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BIODIGESTER ATTRIBUTE TRADEOFFS AMONG FARMERS IN KIAMBU AND MACHAKOS COUNTIES, KENYA

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Abstract The diffusion of biodigester technology can contribute support towards the achievement of the global goals brokered under the auspices of the United Nations. They have been promoted among farmers but low adoption remains a challenge. Meanwhile, since biodigesters come in different technical designs, they have corresponding performance attributes. While theory suggests that potential adopters trade off these attributes, information about these tradeoffs is currently unavailable. Developing an understanding of how a potential adopter trades-off these attributes can reveal important information which technology developers and information providers should consider when promoting the technology.

After presenting the underlying random utility framework, a choice experiment (CE) was designed. Six attributes in the CE describing the technology included its installation cost, reliability, durability, maintenance cost, movability, and ease of defect identification. Based on the modified Fedorov algorithm, an efficient design was constructed. This resulted in 64 hypothetical alternatives in total, split into 2 blocks and presented as a series of 8 choice tasks per respondent. Each choice situation had an opt-out alternative and three generic choice profiles.

A random sample of 455 coffee farmers from Kiambu and Machakos provided data used in the analysis. Estimation was implemented through application of a mixed logit model. Results suggested that respondents were willing to forego a cost of 8,400KES for easy defect identification. This suggests the desirability of coupling individual biodigester units with IoT-based sensor instrumentation. This can enhance the continued functioning of biodigesters and stimulate the adoption of the technology leading to reductions in on-farm methane emissions.

Keywords Choice experiment, · mixed logit · adoption · biodigester defects

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1 Introduction

Small scale domestic biodigesters appeal as options for reducing the reliance by farmers on biomass fuels, reducing health-related impacts of such fuels while at the same time reducing GHG emissions (Somanathan and Bluffstone, 2015; Van de Ven et al., 2019). Despite these embedded benefits, observed adoption of the technology has been low. One of the main reasons given for this low adoption have been credit and liquidity constraints faced by potential adopters (Bond and Templeton, 2011; Mwirigi et al., 2014; Muriuki, 2014). This has prompted studies which assess biodigesters for their economic feasibility. From studies conducted in Ethiopia and Uganda, the general conclusion is the biodigesters are economically feasible. Walekhwa et al. (2014) is one such study which shows that biodigesters are economically feasible[1]. But economic feasibility is only a necessary condition for adoption. To afford a biodigester is always necessary, but not sufficient for one to become an adopter. Other intrinsic considerations such as preferences of the decision maker, their attitudes, and perceptions towards the choice situation also come into the decision making process (McFadden, 1999). Therefore, information about the technology is at the core of creating beliefs and perceptions about biodigesters, which are in turn important in the decision process.

Ten years ago, less than 2000 Kenyan households used biodigesters for their energy requirements. Comparatively, there were over 30 million in China, 3.8 million in India and 0.2 million in Nepal (Rajendran, et al., 2012). Nepal, whose human population is about three fifths the size of the Kenyan population had over 300,000 biodigesters by 2015 (Meeks et al., 2019). This rose from 140,000 biodigesters which had been installed by 2009 (Gautam et al., 2009). This is a coverage of about 4% of the households compared to Kenya whose comparative coverage is less than 0.2% (KNBS, 2018). This difference can be attributed to the strong support provided by many of these Asian country governments as well as accumulated technical knowledge about biodigesters (Bond and Templeton, 2011).

The technology features a suite of different designs. The fixed dome developed in China and floating drum developed in India are among leading designs globally. The plug flow biodigester is the third type of design and unlike the former two, is built over the ground, making it portable. This latter design features a reinforced plastic digester bag, in place of the digester consisting of masonry work in the other designs (Sovacool et al., 2015). Generally, biodigesters have attributes which distinguish them apart. Besides the operating parameters (pH, temperature, hydraulic retention time, organic loading rate and feeding mechanism), the type of biodigester, including materials used determine biogas (methane) yield (Obileke et al., 2020). For instance, given the fluctuating temperatures above ground, designs which feature underground construction may yield more gas (Obileke et al., 2020). Some designs can be fed with both fibrous and non-fibrous feedstock while others can only suitable for non-fibrous feedstock. Others have a longer lifespan while others (especially the portable types) have a shorter lifespan. Nzila et al. (2012) for example provide an overview where they contrast these designs against each other. From their multi criteria sustaibnability assessment, they concluded that the plug flow design was the most sustainable design for Kenya despite its low score in terms of reliability.

Takama et al. (2012) in Ethiopia found that generally, the choice of cooking stove was also dependent on product specific factors. These included the price of the stove, its use costs, and their ability to reduce indoor smoke. From a randomised controlled trial in Bangladesh, Miller and Mobarak (2015) reported that readily observable attributes of a cook stove may determine its eventual adoption. A recent study in India indicates that fuel efficiency and ability to reduce indoor smoke are attributes that attract potential adopters to biodigesters (Talevi, et al., 2022, In Press) However, the willingness to pay (mWTP) for biogas systems, like many improved cook stoves is typically lower than their market price. For instance, for the plug flow biodigester, Kabyanga et al. (2018) in Uganda found that the cost of installation was 10 times larger than the mWTP for these systems. In Nepal, Thapa et al. (2021) estimated mWTP values which were 0.8 times the size of the cost of an installation of the fixed dome design.

In Kenya, authorities have disseminated a single design in the past (Laichena and Wafula, 1997). This has mainly been the fixed dome design. Such standardization has been recommended by others (e.g. Mwirigi et al., 2014), arguing that it makes quality control easier. Meanwhile in Nepal, the Gobar Gas and Agricultural Equipment Development Company (GGC) modified the Chinese fixed dome design and introduced it as the accepted model in Gautam et al. (2009). This was the GGC 2047, which consists of an underground fermentation chamber atop which sits the dome for gas storage. This is similar in many respects to the CARMATEC design from Tanzania. Nontheless, in Kenya, as in other African countries, there has not been much structured and sustained analysis to provide scientifically backed recommendations about which attributes are of great interest to users (Mulinda, et al., 2013). While dissemination of biodigester technology operates from the Energy Centres distributed across the country Laichena and Wafula (1997), empirical observations are that their actual coverage is not enough for the entire farmer population (Mwirigi et al., 2009). In fact, in the Kenyan rural landscape, different designs coexist (Muriuki, 2014). The presence of these different biodigester designs suggests heterogeneity in the interests of users in the attributes embedded in the different designs. This is suggestive evidence that users have gone ahead to adopt biodigesters which are in line with their preferences.

[1] This study uses the NPV criterion and as an indivisible technology with sufficient sunk costs, it is possible that a real options investment approach (ROA) could suggest otherwise. At least, studies applying the ROA in the USA and Canada suggest that NPV is only a necessary but not a sufficient condition to trigger adoption of biodigesters.

The flexi-biogas (a plug-flow design) was recently piloted in Kenya. Through a project launced in 2011 by IFAD, at least 500 of such systems had been built in Kenya (Sovacool et al., 2015). The design is credited for its low cost, fast installation, portability and its applicability in colder high altitude regions. In addition, to encourage adoption, the Kenyan government, through the Finance Act of 2015 exempted plastic digesters, biogas and the lease of biogas producing equiplemt from VAT. This tax break has been maintained in the most recent amendments to the Finance Act by extending the exemptions to prefabricated biodigesters (Republic of Kenya, 2021). While prefabricated biodigesters do not have a precise classification, they work though similar principals as other "traditional" biodigester designs (Cheng, et al., 2014). The only major difference is that prefabs are constructed off site. Meanwhile, the fixed dome design is still the most common biodigester design in Kenya. The Akut and CAMARTEC models are by far the most common fixed dome models (Nzila et al., 2012). By 2017, an additional 13,200 fixed dome biodigesters had been installed in Kenya (Clemens et al., 2018). This was accomplished through support of the African Biogas Partnership Programme, a Dutch government initiative operating in Ethiopia, Kenya, Tanzania, Uganda, and Burkina Faso. The ABPP ran until 2017. In Kenya, the ABPP also featured an improved fixed dome model (KENBIM) which reportedly reduced installation costs by 25% (Clemens et al., 2018). It is difficult to be categorical about whether the growth in biodigester installations through the ABPP was singly a consequence of the subsidy offered for their construction. It is however probable that this may have been a combination of subsidies and a lower cost of installation, the latter being a product specific characteristic.

To the discerning observer, it is clear that most of the biodigesters have been installed in zones where significant dairying occurs. These constitute the highlands, zones above elevations of 1000m above sea level (Bebe et al., 2003). The reason is partly explained by the fact that the zero grazing (cut and carry) dairy system implies ready availability of feedstock in the form of cattle dung. It also suggests the presence of adequate water. These are two important ingredients for the biodigestion process. Generally, smallholder dairying occurs at altitudes above 1500m above sea level (Staal et al., 2002). In such zones with a bimodal rainfall pattern, feed resources are heavily determined by the amount of rainfall and temperature, where precipitation is usually above 800mm per annum (Bebe et al., 2003). Major feed resources for these animals especially for the cut and carry system comes from Napier grass (Pennisetum purpureum) and crop residues (Staal et al., 2002; Jaetzold et al., 2010a; Ortiz-Gonzalo et al., 2017). Characterized by population pressure and resultant small land sizes, Napier has been adopted widely. Napier grass has respectable dry matter yield and is suitable as a cut and carry fodder. These are attributes responsible for its widespread adoption. Dung from these zero grazed ruminants is used as feedstock for the biodigesters. Water (including grey water from other household activities) as well as animal urine can be used to dilute this feedstock (Bansal et al., 2017). Therefore, in addition to socio-economic variables, characteristics of the farming system are important drivers for biodigester adoption (Qu et al., 2013; Sun et al., 2014; Bakehe, 2021). However, while dairying explains much of the spatial distribution of biodigesters in Kenya, it is not enough to explain the inherent heterogeneity. Not all farmers who practice dairy have installed biodigesters.

It has been widely reported that not all installed biodigesters end up being of benefit to their owners. For instance, by 2016, of the ABPP installed plants, 23% had been abandoned. Major reasons for abandonment were technical problems such as broken fixtures and blocked inlets (Clemens, et al., 2018). Similarly, the flexi-biogas design is itself not free from some of these challenges (Sovacool et al., 2015). For example, Nzila et al. (2012) report that the flexi biogas system has a low reliability (40%) compared to the fixed dome and floating drum designs. Here, reliability is the ability of a biodigester to operate as designed, without failure. These challenges however appear to be of similar nature to those reported about three decades ago since often, users do not possess sufficient knowledge on the operation and maitenance of biodigesters (Laichena, 1989). As relatively complex technologies, such a characteristic in turn may reduce its rate of adoption (Rogers, 1983). In fact, Laichena and Wafula (1997) reported that only 25% of fixed dome biodigesters completed before the 1980s were operational.

Like most equipment, age is a significant factor in the performance of biodigesters (Bond and Templeton, 2011). As biodigesters age, performance degrades and they are bound to require maintenance service. It means that for one to contact the Biodigester Construction Enterprise (BCE) offering maintenance servicing, any biodigester owner needs to identify the defects and communicate the same. The fixed dome biodigester features a digester and gas holder made of masonry constructed underground. Without special sealant, this dome is prone to cracks and porosity. Such cracks reduce the amount of accumulated gas and therefore fluctuating pressure in the system. Unfortunately, detecting the presence of cracks is normally difficult if not impossible. But instrumenting the health monitoring of the biodigester can help ease the early identification and reporting of problems and hasten repairs.

An empirical application will suffice to quickly demonstrate the point. In the Rwanda water sector, for example, sensors relaying technical data to a central portal were shown to reduce hand-pump downtime (Nagel et al., 2015). This is accomplished by instrumenting the detection and alerting technicians in real-time. This prompts technicians to perform repairs much earlier. They reduced pump downtime (time to repair) from 152 days to just 21 days. Essentially, these sensors improve reliability of servicing. A reliable service is that which has a high probability of being available in the right quantity and quality when required. In Kitui, Kenya, such instrumentation which improves the speed of service was shown to increase willingness to pay (mWTP) for water services (Koehler et al., 2015). This improvement in service reduced downtime from 27 days to just 2 (Thomson, 2020). Meanwhile, in the biodigester sector, sensor prototypes have revealed their usefulness in monitoring the functioning of digesters (Acharya et al., 2017; Logan et al., 2019). This strongly suggests the possibility of their deployment for improved servicing and maintenance of biodigesters.

Construction subsidies and strong product quality oversight are some of the reasons credited for the strong performance of the biodigestor sector in Nepal (Meeks et al., 2019; Thapa et al., 2021). There, BCEs provided offer to provide service and maintenance for at least three years. In Kenya however, cases are reported of biodigesters due for servicing and maintenance but were not attended because BCEs did not show up (Clemens et al., 2018). In fact, while ABPP trained over 600 masons on biodigester construction, less than 20% were found to be active fulltime. Being masons, other competing construction jobs may keep them away from providing prompt maintenance service. Thus is unlike the situation in Nepal where over 100 registered biodigester companies provide the link through which subsidies administered through a government entity; the Alternative Energy Promotion Centre. These companies employed about 11,000 Nepalese directly (technical, administrative and promotional staff) and an addttional 65,000 indirect jobs (Gautam et al., 2009). The AEPC provided subsidies which covered 40% of installation costs and at the same time, enforced quality standards guiding both installation and maintenance (Meeks et al., 2019). A portion of carbon credits generated were used to sustain this biogas program (Thapa et al., 2021). In the absence of such a structured biodigester sector, adopters in Kenya may need to be assisted to link with the small number of active BCEs. One way through which this can be accomplished is through the deployment of sensors which help link individual biodigesters with BCEs. The mechanism is not fundamentally different from the sensors on hand pumps. Biodigesters can be retrofited with sensors which gather and transmit temperature and pressure data in realtime. This data can be sent via SMS to a central portal manned by the BCE. Thus, the health of the biodigester can be monitored remotely in realtime. This allows BCEs to dispatch technicians on demand, when their service is required: the so called “ambulance service” (Nagel et al., 2015).

However, instrumentation alluded to above has not been rolled out. Yet, its actual installation would entail an extra cost to owners of biodigesters. Nor do many in Kenya know of its existence. As with new introductions, the willingness to pay for this Internet of Things (IOT) based solution has not been studied. Besides, the different biodigester designs feature different attributes (Nzila et al., 2012; Cheng et al., 2014). How potential adopters trade-off these attributes has not been subjected to critical study (Mulinda et al., 2013). Anticipating how potential adopters respond to these different attributes may further guide policy making. Such information is also important for technology developers. Designs can, where technically feasible incorporate or enhance those attributes preferred by potential adopters.

This paper adopts the discrete choice experiment (DCE) method to investigate trade-offs among important biodigester technology attributes among farmers. Smallholder farmers are an important population constituency targeted for adoption. The basis of DCE is random utility theory (RUT) which strongly relies on the work of McFadden (1974), which built on the Lancasterian approach: where utility is derived not from the actual consumption of a good per se, but from the properties or characteristics of the good (Lancaster, 1966). Generally, RUT provides a behavioural framework explaining choice behavior of individuals (Louviere et al., 2010). In this study, we use a mixed logit analytical approach (McFadden and Train, 2000; Hensher and Greene, 2003; Train and Sonnier, 2005; Hole and Kolstad, 2012). The next section details the econometric specification and data. Results are presented and discussed. The paper concludes with what we believe is an opportunity to both understand and incorporate results in biodigester related work by technology developers and promoters in developing countries.

2 Materials and methods

2.1 Stated preferences and discrete choice experiments

While all the biodigester designs come at a different cost, they also feature different attributes (Nzila et al., 2012; Sovacool et al., 2015). A small number of stated preference surveys have therefore been used to value biodigester systems. The mWTP for biodigesters has typically been below their actual cost (see for example, Kabyanga et al., 2018; Thapa et al., 2021). Unlike Takama et al. (2012), these studies employ the contingent valuation method (CVM) to estimate the value of biodigesters from the point of view of the respective population of potential adopters. While these values are generally useful, they cannot be used to elaborate further how the potential adopters value individual attributes of the biodigesters. This is because the CVM has various weaknesses, including the part-whole bias problem. It is notable that CVM is suited for valuing a change as a whole, rather than the small changes which constitute the whole (Hanley et al., 1998; Hanley and Czajkowski, 2019). It is the different attributes from which utility (satisfaction) is derived Lancaster, (1966), rather than the biodigester itself. This is the characteristics theory of value. Applying CVM at the level of attributes rather than the technology to which attributes are embedded is cumbersome. For policy relevance, the method is less preferred than its stated preference choice modeling (CM) counterparts which include paired comparisons, contingent ranking, contingent rating and choice experiment methods (Hanley et al., 2001). As stressed by Louviere et al. (2010), choice experiments are consistent with economic demand theory unlike ranking and rating methods such as conjoint analysis. Conjoint analysis relies on mathematical proofs about mathematical representations of rank orderings, rather than actual human behavior. These CM methods proceed in the stages i) selection of attributes ii) assignment of levels iii) choice of experimental design iv) construction of chooice sets, v) measurement of preferences and iv) estimation procedure (Hanley et al., 2001). While CVM has a longer history, an early empirical application of discrete choice experiments (DCE) based on aggregate data appeared in the 1980s (Louviere and Woodworth, 1983). In its basic form, DCEs provide respondents with a series of alternative scenarios which differ in terms of attributes and their levels and are asked to choose the alternative of their preference (Hanley et al., 2001).

Preferences over technology characteristics have been investigated through various approaches, and the stated Discrete Choice Experiment (DCE) approach is one of the leading candidates that allows estimation of these trade-offs. The other is conjoint analysis, a mathematical rather than a behavioral representation of choice (Louviere et al., 2010). These help reveal the "indirect decision utility", which in "WTP-space" is the monetized incremental utility gained by a change in an attribute (Train and Weeks, 2005; Ben-Akiva et al., 2019). The DCEs are widely used to study preferences in various contexts and fields among them including environmental economics, health policy, marketing, and transportation, where behaviors of interest involve discrete responses or qualitative choices (Louviere et al., 2008; Carson et al., 2009; Hanley and Czajkowski, 2019). As an illustration, DCEs in Kenya have been used to study trade-offs among insurance linked credit products (Shee et al., 2021) maize variety traits, (Marenya, et al., 2021), various livestock attributes (Makokha et al., 2007; Ruto et al., 2008), disease-free zone attributes (Otieno et al., 2011) and features of land leases (Otieno and Oluoch-Kosura, 2019) among other applications.

2.2 Random utility theory and mixed logit

Given the expected heterogeneity in choices among the population, modeling this heterogeneity would be important. To perform such modeling, DCE proceeds by asking respondents to choose between cleverly designed alternatives assuming that preferences would be revealed through the choices made out of these alternatives. In each choice situation, the respondent makes a choice among J alternatives in a series of T choice occasions (Hensher, et al., 2005). The basis for this approach is the conditional logit model (McFadden, 1974). It is in turn related to Lancaster's theory of consumer choice which is structured around objective consumer preferences faced by consumers making a choice decision over fixed characteristics (attributes) of a good. The theory further assumes that in the presence of multiple goods, in addition to making decisions about the attributes represented by the good, the goods in the choice set have more than one attribute, attributes that can be shared by more than one good in set (Lancaster, 1966). Choices revealed are therefore RUT therefore, combines basic economic theory with an econometric specification that utilizes the extreme value distribution for practical purposes (Manski, 2001). In Random Utility Theory, the probability that a random person q choosing i out of the J alternatives offered on occasion t can be expressed as $P(_i) = P[t : u_t(i)u_t(j), jC_t, ij]$ with C_t representing the choice set where i is the utility-maximizing alternative (McFadden, 1974; Manski, 2001; Walker and Ben-Akiva, 2002).

An individual q drawn at random from the population chooses a technology with a set of observed characteristics of the attributes (and may include characteristics of the chooser) represented by a vector $x \in X$. In RUT modeling, an individual's utility function can be separated into deterministic and stochastic components (McFadden, 1974). The choice made between two options reveals which choice provides greater unobserved utility to the chooser (Greene, 2003). Assuming that out of the J options, individual q chooses i (denoted as Y_i), then in this model, the individual's utility function and its related logit probabilities can be written as

$$\mathrm{u}_{iq} = v_{iq} + \epsilon_{iq},\ u \neq \mathrm{v}, \epsilon \approx \mathrm{iid} \quad (1)$$

$$\mathrm{u}_{iq} = \beta x_{iq} + \epsilon_{iq} \quad (2)$$

$$\mathrm{Prob}[\mathrm{Y}_i = |x_{i1}, x_{i2} ... x_{ij}] = \frac{e^{\beta x_{iq}}}{\sum_{r=1}^{J} e^{\beta x_{jq}}} \quad (3)$$

The non-stochastic utility component v in Eq. 1 represents tastes represented by a vector of explanatory variables observed by the analyst while the stochastic component reflects idiosyncrasies of the individual q tastes revealed in how they make choices across alternatives indexed $j = 1 \ldots J$ and choice occasions indexed $t = 1 \ldots T$ (Louviere et al., 2000; Hensher and Greene, 2003; Carlsson and Martinsson, 2008; Brouwer et al., 2017). Representative utility is normally specified as being linear in parameters, thus $v_{iq} = \beta x_{iq}$ as displayed in Eq.2. Now, if and only if the disturbances are distributed iid type I extreme value (Gumbel) whose cumulative density $F(_iq) = exp[-exp(-_iq)], > 0$, this results in the conditional logit model if x contains only choice specific characteristics (Greene, 2003). This implies that the error has a variance equal to $^2/6^2$ where is the scale parameter (Swait and Louviere, 1993; Carlsson et al., 2012). The estimating equation in the conditional logit model (CLM) is shown in Eq. 3 which is essentially the same as a multinomial logit model (MNL). The expression shows that utility depends on x_{qj} which may include aspects specific to the individual as well as those specific to the alternatives (Greene, 2003). The only difference between CLM and MNL is that the former is applicable when data represent choice specific, rather than individual specific characteristics (Greene, 2003).

The observed choice maximizes unobservable utility and the choice made is only a manifestation of this latent utility (McFadden, 1974; Walker and Ben-Akiva, 2002; Greene, 2003). The model arises because although q's utility is observable to him/herself, it contains random components that are unobservable to the analyst (Hensher and Greene, 2003). Assuming a linear utility function, the error term enters the function additively. One of the terms in the matrix of coefficients of attributes in the alternatives in the choice set, , is the estimated coefficient of the cost attribute, $_p$ (marginal utility of income). In many applications, this particular marginal utility is negative of the estimated coefficient (Brownstone and Train, 1999). In such a formulation, the marginal rate of substitution [2] between two attributes x_1 and x_2 characterizing the good would then be given by the expression dx_1/dx_2 such that the expression $\partial p/(\partial x_2) = -\beta_2/\beta_p$ represents the mWTP or the partworths for attribute 2 (Carlsson and Martinsson, 2008; Train, 2009; Vermeulen et al., 2011; Kragt and Bennett, 2012).

However, Eq. 3 is restrictive because the odds ratios are independent of other alternatives where $\frac{p_{qi}}{p_{qj}}$ is independent of other probabilities, hence the Independence from Irrelevant Alternatives (IIA) property (Hensher and Greene, 2003; Greene, 2003; Train, 2009). For instance, in a repeated sequence of choices over attributes, it is expected that the unobserved factors in one period are carried over into subsequent periods. In other instances, a universally beneficial attribute will attract a strictly positive mWTP ($mWTP \in R^+$) estimate suggesting a non-normally distributed unobserved factor (Train, 2009). These represent instances in which the standard logit is deficient in handling. For these reasons, several reformulations including nested logit, heteroscedastic logit, and mixed logit (also called random parameters logit) models have been suggested (Greene, 2003). In mixed logit, the parameters can be allowed to vary randomly over the individuals, a procedure that accounts for unobserved preference heterogeneity between individuals (Brownstone and Train, 1999; Hensher and Greene, 2003; Hensher et al., 2005; Brouwer et al., 2017).

Formally, this utility function in Eq. 1 can be rewritten as $u_{iq} = \alpha x_{iq} + \eta_q x_{iq} + \epsilon_{iq}$ such that the random β_q which comprises the deterministic component of utility has now been decomposed into a population mean and a deviation $[(\beta_q) = (\alpha_q) + \eta_q]$ (Brownstone and Train, 1999; Hensher and Greene, 2003; Train, 2009) . Here, η_{iq} is a random term with zero mean (Hensher and Greene, 2003). It represents stochastic deviations that characterize a decision maker's preferences relative to those of the population, therefore random variations around the parameter means (Revelt and Train, 1998; Lancsar et al., 2017). Its distribution over individuals depends in general on underlying parameters and can take various forms including normal, lognormal, uniform, triangular, or even Johnson's SB distribution

[2] It is usually necessary to hold overall utility constant i.e. $(\partial v_i = \beta_1 \partial x_1 + \beta_2 \partial x_2 + \beta_p \partial p = 0)$

(Ghosh et al., 2013; Hensher and Greene, 2003). The distribution of ϵ_{iq} is iid extreme value independent of β, which is in turn specified (by the analyst) to have a density $f(\beta|\theta)$ with θ representing the deep parameters of the distribution (Hensher et al., 2005; Huber and Train, 2001).

This random utility model (RUM) can then be approximated to any degree of accuracy by a mixed logit with the appropriate choice of variables and mixing distribution of the partworths (McFadden and Train, 2000; Train and Sonnier, 2005; Train, 2009). In Eq. 4, the probability of observing a sequence of choices from an individual is conditional on a vector of parameters β which are a product of conditional probabilities of the alternatives available to the decision maker (Train and Sonnier, 2005; Brouwer et al., 2017). Since we are dealing with repeated choice by a decision maker, mixed logit is a useful choice (Louviere et al., 2000). However, since β is not directly observed, Eq. 4 has to be integrated over all possible values of β using their density function $f(\beta|\theta)$ making the probability of the observed choice sequence conditional on the parameters of this density function (Brouwer et al., 2017). Thus, the unconditional probability is derived from the integral in Eq. 5 and is a mixed logit because it is a product of standard logits mixed over a density of partworths (Brownstone and Train, 1999; Train and Sonnier, 2005; Train, 2009). This model addresses three limitations of standard logit by allowing for taste heterogeneity, unrestricted substitution patterns and correlation in observed patterns over time (Train, 2009). The mixed (random parameters) logit model (McFadden and Train, 2000; Bhat, 2001; Train and Sonnier, 2005; Train, 2009; Brouwer et al., 2017) which is a popular model in discrete choice experiments is specified as Eq.5 given the value of η_{iq}:

$$\mathrm{L}_{qi}(\beta) = \frac{e^{\beta_q x_{iq} + \eta_{iq}}}{\Sigma^J \in C, i \neq j e^{\beta_q x_{iq} + \eta_{iq}}} \tag{4}$$

$$\mathrm{P}_{iq}(\theta) = \int_{-\infty}^{+\infty} L_{qi}(\beta) f(\beta|\theta)\, d\beta \tag{5}$$

If η is a small scalar, then there exists a continuous function $x = (z, s)$ of dimension $1 \times K$ for some integer K (observed attributes of alternative i as well as characteristics s of the decision-maker q) such that $x = (x(z_1, s), \ldots .x(z_J, s))$ for $z \in Z$ and $s \in S$. For the set of choice alternatives $C = z_1, \ldots, z_J$, an individual q from a population $q = 1, \ldots ..N$ may choose alternative i out of the J on offer; β is a $K \times 1$ vector of parameters (McFadden and Train, 2000). The unconditional choice probability p_{qi} is the probability that q chooses the alternative i and L_{qi} is the conditional choice probability for the choice set C or the logit probability evaluated at parameters β; θ is a vector of underlying moment parameters in the mixing distribution characterizing $f(\beta|\theta)$ (Brownstone and Train, 1999; McFadden and Train, 2000; Hensher and Greene, 2003) Typically, this distribution $f(.)$ is assumed to be normal (Brouwer et al., 2017), although other distributions can be specified (Train and Sonnier, 2005; Ghosh et al., 2013). When the response parameter β is expected to be of a specific sign (e.g. negative for a cost parameter), the lognormal or exponential form is usually specified (Louviere et al., 2000; Hole and Kolstad, 2012). Alternative specific constants $_i$ can be included in the utility function and for identification, the no-choice (or another base) alternative can be normalized to zero such that $_N = 0$ (Lancsar et al., 2017). Added as a random parameter interacting with attributes of the technology it can induce a distribution about the mean providing a means for revealing preference heterogeneity in the sampled population (Ghosh et al., 2013).

Parameters are assumed to be randomly distributed across individuals (Ghosh et al., 2013). This mixed logit probability is the weighted average of the logit formula evaluated at different values of the parameters; β, weighted by the density $f(\beta|\theta)$, unlike standard logit where this mixing distribution is degenerate at fixed parameters (Hensher et al., 2005; Train, 2009). Here, θ refers collectively to the parameters of this distribution: the mean, covariance of the β coefficients (Train, 2009). In this formulation, the probability of the observed sequence of choices conditional on knowing $\beta_{iq}s$ then given by $s_q(\beta_q) = \prod_{t=1}^{T} L_{qi(q,t)t}(\beta_q)$ in which $i(q, t)$ represents the alternative made by individual q on choice occasion t; representing a situation where individuals are faced with several (T) choice sets to choose from (Revelt and Train, 1998; Hole, 2008). Here, $s_q(\beta_q)$ is an unbiased estimator of the unconditional $P_{iq}(\theta)$ and is twice differentiable (Revelt and Train, 1998).

Estimating by maximum likelihood the model whose log-likelihood is given as $LL(\theta) = \Sigma_{q=1}{}^N ln p_q \theta$ is difficult since the integral in Eq. 2b is impossible to solve analytically (Revelt and Train, 1998; Brownstone and Train, 1999). It is, therefore, is simulated via maximum simulated likelihood (Revelt and Train, 1998; Bhat, 2001; Hole, 2008). A Bayesian approach that uses Markov Chain Monte Carlo methods with the Gibbs sampler would still provide comparable results from panel data as that contemplated in this study (Huber and Train, 2001; Elshiewy et al., 2017). The simulated log-likelihood is thus defined as:

$$\mathrm{SLL}_{ML}(\theta) = \Sigma_{n=1}{}^N ln[\tfrac{1}{R} \sum_r {}_{=1}{}^{N} {}^{s(\beta^r)]} \tag{6}$$

Here, given repeated choices, the probability is simulated by drawing β from its distribution R times, and the logit formula calculated for each occasion and the product taken and averaged over the R draws (Brownstone and Train, 1999; Train and Sonnier, 2005; Hole, 2008;Train, 2009). The result is the appropriate choice probability. Unlike the conditional logit, mixed logit yields a mean and a standard deviation across the sample, hence the alternative name, random parameters logit.

2.3 Choice of biodigester attributes and design of the discrete choice experiment

Selection of biodigester attributes: Biodigesters come in many designs but three basic designs are reported as the floating drum, fixed dome, and the inflatable tubular (plug-flow) type (Nzila et al., 2012). All these designs also have peculiar attributes in terms of their performance parameters as well as more observable characterizations such as their expected service life, their cost, and even some seemingly benign attributes such as portability. Comparatively, a fixed dome design has a complicated and costly installation process when contrasted with the more modest installation costs of a tubular digesters. However, this high cost of construction is countered by high maintenance costs of tubular designs since the latter may require periodic replacement of the polythene material (Nzila et al., 2012; Rajendran et al., 2012). Generally, while these systems can be characterized by many attributes, some may appear to be more important than others.

In 2018, a series of focus group discussions (FGD) with farmers, BCE technicians, entrepreneurs, researchers and policy makers were conducted. From these discussions, a list of 22 important attributes were identified [3]. Coupled with the FGDs, literature reviews complemented information about the levels with which these attributes could be described. From these list of 22, nine of the most important biodigester attributes were isolated and retained. This exercise was conducted by technical staff of the Kenya Biogas Program in Nairobi. A pilot exercise was subsequently implemented to rank these attributes. Mailu et al. (2019) describe the ranking exercises conducted in 2018 by a heterogeneous group. This group consisted of 59 undergraduate students from Moi University, 70 researchers from the Kenya Agricultural Research and Livestock Organization and 14 of the FGD participants. Of the retained attributes subjected to the ranking exercise, they were ranked in the following order of importance i) amount of gas produced ii) installation cost, iii) durability, iv) maintenance cost, v) reliability, vi) portability of the biodigester, vii) gas pressure, viii) the consistency of producing gas ix) ability for one to detect defects. An important result from this ranking exercise was that though conducted by a heterogeneous group, there was significant consistency in the order in which they ranked these attributes.

From the nine attributes reported, further processing led to their reduction to six. Some were merged as it turned out that they spoke to the same aspect of the attributes i.e. while technically independent, it is not possible to present some attributes unambiguously as truly independent attributes in the context of a choice experiment with farmers. Below is an account of how attributes were reduced from nine to six.

Gas production is a very important consideration, being the main reason why a person would consider having a biogas plant in the first place. Gas production may be dependent on the size of the biogas plant since larger plants accommodate more feedstock for the anaerobic process (Muriuki, 2014). This is an attribute that can be represented by the cost of installing the plant. Larger plants ceteris paribus will require more material to construct and therefore entail larger installation costs. Gas production and installation cost were the highest-ranked attributes in terms of importance, and this closeness might reflect this similar latent attribute (Mailu et al., 2019). Moreover, gas production also depends on the optimal conditions that facilitate the anaerobic process (hydrolysis, acidogenesis, acetogenesis, and methanogenesis) which produces methane gas. These suitable conditions include pH, temperature, substrate, loading rate, hydraulic retention time (HRT), C/N ratio, and mixing (Rajendran et al., 2012).

Pressure on the other hand may also have a significant association with environmental conditions too. Some digester types such as the tubular digester may produce gas at variable pressure (Rajendran et al., 2012), while in others such as the floating drum, gas has relatively constant pressure (Nzila et al., 2012). Besides, the gas from the floating drum biodigester has higher chances of escape, especially if the system is not well maintained, thus compromising pressure buildup (Bruun et al., 2014). Yet, from the accounts of many authors, poor maintenance of these biodigesters is a recurring observation. Improper feeding of the biogas plant with wrongly constituted feedstock/water mixture reduces gas production and thus the buildup of pressure in the system. Besides, temperature, pH, and other conditions determine the efficiency of the anaerobic process and thus, the buildup of gas pressure. Moreover, while pressure is well understood, translating pressure units

[3] Due to space limitations, the interested reader can find more details about the process used in deriving the attributes and their levels here: https://ssrn.com/abstract=3598610

(bars) to respondents in a real choice situation was difficult. For these reasons, the attribute (pressure) was dropped since although partly dependent on the technology design, it also has significant interaction with environmental and day to day management variations.

Just as with pressure, gas consistency may also depend on the same environmental variables. Secondly, gas consistency and reliability speak towards the same underlying latent quality. The original description of the attribute was "Assuming the same substrate, some systems might not be consistent, while others might be more consistent from day-to-day". This suggests an aspect of reliability. Gas consistency was therefore dropped in favor of reliability which can be presented more easily and in more relatable units.

In all, it was felt that used together, gas pressure, gas consistency, and gas amount may introduce splitting bias (Hämäläinen and Alaja, 2008). To a non- expert, in a DCE setting, these may appear to be sub-attributes of the same or closely related latent quality. For instance, when gas is produced from an optimal environment, pressure is expected to rise. Disentangling the pressure buildup associated with the optimal environment from that due to the specific biodigester design would require significant effort. In fact, amount of gas (cause) results in pressure buildup (effect). A casual observation also revealed that even among those who owned biodigesters, few would immediately tell how many units of gas they produced in a given day. The best they could do was observing how much pressure seems to have built up to give them an idea of how much gas was available. However, this is only observable if the biodigester in question is of the plug-flow (e.g. flexi-biogas) design. Luckily, in a DCE setting, the inclusion of cause-effect attributes may not alter parameter estimates as the "cause" and "effect" attributes absorb each other's effects (Blamey et al., 2002). However, the difficulty in presenting these three attributes: gas pressure, gas amount and gas consistency unambiguously led to their absorption in other closely related attributes.

Design of the discrete choice experiment: For this discrete choice experiment, the J alternatives are biodigester plants presented as choice profiles over six attributes viz: installation cost, reliability, durability, maintenance cost, movability/system portability, and ease of identifying system defects. The attribute: maintenance cost was described in the "imprecise" qualitative points as low, moderate, and high. Johnston et al., (2017) have suggested that such descriptors need to be avoided. However, in most of the descriptions around this attribute, most authors have used such categorizations, rather than give precise estimates of how much low/high descriptors portray in an objective way (e.g. Nzila et al., 2012; Cheng et al., 2014). Talevi et al. (2022, In Press) for example in their labelled alternatives used the prefix low / high to describe the maintenance cost attribute. Kabyanga et al. (2018) were only able to estimate biodigester maintenance costs, ex post from their CVM based study. Few exceptions do exist where maintenance costs have been estimated for use in such an exercise. Unlike maintenance costs, biodigester installation costs were monetized in Kenya Shillings. This cost reflects the cost of an 8 cubic meter biodigester. The reason for this choice was that 8m3 is the most common volume installed by farmers who own biodigesters in the country. Reliability on the other hand was represented by the number of days in a year (and for greater clarity, as a percent). Durability was presented in years while portability was described as either possible or impossible. Defect identification was either easy or difficult. These attributes and their levels are presneted in Table 1.

Table 1 Attributes and levels included in the DCE

Attribute	Levels
Durability	2-5 years, 12-15 years, 15-20 years
Reliability	145 days , 335 days, 345 days
	40 percent, 92 percent, 95 percent
Maintenance cost	Low, Moderate, High
Movability	Immovable, Movable
Defect identification	Easy, Difficult
Installation cost	65,000 Ksh, 92,500 Ksh, 102,000 Ksh

Granted the six attributes with levels ranging from two to three, the next stage involved combining these into an efficient experimental design. These six attributes in a full factorial design would require $2^2 3^4 = 324$ combinations. For example, offering these as a pair of two alternatives would require (324323)/2=52326 pairs in total or if in triples, 34884 combinations. This large number of alternative combinations suggested the need to combine them into a smaller set of alternatives. That is, from this full factorial, choosing an efficient design from which the main effects can be estimated (Louviere et al., 2000). Efficient designs are characterized certain criteria i.e. level balance, orthogonality, minimum overlap and utility balance (Huber and Zwerina, 1996). Typically however, some of these criteria are in conflict such that fulfilling one necessitates disregarding another. The interest, being to obtain precise estimates from a small subset of the full factorial requires that this subset be designed. Precision of coefficient estimates is given by the variance-covariance matrix Ω of the coefficients which in turn is a function of β. There are different methods of calculating the size of the matrix which leads to different efficiency measures which include D-efficient designs, A-efficient designs and S-efficient designs (Bliemer and Rose, 2011). Another more recent design is the c-optimal design (Vermeulen et al., 2011). In this study, the more common D-efficient design was chosen. Here, the idea is to minimize the D-error defined by the expression $|\Omega|^{1/K}$ which is an inverse of D-efficiency. Here, K is defined as the number of parameters to be estimated. As suggested by Carlsson and Martinsson (2003) a D-optimal design based on parameter priors is better than one with zero priors which in turn performs better than an orthogonal design. An orthogonal design in fact would by design contain dominant alternatives, thereby yielding different parameter estimates (Bliemer and Rose, 2011).

The minimum number of choice tasks S was also determined using the expression $(J-1)S \geq K$ where $K = 10$ is the number of parameters, and J=4 is the number of alternatives (Rose and Bliemer, 2013). This guideline is based on the requirement of at least as many data points as there are parameters to estimate (Greiner et al., 2014). Providing respondents with four alternatives and given the 10 parameters to estimate, this evaluated to (4-1)410. This therefore indicated a minimum of four choice tasks. Given these above, the study sought to develop a matrix composed of 16 choice sets in 2 blocks of 8 choice tasks per respondent.

The next step involved estimation of priors for use in constructing the design. A conditional logit model was therefore performed on data from the ranking exercise reported by Mailu et al. (2019). This was done by taking the top ranked profile by each of the the 84 researchers and FDG participants as indicative of preference. This estimation yielded the priors (β): -0.00000699 (installation cost), -0.72 (low reliability), -0.31 (high reliability), -0.96 (low durability), -0.78 (high durability), 0 (low maintenance cost), -0.57 (high maintenance cost), 0.45 (movable plants), 1.14 (ease of defect identification) and 0 (constant).

These priors were subsequently used as part of the input for constructing a D efficient design. This involved instructing the algorithm by specifying a design with 16 choice sets, with each set composed of 3 real valued profiles and an opt out. Including an opt-out option was included as one of the alternatives to avoid a forced-choice situation and also increase realism (Lancsar et al., 2017; Campbell and Erdem, 2019). Doing so also allows the estimation of true demand, rather than conditional demand models (Louviere et al., 2000). Adding such a constant in the analysis improves overall fit and allows the modeling changes to the 'no choice' alternative (Kamakura et al., 2001; Ghijben et al., 2014; Ryan and Skåtun, 2004). This alternative specific constant (ASC) allows the estimation to pick up preferences not captured in the set of alternatives offered (Kragt and Bennett, 2012). Since there were no strong theoretical or empirical grounds to include interaction effects, the design was optimized for 10 main effects. These were the four attributes of three levels each (8 main effects) and two attributes carrying two levels each (2 main effects). The design was also blocked so that no respondent would be presented with the full complement of 16 choice sets. This resulting design developed was based on a computerized search algorithm; the modified Fedorov algorithm (Carlsson and Martinsson, 2003). While the design was based on the conditional logit model, it is also efficient for the random parameters logit (Carlsson and Martinsson, 2003; Bliemer and Rose, 2010; Vermeulen et al., 2011; Greiner et al., 2014). From an initial design randomly drawn from a full-factorial design, the algorithm iteratively exchanges alternatives until it is impossible to reduce D-efficiency any further (Carlsson and Martinsson, 2003). These priors yielded a D-efficiency=2.39 for a design composed of 16 choice sets, each inclusive of an opt-out offered in two randomized blocks.

This represents in total, 64 rows (i.e. four alternatives in each of 16 choice sets). Of these, there were 48 real valued choice sets and 16 opt-outs. The alternatives offered to respondents were unlabeled (generic) rather than labelled alternatives as expected from an alternative-specific design (Louviere et al., 2000). A physical check was made to ensure that none of the profiles selected by the algorithm was strongly dominant. For instance, a relatively cheap to install (65,000 Ksh), cheap to maintain (low maintenance cost), reliable (345 days), durable (15-20 years) biodigester, which provided easy defect identification and was portable would be such a dominant set. However, such a profile did not appear in any of the choice sets included in the design.

However, for greater flexibility, these attributes were dummy coded and the algorithm ran a second time. A major reason for this is the caution offered some authors about misspecification errors (Bliemer and Rose, 2010). It was considered that the ranking tasks leading to these data used for estimating the priors were performed by researchers (not a very similar constituency to farmers). Therefore, their use would introduce some misspecification error. Applying zero priors on the other hand yielded a D-efficiency=2.85. However, given that Specification of zero priors was used instead as by looking at these two estimates, they do not look very different from each other. The design though not orthogonal (there were 4 attributes with 3 levels and 2 attributes with two levels) is still efficient. The resulting design was saved in a worksheet and used as input in the sample size calculation.

While deploying these choice sets, the cost attribute was randomly placed in the first position in half of the questionnaires and last in the other half. Doing so was designed to control for any ordering effect that may occur if respondents attach undue weight on the cost attribute when it appears prominently (first) among the list of attributes under consideration. As alluded elsewhere, the cost of installing biodigesters is probably the most prominent of reasons why would-be adopters keep away from the technology. This repositioning of the attribute has been found in a random effect probit model to influence the weighting of the cost attribute vis-à-vis other variables (Kjær et al., 2006).

The questionnaire and all tools were translated by a translation firm from English into three other languages namely Kikuyu, Kamba, and Swahili. This is because of the possible different language preferences that one would encounter in the field. Experience has indicated that respondents prefer to be interviewed in a language they are most comfortable with. The questionnaire was transcribed into a computer-assisted personal interviewing software through which the formal interview would be conducted. With the software chosen (ODK), it was possible to seamlessly incorporate GPS location, the skip logic, and other features to ease data collection. A pretest conducted on the tool was conducted with enumerators allowing them to get the feel of the tool. Also, they were allowed to test the questionnaire among themselves, their friends, and neighbors. In addition to the questionnaire, enumerators were also provided with pictorials which featured different biodigester designs. These were designed to highlight features of the different designs. This was important, especially for any respondent that had not seen these different designs.

2.4 The study site, sampling, and study participants

General characteristics of the study area The present study was part of a work package nested within a larger research project "Optimizing small-scale biogas technology for household energy and improvement of soil fertility within coffee-dairy production systems in Kiambu and Machakos Counties". For this reason, Kiambu and Machakos were purposely selected for purposes of the study. These counties are divided into several agro-ecological zones. The main and marginal coffee zone; Upper Midland (UM2 and UM3) respectively are both represented within these counties (Jaetzold et al., 2010a; 2010b). These are zones which receive between 800-1300mm of rain annually. In Machakos, the area under UM2 is rather tiny. Land sizes are much smaller in Kiambu than Machakos, with less than 1ha per farm household. The UM2 and UM3 classification gives rise to almost similar agricultural production activity. As is typical of market oriented smallholder coffee-dairy systems, a range of crops are planted within these farms (Ortiz-Gonzalo et al., 2017). Apart from coffee, maize and bean intercrop as well as banana are a common feature. Others include irish potato (mainly in Kiambu) and macadamia nuts, avocados, mangoes, guavas, and passion fruits. On many of these small farms, coffee may cover half of the farm area (Ortiz-Gonzalo et al., 2017).

Livestock keeping in the zone is also important and livestock ownership is widespread where between 70 and 85 percent of farmers keep dairy animals (Lekasi et al., 2001). These animals are kept under different systems: free range, semi zero and zero grazing. Animals are grazed (free range) where land sizes are larger but the more intensive cut-and-carry system (zero grazing) is practiced in areas where fodder availability is constrained by small land sizes. For farmers keeping livestock under the cut-and-carry system, napier and crop residues are major feed sources (Bebe et al., 2003). On such farms, a third of the area may be devoted to own fodder production (Ortiz-Gonzalo et al., 2017). Sometimes, especially in Kiambu, farmers may rely on purchased fodder to supplement own produced fodder (Lekasi, et al., 2001). It has been established that in the more densely populated and dairy intensive Kiambu, an inverse relationship exists between land size and the number of livestock kept (Lekasi et al., 2001). This suggests that high stocking rates and intensive cropping may require important soil fertility inputs in order to reduce nutrient mining. Biodigester technology utilizing manure from the dairy enterprise is one of the secondary motivations for farmers adopting the technology in Kiambu as it allows nutrient recycling within the farm (Muriuki, 2014).

Sample size The appropriate sample size was estimated by using the priors indicated elsewhere above. The estimated sample size is a lower bound for finding a statistically significant (p¡0.05) estimate for particular parameters β_j, for each j attribute (Rose and Bliemer, 2013). The estimation was implemented using the R script provided for such estimation (de Bekker-Grob et al., 2015). To estimate sample size, this script uses the expression;

$$\mathrm{n}_j \geq (\frac{1.96 \times se(\beta_j)}{\beta_j)})^2 \quad (7)$$

In this expression, β_j is a prior parameter estimate for attribute j and se its standard error while 1.96 is the t-ratio. This expression is derived from the condition $\beta_j(se_n(\beta_j)1.96)$ which allows one to state with certainty p¡0.05 that the parameter estimate obtained from such sample size will be different from zero (Rose and Bliemer, 2013). The respective priors used in the design stage of the DCE yielded sample sizes of 165, 11, 78, 6, 14, (Inf), 19, 34, 6, and (Inf) respectively. These are theoretical lower bounds of the sample size for finding a significant effect for respective parameters. This result suggested that assuming a conditional logit, a sample size of at least 165 respondents was required to obtain the desired power 1- of 0.8 for finding an effect when testing at a confidence level α of 0.05. Low maintenance cost and the constant were entered as zero priors since these coefficients were not significantly different from zero (p¡0.2) in the conditional logit model. Therefore, they would require infinitely large sample sizes. Likewise, installation cost and high reliability had p-values greater than the usual benchmark (p¡0.05). Installation cost was retained for the practical reason that dropping such an important attribute would jeopardize mWTP calculations. Including these zero priors yielded sample sizes as large as n=582 (low maintenance cost) and over n¿9000 for the constant. The particular R script was designed for the conditional rather than a mixed (random parameters) logit. Since the design was optimized for conditional logit, using the largest lower bound sample size n=165 to estimate parameters using a different model could herald a loss of statistical efficiency (Bliemer and Rose, 2010). However, Bliemer and Rose (2010) simulated sample size estimations for case studies featuring different number of attribute and level combinations and alternatives. They also optimized these for conditional / multinomial logit, cross-sectional mixed logit and panel mixed logit. The lower bound sample sizes for the conditional logit were typically larger than those of the panel mixed logit (Bliemer and Rose, 2010). Therefore, to achieve similar level of statistical significance this lower bound of n=165 was deemed adequate for estimating a mixed logit.

A sample size of 582 for example translated into a budget which was 27 percent greater than what was available for research. Therefore, a judgment call was made considering resource availability. A sample size of n=480 respondents was estimated heuristically. It was considered adequate as this is greater than the largest (n=165) estimate obtained from the informative priors. For DCEs, Johnson et al. (2013) indicate that precision increases rapidly for sample sizes n¡150 and levels out at n=300. Therefore, a sample size of n=480 was considered adequate as it is greater than the calculated n=165; a lower bound.

Sampling: A sampling frame covering both dairy-coffee farmers was unavailable. First, it is probable that close to 70 percent of farmers would integrate crop and dairy farming (Bebe et al., 2003). Secondly, all active coffee farmers in a given location are registered through their farmer cooperative (FC) which is in turn linked to the nearest coffee factory. Thus, a sample obtained from all coffee farmers may also capture a sizable percentage of farmers who integrate coffee with dairy farming. Each of these FCs operates within a geographic area and serviced by a coffee mill. Large FCs on the other hand may run several coffee mills. Therefore, rather than sample coffee mills, the study settled on the FC as the primary sampling unit.

A list of all farmer cooperatives active in both Kiambu and Machakos was procured from the Coffee Directorate. Information from this list indicated that Kiambu and Machakos respectively have a total of 22 and 33 coffee cooperatives. Inactive cooperatives were dropped as it is assumed that these farmers were probably not likely to be involved as coffee-dairy producers. Kiambu had one inactive cooperative while Machakos had seven. In total, Kiambu had 55,658 active members while 60,887 active members.

Using the FC as the Primary Sampling Unit (PSU) at stage 1, six farmer cooperatives were selected from each County. In Kiambu, selected cooperatives included 3GS FCS, Gititu, Komothai, Ndumberi, Gitwe and Muhara. In Machakos, selected farmer cooperatives were Muthunzuuni, Kaliluni, Ithaeni, Mungala, Mwatati, and Kawethei. As stage 2, 40 households were then randomly selected (without replacement) from each of the cooperatives selected at stage 1. Six enumerators were subsequently recruited for the survey. The criteria for their selection included academic qualifications (at least a Bachelors' degree in a social science discipline) and previous survey experience. Being a resident of the sub-locations where the sampled farmers were drawn was another requirement since it would almost ensure that enumerators were comfortable in the language of the interview. Traveling from their home for the interviews would ensure that they are not in a rush at the end of the day. They were subsequently invited for 2-day training and briefing sessions held at the Waruhiu ATC farm in Githunguri during August 2019. Some of the topics covered at the briefing included a background on biodigester technology as well as the basics of choice experiments including how the sample had been arrived at. They were also provided with tablets and instructions on how to handle the interviews, replace households that are not

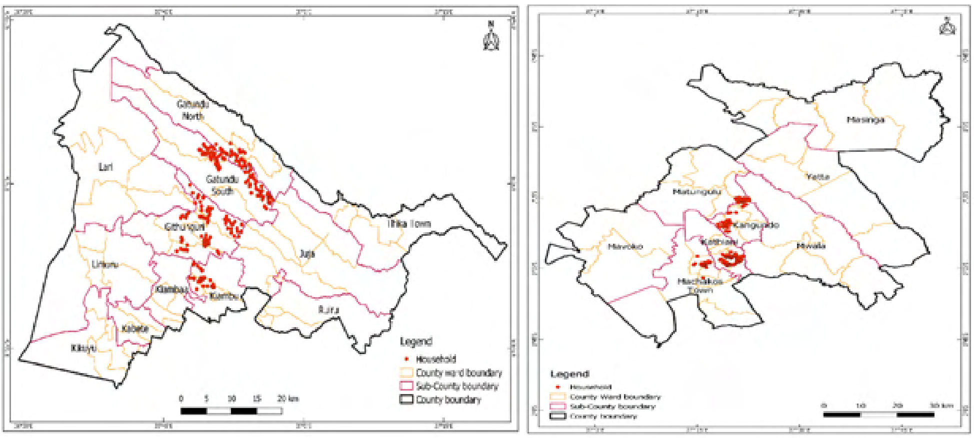

Fig. 1 Kiambu and Machakos Counties and distribution of respondent households

traced during the interview among other relevant logistics.

3 Results

3.1 Sample summary

In September 2019, following training and piloting the survey instrument, a team of six experienced enumerators (two females, four males) administered a questionnaire in either of the languages Kikuyu (32%), Kamba (45%), Swahili (6%) or English (17%). Respondents chose the language with which they preferred the interview to proceed. While 480 was the target, a total of 455 households were interviewed during the survey period which took place between 2 and 19 Sept 2019. This represents a response rate of 95%. The resulting data yielded $8 \times 4 \times 455 = 14560$ rows of choice data. However, in the end, some of the respondents did not attend to the choice questions or skipped some of these representing 3% attribute non-attendance. The 552 represents individual choice profiles that were skipped or not answered, therefore differentiating these from the opt-out, a valid choice. The resulting dataset represents 14560-552=14008 rows of usable data for the choice experiment. This represents a choice task completion rate of 96% for respondents that were interviewed and ¿10 cases per independent variable. There were 3502 completed choice tasks in total. A map showing the distribution of respondents captured in this study is shown in Fig 1.

From the data, respondent households were resident at altitudes between 1326 and 1975m asl which covers a substantial dairying zones. Given the way the sample was derived, virtually all respondents grew coffee but ruminant livestock owning households comprised 67 percent of the sample. On average there were 1.3 Tropical Livestock Units (TLU) per household ranging between zero (0.32 LUs considering only households owning ruminant livestock) and 11.8 TLUs. While ruminant livestock ownership has been the main target constituency for biogas, other livestock such as poultry can indeed be a source of feedstock. However, although a majority of households own poultry, given the current numbers reared and the production system under which production takes place, it makes this source of feedstock unlikely.

Interviewed respondents were aged between 17 and 96 years with an average of 55 years. Eighteen percent

Table 2 Summary statistics

Variable	Unit	Min	Max	Mean	StDev
HH size	No	1	15	4.7	2.2
Age					
<40 yrs		0	1	0.18	0.38
<30 yrs		0	1	0.13	0.33
40-60 yrs		0	1	0.4	0.49
60> yrs		0	1	0.41	0.49
Education					
No educ	percent			9.7	
Primary	percent			41.6	
Secondary	percent			39.6	
Post secondary	percent			9	
Fuel					
Purchase$_f$	prop	0	1	0.25	0.43
Collect$_f$	prop	0	1	0.49	0.50
Purchase$_p$	prop	0	1	0.36	0.48
Fuel	prop	0	1	0.34	0.47
TLU	No	0	11.8	1.28	1.48
Owning TLU	Percent			33.3	
Elevation	masl	1326	1975	1702	149
TLU own	Prop	0	1	0.67	0.47
Respondents	No			455	
Completed	No			440	
Completed tasks	No			3502	
Datapoints	No			14008	
Certainty	Percent	15	100	68	16

of the household heads were below 40 years of age while 40 percent were aged between 40 and 60 years, an age bracket associated with a higher likelihood of adopting biodigesters in Kiambu (Muriuki, 2014). Only 10 percent had not attended any formal schooling (Table 2). Whereas none of those interviewed had a biodigester plants, 70 percent responded concerning their current fuel sources. Of these, 25 percent purchased firewood while 49 percent collected firewood just as a similar fraction purchased charcoal. Respondents were also allowed to indicate the certainty with which they thought of their answers. On average, respondents had 68 percent confidence in their responses where less than 1 percent had no confidence in their responses while 7 percent had complete confidence in their choices. The results in the following sections have to be reviewed with the level of certainty with which the respondents had about their choices. About 20 percent had a certainty of 50 percent or less in their choices.

Table 3 Tetrachoric correlation coefficients among socioeconomic variables

	HHsize	Fuel	Educ	Youth	TLUs	Elev
HHsize	1.00					
	(0.00)					
Fuel	0.33⋆	1.00				
	(0.01)	(0.00)				
Educ	0.02	-0.17⋆	1.00			
	(0.02)	(0.19)	(0.00)			
Youth	-0.07⋆	-0.05⋆	-0.41⋆	1.00		
	(0.02)	(0.01)	(0.02)	(0.00)		
TLUs	0.07⋆	-0.02	-0.46⋆	-0.11⋆	1.00	
	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	
Elev	0.016	-0.091⋆	0.09⋆	-0.08⋆	-0.07⋆	1.00
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.00)

*Educated (1=household head has some formal schooling, 0 otherwise) Household size (1= household has more than 5 persons, 0 otherwise); youth (1=respondent age ¡ 35 years, 0 otherwise); Fuel (household reports ¿0 expenditure on firewood, charcoal or paraffin, 0 otherwise); TLUs (1=household has cattle at present, 0 otherwise); Elevation (1=household located less than 1500m asl, 0 otherwise). Figures in brackets are p-values and a * indicates that the correlation is significant at* $p < 0.01$.

3.2 Model fitting

This analysis is based on estimation sample consisting of 3502 usable responses. From this data, a conditional (fixed-effects) logistic regression (Eq. 3) employing only the six biodigester attributes (and the Alternative Specific Constant (ASC) as well as the ASC x block and ASC x price position interactions) was estimated as the "base" model (M1). All coefficients except for "low" maintenance costs had the expected sign. The sign on the ASC was negative and significant ($p = 0.000$). From these models, the non-significance ($p = 0.847$) of the block parameter suggests that there were no significant differences in the two sets of questionnaires i.e. no block effect exists. Similarly, no significant effect ($p = 0.616$) from the positioning of the cost attribute within the offered alternatives was found. Nor was there a significant ($p = 0.319$) effect when the position of the cost attribute was interacted with the level of cost.

Next, additional covariates representing the socioeconomic variables were considered (M2). The variables household size, herd size (TLU), fuel expenditure, age of household head, and education level were considered as possible covariates. Their inclusion is based on results from studies which suggest these variable as important in the decision to invest in biodigesters (Walekhwa et al., 2009; Qu et al., 2013; Sun et al., 2014; Muriuki, 2014; Bakehe, 2021). Since these are individual-specific variables, they cannot enter the conditional logistic model directly and they were therefore entered as interaction terms with the ASC (opt-out). Also considered was the influence of environmental variables which are important antecedents for technology adoption (Qu et al., 2013; Sheahan and Barrett, 2017). Rather than look at the exact geographic location of the respondent, elevation was used to stand in for this location gradient. Altitude was likewise interacted with the alternative specific constant. Adding these covariates does not compromise the estimation since each respondent had 8 choice tasks and (4-1) × 8≥ k with k representing the maximum number of estimable parameters. This suggests that the estimable models have an upper bound of 24 parameters. This is important to keep track of in mixed logit models which estimate parameter means and their respective standard deviations.

A likelihood ratio test showed that their addition improved model fit $\chi^2{}_{(13,19)}$=354.94, $p = 0.000$. However, they were found to be collinear and this would introduce multicollinearity if included in their entirety or their untransformed form. Hoping to reduce the possibility of multicollinearity, they were converted to binary variables using the arguments shown at the bottom of Table 3. The tetrachoric correlation coefficients were significant among some variables as appearing in Table 3. As expected, household size and fuel costs were positively correlated. Education, age and the index of livestock owning (TLUs) were correlated. Since the major objective in this paper was to demonstrate rather than explain the likely place of socioeconomic characteristics in these tradeoffs, some individual specific variables were dropped. This included education as well as household size. For simplicity and parsimony, only the non-collinear variables; fuel, TLUs, and elevation were retained. The resultant fit was improvement from the base model $\chi^2{}_{(13,16)}$=96.28,p=0.000. These are discussed in the subsequent analysis and are the subject of §3.4.

A mixed multinomial model (Eq. 4) was used to estimate the parameters of the mixed logit model. In model (M3), only the dummy coded attributes were assumed to be random while the cost of installation was assumed fixed. In model (M4), installation cost, which enters as a real value was also assumed random. In model (M5), the cost variable was assumed to be log normally distributed. In model M6, just unlike M5, the coefficients were allowed to be correlated. These mixed logit models were estimated through simulated maximum likelihood using Halton draws with 500 replications. For the distributional assumptions on the random parameters, the mixed logit was ran separately specifying the attributes as random but a fixed price coefficient (M3), assuming that these are normally distributed coefficients. The results also serve to show that there is substantial heterogeneity. The standard deviations were all significant. The likelihood ratio test for the joint significance of the standard deviations reveals that the null hypothesis of zero standard deviation is rejected. The non-zero standard deviations suggested that a random parameters specification was ideal for this data. The goodness-of-fit was measured through the likelihood ratio index which raises from 0.13 to 0.118 as coefficients are allowed to vary. These models (M3, M4 and M5) in WTP space were also attempted. They allow estimation of mWTP directly and conveniently (Hess and Train, 2017). Scarpa et al. (2008) also suggest that in some cases, WTP space models outperform those in preference space unlike (Train and Weeks, 2005; Hole and Kolstad, 2012) who suggest those in preference space outperform WTP space. Convergence problems with the WTP-space models were noted and these were not considered further.

In the mixed logit models, the coefficients were larger in magnitude than those obtained from their conditional logit counterparts (Table 5). This was not be surprising since the coefficients from different models are confounded by their scale factors, and therefore not directly comparable (Swait and Louviere, 1993). Besides, the variance in the error term in models M1 and M2 was greater than that in the extreme value component of the error term in models M3, M4 and M5 hence the larger coefficients from the mixed logit (Revelt and Train, 1998). The AIC was used to compare these models AIC_{M2} =8482.3 and AIC_{M3} =7465.14 and this suggests that M3 had a better fit than M2. The BIC statistics point to a similar conclusion. A likelihood ratio test for model fit $\chi^2_{(16,24)}$ =1033.5, $p =$ 0.000 suggested this improvement. This suggests that

Table 4 Model fit statistics

Statistic	M1	M2	M3	M4	M5	M6
N	14008	14008	14008	14008	14008	14008
No of par	13	16	24	25	25	61
LR χ^2	–	–	1033	2121	2164	2419
df			8	9	9	45
Ln(L_0)	-4329	-4280	-4204	-3851	-4176	-4114
Ln(L)	-4273	-4225	-3708	-3164	-3140	-3015
LRindex	0.013	0.013	0.118	0.178	0.248	0.267
AIC	8572	8482	7465	6378	6330	6152
BIC	8670	8603	7646	6567	6519	6612

*The number of parameters in M1 include nine that relate to the attributes, one an ASC, and three representing i) an association between the position of the cost attribute on the questionnaire and cost iteslf, ii) ASC*block, iii) ASC*cost position parameters. The extra two parameters in M2 are the ASC interactions with TLU, fuel cost, elevation. In the mixed logit models, they almost double because of the presence of standard deviations which are additional parameters*

the mixed logit was an improvement to the conditional logit. The next estimation entered the cost variable as a random rather than fixed parameter M4. The improvement in the fit is revealed through the likelihood ratio test $\chi^2_{(24,25)}$=1088.5, $p = 0.000$. In this particular model (M4), it was assumed that all attribute coefficients are normally distributed, thereby allowing consumers to place positive as well as negative values on the attributes.

Next, in addition, a log-normal distribution on the cost variable was assumed (Ghosh et al., 2013). This assumption is in line with common-sense expectations that this coefficient is restricted to being negative (Meijer and Rouwendal, 2006; Hess and Train, 2017). In M5, the log-normally distributed cost parameter was negative with its mean, median, and standard deviation being -0.0939, -0.0254, and 0.333. The AIC statistic suggested that a log-normally distributed cost coefficient improved model fit. Using this result, a mixed logit with log-normally distributed random parameters can be picked as the model of choice. In fact, as stressed by Hess and Train (2017), mWTP estimation requires that the price coefficient does not overlap zero. The likelihood ratio index, $1-\frac{Ln(L)}{Ln(L_0)}$ which is derived from the log-likelihood function and an analog to the R^2 was also computed (Greene, 2003). This has been reported in Table 4 for all of the regressions. This index is analogous (but not similar) to the multiple correlation coefficient in linear regression (Domencich and McFadden, 1975). This also includes the log-likelihood and other relevant sample and regression statistics as shown in Table 4.

Observing the significant standard deviations suggested that there was substantial heterogeneity. It dawned later that at the time of the experimental design, allowance for correlation among attributes (interaction effects) had not been accommodated. In model 6 (M6), in addition to a log normally distributed cost variable and normally distributed random coefficients, the restriction of independent coefficients was relaxed, allowing for correlation among these coefficients. This flexibility acknowledges that for instance, respondents who prefer a durable biodigester may have a strong preference for a reliable biodigester. Or that one who prefers a movable biodigester would also prefer a cheaper biodigester. A cheaper biodigester implies a smaller sunk cost, and if movable, it increases the possibilities of disposing it through sale to a neighbor. Adding such flexibility allowed all forms of correlation (Hess and Train, 2017). It comes at a cost of inflating the number of parameters (Hole, 2008). This appeared to improve model fit. Comparing M5 and M6, the comparative statistics were $AIC_{(M5)} = 6330.6$ and $AIC_{(M6)} = 6152.78$ suggesting an improvement. A likelihood ratio test also confirmed this improvement $\chi^2_{(25,61)} = 250.24, p = 0.000$. The saturated model (M6) had a deviance $D_{(M6)} = 6030.38$ compared to a deviance of $D_{(M5)} = 6280.64$ in M5 and therefore $\chi^2_{(25,61)} = 250.26$ which was greater than the critical chi square statistic $\chi^2_{(df=36,0.05)} = 50.9$ leading us to reject the null of independent coefficients. However, the Bayesian Information Criterion derived from these two were $BIC_{(M5)} = 6519.32$ and $BIC_{(M6)} = 6612.78$.

This result left some uncertainty about which model to choose between M5 and M6 based on the BIC as it appeared to conflict with the AIC and the LR test. However, the reason for fitting these models was for the purposes of *inference* (how attributes are traded off against each other). Once this inference is made, the next decision was to *predict* the underlying mWTP estimates implied by these parameters. It is also conceivable that BIC penalizes heavily those models with a large number of predictors. Therefore, choice of the best fit was based on the AIC statistic. While the McFadden pseudo R^2 also suggested M6 to be superior, choice between M5 and M6 can also be disentangled by considering the criterion suggested by Glover and Dixon (2004). This uses the Bayesian posterior odds assuming uninformative priors. This indicated M5 as the model of choice. A further check was conducted by considering the correlation coefficients between attributes. Since some attributes are diametric opposites (e.g. low durability vs high durability), then logically, the correlation between such opposites should be negative. In M5, this condition was met, but this was not consistent in M6. When coefficients were allowed to be correlated (M6), the correlation between the two extremes of the opposites for both maintenance cost and durability were positive. This for example would be interpreted to mean that respondents who had a preference for low durability also have a preference for high durable biodigesters. While this result does not make logical sense, the presence of complex interactions is not new. This is because of the presence of both pure correlation and scale heterogeneity in these estimates which are difficult to disentangle (Hess and Train, 2017; ; Mariel and Artabe, 2020).

This study sought to estimate mWTP and the most pressing requirement of a log normal cost variable was both contained in these two models. Comparing fit across the six models showed that the log likelihood increased indicating better fit from left to right (Table 4) as the number of coefficients increases. In M6, the number of parameters increased by 45. These extra parameters represent correlations among attribute coefficients. A likelihood ratio test of joint significance in M6 led to the rejection of the null hypothesis of independent (uncorrelated) coefficients. The standard deviations were significant indicating that there was substantial variation in these parameters. Allowing these parameters to vary in the mixed logit improved the explanatory power i.e compared to the conditional logit, and allowing for a log normal distribution on the cost variable as well as correlation among the coefficients had a better fit.

The main results from this analysis are presented in Table 5. Generally, the regression coefficients have the expected signs. Broadly, respondents had preferences for biodigesters with high reliability, were durable, movable and subject to easy defect identification and cost less to install. The inclusion of a log normally distributed cost parameter however appeared to interfere with the sign and significance of other parameters. For instance, in M5, the TLU parameter was no longer significant while the block parameter was now significant with a sign reversal. A similar observation was made with respect to M6. Meanwhile, although the regression coefficients in M4 appear sufficient, the distribution of the individual level installation cost coefficient was checked in order to be in line with apriori expectations. The distribution of this coefficient for individuals spanned across both sides of zero. This has the interpretation that while some acted as expected (preferring lower cost), others appeared to prefer a larger cost. Despite these inherent inconsistencies, M6 was picked as the model of choice.

The correlations between coefficients in model (M6) are shown in Figure 2. These are derived using the procedure outlined by (Mariel and Artabe, 2020). In these results, the coefficients in M6 as appearing in Table 5 which are negative were transformed to be positive. These are those relating to low reliability, both maintenance cost coefficients, low reliability as well as immov-

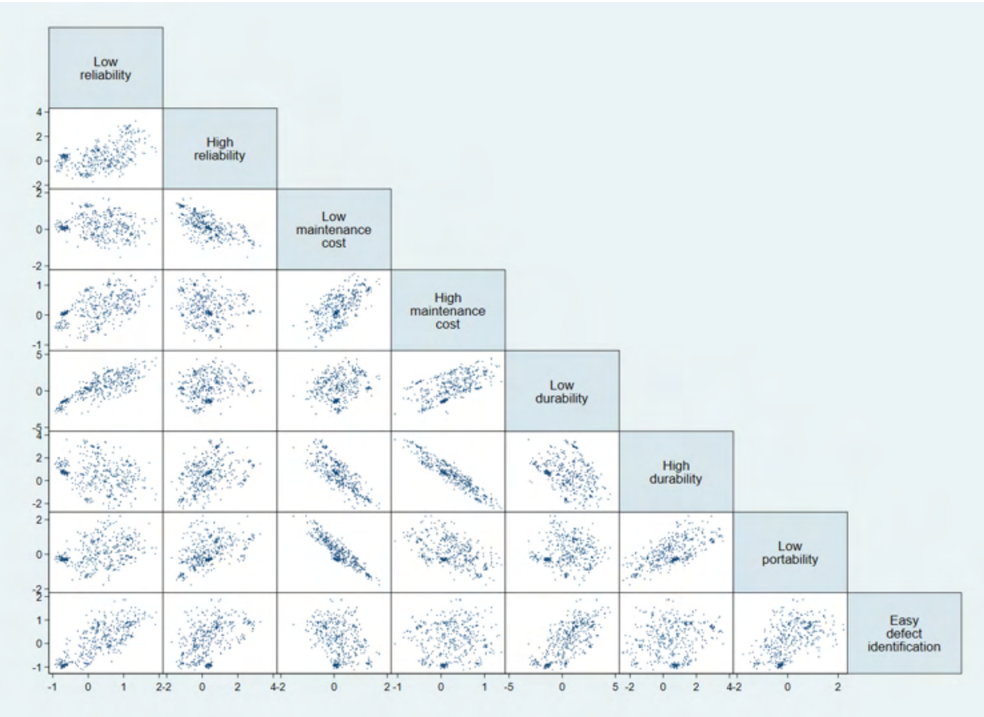

Fig. 2 Correlations among individual-level attribute coefficients

able biodigesters. An auxiliary regression on M6 was therefore performed where the signs of the coefficients were altered in order for all to bear a positive sign. In so doing, a correlation matrix of the random coefficients can be developed. This method proposed by Mariel and Artabe (2020) is based on the idea that scale heterogeneity shifts covariance to the right and a small shift will keep the final covariance between two parameters negative but a large shift reverses the sign. Rather than Pearson correlations (ρ), Spearman correlation (ρ_s) coefficients were calculated. This was because some of the variables (installation cost) were log-normally distributed and may display some non-linearity. In this figure, the coefficient on installation cost has not been converted and raw values from the regression have been displayed instead. For this reason, the coefficient appears to straddle the positive and negative spectrum. This attribute was dropped from Figure 2.

4 Discussion

Many of the respondents in this study used biomass fuel sources. While the data did not include that about challenges faced while obtaining these fuels, such challenges are not unexpected. The stated drive by many governments including Kenyan authorities to ensure that such traditional fuels are replaced by cleaner fuels is based on the economic, environmental and health benefits that accrue (Somanathan and Bluffstone, 2015; Van de Ven et al., 2019; Talevi et al., 2022, In Press). But given the heterogeneity in available feedstock, the suitability of a biodigester design also needs to go hand in hand with the different types of feedstock available to farmers. At the time of this study, separate research was underway to establish the usability of coffee waste as a source of feedstock for anaerobic digestion. Separate results in Ethiopia suggest that while coffee husk, pulp and mucilage have a potential as feedstock for biodigesters, the same cannot be said of parchment (Chala et al., 2018). Research at identifying these choke points, when designing and disseminating biodigester systems which fit well with the preferences of potential adopters is encouraged. This, it is hoped would provide coffee farmers with another viable source of feedstock, since besides water availability, as feedstock availability is also one of the factors enumerated as posing a challenge to the adoption and continued use of biodigesters (Lwiza et al., 2017; Clemens et al., 2018).

4.1 Socioeconomic variables and opt-out

The alternative specific constant (opt-out) was negative and significant ($p < 0.05$) in all models considered. This statistically significant negative parameter can be interpreted to mean that respondents are less likely to choose the opt-out over the three options provided in the choice sets. In fact, qualitatively, these results are in contrast to those by Thapa et al. (2021) in Nepal where they found a latent unwillingness to demand for biodigesters. Why actual adoption of the technology is still low while this parameter suggests a higher probability of preferring a biodigester was not immediately clear. However, it may be expected that most farmers are risk-averse as found in China (He et al., 2018). Such intrinsic preferences were however not measuresd in this survey. Moreover, risk and uncertainty loss aversion was found to affect the probability of selecting offered alternatives rather than the opt-out in a DCE over new rice varieties in India (Ward and Singh, 2015). In the present study however, only directly observable respondent characteristics were used to account for some of the choice heterogeneity.

Variables that relate to the respondent characteristics (i.e. size of the cattle herd and fuel costs) and their environment (elevation) were used in the estimations to control for observed heterogeneity. It was suspected that just as in Uganda where these factors determine biogas adoption (Walekhwa et al., 2009; Lwiza et al., 2017), so should they be important in our case. Assuming that the opt-out is a preference for the status quo (preference for a biodigester plant with "zero attributes"), we could stretch our imagination and suggest that these coefficients would at least tell us something about potential non-adopters. However, at this point, it is necessary to point out that this does not strictly represent adoption per se, but indicates the probability of choosing the opt-out, conditional on certain observable socioeconomic characteristics. Further, the opt-out option was also not strictly an individual specific status quo alternative as defined by (Carlsson et al., 2012) but an alternative specific constant. In the study, this opt out was undefined. This was done to avoid forcing respondents to formally define this opt-out. Doing so, it was thought would provide them an opportunity to define a plant with all desirable attributes and hence a dominant alternative (Bliemer and Rose, 2011).

Livestock holding: The coefficient on livestock numbers (TLUs) was significant ($p < 0.05$) and negative in M4. It is expected that herd size is not truly random but has a distinct environmental signal. Keeping in mind results from LSMS study data, geography and biophysical factors appear more important than micro-level factors in the adoption decision (Sheahan and Barrett, 2017). The result suggests that those with larger flocks (the estimation used tropical livestock units) have a probability of preferring to have a biodigester than without (opt out). Large numbers of livestock allow one to have enough feedstock in the form of manure for their biogas plants. This is true from studies in Kenya (Muriuki, 2014), Uganda (Walekhwa, et al., 2009; Lwiza, et al., 2017), and China too (Sun, et al., 2014). The type of cattle production system employed by the different households to raise livestock may determine how easily manure is fed into the biogas system. While there may be major differences across different households, no major differences may exist in the sample because the AEZ from which the sample was drawn are not far from each other. That said, smaller land parcels in Kiambu (Jaetzold, et al., 2010a) where commercial small dairying is more prominent suggests that the system here is zero-grazing. Despite the smaller land sizes, especially in Kiambu, farmers keep animals under confinement and are therefore able to raise feedstock for to run a biodigester. To assess the possible association between livestock numbers and environmental variables (here represented by altitude), a Spearman correlation coefficient was estimated. The correlation between altitude and livestock numbers was significant though weak ($\rho = -0.0713$, $p = 0.0161$). The households interviewed in Machakos lie at lower elevations than those in Kiambu. This may be a reason why Kiambu has a larger density of plants than Machakos.

Fuel costs: The household size on the other hand was dropped in favor of fuel costs since the correlation between these variables in the data was significant and sizable ($\rho = -0.326$, $p = 0.013$). The fuel cost parameter was positive suggesting that those with large fuel costs (presumably large households) would choose the opt-out. This was unexpected as it would appear that a large household represents a source of labor required to collect firewood, take care of the animals as well as feed a biodigester. The result looks counterintuitive at first. However, as argued from recent studies, labor markets are not missing and farmers are players in the labor market. Available labor is thus directed to other activities and is not as abundant as previously thought. However, while such factor markets are not completely missing, they are incomplete (Dillon and Barrett, 2017). This failure does not reveal why the coefficient may be positive. In Uganda, the probability of adoption is higher for larger household sizes and those with large fuel costs (Walekhwa et al., 2009), but our results suggest the opposite. In hindsight, the description of the technology that respondents were asked to picture (8 cubic meters) might explain his result. Such a biodigester size may not produce enough gas for the average household and therefore this surprising result. A common finding is that even among households that adopted biodigesters, they still maintain other fuel sources on the side.

Elevation: Respondents located in elevations lower than 1500m asl were less likely to choose the opt-out. This means that those in higher elevations were likely to choose the opt out. This was as expected. Households located in higher elevations where dairying is kept under zero grazing units would have a preference for biodigesters. There could be many reasons why this is so. On the one hand, zero grazing farmers here have ready access to feedstock. Secondly, most biodigesters are already located in these dairying zones and there are ample opportunities for neighbors and friends to learn about biodigesters from each other. This result while only suggestive, does not imply that other zones should be left out in any dissemination efforts. In fact, it may suggest just the opposite. The heterogeneities observed in these regressions (Model 6 in particular) suggest that there may be pockets in zones lower than 1500m asl where preferences for biodigesters are favorable.

Table 5 Moran's I coefficient at different radius bands

mWTP	0.1	0.2	0.3	0.4	0.5	1.0
low relaibilty	0.008	14008	14008	14008	14008	14008
No of par	13	16	24	25	25	61
LR χ^2	–	–	1033	2121	2164	2419
df			8	9	9	45
Ln(L_0)	-4329	-4280	-4204	-3851	-4176	-4114
Ln(L)	-4273	-4225	-3708	-3164	-3140	-3015
LRindex	0.013	0.013	0.118	0.178	0.248	0.267
AIC	8572	8482	7465	6378	6330	6152
BIC	8670	8603	7646	6567	6519	6612

*The number of parameters in M1 include nine that relate to the attributes, one an ASC, and three representing i) an association between the position of the cost attribute on the questionnaire and cost iteslf, ii) ASC*block, iii) ASC*cost position parameters. The extra two parameters in M2 are the ASC interactions with TLU, fuel cost, elevation. In the mixed logit models, they almost double because of the presence of standard deviations which are additional parameters*

4.2 Attributes and their tradeoffs:

To the best of our knowledge, this study is the first DCE study conducted to investigate tradeoffs among biodigester attributes. As is common with such studies, cost or price attribute is crucial. As expected, the parameter on installation cost was negative just as is the parameter reflecting low reliability, and low durability. That is, ceteris paribus, respondents discount a plant that is low in reliability, movability and durability or is pricey and presents difficulties in identifying any defects. An interpretation of the different parameter estimates is given below. As the numeraire, the installation cost parameter as expected had the expected sign in all models. For instance, it was estimated as -0.02 in M1 and -0.09 in M5. This parameter was used in the mWTP estimations appearing in Fig 2. Interestingly, the Global Moran I statistic was significant indicating that for parameter, respondents close together tended to have similar values. This parameter $I = 0.06, (p = 0.000)$ suggests a significant, though quantatitatively small correlation.

Ability / Ease of defet identification: The defect identification parameter is positive and significant ($p < 0.05$) suggesting that ceteris paribus, a biodigester that offers ease in identifying defects is a good thing. The provision of information about the health of the biogas plants is a critical requirement for timely repairs to be undertaken. Anecdotal evidence suggests that for the majority of defective biodigester plants, few end up being reported to Biogas Construction Enterprises (BCEs). As pointed out, most biodigesters will present difficulties in defect identification. Further, in only a few occasions of reported cases are assurances given that the defects would be fixed. This reflects results in Uganda that suggest that inaccessible BCEs are among the leading causes for abandoned plants (Lwiza et al., 2017). With sensors relaying real-time data, technicians from BCEs can determine the health of each plant. From a technical perspective, the likelihood of detecting a defect before it becomes catastrophic increases. In turn, the possibility of increasing the plant's operational reliability increases. It is reasonable to assume that reliability is an important signal to potential adopters. It is such signals that will be shared by local opinion leaders.

For this information to be transmitted, the defect will need to have been identified in the first place. This reorganizes the context in which BCEs make decisions and hence, can act as a nudge towards action (Benartzi et al., 2017). From a behavioral angle, information so transmitted is visible to all BCEs and their associated technicians. This differs from the current situation where reports of defects are shared with one or a few technicians. Just as with the findings in Kitui (Koehler et al., 2015), sensor data can alter the choice architecture available to the BCEs (technicians). Since this information is in "the open/is public", this in turn may speed servicing. For these reasons, respondents have a preference for easy defect identification and thus, the parameter is significant (p¡0.05) and positive. This was true for 69% of respondents. However, moving from the default situation where such instrumentation has not been rolled out would entail a cost to farmers. This comes in the form of the initial installation and running costs (e.g. mobile data subscriptions) of these sensors.

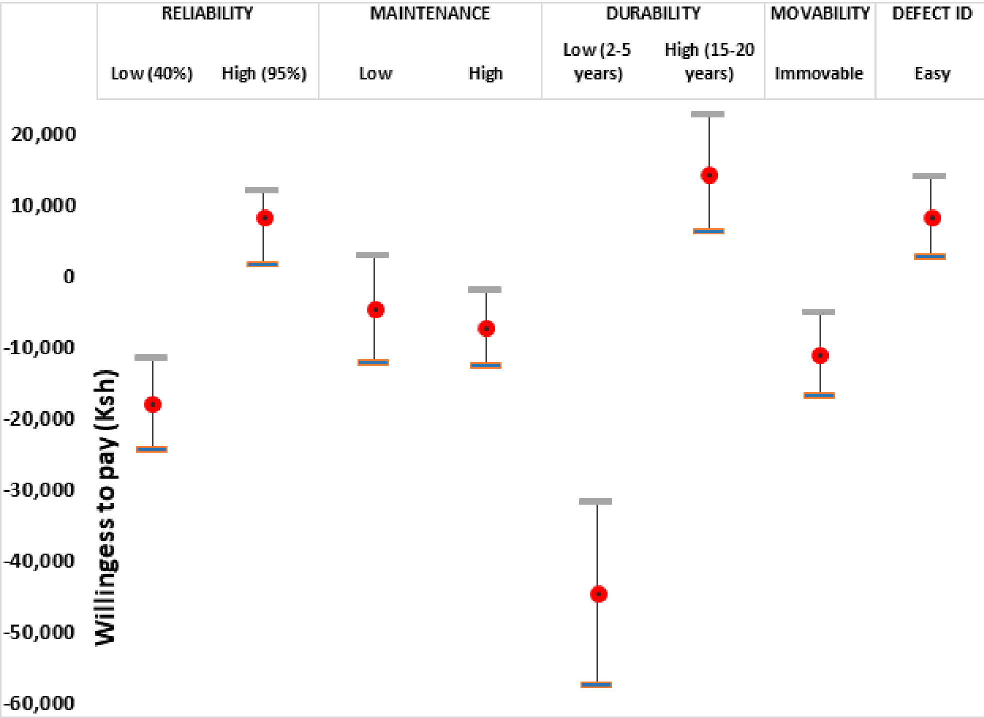

Fig. 3 Mean willingness to pay for different biodigester attributes

The mWTP was estimated from M5 and M6. However, the resultant estimates were considerably lower than for other candidate models. While low mWTP for biodigesters is not surprising Kabyanga et al., (2018), this result was probably statistical. A strong possibility was that this is because mWTP in M5 and M6 was derived from a ratio of a log normally distributed coefficient and a normally distributed coefficient. Train and Weeks (2005) noted that working with WTP values that take this inconvenient distribution is difficult. Besides, Hensher and Greene (2003) also noted that long fat tails associated with the log normal distribution could inflate mWTP estimates when the attributes are also log normal. Models in WTP space would've avoided the need to convert these estimates, but as indicated, convergence problems were encountered. One solution to this problem would be to simulate WTP values using estimated mixing distributions. An interim solution was to use M3 since the coefficients have a common distribution (normal) and are random while the cost attribute is fixed. In M4, all the coefficients are random, and therefore the resulting distribution of mWTP might be difficult to characterize (Talevi et al., 2022, In Press). Besides, the model had not exceeded the maximum number of parameters estimable. It however appears that some have estimated more parameters in their random parameter models and proceeded to publish their results (e.g. Hole, 2008).

One other caveat here was that the cost parameter in M3 was not constrained to be log-normal, and no correlations among coefficients were allowed. A consolation is that in M5 and M6, the median (-0.0254 and -0.0199) are qualitatively close to the parameter in M3 which is -0.027. The mean of the cost coefficients in M5 and M6 were -0.093 and -0.101 respectively. A normally distributed cost coefficient implies that some share of the respondents have a positive coefficient on cost. The WTP estimate of Ksh 8400 using M3 is slightly greater than the possible cost of the sensors at the shelf (Figure 2). It was not immediately clear if and by how much these WTP estimates were mis-estimated. But a quick check appears to suggest that the mWTP estimates may be over-estimated since the coefficient ratios in M5 and M6 are considerably different from those obtained from M3. This suggests that the mWTP from M3 may have been overestimated by a factor or 3 or 4. A quick check for example confirms that the ratio between the cost and other attribute coefficients declines as one moves from M3 to M6 (Table 5). However, the mWTP estimates derived from M3 provide an idea about how attributes compare in relative terms.

With this particular attribute, a few clarifying points may be necessary. A clear separation of the sensor running costs (which would be part of typical operation and maintenance costs) from maintenance costs was not explicitly made. Otherwise, doing this would entail specifying attributes that make the choice experiment difficult to comprehend. Whether respondents lumped the ability to identify defects with typical maintenance costs (which returns a negative coefficient) is only speculative.

The correlations from the procedure outlined by Mariel and Artabe (2020) applied to M6 were used to check for interactions among these random coefficients. The method is only limited to interpreting negatively correlated coefficients. The negative but weak correlation ($\rho_s = -0.309$) between defect identification and low maintenance cost suggested that respondents with a high preference for easy defect identification have a negative preference for biodigesters with low maintenance costs.

Maintenance costs: Maintenance costs (both low and high) all returned a negative coefficient. In fact, the expectation was that respondents would place a premium on low maintenance biodigesters (a positive coefficient). Moreover, that on low maintenance was not different from zero ($p = 0.726$). Besides, 28% of respondents preferred any cost other than high costs—possibly moderate or low costs. The mWTP estimate was Ksh -7200 for a high maintenance cost plant. A possible interaction between maintenance cost and the ability to detect defects (through sensors that imply running costs) would have been a welcome parameter to test. However, this was not foreseen during the design phase of the experiment and such a hypothesis has therefore not been tested in this paper. Maintenance costs to respondents that have not been exposed to such technology may have been a source of ambiguity. That is, respondents do not have a map of the maintenance cost distribution and cannot formulate the expectations around this variable (Ward and Singh, 2015). However, it was interesting to note that even in the pilot, maintenance cost similarly was not significant. Whether this was because this attitude was presented by adjectives (high – low) was not clear. That even low maintenance cost returned a negative parameter however suggests that respondents appear to consider low costs unacceptable. Although Talevi et al. (2022, In Press) found this parameter to be significant, it was not large in comparison to other attributes employed in their study. Similar interpretation can be made when eyeballing the relative size of the maintenance cost parameter vis-à-vis other attributes (Table 5). In their study, Talevi showed that present biased (impatient) respondents had larger mWTP for maintenance assistance. It therefore appears that our result is not an artefact of the experiment itself, but that something more substantial can be learnt. The large standard deviations suggest substantial heterogeneity, which appears to be a similar case in the Indian study. The spread of the high maintenance cost parameter in M6 was significant ($p = 0.000$).

The correlation between maintenance cost and durability was strong ($\rho_s > 0.7$). This suggests that respondents with preferences for durable biodigesters had low preferences for maintenance costs. This result makes perfect sense. Durability implies long service life and coupling such with maintenance costs is not expected to be a situation that respondents would like to face. While the correlation between these attributes was negative, that of high maintenance costs was greater ($\rho_s = -0.933$) than that of low costs ($\rho_s = -0.795$) suggesting a greater sensitivity to higher maintenance costs.

Reliability: The parameter on low reliability was negative while that on high reliability was positive as expected. Both parameters were significant ($p = 0.000$). For this particular attribute, explicit information cues were provided. These were made by making reference to how one would describe a plant as high, moderate, or low in reliability. The choice experiment made reference to the count of days of a year when the plant that is reliable would be able to provide gas. To frame this reliability, the study indicated to the respondents that a reliable plant would be able to give gas for 345 days in a year. Low reliability on the other hand would afford 145 days (40%) of the time in a year. Such framing effects may not have significant effects on choices made (Kragt and Bennett, 2012). While 27% of respondents would prefer a plant that is not low (40% reliability or 145 days in a year) in reliability, 37% prefer plants that are not highly (95% reliability or 335 days in a year) reliable. A plant whose reliability is high (Nzila et al., 2012) for instance had a mWTP of Ksh 8,300 while one whose reliability is only 40% was estimated to have a mWTP of Ksh -17,900. High maintenance and low reliability may be correlated since a plant that fails too often may increase maintenance costs and is, therefore, becomes less reliable. As with other coefficients, this possible interaction was not factored in the experimental design, and adding such interactions ex-post would not be feasible.

Generally, a negative correlation existed between low reliability and low maintenance costs. An estimated correlation ($\rho_s = -0.661$) was moderate. Respondents with above average mWTP for low reliability are likely to have a lower than average mWTP for low maintenance cost. In other words, this result suggested that those with a preference for biodigesters that were cheap to maintain had a low preference for biodigesters were unreliable.

Durability of biodigester: A durable plant described as one that would last 15-20 years was as expected more preferable than one that offered less service time (2-5 years). Biodigesters that are less durable as described by some authors (e.g. Nzila et al., 2012; Cheng et al., 2014) are mainly the tubular design. They are made of materials that may be subject to environmental and other chance stress variables. For instance, tubular digesters may be trampled over by animals. In other cases, curious children may puncture the inflated balloon and destroy its capacity to hold gas. Of the WTP estimates, durability appears to be the most valued of the attributes subjected to testing in this study. Respondents showed a strong dislike for low durability plants. Taken alongside a study of subsidy policy in China (Wang et al., 2016), the long-term use of biodigesters can be sustained by providing maintenance support. This would be in addition to installation subsidies. This is because, many seem to agree that in the long run, biodigesters can pay back the investment even at modest carbon prices (Somanathan and Bluffstone, 2015). Some of the designs being fairly long-lasting may provide ample opportunity for peer learning. Since learning from others is common for this particular technology, the presence of durable neighboring plants is a relevant signal for potential adopters to use in their own decisions. For instance, Milller and Mobarak (2015) were able to show that opinion leaders had a significant influence on the uptake of cooking technologies in Bangladesh. What was more important was that their influence was stronger when the technology in question did not meet expectations. In India, those who had undergone a bad experience with biodigesters had low mWTP for the technology. Drawing parallels with biodigesters in Kenya is not difficult. Since biodigesters degrade with age, there are always a greater probability of negative experiences as the biodidigester ages. This therefore implies the need for constant maintenance, which as we argued above, may be enhanced by embracing sensor technology.

The correlation between the two coefficients representing durability was negative ($\rho_s = -0.369$) but weak. This result was expected. Those who have a preference for a durable biodigester have a low preference for less durable biodigesters. While not unexpected, this result can be used as auxiliary evidence that the responses to the DCE (at least for this attribute) were consistent with apriori expectations. What was also clear was that the related coefficients for this attribute were typically larger, signaling that this is possibly the most important characteristic to respondents.

Portability of biodigester: Finally, respondents had preferences for portable biodigesters ($p = 0.000$). Portability in a biodigester was estimated to be valued at Ksh 10,900. This result was not surprising. Some designs by their nature (especially those involving masonry works such as fixed dome) are immovable. As others have suggested, portability of prefabricated biodigesters is one of their strong points. These biodigesters are usually cheaper to acquire, although they are less durable. Unlike fixed dome designs, they can be described as having low sunk costs. In addition, their investment can be reversible (can be sold to neighbors). Some authors have suggested that the investment trigger for biodigesters may be higher than is usually thought (Anderson and Weersink, 2013). This is in part due to the fact that they are expensive to install, and once installed, are difficult to liquidate. This result contrasts with similar work in settings similar to those in Kenya. For instance, Walekhwa et al. (2014) in Uganda concluded that biodigesters are economically viable. While they applied classical investment theory, a critical assumption therein was that biodigesters do not involve significant sunk costs. With this in mind, and as expounded earlier, the immovable fixed dome design which has these characteristic is the most common in Kenya. It is therefore not surprising that its adoption is low. Perhaps, under conditions of increasing land scarcity and small land sizes, respondents prefer to postpone investment in such an immovable fixture. However, thirty-one percent of respondents prefer immovable to movable plants.

The need to move plants from time to time may not be common. However, this decision may be important in places where land ownership is fragile (e.g. lack of secure tenure) or subject to changing tenure status. Therefore, without compromising on performance, designing movable biodigesters would be an important consideration for engineers. Luckily, such design features have been incorporated in some plants, using durable plastics in place of masonry work (Cheng, et al., 2014). The materials used on these biodigesters may include polyvinyl chloride (PVC), polyethylene (PE), high-density polyethylene (HDPE) among others. It is notable that through the Finance Act, tax waivers have been granted for such prefabricated biodigesters (Republic of Kenya, 2021). While the text talks of prefabricated biodigesters, it is not clear whether this waiver extends to materials which go towards their construction.

5 Conclusion

This paper presents what we think is the first formal treatment of the subject of biodigester plant attributes and their tradeoffs. The attributes: durability, reliability, movability, and defect identification show a clear preference structure. The results also suggest that there is substantial unobserved preference heterogeneity. This was revealed by the significant standard deviations in all mixed logit regressions, even after controlling for some respondent characteristics. In addition, the ASC suggests that at least for the respondents comprising this sample, the preferences towards bidigesters can be described as enthusiastic. While costs have been the key impediment highlighted in many studies, this paper points towards other product specific demand modifiers, which presumably are linked to adoption of the technology. For instance, these results suggest a strong preference for reliable but durable biodigesters. The significant mWTP for defect identification suggests that retrofitting biodigesters with sensors can be a feasible direction to take. A caution in interpreting the mWTP values however is given because they may have been over-estimated by a factor of between 2 and 4. If so, this means that at an off the shelf cost of Ksh 5000, a subsidy covering $\frac{2}{7}$ or $\frac{5}{8}$ of the cost of a retrofit may also need to be provided.

From a more practical perspective, technology developers and promoters would consider using these results to direct and enrich their work. Where technically possible, preferred attributes can be enhanced without compromising on attributes seen as utility enhancing. Of immediate application is the deployment of sensor technology on existing plants. Retrofitting existing biodigesters with these sensors is a recommendation coming from this study. Doing so, we contend, can help deal with the problem of numerous defective plants. This in turn could result in a reduction of the number of failed plants. This has immediate benefits to biogas plant owners. It can in turn leads to increased adoption and diffusion of the technology. In an environment where learning from others (neighbors and friends) is important, this may serve to paint biodigesters in positive light. From the observations of others before, a negative perception about biodigesters among the population can be traced back to failed biodigesters. It therefore is not a surprise that this study revealed a strong preference for durable biodigesters. Highly durable biodigesters allow users enough time to reap from its benefits, hence the high premium placed on the attribute.

As with studies of this type that rely on stated preferences, the results are only an approximation of reality. A key feature of this reality is heterogeneity in preferences as well as personal context. Many of the possible sources of heterogeneity were not explicitly incorporated in this study. For instance, the study did not control for risk and ambiguity preferences as some authors suggest these may be important in decision making. Since a DCE as applied in this study mimics decision making, albeit under hypothetical conditions, a replication of this study which incorporates such intrinsic characteristics is called for. Further a careful consideratin of the precise meaning of the significant correlations among the attributes can also shed further light towards the tradeoffs.

Social learning from neighbors is important for biodigesters. The present study had a major failing in incorporating what respondents actually knew about biodigesters. Kiambu, unlike Machakos for instance has a higher (but small) concentration of biodigesters. It is possible that responses to this experiment are also contaminated by what respondents have learnt from their social network. Although results from a DCE are based on responses to hypothetical situations, it is difficult to ensure that responses are only based on those variations contained in the experiment. In the case of a highly observable technology as biodigesters, it is conceivable that learning from others engenders significant heterogeneity. While none of the respondents in this study owned a biodigester, it is plausble that a number of them had come into contact with neighbors who owned the technology. This contact may induce learning. This is because most social interaction based learning is local. An attempt to control for such inherent heterogeneity by including a simple dummy may not have been sufficient. Importantly, data on what respondents had learnt and from whom was not collected. Extending these analytical models to incorporate other forms of heterogeneity would be one recommendation from this study. While some have extended discrete choice analysis to incorporate spatial heterogeneity (e.g. Bhat and Sener, 2009; Smirnov, 2010; Brouwer et al., 2010; Meyerhoff, 2013; Liu et al, 2020; Toledo-Gallegos et al., 2021) the authors have not come across similar extensions incorporating social interaction in the analysis of DCE data. How such learning may translate to actual behavior (considering the salience of failed plants) is an important question for future research.

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Table 6 Results from conditional (fixed effects) and mixed logit models

b height Variable	Attribute Level		M1	M2	M3	M4	M5	M6
Installation cost ’000		mean	-0.020***	-0.020***	-0.027***	-0.041***	-3.670***	-3.917***
			(0.003)	(0.002)	(0.002)	(0.005)	(0.140)	(0.179)
		s.d.				0.074***	1.615***	1.804***
						(0.003)	(0.119)	(0.162)
Reliability	low	mean	-0.268***	-0.268***	-0.488***	-0.489***	-0.418***	-0.432***
			(0.047)	(0.047)	(0.079)	(0.072)	(0.068)	(0.077)
		s.d.			0.899***	0.634***	0.600***	0.824***
					(0.112)	(0.137)	(0.115)	(0.104)
	High	mean	0.286***	0.286***	0.226**	0.433***	0.463***	0.193*
			(0.071)	(0.057)	(0.099)	(0.097)	(0.089)	(0.102)
		s.d.			1.415***	1.208***	1.055***	1.217***
					(0.092)	(0.100)	(0.085)	(0.127)
Maintenance cost	Low	mean	-0.074	-0.076	-0.126	-0.033	0.088	-0.109
			(0.078)	(0.077)	(0.100)	(0.104)	(0.094)	(0.111)
		s.d.			0.136	0.085	0.037	0.255*
					(0.147)	(0.186)	(0.107)	(0.142)
	High	mean	-0.122***	-0.122***	-0.198***	-0.184***	-0.099	-0.213***
			(0.047)	(0.046)	(0.069)	(0.068)	(0.063)	(0.075)
		s.d.			0.540***	0.029	0.264**	0.491***
					(0.104)	(0.177)	(0.119)	(0.097)
Durability	Low	mean	-0.465***	-0.467***	-1.215***	-1.157***	-0.870***	-0.973***
			(0.078)	(0.060)	(0.144)	(0.130)	(0.114)	(0.142)
		s.d.			1.852***	1.559***	1.460***	1.753***
					(0.140)	(0.138)	(0.132)	(0.142)
	High	mean	0.320***	0.319***	0.394***	0.414***	0.554***	0.456***
			(0.084)	(0.065)	(0.116)	(0.115)	(-0.102)	(0.124)
		s.d.			1.607***	0.933***	0.984***	1.281***
					(0.107)	(0.112)	(0.101)	(0.123)
Movability	Immovable	mean	-0.215***	-0.216***	-0.299***	-0.312***	-0.387***	-0.074
			(0.066)	(0.058)	(0.089)	(0.081)	(0.076)	(0.095)
		s.d.			1.062***	0.484***	0.494***	0.786***
					(0.095)	(0.113)	(0.089)	(0.106)
Defect identification	Easy	mean	0.199***	0.199***	0.229***	0.331***	0.403***	0.370***
			(0.061)	(0.055)	(0.084)	(0.077)	(0.072)	(0.092)
		s.d.			0.852***	0.499***	0.376***	0.712***
					(0.097)	(0.103)	(0.125)	(0.098)
ASC		mean	-3.414***	-2.916***	-3.413***	-9.745***	-14.987***	-14.020***
			(0.429)	(0.220)	(0.217)	(0.664)	(1.246)	(1.325)
ASC*Block		mean	-0.064	-0.127	-0.372	-0.137	3.923***	2.433***
			(0.333)	(0.125)	(0.163)	(0.487)	(0.893)	(0.790)
ASC*position		mean	0.241	0.259	-0.407	-0.006	0.724	-1.017
			(0.480)	(0.23)	(0.321)	(0.530)	(0.799)	(0.707)
ASC*TLU		mean		-0.811***	-0.894***	-0.957**	-0.081	0.203
				(0.123)	(0.155)	(0.477)	(0.734)	(0.731)
ASC*Elevation		mean		-1.771***	-1.847***	-1.952***	-4.858***	-5.216***
				(0.344)	(0.376)	(0.715)	(1.724)	(1.518)
ASC*Fuel		mean		0.349***	0.209	1.527***	3.252***	6.375***
				(0.125)	(0.158)	(0.490)	(0.799)	(0.893)
Position*install cost		mean	0.004	0.004	0.009***	-0.0006	-0.0005	0.005
			(0.004)	(0.002)	(0.003)	(0.0069)	(0.0041)	(0.0043)
No of respondents			440	440	440	440	440	440
No of choice tasks			3502	3502	3502	3502	3502	3502
No of datapoints			14008	14008	14008	14008	14008	14008
log normal cost			NO	NO	NO	NO	YES	YES
Randomly dist cost			NO	NO	NO	YES	YES	YES
Randomly dist parameters			NO	NO	YES	YES	YES	YES
Independent coefficents			YES	YES	YES	YES	YES	NO
McFadden’s pseudo R^2			0.013	0.013	0.118	0.178	0.248	0.273

*Standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$. In M5 and M6 which employ a log normal distrubution on the installation cost parameter, the coefficnent needs to be transformed into its respective mean, median and standard devision. They are defined as $exp(\beta)$, $exp(\beta + \sigma^2/2)$ and $exp(\beta + \sigma^2/2) \times \sqrt{exp(\sigma^2 - 1)}$ (Train 2003). The values β and σ are as estimated from the regressions where the cost parameter is specified as log-normally distributed. For example, the resultant values are β_{M5} = -0.0939, $\tilde{\beta}_{M5}$ =-0.0254, and σ_{M5} = 0.333 for M5 and β_{M6} = -0.101, $\tilde{\beta}_{M6}$ =-0.0199, and σ_{M6} = 0.414 for M6*