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The stated preferences of community-based volunteers for roles in the prevention of violence against women and girls in Ghana: A discrete choice analysis

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ABSTRACT

Violence against women and girls (VAWG) is a human rights violation with substantial health-related consequences. Interventions to prevent VAWG, often implemented at the community level by volunteers, have been proven effective and cost-effective. One such intervention is the Rural Response System in Ghana, a volunteer-run program which hires community based action teams (COMBATs) to sensitise the community about VAWG and to provide counselling services in rural areas. To increase programmatic impact and maximise the retention of these volunteers, it is important to understand their preferences for incentives.

We conducted a discrete choice experiment (DCE) among 107 COMBAT volunteers, in two Ghanaian districts in 2018, to examine their stated preferences for financial and non-financial incentives that could be offered in their roles. Each respondent answered 12 choice tasks, and each task comprised four hypothetical volunteering positions. The first three positions included different levels of five role attributes. The fourth option was to cease volunteering as a COMBAT volunteer (opt-out).

We found that, overall, COMBAT volunteers cared most for receiving training in volunteering skills and three-monthly supervisions. These results were consistent between multinomial logit, and mixed multinomial logit models. A three-class latent class model fitted our data best, identifying subgroups of COMBAT workers with distinct preferences for incentives: The younger 'go getters'; older 'veterans', and the 'balanced bunch' encompassing the majority of the sample. The opt-out was chosen only 4 (0.3%) times.

Only one other study quantitatively examined the preferences for incentives of VAWG-prevention volunteers using a DCE (Kasteng et al., 2016). Understanding preferences and how they vary between sub-groups can be leveraged by programme managers to improve volunteer motivation and retention. As effective VAWG-prevention programmes are scaled up from small pilots to the national level, data on volunteer preferences may be useful in improving volunteer retention.

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1. Introduction

Violence against women and girls (VAWG), which includes physical, sexual and/or emotional forms of violence, is a threat to the human rights and wellbeing of women. Its consequences transcend the negative psychosocial, economic, physical and mental health outcomes of the victims, also impacting the nutritional and other long term life outcomes of their children (Chai et al., 2016). Globally, one in three women experience violence by an intimate partner in their lifetime (World Health Organisation, 2021). In sub-Saharan Africa, between 30% and 65% of women and adolescent girls over the age of 15 years experience intimate partner violence (IPV) (Devries et al., 2013), making it the region with the highest burden of IPV in the world. Rates of VAWG in Ghana are high: 38.7% of ever-married women between ages 15–49 years reported having experienced physical, sexual or psychological violence perpetuated either by current or previous partners in their life times, and 28% of women report having experienced at least one type of domestic violence in the past year (Asante and Premo-Minkah, 2016).

While the majority of VAWG prevention interventions have historically focussed only on prevention (Abramsky et al., 2014), more recently there has been a shift in developing interventions that prevent VAWG by transforming gender norms and relations at the community level (Heise, 2011). In 2002, the Gender Studies and Human Rights Documentation Centre in Ghana (henceforth Gender Centre) developed one such intervention called the ‘Rural Response System to Reduce Violence against Women’ (henceforth RRS). The intervention uses a community response model and is responsible for the recruitment and training of Community Based Action Teams (COMBATs) who undertake sensitization activities to mobilise the community about the ill effects of VAWG while educating them about the benefits of equitable relationships. Their other jobs include providing individual counselling to people affected by VAWG, liaising with state agencies and carrying out referrals where necessary. COMBATs comprise male and female volunteers, nominated by local communities and their leaders, and are trained and supervised by the Gender Centre (Addo-Lartey et al., 2019) (The Prevention Collaborative, 2020). They are paid a small per-diem during training, however once the training is complete, COMBATs work as unpaid volunteers. They are, however, reimbursed for costs incurred during intervention activities, such as transportation costs during sensitization visits. Staff at the Gender Centre provide technical support and supervision during the intervention.

A recent trial evaluating the effectiveness of the RSS program showed a 9.3% reduction in women’s past year experience of sexual IPV, a 15% reduction in emotional perpetration of IPV, and significant reductions in women’s depression scores and reported male partner controlling behaviour in treatment areas in comparison to control areas (Ogum Alangea et al., 2020). In addition to effectiveness, the programme was also estimated to be cost-effective. Ferrari et al. (2022) report that from a health sector perspective, the RRS program had a 52% probability of being cost-effective for women and men jointly, and 95% probability for women only, compared to Ghana’s opportunity cost threshold of $497. Some studies report that community health worker programs that shift healthcare provision from health facilities to the community by engaging unpaid volunteers often appear more cost-effective from a health sector perspective than they are from a societal perspective (Kasteng et al., 2016). The RSS program, however, also had a 98% probability of being cost-effective under the societal perspective for both men and women (Ferrari et al., 2022).

The evidence thus suggests that established community-based interventions such as the RRS/COMBAT warrant consideration for scale up to prevent VAWG in similar contexts. Yet, this is only the second study to our knowledge that looks at the labour market preferences of VAWG-prevention volunteers (Kasteng et al., 2016). Understanding individuals’ motivation for volunteering will enable programmers and policymakers to retain volunteers, who account for the majority of the human resources behind community-based interventions in these settings, especially in regions like Africa where many VAWG interventions are run largely by unpaid volunteers (Heise, 2011; Torres-Rueda et al., 2020).

Discrete choice experiment (DCE) is a quantitative method used to elicit individual preferences. It allows researchers to understand how individuals value selected attributes of a programme, product, or service by asking them to state their choice over different hypothetical alternatives. (Mangham et al., 2009). They are also useful in understanding the determinants of choices among health workers, and are increasingly used to determine the driving factors behind their incentive preferences, without expensive trials or pilot studies (Hensher et al., 2005; Lagarde and Blaauw, 2009). Based on Lancaster’s theory of consumer behaviour (Lancaster, 1966), DCEs can be used to capture how respondents trade off between different attributes of their jobs to reveal the extent to which they value key characteristics of their jobs. Although based on stated preferences, the trade-off design in DCEs can resemble real-life decision making by selecting attributes which are relevant to respondents and feasible to be implemented within the larger policy context. A systematic review of DCEs aimed at eliciting job preferences of health workers in low-and middle income countries (LMICs) found 27 studies conducted with a range of health practitioners, including doctors, nurses, midwives, and nursing students all of whom tend to be the most studied cadres in the health workforce (Mandeville et al., 2014). While the body of work on the stated preferences of community heath providers hired to deliver primary healthcare in LMICs is increasing (Gopalan et al., 2012; Lamba et al., 2021; Saran et al., 2020) (Abdel-All et al., 2019), there is still a dearth of quantitative literature on the incentive preferences of unpaid community health volunteers in Africa (Kasteng et al., 2016), particularly those providing VAWG-prevention services.

This study will be the first to quantitatively examine the stated preferences of VAWG-prevention volunteers using a DCE. In addition, since it is important to acknowledge that different sub-groups of volunteers would have different incentive preferences, we also account for heterogeneity in their preferences in the analysis of our DCE.

2. Data and DCE design

All 120 COMBAT volunteers based in the study regions were contacted to participate in the DCE, as part of the DFID funded *What Works* project (UK Aid, W., 2019). The intervention was implemented in two districts - KEEA and Agona - in the Central region of Ghana in 2018, alongside a cluster randomised controlled trial to assess the effectiveness of the RSS/COMBAT program (Ogum Alangea et al., 2020; Torres-Rueda et al., 2020). The sample size was chosen in line with rules of thumb from previous health worker DCEs, which indicated that a minimum sample size of 50 from each stratum (district) was sufficient to power the study (de Bekker-Grob et al., 2015). Further, given the use of NGENE (Choice Metrics, 2012) to create choice tasks, described below, the priors from the pilot were applied to develop an informed design and the s-estimate from NGENE was used to check the adequacy of the sample size required to estimate coefficients for individual attributes. The DCE was administered individually. After the tasks had been explained by interviewers and respondent questions answered, respondents were asked to complete the DCE alone, though the data collector sat nearby in case the respondent had questions. Additional sociodemographic data were collected alongside the DCE, including personal characteristics listed in Table 2. Informed consent was obtained from all participants before data were collected, and the study was undertaken with ethical approval from the Research Ethics Committees of the London School of Hygiene and Tropical Medicine, the Kintampo Health Research centre, and the University of Ghana.

2.1. DCE development and design

To identify potential attributes and levels for the DCE, we appraised peer-reviewed literature to study the range of financial and non-

Table 1
DCE attributes and levels.

Attribute	Levels
Financial remuneration (per diem) per sensitization activity	1.0 Cedis 2.10 Cedis 3.20 Cedis
Frequency of volunteering activities undertaken per month	1.1 2.4 3.8
Reimbursement of transportation expenses incurred during volunteering	1. No reimbursement 2. Half reimbursement (50%) 3. Full reimbursement (100%)
Trainings offered per year	1.No training offered 2.Training on volunteering offered 3. Professional training offered
Frequency of supervision visits per year	1. No supervision offered 2. Supervision every 3 months 3. Supervision every 6 months

Note: 1 Ghanaian Cedi = USD 0.16 (January 2022).

Table 2
Participant socio-demographic characteristics.

Socio-demographic characteristics		
Gender N (%)	Female	54 (50.5%)
	Male	53 (49.5%)
Age Mean (SD)		46 years (12.2)
Marital Status N (%)	Single	11 (10.3%)
	Married	77 (71.9%)
	Separated	1 (0.9%)
	Divorced	12 (11.2%)
	Widowed	6 (5.6%)
Number of children Mean (SD)		4.26 (2.5)
Level of education N (%)	None	10 (9%)
	Primary	10 (9%)
	Middle school/Junior Secondary school	54 (50%)
	Secondary school	18 (17%)
	Tertiary education	15 (14%)

Note: All participants had been volunteers for the same amount of time.

financial incentives that have been offered to community health workers and volunteers by governments in sub-Saharan Africa. A focus group discussion (FGD) topic guide was then developed, with probes exploring the most offered incentives obtained from the literature review, to capture DCE attributes along with the possible levels for these attributes. We carried out two FGDs (n = 8 and n = 5) in June 2018 with a total of 13 COMBAT volunteers in the central region in Ghana. We recorded and transcribed the discussion in one group and took notes in the other. We coded and thematically analysed the FGD transcripts and notes, identifying multiple themes. Our DCE represents these themes using five attributes with three levels each, minimising, where possible, the cognitive burden of the DCE for respondents. The attributes were: financial remuneration (per diem) offered for each sensitization activity, frequency of sensitization activities undertaken per month, reimbursement of transportation expenses incurred during volunteering, training type offered per year, and the frequency of supervision visits made by the management team per year. These attributes are shown in Table 1 along with their levels.

We piloted the DCE in September 2018 with 13 COMBAT volunteers who had participated in the FGDs. The pilot had a 12-task fractional factorial design, with 4 alternatives and attribute levels represented by text and images, both, to account for different levels of literacy. Research assistants described the experiment to participants in detail before they went on to attempt it. After conclusion, each of the 13 participants filled out a detailed qualitative questionnaire expressing their views on each attribute and overall understanding of the experiment. Minor changes were made to attribute levels and to the pictorial representations of attributes on the basis of the information collected from these questionnaires. For example, we changed the levels of the attribute on remuneration from 5, 10, 15 Cedis to 0,10,20 Cedis as respondents reiterated their keenness to work as volunteers even without payment. We also changed the picture of Ghanaian Cedis shown in the choice tasks to make it look more like real money. Results of the pilot were analysed using a multinomial logit model (MNL) on Stata (StataCorp, 2013) to obtain the priors, which were then used to generate a 12-task, D-optimal design on NGENE (Choice Metrics, 2012).

In each task, respondents were presented with four unlabelled voluntary options each representing a generic COMBAT role. The first three options included different levels of the five attributes. The fourth option was a generic opt-out, labelled as "I would stop volunteering". Respondents who chose the opt-out option rejected all other voluntary positions. The opt-out option ensured the experiment reflected 'real world' choices. It also enabled us to estimate unconditional demand, modelled as a constant with no attribute levels. An example choice task is given in Fig. 1.

After looking at hypothetical voluntary positions A, B, and C, and imagining all else between these positions is equal, which position do you prefer?

3. Modelling Methodology

DCE data were analysed using the random utility framework which assumes that respondents compare all options presented to them in the choice task and pick the one that maximises their utility (McFadden, 1986). For respondent *n*, alternative *i*, and choice situation *t*, their utility, *U*, can be given by:

$$U_{i,n,t} = V_{i,n,t} + \varepsilon_{i,n,t} \quad [1]$$

Where , *U*, has a deterministic component $V_{i,n,t}$, and a random component $\varepsilon_{i,n,t}$ which is assumed to be an independently and identically distributed Extreme Value Type I function (Hensher et al., 2005; Manski, 2001). For each alternative, the deterministic part of the utility can be re-written as:

$$V_{i,n,t} = f\left(\beta_n, x_{i,n,t}, z_n\right) \quad [2]$$

Where β_n is a vector of sensitivities for respondent *n*; $x_{i,n,t}$ is a vector of attributes for alternative *i* I choice situation t; and z_n is a vector of socio-demographic characteristics of respondent *n*.

In this DCE application, the deterministic part of the utility for a voluntary option *i*, for individual *n* was characterised by the selected set of five attributes, and given by:

$$\begin{aligned}\boldsymbol{\beta_n} X_{n,i} &= \beta_{ASC_i} + \beta_1 Perdiem_i + \beta_2 Frequency_i + \beta_3 Vol\_training_i \\ &+ \beta_4 Pro\_training_i + \beta_5 Half\_transport_i + \beta_6 Full\_transport_i \\ &+ \beta_7 three\_month\_supervision_i + \beta_8 six\_month\_supervision_i \quad [3]\end{aligned}$$

Where β_{ASCi} corresponds to the alternative-specific constant (ASC) for alternative *i*. We introduced three ASCs, one each for job choices A, B, and C, while the opt-out was coded simply as 0 (zero). The preference weights of attribute levels used to characterise the voluntary roles included in the DCE are represented by β_1 to β_8. Per diem and frequency of visits were specified as continuous variables after being tested against a specification where they were treated as categorical variables. Type of training, number of supervisions, and amount of transport reimbursement were categorical variables, where each category was dummy coded. No training, no transport per diem and no supervision visits were selected as reference categories for the three categorical attributes.

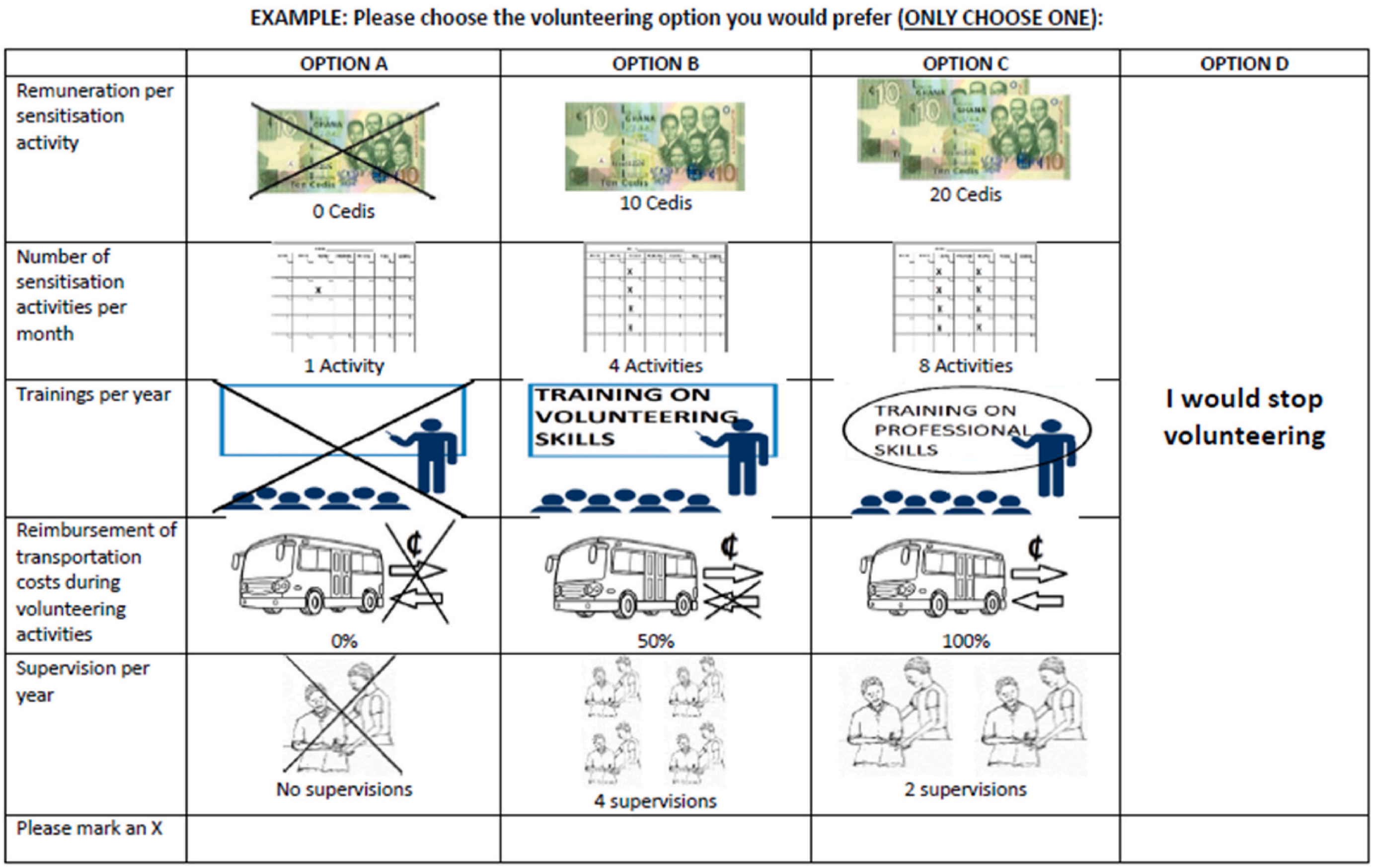

Fig. 1. Example DCE choice task.

We conducted an initial exploratory analysis using a multinomial logit model (MNL), where the probability of an individual n choosing alternative i in choice situation t can be given as below.

$$P_{int} = \frac{\exp(X_{i,n,t}\beta)}{\sum_i \exp(X_{i,n,t}\beta)} \quad [4]$$

Since the MNL assumes independence of irrelevant alternatives (IIA) and homogeneity in respondent preferences (Hensher et al., 2005), we estimated a mixed multinomial logit model (MMNL) to relax these assumptions and allow for a continuous distribution of coefficients over respondents. This enabled us to examine if heterogeneity in respondent preferences can be captured by random parameters such that $\beta \sim f(\theta_n|\Omega)$ where θ_n was a vector of random parameters and Ω the parameter's distributions (Quaife et al., 2018a). The unconditional probability of the sequence of choices, Y_n for respondent n was thus given by:

$$\Pr(Y_n|x_n,\Omega) = \int \prod_{t\in T_n} \frac{\exp(\beta' x_{i,n,t})}{\sum_{j\in J}\exp(\beta' x_{j,n,t})} f(\theta_n|\Omega)d(\theta_n) \quad [5]$$

Another way of relaxing the IIA assumption is through estimating latent class models (LCM) which do not require parametric distributional assumptions, like those needed for an MMNL, to be made by the analyst and can help in identifying subgroups of people with different taste heterogeneity (McFadden and Train, 2000). These subgroups are important to identify in research to inform policy as targeted strategies can then be identified to fit people with different preferences. LCMs posit that individual behaviour depends on observable attributes as well as on unobserved (latent) heterogeneity, that varies with factors that can be observed by the analyst (Greene and Hensher, 2003). In LCMs, this latent heterogeneity is accommodated across discrete classes, assuming that there are sub-groups of respondents who will differ in their preferences across classes (i.e., they are defined by different parameter vectors) but have the same preferences (and parameters) within a class. Allocation of individuals to a certain class is probabilistic, and which class contains any particular individual is unknown to the analyst. The central behavioural model generating choice probabilities within each class is often an MNL, though it is also possible to account for random heterogeneity in preferences within each class by allowing the behavioural model within each class to be an MMNL. The analyst stipulates the number of classes and which observed variable to include in the model which can affect the class allocation probability of respondents (Lagarde et al., 2015; Mandeville et al., 2016). The optimal number of classes to be included in the LCM are identified based on goodness of fit measures such as an information criteria that penalise improvements in fit as the number of included parameters rise (Greene and Hensher, 2003; Heidenreich et al., 2018). In an LCM, the unconditional probability of respondent n choosing alternative i in choice situation t, can thus be given by

$$P_{it}(i|\beta_k) = \sum_{k=1}^{K} \pi_{nk} \frac{\exp(X_{i,n,t}\beta_k)}{\sum_i \exp(X_{i,n,t}\beta_k)} \quad [6]$$

where the probability of respondent n belonging to class k is given by π_{nk} (Matthew Quaife et al., 2018a). Further, the posterior expected values (conditionals) of class allocation probabilities for each respondent can be produced by the LCM, to allocate each respondent to a class based on their highest probability of falling in a class, and then respondent characteristics can be compared between classes (Lagarde et al., 2015). LCMs are thus well suited for policy-facing research as specific policy recommendations can be made for distinct classes, for targeted policy action.

We estimated LCMs with two to five classes and a panel specification (with multiple responses per individual), and compared their model fit measures including log likelihood, Akaike and Bayesian Information Criteria and McFadden's adjusted Pseudo R^2.

3.1. Model estimation

We used Apollo version 0.2.6 (Hess and Palma, 2019) in R (version 4.0.2) to estimate our models, using the maximum likelihood approach. The MMNL model was estimated using 2000 Sobol draws, with starting values obtained from the corresponding MNL. The choice of draws was driven by recent literature that favours Sobol draws over Halton or MLHS draws due to correlation concerns in the latter (Czajkowski and Budziński, 2019). All attributes in the MMNL were specified as randomly distributed. All parameters except per diem were set to follow a normal distribution to acknowledge our uncertainty in the nature and direction of heterogeneity around those coefficients. Per diem was set to follow a positive μ-shifted log-normal distribution as the coefficient of per diem was expected to be positive. Recent literature has shown that μ-shifted log-normal distributions can be more desirable in mixed multinomial models for the monetary parameter, in comparison to standard log-normal distributions, when computing welfare estimates. They contribute to mitigating the chances of 'exploding' coefficients as their point mass is further away from zero (Crastes dit Sourd and Romain, 2021).

4. Results

4.1. Respondent characteristics

The final DCE sample comprised 107 out of the 120 COMBAT volunteers contacted. Thirteen COMBATs (11%) were either unavailable during data collection or had relocated outside of the study area and were not traceable. The sample was evenly split between men (50.5%) and women (49.5%), reflecting the composition of COMBATs. The mean age of participants was 46 years (SD 12.2), the majority (77%) were married with 4 children on average (SD 2.5). Less than a third of the respondents had completed secondary school (31%). Table 2 provides key sociodemographic characteristics.

4.2. Population level preferences

Most of the 107 respondents answered all 12 choice tasks, except two respondents who answered only 11, making the total number of observations analysed 1282. The opt-out was selected only 4 times (0.3% of choices).

Results from the MNL are given in the supplementary file, Table 6. MMNL results are given in Table 3, where we report the log likelihood, Akaike and Bayesian Information Criteria (AIC/BIC) as measures of model goodness of fit, as well as the coefficients of each attribute level parameter along with its standard deviation. We see that all three measures are better for the MMNL in comparison to the MNL, suggesting that the MMNL fits our data better, perhaps because there is random heterogeneity in respondent preferences which the MMNL is better able to capture. The non-monetary parameters for which the coefficients are positive can be interpreted as having a positive impact on the utility of COMBATs for most participants (bearing in mind that the parameters are normally distributed) while those with negative coefficients can be seen as contributing to disutility for a majority of the respondents. The coefficient and standard deviation of the per diem attribute correspond to the mean and standard deviation of the underlying normal distribution. Given that this attribute is assumed to be positive μ-shifted, the respondents are assumed to always derive positive utility from a marginal increase in compensation. As expected, and in line with results from the MNL, we see that the coefficients for all the non-monetary attributes were positive and highly significant. COMBATs gained most utility from training in voluntary skills (compared to no training), followed by supervision visits held every three months (compared to no supervision offered). However, the standard deviation for both these parameters was large and significant indicating heterogeneity in the sample around preferences for these parameters. COMBATs gained utility from other attributes as well, but to varying degrees (Table 3). Given that all three ASCs were statistically significant, we also conclude that the respondents had baseline preferences for choosing one of the three unlabelled alternatives, compared to choosing the opt-out. However, they preferred choosing one of three alternatives more or less equally across the sample.

Table 3
MMNL results.

AIC	2239.91			
BIC	2353.34			
Log likelihood	−1097.95			
No of parameters	22			
No of respondents	107			
No of observations	1282			
Category	**Parameter**	**Estimate**	**SE.**	**T ratio**
Mean (μ)	ASC_a	1.68*	0.84	2.00
	ASC_b	1.78 *	0.83	2.14
	ASC_c	1.82*	0.83	2.20
	Per diem	−3.48**	0.11	−32.25
	Frequency of visits	0.07 **	0.02	3.70
	Half transport reimbursement	0.73**	0.11	6.65
	Full transport reimbursement	0.58*	0.22	2.66
	Volunteering training	1.30**	0.19	6.61
	Professional training	0.84**	0.21	4.07
	3 monthly supervision	1.08**	0.14	7.84
	6 monthly supervision	0.90**	0.12	7.99
Standard Deviation (σ)	ASC_a	0.57**	0.14	−4.03
	ASC_b	0.05	0.06	−0.87
	ASC_c	0.00	0.04	0.15
	Per diem	0.05**	0.11	8.92
	Frequency of visits	0.10**	0.03	−3.70
	Half transport per diem	0.15	0.28	−0.53
	Full transport per diem	0.70*	0.32	−2.20
	Volunteering training	1.06**	0.16	6.66
	Professional training	1.11**	0.24	−4.61
	3-monthly supervision	0.68**	0.11	−5.94
	6-monthly supervision	0.03	0.08	0.34

Note: ** significant at 1% level, * significant at 5% level. AIC = Akaike Information Criterion, BIC= Bayesian Information Criterion. Since per diem followed a positive μ-shifted log-normal distribution, to interpret the coefficient take the exponent of −3.48 which is 0.031. Further, all three ASCs were included as random terms in the model following recommendations by Walker (2002) and to capture a potential ordering effect.

4.3. Latent class analysis

Below we present results of the LCMs. Table 4 reports model goodness of fit results for LCMs with 2–5 classes. A comparison of model fit measures including the log-likelihood, pseudo R^2 and the Akaike

Table 4
Model goodness of fit results.

Number of classes	2	3	4	5
Log Likelihood	−1134.44	−1096.13	−1058.51	−1045.22
Adjusted Pseudo R^2	0.35	0.37	0.38	0.39
AIC	2308.87	2250.26	2193.01	2184.44
BIC	2433.97	2439.99	2450.1	2510.99
Number of parameters estimated	20	29	38	47

Notes: AIC = Akaike information criterion; BIC = Bayesian information criterion.

Information Criterion (AIC) suggests that the LCM with 5 classes fitted our data best. However, an assessment of the Bayesian Information Criterion (BIC), which incorporates a more stringent penalty term for the number of parameters included in the model, suggests that the model with 2 classes fitted our data better. Further, an assessment of the class allocation probability for each of the classes for the LCM with 5 classes showed that the mean probability of belonging to classes 4 and 5 was <10%, with parameters in these classes being statistically insignificant at the 5% level. An assessment of fit measures for the three-class LCM, however, shows all fit measures except BIC to be better than those of the LCM with 2 classes and the mean class probability for each of the three classes was >15%, with most parameters being significant at the 5% level. We therefore used the three-class LCM as our main model because we thought it was a better behavioural fit for our data than the other estimated LCMs.

Results of the three-class LCM (Table 5) show the differing preferences of population sub-groups for different role-attributes. Based on posterior probabilities, every participant was further assigned to the class where their choice patterns best fitted, and data on respondent characteristics was compared for each class to highlight broad descriptions of each subgroup. The three subgroups were given qualitative titles based on their preferences: 'the go getters', 'the veterans', and 'the balanced bunch'.

The 'go getters' (Class 1), comprising a third of the participants, were the most educated subgroup. They were majority men and gained most utility from being trained in volunteering skills, followed by professional skills. They wanted their work to be supervised every 3 months. Some of the COMBATS in this group showed most inclination to stay in their jobs for the longest, though there was large variation in the group. They reported the highest number of counselling sessions in the past month.

The 'veterans', Class 2 and the smallest percentage of participants (15%), were comparatively older than other respondents, mostly married and somewhat more likely to be women, with higher number of children on average compared to the other two sub-groups. They had the lowest level of education but reported delivering the most sensitization activities in the past month. They disliked receiving further training and supervision. However, they valued delivering more sensitization visits per month and higher per-diems. They surprisingly also disliked receiving reimbursement for the travel cost incurred during volunteering.

The "balanced bunch", in Class 3 and comprising most COMBATS (51%) were largely women, married and showed that their utility gained from all the attributes was more or less the same. They reported wanting to stay in their volunteering roles for the least number of years in comparison to the other sub-groups.

5. Discussion

Using DCE data on COMBAT volunteers in Ghana, we analysed the trade offs for relevant work characteristics made by VAWG-prevention volunteers, who are crucial to the delivery of interventions proven to be effective and cost-effective. We used MMNL and LCMs to account for random and discrete heterogeneity in preferences within the population, respectively. While the MMNL showed better model fit in comparison to the 3-class LCM, the LCM was considered to be a better behavioural fit for the data as the focus of the paper was to understand the discrete preferences of respondent sub-groups. Since the LCM did not severely underperform in comparison to the MMNL, it was acceptable to present the 3-class LCM as the preferred specification.

Overall, we found that the incentive preferences of COMBATs were in line with previous literature on the behaviour of community volunteers in sub-Saharan Africa (Alem Getie, 2015; Arora et al., 2020; Chandler et al., 2009; Kasteng et al., 2016; Strachan et al., 2015). We found that COMBATs gained most utility from getting trained in voluntary skills followed by professional skills. We think that this is because our respondents, the COMBATs, were volunteers and thus to them building skills in volunteering was more relevant for their work in comparison to building professional skills. The respondents also highly valued supervision visits every 3–6 months. It was interesting to note that respondents on average gained less utility from the per diem attribute than other role characteristics such as training and supervision. There are some microeconomic theories which suggest that volunteers may perceive benefits of volunteering to outweigh the opportunity costs associated with the activity and thus value the financial attributes less

Table 5
Estimation results for the three-class LCM.

Class	1			2			3		
	The go-getters			The veterans			The balanced bunch		
Class allocation probability	33.4%			15.4%			51.2%		
DCE parameters	**Coefficient**	**SE**	**T ratio**	**Coefficient**	**SE**	**T ratio**	**Coefficient**	**SE**	**T ratio**
ASC	1.86**	0.55	3.3872	1.92**	0.55	3.5077	1.93**	0.55	3.5135
Per diem	0.03**	0.01	3.3955	0.33**	0.07	4.8686	0.057**	0.01	9.5302
Frequency of visits	0.05*	0.02	2.2481	0.84**	0.22	3.6948	0.04	0.02	1.7315
Half transport reimbursement	0.52**	0.13	4.1401	−0.28	0.58	−0.4827	0.61**	0.14	4.3837
Full transport reimbursement	0.63*	0.30	2.1487	−3.58**	1.16	−3.0783	0.54*	0.25	2.1723
Volunteering training	3.24**	0.51	6.3802	−1.92*	0.81	−2.3793	0.59**	0.18	3.3558
Professional training	2.97**	0.63	4.7798	−2.94*	0.75	−3.9436	0.23	0.19	1.2122
3-monthly supervision	1.18**	0.32	3.737	−0.86	0.48	−1.7792	0.94**	0.21	4.4705
6-monthly supervision	0.82**	0.22	3.829	−0.43	0.48	−0.9043	0.95**	0.14	6.8367
Participant characteristics	**Class 1**			**Class 2**			**Class 3**		
Female N, (%)	16 (44%)			11 (61%)			27 (51%)		
Median Age in years (SD)	45.7 (11.9)			49.9 (10.4)			45.9 (12.9)		
Married N, (%)	24 (67%)			14 (78%)			39 (74%)		
Secondary school or above N, (%)	14 (39%)			3 (17%)			16 (30%)		
Number of children (SD)	4 (2)			5 (2.5)			4 (2.6)		
Mean additional years willing to volunteer (SD)	12 (11.4)			11 (5)			9 (7.6)		
Mean sensitization activities carried out in the past month (SD)	3 (2.3)			4 (2.3)			3 (3.2)		
Mean of individual counselling sessions undertaken in the past month (SD)	6 (5.5)			4 (2.3)			3 (3.1)		
Mean referrals carried out in the past month (SD)	0 (1)			1 (0.8)			1 (1.5)		

Note: ** significant at 1% level, * significant at 5% level. Note: The ASCs have been considered as homogeneous across classes based on results from a series of unreported likelihood ratio tests, which showed that assuming heterogeneity in ASCs across classes did not improve data goodness of fit

(Kasteng et al., 2016). While benefits of volunteering vary based on individual preferences, they include positive emotions from being helpful and other similar personal stimuli from volunteering (Bénabou and Tirole, 2006). It was also surprising to see that participants valued a half transportation reimbursement almost equally as a full transportation reimbursement. We can't be certain about the reason behind these results without collecting follow-up data, however, we think that this could have been due to participants protesting towards this attribute as they may have felt that the comparison behind the two levels (50% reimbursement Vs full reimbursement) was not valid for some of them. From our knowledge of the context, we think it could also have been because a higher reimbursement may require greater scrutiny and take longer to process. Respondents may prefer to put in a reimbursement for a smaller amount that they know will be processed with less hassle and more quickly, rather than risk it being rejected or take too long.

We also found variation in incentive preferences of respondents and identified three different sub-groups through the first use, to our knowledge, of a latent class model in this area of application. Results showed that COMBAT volunteers with higher education cared most about being trained in voluntary skills, followed by three monthly supervision visits from the Gender Centre. These findings were in line with literature from labour economics, where the human capital model suggests that individuals invest in building longer term human capital (through studies and training) leading to the accumulation of different skills, which can in turn determine labour productivity and higher salaries in the future (Mincer, 1958). These findings may also suggest that people who have previously invested in training and education have a clear affinity for acquiring information and is why they chose options with lower per-diem but better training opportunities.

In contrast, older, more experienced but less educated COMBATs disliked attributes such as training and supervision and preferred a higher frequency of sensitization visits and higher per-diems. This was not surprising because the expected returns from training are likely to decrease as one grows older, which could be why more experienced COMBAT volunteers were less likely to invest in training, or care too much for supervision. This group seems to be the most prosocial of all as their coefficient for delivering the sessions is by far the highest across the three groups. One unusual finding was that they gained disutility from reimbursements for transportation expenses incurred during their work. This could be because in contrast to per diems which are fungible, transport reimbursements were not because reimbursements were only against expenditure. In addition, respondents could have had other ways of securing transport. Since the respondents in this sub-group were mostly older women with more children in comparison to other groups, they may have found it to be an inconvenience to have to recoup part of the public transport fare, especially if a cheaper way to commute was available.

The balanced bunch comprised most COMBATs. These respondents gained more or less the same amount of utility from all the attributes included in the DCE. This was an interesting finding as it could mean that perhaps the RSS/COMBAT program runs at an optimal level and COMBATs are in general happy with the way the program is currently set up. However, since the DCE only provides insights into the preferences of these volunteers at one point in time, it is not clear for how long the program will remain optimal and what the duration of such interventions should be for them to be successful. No studies have so far investigated the optimal longevity of VAWG prevention interventions, to our knowledge. We do not know how long volunteers should be retained for these programs to have maximum impact on the community given available resources. Additional research is needed in this area to help policy makers and programme managers understand how volunteers' preferences for incentives evolve.

The broad conclusions from our results are likely to be important for many other sub-Saharan African countries, especially as the *RRS/COMBAT*, much like other VAWG prevention interventions, relies heavily on volunteers to deliver services. We present key evidence on how policy makers can leverage the use of non-financial incentives for the retention of such volunteers. While it may be difficult to offer different incentives to different groups based on demographics alone, our results could be used to offer the most desired set of incentives to all volunteers—or to offer different packages of incentives and volunteers can choose themselves which ones they prefer. However, there are often methodological challenges and limited evidence on how to best value the time of such, unpaid volunteers. More than the financial costing perspective, where the main cost of unpaid labour includes training cost, it is important to understand the total economic costs of a programme (i. e., the total value of the resources that go into an intervention), in order to determine feasibility and sustainability across settings. Approaches that measure opportunity costs (i.e. the benefits foregone of the next best possible alternative, be it work or leisure) have been used to calculate economic costs of volunteer labour (Drummond et al., 2015). However, in settings with high levels of informal employment, the opportunity cost of volunteering is not easily determined, and the replacement cost method presents a more viable way to value volunteer time (Kasteng et al., 2016). For the majority of prevention interventions, the evidence shows that funding should be provided by the health sector in LMICs for them to be cost-effective (Ferrari et al., 2022). Our findings therefore suggest consideration for further investment in the RRS/COMBAT by the Ghanaian government, leading to full-funding or co-funding with the Gender Centre, for its sustainability.

Our study is subject to some limitations. First, we recognise that the study draws out the stated preferences of COMBAT volunteers under hypothetical situations which may not accurately predict their real-life choices, potentially leading to hypothetical bias (Hensher et al., 2005). However, sufficient research now exists to suggest that DCEs with relevant attributes can minimise hypothetical bias (Quaife et al., 2018b) and extensive piloting was done to ensure the relevance of selected attributes. Further, when considering how useful DCEs can be in predicting the labour market choices of health workers, one must consider the alternative data sources available to decision-makers. There is likely to be no revealed preferences data to base forecast on preferences for incentives, particularly when planning to make policy decisions around incentive packages that don't currently exist. Second, this study does not include estimates for willingness-to-pay, which can be useful to compare how much the COMBAT workers are willing to be paid for trade-off between attributes in their roles. We felt that this was not a pertinent question to answer as COMBATs are currently unpaid volunteers so trading off payment for role attributes may not be the most relevant to them.

6. Conclusion

Preventing VAWG is imperative in mitigating physical and emotional harm on women and girls. In sub-Saharan Africa, where the burden of VAWG is the highest, most violence prevention programs are delivered by unpaid volunteers whose preferences for role attributes are not known. How these volunteers value different role characteristics is important to retain them in their positions for the sustained delivery of VAWG interventions deemed effective and cost-effective. Our study is the first to generate a key body of evidence on the incentive preferences of VAWG-prevention volunteers in Ghana, which can also be reflective of similar cadres in other African countries.

Our findings were in line with other literature which suggests that policy levers such as training and human development, supervision and mentorship are often preferred more than remuneration within volunteer cadres. We also provide robust findings capturing the heterogeneity in respondent preferences and demonstrate the first application of latent class models to identify three sub-groups with distinct incentive preferences within the sample.

Our findings present a step forward towards justifying the scale-up and sustained response of VAWG-prevention through volunteers. We present key evidence on how policy makers can leverage the use of non-financial incentives for the retention of these volunteers who are important in the response needed to meet sustainable development goals and effectively address VAWG in Sub-Saharan Africa.

Credit author statement

Nikita Arora: Methodology, Formal analysis, Writing-from original draft preparation to final editing. **Romain Crastes dit Sourd**:Formal analysis, Writing – original draft preparation. Matthew Quaife: Methodology, Writing-reviewing and editing. **Kara Hanson**: Writing-reviewing and editing **Giulia Ferrari**: Conceptualization, Methodology, Data collection, Writing-reviewing and editing. **Deda Ogum Alangea**: Conceptualization, Methodology, Writing-reviewing and editing. **Rebecca Kyerewaa Dwommoh Prah** Conceptualization, Data collection, Formal analysis, Writing-reviewing and editing. **Rachel Jewkes**: Conceptualization, Methodology, Writing-reviewing and editing. **Sergio Torres-Rueda:** Conceptualization, Methodology, Data collection, Formal analysis, Supervision, Writing – original draft preparation, Writing-reviewing and editing. **Anna Vassall:** Conceptualization, Methodology, Supervision, Writing-reviewing and editing. **Theresa Tawiah** Conceptualization, Data collection, Formal analysis, Writing-reviewing and editing

Data availability

Data will be made available on request.

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Supplementary file

The MNL performed well showing statistically significant attribute parameters, all at the 1% level. Table 6 gives the estimation results.

Table 6
MNL results

AIC	2377.71		
BIC	2434.43		
Loglikelihood	−1177.857		
	Estimate	**SE**	**T ratio**
ASC_a	2.12709*	0.817388	2.602
ASC_b	2.15987*	0.812719	2.658
ASC_c	2.19952*	0.810056	2.715
Per diem	0.05786**	0.004668	12.396
Frequency of visits	0.04321**	0.013033	3.316
Half transport per diem	0.55348**	0.079575	6.955
Full transport per diem	0.65078**	0.157391	4.135
Volunteering training	1.06893**	0.133156	8.028
Professional training	0.78824**	0.147366	5.349
3 monthly supervision	0.86294**	0.103352	8.349
6 monthly supervision	0.72955**	0.094088	7.754

Note: ** significant at 1% level, * significant at 5% level.
AIC = Akaike Information Criterion, BIC= Bayesian Information Criterion.

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