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Capturing and analysing heterogeneity in residential greywater reuse preferences using a latent class model

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ABSTRACT

To legally permit greywater reuse as a management strategy, it is necessary to establish allowed uses, as well as guarantee legitimacy, safety and maintain public trust. Cities with previous experience in greywater reuse have reconfigured their regulations according to their own evidence with decentralized water reuse systems. This has allowed them to encourage or restrict certain indoor uses of treated greywater. However, cities starting to use these residential schemes lack the experience to reconfigure their water and sanitation regulation, and thus need "blindly" decide on the type of greywater uses to allow in order to achieve a balance between users' acceptability and avoiding public health problems.

In this research, we analyse hypothetical situations of greywater reuse based on real evidence related to decentralized water systems. The main objective of this study is to evaluate the heterogeneity of individuals' preferences regarding residential greywater reuse for six intended indoor uses, using stated choice experiments and a latent class model. Hence, we obtain preliminary evidence about the direction that the regulation or pilot tests should take. We use the context of Santiago (Chile) as a reference, where although allowed, greywater reuse is not taking place widely. Our results show that survey respondents can be classified into four classes (enthusiasts, greywater sceptics, appearance conscious and water expenditure conscious), according to the preferences for the different types of indoor greywater reuse and the appearance of the treated greywater. From a policy perspective, our results show differences across classes as a function of socioeconomic characteristics and previous greywater reuse knowledge, as well as wider household characteristics, including the presence of sensitive individuals (under 15 and over 74 years old), number of residents, number of sanitary devices, and location and type of garden. Along with presenting empirical results for the specific case of Santiago de Chile, the paper provides a demonstration of the method that can be replicated in other countries that need an empirical approach to acquire knowledge about people's preferences for greywater reuse allocation, before including greywater reuse schemes in their water and sanitation regulation.

Keywords: *Greywater reuse preferences, choice modelling, latent class model, class allocation.*

1. INTRODUCTION

Opportunities for using new alternative sources of water supply for households and the availability of new technology for reusing water are reshaping the way water is managed in cities (Wilcox et al., 2016). In particular, now there exist decentralized hybrid water supply systems that draw only part of the water from the mains network (between 50-70%) while the remainder (50-30%) comes from reused greywater that is locally treated (Lefebvre, 2018; Vuppaladadiyam et al., 2019). The source is greywater from the same household, that is, water that is free of faeces, food residues, oil and fats, collected from washing machines, showers, tubs, and washbasins (Lambert & Lee, 2018).

Experience in urban settings such as the Persian Gulf region and the broader Middle East (Lambert & Lee, 2018), and Sydney (Pham et al., 2011), indicates that individuals prefer to allocate reclaimed water for two non-potable purposes, namely toilet flushing and garden irrigation. Both uses are very attractive due to a higher perceived safety (i.e. no direct contact with the skin) and lower treatment costs, as high-quality standards are not needed, and also because they are two of the uses that consume the largest water volumes in the household (Roshan & Kumar, 2020). However, at certain times of the year (e.g. winter or rainy months), garden irrigation is not a daily practice, or depending on rainfall, may not be required[1]. As a result, at those times, the amount of greywater available would be higher than what consumers can use for other residential uses Dolnicar & Schäfer, 2009). Discharging the extra greywater to the conventional sewage system would be an economic loss for users who pay for the maintenance and operation of the treatment technology (Lambert & Lee, 2018). Thus, if allowed by law, allocating treated greywater for other uses could be beneficial since a higher volume of the greywater that was treated can be used.

The perceptions that consumers hold about greywater reuse are fundamental for the success of a decentralized hybrid water supply system, since they are the primary agents that interact with the greywater, as well as operate and take care of the technology (Domnech & Saurí, 2010). To ensure that laws, regulations, and policies contribute to making these systems more attractive and to remain successful over time, an understanding of the key determinants of consumer preferences is essential (Mukherjee & Jensen, 2020). Several studies on water reuse have empirically demonstrated that there is heterogeneity in preferences and that this is mainly linked to socio-demographic characteristics, and other psychological constructs (Amaris et al., 2021; Oteng-Peprah et al., 2020). The starting point of our work is that even within the same sociodemographic group, differences in preferences may exist, in terms of which (if any) uses of greywater are desirable, and what the role of the appearance of the water is (Amaris et al., 2021). We postulate that classes or groups of individuals can be established to

[1] https://www.organicgardener.com.au/blogs/watering-winter

capture this heterogeneity, and that consumer characteristics can be used to at least partially explain which group an individual is more likely to belong to (Hess, 2014). In particular, our study focuses on exploring different population segments, each with its own behaviour (choice regarding preferences) in the allocation of treated greywater for six domiciliary uses that vary according to the level of skin contact, based on our earlier survey work in (Amaris et al., 2020).

Our modelling context is based on hypothetical scenarios that replicate real experiences of water reuse in dwellings in Spain (Domnech & Saurí, 2010) and South Africa (Ilemobade et al., 2013). This method uses SC experiments to explore the preferences of respondents for the qualitative and quantitative characteristics of mutually exclusive alternatives (Louviere et al., 2000). Due to the nature of the data and our study objectives, we analyse the choices in the hypothetical scenarios using latent class discrete choice models allowing for heterogeneity in preferences across consumers. These types of data and models are becoming more common in studies of technological innovations (Su et al., 2018; Franceschinis et al., 2017), mainly because they can produce insights on preferences in the absence of an existing market (Ortúzar & Willumsen, 2011, sec. 8.6.3.2). They also offer a way of knowing about how feasible and successful a project can be and understanding which characteristics should be improved to achieve higher acceptability before it goes on the market, or prior to regulations being established.

Discrete choice models of the type used here explain choices under the assumption that consumers maximize the "utility" or benefit they receive by choosing a particular alternative. This utility is based on the characteristics or attributes that define the alternative (Ortúzar & Willumsen, 2011, sec. 7.1), and the sensitivities of the user towards them. In the particular context of our study, the characteristics defining treated greywater in the hybrid water system are: (i) it's different levels of colour and odour, (ii) possible uses (e.g. toilet flushing) and (iii) the resulting savings in mains water. Our work seeks to uncover different classes of respondents, with different sensitivities to the attributes, and to understand why individuals belong to each class. We leave aside traditional economic theory (which would consider a full cost-benefit approach), since, although the cost of technology is known to be highly influential, the inclusion of cost would have dominated the scenarios and precluded our focus on understanding other subjective elements that may influence individuals' acceptability of treated greywater, and the heterogeneity in this across people.

The study context is Santiago, the capital city and largest conurbation in Chile (INE, 2017), a place with seasonal water availability problems, and where its population has no previous experience about greywater reuse (even the concept itself is largely unknown). Although mandatory water quality standards are not established, the permitted uses for greywater are known to be garden irrigation and toilet flushing (as prescribed in the law 21,075[2]). With this research we aim to provide evidence, with statistical support, to show that regulations could allow other greywater uses considering the preferences in different population segments. We also provide statistical evidence suggesting that it is possible to preserve the balance between recovered water volumes and the amount of water used, while ensuring that the system's operation provides the greatest benefits without compromising individuals' health. Along with presenting empirical results for the specific case of Santiago de Chile, the paper provides a demonstration of the method that can be replicated in other countries that need an empirical approach to acquire knowledge about people's preferences in greywater reuse allocation, before including greywater reuse schemes in their water and sanitation regulation.

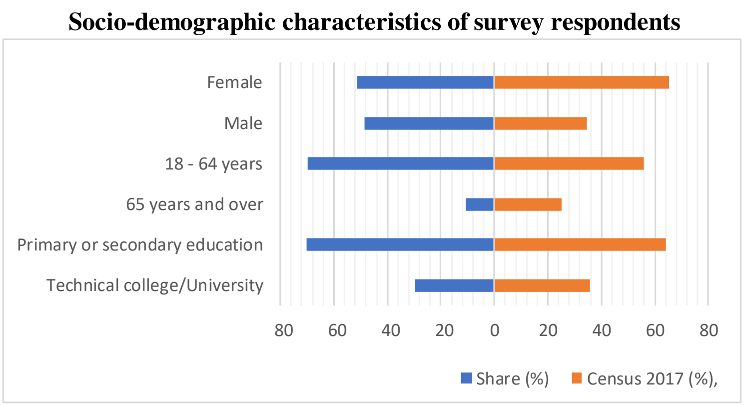
2. DATA

Data for our analysis come from a Stated Choice (SC) survey carried out in Santiago. The Metropolitan Region, where Santiago is located, has water stress problems nowadays (with periods of one to four weeks with very low flows, (Vicuña et al., 2018) and is predicted to become the area with highest deficit in Chile by 2025 (Valdés-Pineda et al., 2014). Currently, residential water demand per capita varies between 150 l/day and over 600 l/day depending on the irrigation of green areas (Bonelli et al., 2014), while water losses due to pipe leaks in the mains water system are around 30% (Aguas Andinas, 2019). Although the main water supply system has been strengthened over the years, it continues to be fragile in the face of significant threats due to climate variability, climate change and population growth (Vicuña et al., 2018).

[2] https://www.bcn.cl/leychile/navegar?idNorma=1115066

The survey was carried out *face to face* in 29 of the 37 municipalities of the city, and only household heads or their partners over 18 years of age were interviewed. The information was collected by a company with experience with this type of survey. Municipalities were selected from the city areas with drinking water and sanitation services provided by *Aguas Andinas*, the main water company. In each municipality, the survey was carried out in different non-neighbouring blocks and the households participating in the survey were randomly selected. A final sample of 510 individuals were retained for analysis, of which 65.3% were women, 55.9% were between 18 and 54 years of age, 64.1% had lower than secondary educational level, and 71.4% had no previous knowledge about greywater reuse. These characteristics partially replicate census data reported by (INE, 2018) as shown in Figure 1.

Figure 1. Overview of socio-demographic characteristics sample and census INE (2017).



Life expectancy (Census 2017)	
Women	*Men*
80-90 years old	75 - 85 years old

Average people per household	
Sample	*Census 2017*
3.4	3.1

Type of house: Apartment	
Sample	*Census 2017*
11%	30%
Type of house: House	
89%	67%

2.1. Survey overview

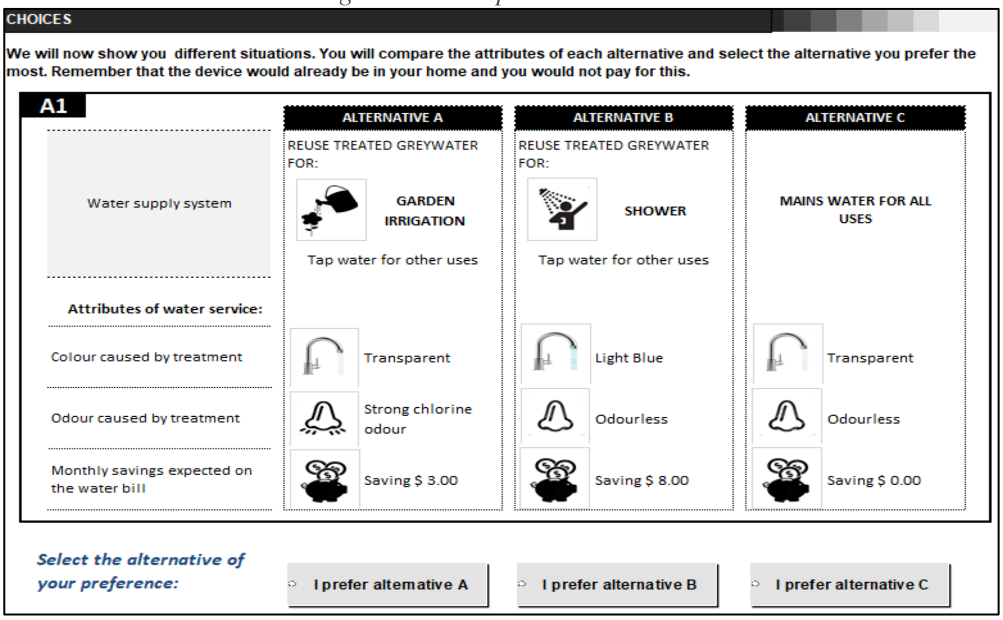
Although allowed and regulated by Law 21,075, greywater reuse in Chile is not a common practice at present. Hence, the survey first presented individuals with a schematic representation to explain the concepts of greywater and sewage, and showed them how a greywater reuse technology system would work inside their homes. In the next sections, the survey collected answers/ratings related to individuals' reactions to the concept of greywater reuse, characterization of the household (e.g. age, gender), the dwelling (e.g. house size, presence of garden and coverage percentage, kind of coverage – grass or another kind of vegetation). The choice experiment and the development of the survey are described in Amaris et al., (2020), and supplementary materials in the present paper gives more detail about the survey form. In what follows, we give an overview of the parts most relevant to this paper (i.e. personal water reuse choices).

2.2. Choice context

Personal greywater reuse choices have been studied using hypothetical SC scenarios that were based on real experiences in Spain (Domnech & Saurí, 2010), South Africa (Ilemobade et al., 2013) and the USA (Wester et al., 2016). The aim of the SC component was to estimate the acceptability of reusing treated greywater for different purposes inside the home, measuring respondents' sensitivities to changes in the type of use and changes in water appearance and water bill savings.

Each respondent was shown six different choice scenarios (see Figure 2 for an example of choice scenario), leading to a final sample of 3,060 observations. Each scenario had three alternatives for water supply inside the home, from which the respondent had to choose only one. One of these alternatives was to continue using the conventional water supply system (*status quo*), while the other two used a hybrid water supply that allowed the reuse of greywater for a specific purpose and mains water for other uses.

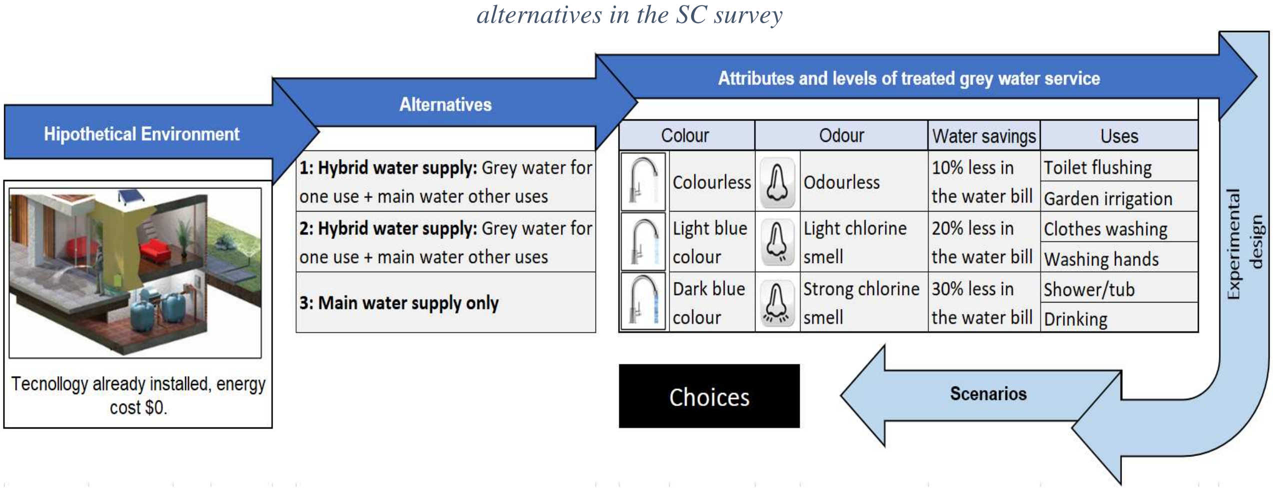
Figure 2. Example choice scenario 1



In the case of the hybrid system the individual had to assume that the greywater treatment device was already installed, was as easy to use as a washing machine, and that there was no additional energy cost, as a solar panel was also already installed. For the two reuse alternatives in the SC scenarios, the treated greywater in the hybrid system was described by four characteristics at different levels (Figure 3): (i) type of use, (ii) colour (iii) odour, and (iv) the percentage savings on the water bill (shown as the actual amount of money saved).

The values for each attribute in each scenario were determined on the basis of a D-efficient experimental design (cf. Rose & Bliemer, 2014). The type of greywater uses corresponded to the six most common uses within the house, which consider different levels of contact with the skin. Colour and odour (both with three levels) after treatment, could be caused by the type of treatment (e.g. water purification tablets), or could be introduced deliberately to indicate the contaminant removal success, or to distinguish treated water from that of the mains system (Domnech & Saurí, 2010). Water savings are the result of the lower use of mains water at home due to greywater reuse (Lambert & Lee, 2018; Chen, et al., 2017) . This attribute (also with three levels) differed across two reference groups in the choice scenarios: *group 1* with 290 households (T1) and *group 2* with 220 households (T2); these groups were associated with a monthly water consumption bill below and above US$ 28.8, respectively.

Figure 3. Attributes and levels of treated greywater in hybrid decentralized water supply system alternatives in the SC survey



3. MODEL FORMULATION AND SPECIFICATION

We formulated and estimated a latent-class (LC) choice model to identify different segments in the population, each with its own preferences for reusing treated greywater in different uses inside the house. A LC model probabilistically segments the sample population into a number of segments with different behaviour/preferences. In our application, each class was based on random utility theory, which postulates that individuals form a utility for each alternative, based on their perceptions about what characteristics describing a good or service are desirable or undesirable. Decision makers then choose the option that provides them with the highest utility. As the process of utility formation is not observed by the analyst, the models incorporate a random component and the choices become probabilistic (Train, 2009). In our LC model, the different classes are characterised by different sensitivities to the characteristics of the greywater system (Greene & Hensher, 2003). We now describe the two main components of the analysis, namely the model specification and estimation, and the post-estimation processing of the estimates.

3.1. Model specification and estimation

The LC model uses a probabilistic class allocation model, where respondent n belongs to class k (out of a total of K classes) with probability $\pi_{n,k}$, where $0 \leq \pi_{n,k} \leq 1$ $\forall k$ and $\sum_{k=1}^{K} \pi_{n,k} = 1, \forall k$. LC models are generally specified with an underlying multinomial logit (MNL) model inside each class, but can easily be adapted for more general underlying structures (Hess, 2014). Let $P_n(j_{n,t} \mid \beta_k)$ give the probability of respondent n choosing alternative j in task t, conditional on respondent n falling into class k, where the model in this class uses the vector of parameters β_k.

We observe a sequence of T_n choices for person n, say j_n^*, where alternative $j_{n,t}^*$ is chosen in choice situation t. With an underlying MNL model, we have that:

$$P_n\,(j_{n,t}^* \mid \beta_K) = \frac{e^{V_{j_{n,t}^*}}}{\sum_{j=1}^{J} e^{V_{j_{n,t}}}} \quad (1)$$

where $V_{j_{n,t}}$ is the deterministic component of utility (i.e. the fraction of utility associated with attributes that the analyst can measure or observe) for person n, alternative j, in choice situation t, given by:

$$V_{j_{n,t}} = f(x_{j_{n,t}}, z_n, \beta_k) \quad (2)$$

where $x_{j_{n,t}}$ are characteristics of alternative j in choice situation t, z_n are characteristics of individual n, and β_k are parameters to be estimated. The functional form $f(x)$ is typically linear in attributes.

Equations (1) and (2) are conditional on respondent *n* falling into class *k*, but this is not observed by the analyst. The unconditional (on *k*) choice probability for this sequence of choices for respondent *n*, $L_n\ (j_n^* \mid \Omega)$, is then given by:

$$L_n\ (j_n^* \mid \Omega)\ =\ \sum_{k=1}^{K} \pi_{n,K} \left(\prod_{t=1}^{T_n} P_n\ (j_{n,t} \mid \beta_K) \right) \qquad (3)$$

that is, the weighted sum across the *K* classes of the probabilities of the sequence of choices, with the class allocation probabilities being used as weights. The vector Ω groups together all parameters used in the model.

As seen in Equation (3), the LC model uses a weighted summation of class-specific choice probabilities. In the most basic version of an LC model, the class allocation probabilities are constant across respondents, such that $\pi_{n,k} = \pi_k, \forall n$. However, the real flexibility arises when the class allocation probabilities are not constant across respondents and a class allocation model is used to link these probabilities to characteristics of the respondents. Typically, these characteristics take the form of socio-demographic variables, such as income, age and employment status. With z_n representing the vector of characteristics for respondent *n*, and with the class allocation model taking a MNL form, the probability of respondent *n* falling into class *k* is given by:

$$\pi_{n,k} = \frac{\left(e^{\ \delta_k + g(\gamma_k, z_n)} \right)}{\sum_{l=1}^{K} e^{\ \delta l + g(\gamma l, z_n)}} \qquad (4)$$

where δ_k is a class-specific constant, γ_k is a vector of parameters to be estimated, and g (·) corresponds to the functional form of the utility function in the class allocation model.

Here, a major difference arises between class allocation models and choice models. In a choice model, the attributes vary across alternatives while the estimated coefficients (with a few exceptions) stay constant across alternatives. In a class allocation model, the attributes normally stay constant across classes while the parameters vary across classes, and are set to zero for one class for normalisation. This allows the model to allocate respondents to different classes depending on their socio-demographic characteristics. For example, a situation where high-income and low-income respondents are allocated to two classes could be represented with a positive income coefficient for the first class (with the coefficient normalised to zero for the second class). In a LC model, taste heterogeneity is accommodated as a mixture between a deterministic and a random approach.

A probabilistic model is used to allocate respondents to the different classes that characterise different tastes in the sample. However, the class allocation in Equation (4) is not purely random, but a function of socio-demographic characteristics of the respondents. In addition, it is also possible to incorporate heterogeneity in preferences directly in the utility functions in Equation (3), for individual classes, rather than in the class allocation model. In some cases, such as for example an income effect on cost sensitivity, it also makes sense to keep these effects the same across classes.

The LC model was estimated using Apollo v 0.1.1 (Hess & Palma, 2019). The estimation of a discrete choice model involves the maximisation of the likelihood of the observed choices, where we typically work with the log-likelihood function, given by:

$$LL(j_n^* \mid \Omega) = \sum_{n=1}^{N} \log\left(L_n\left(j_n^* \mid \Omega\right)\right) \quad (5)$$

where N is the number of individuals, $L_n\ (j_n^* \mid \Omega)$ is given by Equation (1), which itself uses Equations (2) and (4). The log-likelihood function for a LC model is notoriously difficult to maximise, with a risk of convergence to poor local optima. We address this issue by moving away from gradient based approaches and using an expectation-maximisation process (Train, 2009, Chapter 14).

3.2. Posterior analysis

The estimation of a LC model provides parameters for the choice model used inside each class, in this case always a MNL model. In addition, we obtain estimates for the parameters used in the class allocation models. The utility parameters provide insights into the preferences and sensitivities within each class, while the class allocation parameters explain the allocation of individuals to different classes. The differences in parameters across classes give insights into the sample level patterns of heterogeneity. Each individual belongs to each class up to a probability, where this probability varies across individuals as a function of their characteristics. For example, in a model that retrieves two classes characterised by differences in the sensitivity to cost, the class allocation model will likely show that higher income individuals have a higher probability of belonging to the class with lower cost sensitivity. However, this treats two individuals who are identical on the socio-demographics used in Equation (4) as also having identical sensitivities, contrary to the notion of random heterogeneity. In addition, it does not provide information about how preferences may vary as a function of socio-demographic (or other) characteristics that were not included in Equation (4).

Further insights can be obtained, post estimation, in a Bayesian manner by calculating information relating to a given individual's sensitivities on the basis of the sample level model estimates and her observed choices. Let us return to the example with the classes used above. Two individuals with the same income may still make different choices in our data. Bayesian analysis then allows us to further disaggregate the class allocation of these individuals. If one of the two chooses more expensive options than the other on average, her likelihood of falling into the low cost sensitivity class is higher. On the other hand, if we have two individuals with different income but the same choice patterns, then the person with lower income will still have a lower probability of falling into the low cost sensitivity class. This is an illustrative example, just to explain the concept, which is now formalised using Bayesian analysis as follows.

The first step is to calculate posterior class allocation probabilities, where the posterior probability of individual n for class k is given by:

$$\widehat{\pi_{n,k}} = \frac{\pi_{n,k} L_{n,k}\ (j_n^* \mid \Omega_{\mathrm{k}})}{L_n\ (j_n^* \mid \Omega)} \tag{6}$$

where $\pi_{n,k}$ and $L_n\ (j_n^* \mid \Omega)$ are given by Equations (4) and (3), respectively, and where $L_{n,k}\ (j_n^* \mid \Omega_{\mathrm{k}})$ is the likelihood of the observed choices for individual n, conditional on class k, that is, the term inside the sum across classes in Equation (3).

We then use the output of Equation (6) to produce a membership profile for each class. From the parameters in the class allocation probabilities, we know which class is more or less likely to capture individuals who possess a specific characteristic. Crucially, this can be done for characteristics not included in the model specification during estimation. Let us use the example of a given socio-demographic characteristic z_c. We can then calculate the likely value for z_c for an individual in class *k* as:

$$\widehat{z_{c,k}} = \frac{\sum_{n=1}^{N} \widehat{\pi_{n,k}} z_{c,n}}{\sum_{n=1}^{N} \widehat{\pi_{n,k}}} \tag{7}$$

where $z_{c,n}$ is the value for this characteristics for individual *n*. Thus, Equation (7) considers the weighted average of the value for characteristic z_c for all individuals in class *k*, using the posterior class allocations from Equation (6) as weights. Alternatively, we can also calculate the posterior probability of an individual in class *k* having a given value κ for z_c by using:

$$P\left(\widehat{z_{c,k}} = \kappa\right) = \frac{\sum_{n=1}^{N} \widehat{\pi_{n,k}} \left(z_{c,n} == \kappa\right)}{\sum_{n=1}^{N} \widehat{\pi_{n,k}}}, \tag{8}$$

where $\left(z_{c,n} == \kappa\right)$ will be equal to 1 if and only if $z_{c,n}$ equals *k*.

The calculation of these posterior values for characteristics in each class opens up the possibility of graphical analysis, using three dimensions, as we will demonstrate in Section 4.2.2. In particular, this allows us to study the relationship between the posterior class allocation probabilities (Z dimension) and two different socio-demographics (X and Y) at the same time. In the graphical analysis, the inverse distance weighting method (IDW) was implemented to interpolate the estimates of Z within the data range, which implies that the assigned weights will be bigger at the points closest to the prediction location and that these will decrease as a function of distance. The reason for this is that the IDW method assumes that closer points are more similar than those that are further away. To have a common reference system, the data used for the X and Y axes were standardized.

3.3. Initial model specification considerations

A number of decisions are needed prior to specify the models. These decisions relate to the levels used as reference for categorical variables, the inclusion of socio-demographic characteristics in the model, the existence of any generic parameters across classes, and the number of classes to use.

The survey used three alternatives, two of which were greywater reuse (GWR) options, and the third implied using mains water. We specified mains water as reference and, thus, a parameter for each of the six types of greywater reuses could be estimated. In addition, we estimated a constant for the left-most alternative, to capture any left-to-right (reading) bias in the data. The other categorical variables were related to odour and colour; here we again used dummy coded coefficients, with the best level (i.e. clear for colour, and odourless for odour) being the reference and fixing its parameter to zero for identification.

In LC models, the socio-demographic parameters are typically used only in the class allocation model, (i.e. to explain which types of individuals are more or less likely to fall into given classes). For extra flexibility, we additionally incorporated some socio-demographic variables directly in the utility functions. These variables related to differences in the preferences for different GWR uses as a function of gender and past knowledge, and in the sensitivity to water bill savings as a function of the current level of water expenditure in the household. These socio-demographics were kept generic (i.e., with the same parameter) across classes. In addition, the sensitivity to the water bill savings was kept constant across classes, as earlier results showed that segmenting by level of expenditure was sufficient to capture the heterogeneity in cost sensitivity.

Within individual classes, we also tested for the significance of differences between parameters, and imposed some constraints where appropriate; for example, if the preferences for two or more uses were found not significantly different from each other. These constraints are highlighted in the presentation of the results. Similarly, some parameters were excluded from specific classes if the associated attributes did not have a significant impact on utility in those classes (marked in the tables as n.s., for non-significant to distinguish from those parameters fixed to zero as reference). Finally, socio-demographic characteristics were also incorporated in the MNL class allocation model. For identification purposes, we set class 1 as reference and estimated an offset (δ_k in Equation (4)), as well as socio-demographic effects (γ_k), for the other classes.

A key decision in specifying a LC model relates to the number of classes to use. We evaluated different models to define the optimal number of classes (Table 1). The log-likelihood (LL) improves with additional classes, but at the cost of additional parameters. In line with best practice for LC models, we compared models on the basis of the Akaike Information Criterion (AIC) and Bayesian Information

Criterion (BIC). While the former favoured a 5-class model, the latter narrowly favoured a 3-classs model. The 4-class model provided a good balance between the two, with additional behavioural insights over the 3-class model. Some further parameter constraints (i.e. removing insignificant parameters) in this model led to our final specification.

Table 1. Determining the number of classes

Number of classes	LL	Nº of parameters	AIC	BIC
1	-3,129.02	18	6,294.04	6,370.25
2	-2,398.48	31	4,858.96	4,990.23
3	-2,319.93	45	4,729.85	4,920.40
4	-2,282.31	58	4,680.63	4,926.22
5	-2,262.79	69	4,663.58	4,955.75
4 (with additional Constraints)	-2,304.57	34	4,677.15	4,882.04

4. RESULTS AND DISCUSSION

4.1. Estimation results for final model

When working with LC models, an analyst needs to make a decision between an “exploratory” LC model and a “confirmatory” LC model (cf. Hess, 2014). While “confirmatory” LC is useful for testing for the presence of specific behavioural traits, “exploratory” LC lets the data “speak”, that is, the preferences in the classes as well as their composition are revealed by the data, rather than pre-imposed by the analyst. We use such an “exploratory” LC model, where the four classes can then be interpreted by studying the estimated sensitivities to different characteristics, including the type of use and the appearance of the treated greywater.

The results in Table 2 show the parameter estimates (which give the impact on utility by a given attribute) alongside the robust t-ratios (given by dividing estimates by their robust standard errors, with for example 1.96 implying a 95% significance level for rejecting the null hypothesis that the parameter is not different from 0 in a two-sided test). The parameters show the impact of the attribute on utility, with a negative sign implying a reduction in utility (i.e. an undesirable attribute), and the opposite applying for a positive estimate.

Table 2. Estimation results for latent class model

	Class 1		Class 2		Class 3		Class 4	
	Estimate	**Robust t- ratio**	**Estimate**	**Robust t-ratio**	**Estimate**	**Robust t-ratio**	**Estimate**	**Robust t-ratio**
(1) ALTERNATIVE SPECIFIC CONSTANT								
***Left alternative*†**	-0.367	-6.39	-0.367	-6.39	-0.367	-6.39	-0.367	-6.39
(2) GREY WATER APPEARANCE								
Colour								
… Clear (reference)	0	*reference*	0	*reference*	0	*reference*	0	*reference*
… Light blue	0	n.s.	0	n.s.	0	n.s.	-1.301‡	-2.05
… Dark blue	-0.313	-3.13	0	n.s.	-0.619	-5.09	-1.301‡	-2.05
Odour								
… Odourless (reference)	0	*reference*	0	*reference*	0	*reference*	0	*reference*
… Light chlorine	-0.169	-1.45	0	n.s.	-0.472	-3.53	0	n.s.
… Strong chlorine	-0.816	-6.48	-11.057	-21.08	-1.032	-6.4	0	n.s.
(3) USES								
0. Mains water (reference)	0	*reference*	0	*reference*	0	*reference*	0	*reference*
1. Toilet flushing	3.963‡	6.74	-4.959‡	-9.79	0.303‡	2.14	5.957‡	2.1
… shift for female†	0.728	4.26	0.728	4.26	0.728	4.26	0.728	4.26
… shift for previous knowledge†	0.375	1.35	0.375	1.35	0.375	1.35	0.375	1.35
2. Garden irrigation	3.963‡	6.74	-4.959‡	-9.79	0.303‡	2.14	5.957‡	2.1
3. Clothes washing	3.963‡	6.74	-4.959‡	-9.79	0.303‡	2.14	0	n.s.
… shift for female†	0.257	1.75	0.257	1.75	0.257	1.75	0.257	1.75
… shift for previous knowledge†	0.448	2.22	0.448	2.22	0.448	2.22	0.448	2.22
4. Hands washing	3.71‡	5.98	-4.959‡	-9.79	0	n.s.	0	n.s.
… shift for female†	0.289	2.05	0.289	2.05	0.289	2.05	0.289	2.05
5. Shower/Tub	3.71‡	5.98	-15.29‡	-18.02	0	n.s.	0	n.s.
6. Drinking	2.397	3.88	-15.29‡	-18.02	-0.82	-3.33	0	n.s.
… shift for female†	0.448	2.15	0.448	2.15	0.448	2.15	0.448	2.15
(4) SAVINGS ON WATER BILL								
Low water expenditure group†	0.089	4.26	0.089	4.26	0.089	4.26	0.089	4.26
High water expenditure group†	0.039	3.39	0.039	3.39	0.039	3.39	0.039	3.39

	Class 1		Class 2		Class 3		Class 4	
	Estimate	**Robust t-ratio**	**Estimate**	**Robust t-ratio**	**Estimate**	**Robust t-ratio**	**Estimate**	**Robust t-ratio**
CLASS ALLOCATION MODEL								
Constant	0	*reference*	-1.574	-3.7	-0.595	-2.41	-8.091	-5.52
Low educational level	0	*reference*	0.723	2.75	0.471	1.79	-1.046	-1.95
Garden	0	*reference*	-0.824	-2.49	0	n.s.	6.771	4.34
House	0	*reference*	1.402	2.98	0	n.s.	0	n.s.
Class weight	40%		24%		30%		6%	

†: parameter shared across classes
‡: parameter shared across multiple uses or multiple levels of categorical attribute
n.s.: parameter constrained to zero after initial estimate was not significantly different from zero

4.1.1. Generic parameters

Parameters indicated with the symbol *†* in Table 2 are generic across classes. They fall into three categories. First, there is an alternative specific constant (ASC) for the left-most alternative, which captures the difference in baseline utility between the two greywater reuse options. The negative value shows that, all else being equal, respondents will choose the middle option (i.e. the second GWR alternative) more often than the first. There is no apparent reason for this, as the survey design was balanced. Second, there are a number of generic socio-demographic effects. These relate to differences in sensitivities between men and women, and between those with and without prior knowledge. Women, for example, have an additional increase in utility compared to men, if water reuse is for flushing toilets (0.728), laundry (0.257), handwashing (0.289) and drinking (0.448). Previous knowledge only results in an additional increase in utility if water reuse is for toilet flushing (0.375) and clothes washing (0.448). Note that the impact of gender on the utility of reusing greywater for toilet flushing is much larger than that of having prior knowledge, while the opposite is true for laundry.

The third and final generic set of parameters relate to the savings in the water bill. This is subject to household water consumption, so the model contains two estimates, one for the low consumption group and another for the high consumption group. Each time, the coefficient multiplies the actual saving expressed in 1000s of Chilean pesos (CLP). The results show that the impact per 1000 CLP in savings for the low water consumption group are more influential (0.089) than for the high water consumption group (0.039). The influence exerted by the savings attribute is positive, which is an indication that this attribute is key to achieving higher acceptability of reusing water for different uses.

4.1.2. Class specific parameters

We now look at those parameters which vary across the four classes, as well as giving a behavioural interpretation to each class.

Class 1 – Enthusiasts: this class corresponds to individuals who have a positive perception of reusing treated greywater for the six uses considered. Table 2 shows that toilet flushing, garden irrigation and laundry are perceived the same in terms of benefits and are also the uses with greater utility. Reusing greywater for washing hands or shower/tub has the same utility in this group, slightly lower than the previous three uses, but still with a substantially higher utility than reusing treated water for drinking. Regarding the impact of appearance on utility, increased colour (though not if only increasing to light blue) and odour levels negatively influence acceptability, especially if the treated water has high levels of odour (-0.816). In this class, the influence of appearance (colour and odour) on utility is small compared to its influence in the other classes. Furthermore, for this group, the positive impact of using treated greywater on utility is much higher than the negative utility resulting from changes in the appearance that the use of treated greywater would produce.

Class 2 – Greywater sceptics: this class corresponds to individuals who have a negative perception of greywater reuse, especially those uses that require more direct skin-to-water contact (shower/tub and drinking). The size of the estimates shows that, in this class, the difference in utility between mains water and greywater is much larger than in other classes, with a substantial loss of utility for greywater options. This loss is further amplified if the water has a strong chlorine smell, while colour is not a characteristic that influences the utility in this class.

Class 3 – Appearance conscious: this class corresponds to individuals who perceive positively greywater reuse for toilet flushing, garden irrigation and laundry if the treated greywater is odourless and clear/transparent. In this class, individuals are more sensitive to changes in the appearance of treated water than to the uses themselves (comparing the weights of the appearance attributes with the weights for uses). The three uses with a positive utility (compared to mains water) are those that require less skin contact.

Class 4 – Water expenditure conscious: this class corresponds to individuals who have an increase in utility when treated greywater is available for toilet flushing and garden irrigation. We label these as expenditure conscious, as the preferred uses for these consumers are those with highest water consumption (toilet flushing between 10 and 20 litres per flush, while a 100 m^2 garden area can use up to 1000 litres, SISS, 2019). Additionally, in this class, changes in the colour level of water are highly influential compared to individuals from other classes. However, the utility of using treated greywater for toilet flushing and garden irrigation is much higher than the loss of utility associated with changes of appearance.

4.1.3. Class allocation model

The final part of the model estimates relates to the class allocation model (see Table 2). This component explains which respondents are more likely to fall into specific classes. At the sample level, the probability of belonging to Class 1 is 40%, of belonging to Class 2 is 24%, 30% for Class 3 and only 6% for Class 4. These sample level class allocation probabilities are driven in large parts by the offset (δ_k in Equation (4)) included in the class allocation model, where with Class 1 taken as reference, negative constants for the remaining classes are observed. These constants relate to an individual in the base socio-demographic group (mid or high education, without a garden and living in a flat), where the probability of belonging to Class 1 is the highest (and the lowest for Class 4). However, these probabilities vary as a function of respondent characteristics. Note that having a lower level of education increases the likelihood of belonging to the sceptic class (Class 2) or the class concerned about greywater appearance (Class 3). Having a garden reduces the likelihood of falling into the sceptic class (Class 2) and substantially increases the likelihood of falling into Class 4, which assigns high utility for using greywater for garden irrigation (with Equation (4) implying a change in probability for class 4 from near zero to 14%). Thus, this finding is entirely in line with expectations. Finally, those living in a house as opposed to a flat, have an increased likelihood of falling into Class 2.

4.2. Posterior - analysis

The discussion in Section 4.1.3 focussed on the sample level class allocation probabilities. This process only requires the class allocation model, and thus implies that the class assignment probabilities are identical for individuals with the same characteristics. We now go a step further, making use of the approach in Section 3.2 to determine posterior class allocation, using the estimates of the sample level model and the observed choices of each individual. Unlike the direct results from the class allocation model, this posterior analysis makes use of respondent characteristics that were not included in the class allocation model.

4.2.1. Posterior values of socioeconomic characteristics across classes

In Table 3 we compare the posterior share (cf. Section 3.2) of given sociodemographic characteristics across classes. For each characteristic, the crucial comparison is against the sample average, showing whether individuals with given characteristics are more likely to fall into specific classes. There is also some insight to be gained by comparing the posterior across characteristics (e.g. male vs. female), but care needs to be taken if there are differences in the sample level representation.

Table 3.Socio-demographic characterization into the classes

Socio-economic characteristic	Class 1	Class 2	Class 3	Class 4	Sample average
Gender					
… Male	0.37	0.32	0.34	0.34	0.35
… Female	0.63	0.68	0.66	0.66	0.65
Age					
… Under 30 years old	0.16	0.09	0.06	0.10	0.11
… Between 30 and 60 years old	0.57	0.55	0.62	0.65	0.58
… Over 60 years old	0.28	0.36	0.32	0.25	0.31
Education level					
… Elementary school	0.18	0.22	0.10	0.10	0.16
… High school	0.37	0.48	0.54	0.24	0.44
… Technical education	0.17	0.13	0.14	0.21	0.15
… University studies	0.23	0.11	0.14	0.42	0.18
Main occupation					
… Stay at home	0.24	0.31	0.26	0.25	0.26
… Retired	0.15	0.19	0.15	0.12	0.16
… Part-time	0.05	0.04	0.06	0.12	0.05
… Full-time	0.48	0.41	0.50	0.40	0.47
Income					
… Under 600 USD	0.42	0.47	0.42	0.40	0.43
… Between 600 – 1,820 USD	0.48	0.44	0.49	0.40	0.47
… Over 1,820 USD	0.10	0.09	0.09	0.21	0.10
Previous knowledge about water reuse					
… None	0.65	0.79	0.68	0.48	0.68
… Medium	0.11	0.06	0.12	0.17	0.10
… High	0.25	0.15	0.20	0.35	0.21

Gender. Women have a larger overall representation in our sample. We see only small differences in the posterior allocation to the different classes. The highest female concentration is in Class 2 and the highest male concentration is in Class 1. This indicates a more negative view of GWR by women than by men, which is in agreement with results obtained in other studies (Amaris et al., 2021; Wester et al., 2015), which have been linked to the higher susceptibility of women to associate reuse with high levels of risks (Mankad & Tapsuwan, 2011). However, it is important to highlight that other studies have also found the opposite effect or no relation between gender and water reuse acceptability (Garcia-Cuerva et al., 2016; Mason et al., 2018).

Age. Individuals between 30 and 60 years old are predominant in the sample. Our posterior analysis shows that individuals under the age of 30 have a higher representation in the enthusiasts class (Class 1) and a much reduced share in the class caring about appearance (Class 3). People between 30 and 60 years old have a higher representation in classes 3 and 4, where reusing water is desirable if greywater has a similar appearance to the mains water, or if more indirect uses are considered (i.e. toilet flushing and garden irrigation). Individuals over the age of 60 have a higher representation in Class 2, where reusing greywater for any option is undesirable, and a reduced share especially in Class 4.

Education level. Our sample had a majority of individuals with high school, followed by individuals with university studies, technical education, and elementary school. Our results show that people with higher educational levels are more likely to belong to classes that have a positive perception of reusing water for two or more uses (classes 1, 3 and 4). People with elementary school only are most likely to belong to Class 2 (water reuse sceptics), people with high school education have a greater frequency in Class 3 (appearance matters), and people with technical or university education have a greater frequency in Class 4 (greywater for indirect uses) and Class 1 (water reuse enthusiasts). In general, our results are consistent with outcomes revealed Gu et al. (2015) who suggest that people with higher educational levels are more willing to reuse greywater. However, our results also show detailed information indicating that according to the educational group of the individual, the appearance and the uses could have a greater or reduced level of importance.

Main occupation. The sample was composed mainly of individuals working full-time, followed by people that stay at home, old age pensioners and, finally, individuals with a part-time job. Our results indicate that individuals who are at home or retired have a higher concentration in Class 2, i.e. those who would dislike reusing water, people with a part-time job have a greater presence in Class 4, while this class is the least likely one for people with a full-time job.

Income: Households with the lowest monthly income (under 600 USD) have a higher frequency in Class 2 (greywater reuse sceptics) than in any other class. Households with an intermediate monthly income (between 600 USD and 1,820 USD) have their highest frequency in classes 1 (enthusiasts) and 3 (appearance conscious). Finally, households with highest income (over 1820 USD) are more prevalent in Class 4 (water expenditure conscious), and this is likely correlated with having gardens and larger properties.

Previous knowledge about water reuse. Most individuals in our sample had no previous knowledge about water reuse, as expected in a country only starting to allow residential greywater reuse. As anticipated, individuals without previous knowledge about water reuse have the highest presence in Class 2 (greywater sceptics). In contrast, people with high knowledge have a notable greater presence in Class 4 (most indirect uses) and Class 1 (enthusiasts); this has also been reported before (Garcia-Cuerva et al., 2016; Dolnicar et al., 2011). Likewise, individuals with medium knowledge have a similar incidence in the classes with a positive perception of reusing water for two or more uses (classes 1, 3 and 4).

4.2.2. Posterior values of household characteristics across classes

Section 4.2.1 focussed on socio-demographic characteristics of the survey respondent. As it is quite conceivable that household and dwelling characteristics might also influence preferences, we extended the analysis to such variables, focusing on household composition, and two key dwelling influences on water consumption, namely the number of bathrooms and the presence of gardens. The results of this analysis are summarised in Table 4, using the same approach as in Section 4.2.1.

Table 4.Household characterization into the classes

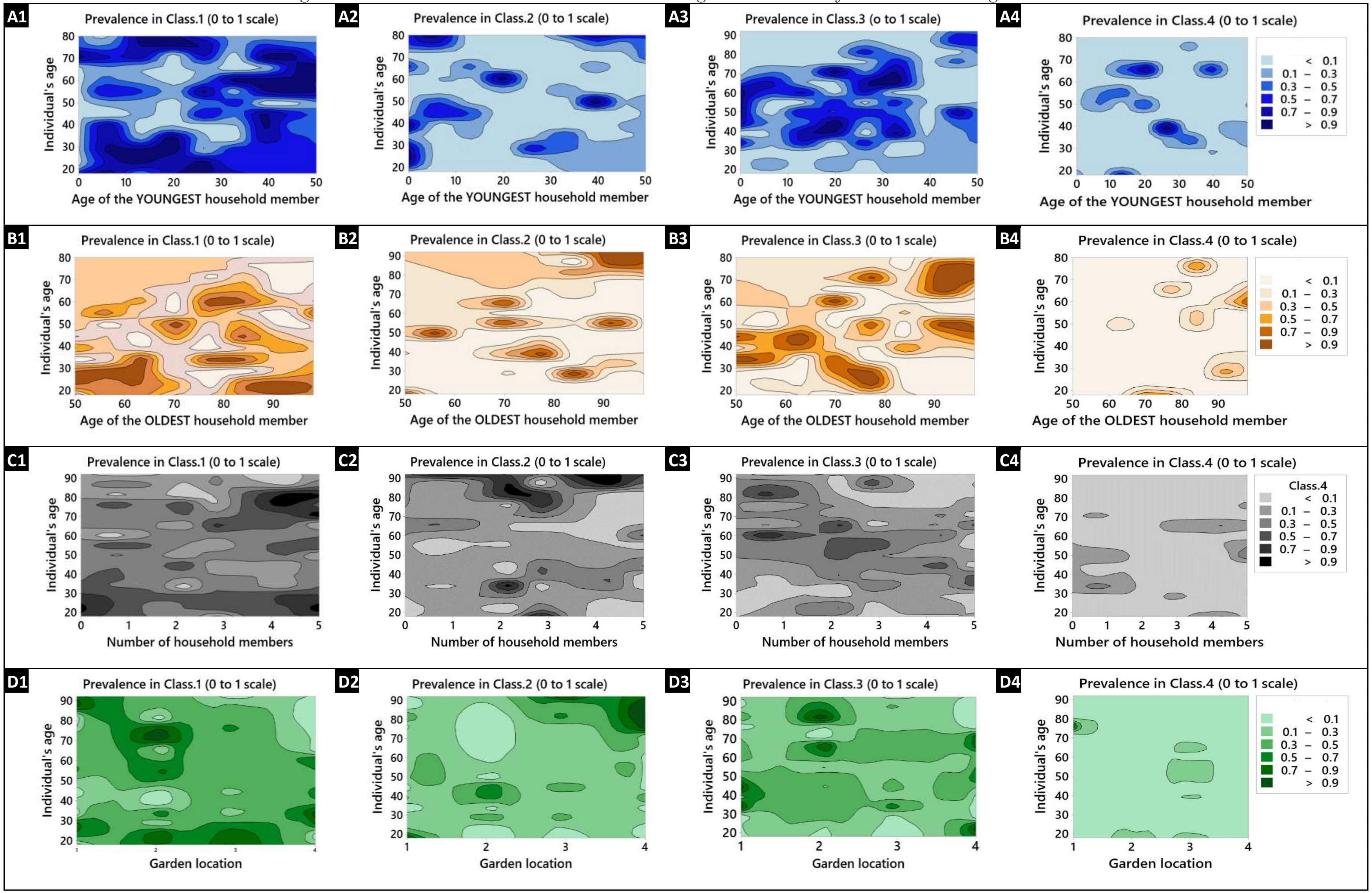
Socio-economic characteristic	**Class 1**	**Class 2**	**Class 3**	**Class 4**	**Sample average**
Presence of sensitive population					
… Homes with kids under 15	0.41	0.43	0.41	0.39	0.41
… Homes with adults over 74 years old	0.17	0.22	0.14	0.18	0.17
Number of people living in the same place					
… 1 to 2	0.28	0.29	0.35	0.24	0.30
… 3 to 5	0.61	0.60	0.53	0.64	0.59
… Over 5	0.11	0.11	0.12	0.12	0.11
Number of bathrooms					
… 1 to 2	0.65	0.62	0.71	0.47	0.65
… 3 to 5	0.35	0.38	0.28	0.49	0.34
Garden					
… Front garden (1)	0.25	0.25	0.27	0.18	0.25
… Rear garden (2)	0.09	0.06	0.10	0.01	0.08
… Front and rear garden (3)	0.51	0.50	0.47	0.81	0.51
… None (4)	0.15	0.19	0.17	0.00	0.16
Type of garden					
… Front garden with grass	0.28	0.31	0.33	0.43	0.31
… Front garden with another type of vegetation	0.59	0.65	0.55	0.85	0.61
… Rear garden with grass	0.14	0.12	0.13	0.41	0.15
… Front garden with another type of vegetation	0.39	0.36	0.32	0.52	0.37

In addition, we produced contour diagrams (Figure 3), where we summarize the prevalence of characteristics across classes for the three most influential features of the households: presence of sensitive population (i.e. with people under the age of 15 and over the age of 74), household size, and presence and location of gardens. The highest concentrations are shown in darker colours and correspond to values higher than 0.5 on a 0 - 1 scale. We used three dimensions: (i) the characteristics of the home on the X-axis, (ii) the age of the individual making the decision on the Y-axis, and (iii) the latent classes 1, 2, 3 and 4 in the Z-axis.

Presence of a sensitive population: Respondents whose households include sensitive population were more prevalent in Class 2 (0.43), i.e. the greywater sceptics (Table 4). A reason for this could be that people in these age ranges are more susceptible to acquiring infections (Leng & Goldstein, 2010). Additionally, the prevalence in each class was found to vary as a function of relative age. For example, if the youngest family member is between 0 and 30 years old, then respondents between 20 and 35 have a higher probability of belonging to Class 1 (greywater enthusiasts – Figure 4-A1). If the youngest person among the household's members is between 20 and 40, then individuals between 50 and 65 have a higher probability of belonging to Class 1. We also found that if the oldest family member was between 50 and 70 or over 85, then individuals between 25 and 30 had a high probability of belonging to Class 1 (Figure 4-B1).

In the case of Class 2, individuals whose youngest family members were under the age of five had a higher probability of belonging to this class. Moreover, the highest probability of belonging to this class is for 60-year old individuals with the youngest family member being in their twenties. Concerning people more likely to belong to Class 2, there are different sensitivities between the different age ranges and the age of the household's members. For example, younger individuals (20 - 35 years of age) are more likely to belong to this class if the oldest family member is more than 80 years old. People in other age ranges are likely to belong to this class if they have family members older than 65.

Figure 4. Posterior share in classes according to the most influential dwelling characteristics



The predominant individuals in Class 3 would be mainly: (i) people between 20 and 30 years old whose family has one or more adults between 65 and 80 (Figure 4-A3); (ii) individuals between 30 and 45 years old with the youngest member of the family being between 15 and 20, and if there are adults over 50 years old among the household (Figure 4-B3); (iii) individuals between 45 and 60 years old living with children under the age of 5.

Class 4 is dominated by three groups, namely: (i) individuals near to 20 years of age living with younger family members (Figure 4- A4) or family members older than 65 years old (Figure 3- B4); (ii) individuals of approximately 35 years of age, whose family members have similar ages (Figure 4- A4) or family members older than 90 (Figure 4- B4); and (iii) individuals over 50 living in households with one or more individuals aged around 20 years (Figure4-A4, or in the case that there are family members over 70-year-old, Figure 4-B4).

Household size: Single-person household have a greater prevalence in Class 3, where the appearance of greywater matters most. Households with 3 to 5 people have greater representation in Class 4, and households with more than 5 people are homogeneously distributed across classes. Household size is a characteristic that has been previously defined as relevant. For example Mason et al. (2018) found that the likelihood of using greywater during dry seasons increases by 24% for each additional household member. Nevertheless, our results complement that information with a more detailed analysis about uses and types of consumers.

Garden presence and its location: Overall, households belonging to Class 4 have a higher incidence of gardens, with a prevalence of mixed gardens with vegetation different from grass, mainly in their front yards. Dwellings of respondents belonging to classes 1, 2 and 3 consistently have a small presence of gardens with grass, and a higher presence of front yards with vegetation other than grass. Note that these characteristics, which are associated with bigger dwellings (i.e. large number of bathrooms, presence of gardens), and more household members, are associated with households who tend to have a higher prevalence in class 4.

5. CONCLUSIONS

This study aimed to extend our understanding about heterogeneity in the acceptability of uses for treated greywater and the factors that influence it, by focusing on the interaction of variables that rarely receive attention. The most novel finding is associated with the possibility of quantifying the relationship between the acceptability of reusing water, by use, and the characteristics of a consumer, their household and their dwelling. Our approach offers numerical support for making predictions about how different latent classes of individuals may behave when facing different reuse options.

In particular, the method implemented has been more commonly used in other disciplines such as transport research, health and most recently in innovation appliances. The latent class approach we used is valuable in showing that a pre-feasibility empirical analysis can be carried out to assess greywater projects or initiatives in zones with no experience in reusing water. Likewise, these results are valuable to demonstrate that uses other than flushing toilets and garden irrigation can also be accepted once the potential users are aware of all possible uses of treated greywater.

This study considers the case of residents in future buildings that must adhere to new greywater regulations, which establish that new buildings must have a parallel greywater system. However, future studies should incorporate the cost of technology, operation and maintenance in order to include those consumers that want to adopt these new systems in their existing dwellings. These studies can be based on real-world pilot experiences carried out in areas with a high concentration of people, with characteristics similar to those identified in our study as having the highest level of acceptability of GWR. On the basis of that new evidence, policies can then be updated to produce management strategies that can achieve greater user acceptability.

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LIST OF ACRONYMS

Acronyms:
AIC: Akaike Information Criterion
ASC: alternative specific constant
BIC: Bayesian Information Criterion
CLP: Chilean pesos
GWR: greywater reuse
IDW: inverse distance weighting
INE: National Statistics Institute (Instituto Nacional de Estadísticas)
LC: latent class
MNL: multinomial logit
n.s.: not significant
SC: stated choice
T1: households with monthly water bills below US$28.8
T2: households with monthly water bills above US$28.8

Symbols in equations:
Vectors in data:
$x_{j_{n,t}}$: characteristics of alternative *j* in choice situation *t* for respondent *n*
z_n: characteristics of respondent *n*
j_n^*: sequence of observed choices for respondent *n*
$j_{n,t}^*$: observed choice for respondent *n* in task *t*

Probabilities and likelihoods:
$\pi_{n,k}$: class allocation probability for respondent *n* for class *k*
$P_n(j_{n,t} \mid \beta_k)$: probability of respondent *n* choosing alternative *j* in task *t*, conditional on being in class *k*
$L_n\ (j_n^* \mid \Omega)$: likelihood of observed sequence of choices for respondent *n*, conditional on vector of parameters Ω
$LL(j_n^* \mid \Omega)$: log-likelihood of observed sequence of choices for respondent *n*, conditional on vector of parameters Ω

Parameters and functional form:
β_k: vector of utility parameters in class *k*
$V_{j_{n,t}}$: deterministic component of utility for person *n,* alternative *j*, in choice situation *t*
$f(x)$: functional form for utility function in within-class model
Ω: vector grouping together all parameters used in the model
g(·): functional form of the utility function in the class allocation model
δ_k: class-specific constant for class-allocation model
γ_k: vector of parameters for class-allocation model utility for class *k*

Indices:
j: index for alternatives (*j=1,…,J*)
k: index for latent classes (*k=1,…,K*)

n: index for individuals (*n=1,…,N*)

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6. SUPPLEMENTARY MATERIALS

6.1. Survey

SECTION 1 - RESIDENTIAL WATER REUSE OPINION

Here are some questions to do about your opinion on the reuse of water in homes:

1 Before today, had you heard about residential water reuse?

Yes	No
1	2

No → **Skip to 3**

2 From what you had heard about water reuse, how much do you feel you previously knew about this subject? Use a scale from 1 to 5 to respond, with 1 being "little, I've only heard comments" and 5: "a lot, I found out information about it".

Little, I've only heard comments				A lot, I found out information about it
1	2	3	4	5

3 Have you ever reused water?

Yes, I reused water, but not any more.	Yes, I currently reuse water	NO, but I would like to	NO, and I would NOT like to
1	2	3	4

4 **The following questions are related to the reuse of treated greywater inside the home, for that, we want to show you how this system works [SHOW CARD 3].** The water from washing machine, shower/bath and sink, "called grey water" goes through treatment, storage and finally can then be used in various applications. The best treatment conditions allow to obtain water of quality sufficient for several uses. What would you be willing to use your own **treated** greywater for after such treatment? You can select more than one option.

None	Garden irrigation	Toilet flushing	Clothes washing	Shower / bath	Hand washing	Drinking
0	1	2	3	4	5	6

SECTION 2 - STATED PREFERENCES

<u>**To answer this section:**</u> Imagine that your home has this device to treat greywater with highest water quality standards, and the device is activated by pressing a button, and the cost of energy is 0.0 USD (Energy: Solar panel).

Other features:

- Saving of drinking water in the house.
- Good water quality at low maintenance costs (2 and 10 USD per month).
- <u>Limitations</u>: Depending on the treatment applied to greywater, colour and odour levels may vary as follows:

CHOICES

We will show you now, different situations. You will compare the attributes of each alternative and select the altternative you prefer the most. Remember that the device would already be in your home and you would not pay for this.

A1

	ALTERNATIVE A	ALTERNATIVE B	ALTERNATIVE C
Water supply system	REUSE TREATED GREYWATER FOR: GARDEN IRRIGATION Tap water for other uses	REUSE TREATED GREYWATER FOR: SHOWER Tap water for other uses	TAP WATER FOR ALL USES
Attributes of water service:			
Colour caused by treatment	Transparent	Light Blue	Transparent
Odour caused by treatment	Strong chlorine odour	Odourless	Odourless
Monthly savings expected on the water bill	Saving $ 3.00	Saving $ 8.00	Saving $ 0.00

Select the alternative of your preference:

- I prefer alternative A
- I prefer alternative B
- I prefer alternative C

SECTION 5 - HOUSEHOLDS AND DWELLING CHARACTERISTICS

Now I'll ask some general questions about household members.

10 Number of people living in the house:

11 How many of the people living in your household are under 18:

12 How many of the people living in your household are over 74:

13 How many of the people living in your household need special care:

14 Indicate the type of dwelling you live in:

- House
- Apartment

15 This property is

- Owned/mortgaged
- Rented
- Informal settlement
- Another condition
- Do not know

16 Does your house have a private garden?

- Yes
- No

17 The garden is ...

- Front
- Rear
- Front and rear