers with significant experience with the Kenyan health system, and one, who is based in Ghana, contributed significant expertise in DCE methodology. The conceptualization, analysis, and writing for this study involved a balanced representation based on multinational, experience, and gender-balanced research project team.

## Ethical considerations

Ethical approval for the study was issued by the Kenya Medical Research Institute (KEMRI) Scientific and Ethics Review Unit (SERU 4710) and Kenya National Commission for Science, Technology and Innovation (NACOSTI), License No: NACOSTI/P/23/28410 prior to data collection. Written and oral informed consent was obtained from the participants before data collection.

## Ethical approval

No ethical approval was required for this study.

## Data availability

The data underlying this article will be shared on reasonable request to the corresponding author.

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