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Using hybrid choice models to capture the impact of attitudes on residential greywater reuse preferences

Authors: Gloria Amaris[1], Stephane Hess[2], Jorge Gironás[3], Juan de Dios Ortúzar[4]

1 Ph.D. student, Departamento de Ingeniería Hidráulica y Ambiental, Pontificia Universidad Católica de Chile; and Centro de Desarrollo Urbano Sustentable (CEDEUS), Santiago, Chile; e-mail: geamaris@uc.cl (ORCID: 0000-0002-6577-7852)

2 Professor of Choice Modelling, Choice Modelling Centre & Institute for Transport Studies, University of Leeds, Leeds, UK; e-mail: s.hess@leeds.ac.uk (ORCID: 0000-0002-3650-2518)

3 Associate Professor, Departamento de Ingeniería Hidráulica y Ambiental and Centro Interdisciplinario de Cambio Global, Pontificia Universidad Católica de Chile; CEDEUS; Centro de Investigación para la Gestión Integrada de Desastres (CIGIDEN), Santiago, Chile; e-mail: jgironas@ing.puc.cl (ORCID: 0000-0002-6933-2658)

4 Emeritus Professor, Department of Transport Engineering and Logistics, Instituto Sistemas Complejos de Ingeniería (ISCI), BRT+ Centre of Excellence, Pontificia Universidad Católica de Chile, Santiago, Chile; e-mail: jos@ing.puc.cl (ORCID: 0000-0003-3452-3574)

Abstract:

The reuse of treated greywater in a residential setting could contribute substantially to easing problems with water scarcity. This paper argues that preferences in relation to reusing greywater for different uses within the home vary across households and can be driven at least in part by psychological constructs, such as attitudes and perceptions, which might appear irrational at face value from an economic perspective. To better understand heterogeneity in behaviour in a greywater reuse context, data from a stated choice survey were analysed using a hybrid choice model with latent variables, allowing us to incorporate measurable characteristics of the decision makers as well as other elements that cannot be measured directly (e.g. attitudes towards greywater reuse). Our results provide evidence on the preferences for different uses of treated greywater, and about the heterogeneity of choices among individuals and uses. The model suggests that heterogeneity in the acceptance of greywater reuse can be linked back mainly to underlying attitudes, for all uses except drinking. This knowledge can be used as an input to evaluate diffusion strategies to increase greywater reuse acceptability focused on messages about its direct (i.e. water bill savings) and indirect benefits (environmental benefits, water security, autonomy).

Keywords: *Greywater reuse; attitudes; hybrid choice model; discrete choice*

1. INTRODUCTION

Problems with water scarcity are affecting many large cities around the world (Liu et al., 2017; Mekonnen & Hoekstra, 2016). Successful experiences of water reuse in Australia, California, Singapore, Spain and areas of South Africa, have clearly shown that greywater offers a promising avenue for improving the sustainability of urban water supply (Roshan & Kumar, 2020; Vuppaladadiyam et al., 2019; Lefebvre, 2018; Muthukumaran et al., 2011). There are also substantial environmental benefits given the volume of water that may be recovered (50-80%), proportional to household consumption, and the optimization in its allocation (Wilcox et al., 2016). By being based on water free from faeces, food residues, oil and fats (i.e. not from the toilet or dishwasher), the treatment required to allow greywater reuse is much cheaper than in the case of water coming from desalination and wastewater treatment processes (Lambert & Lee, 2018). Treated greywater can be suitable for different uses ranging from drinking water to flushing toilet, as long as the water is properly treated considering the level of human contact (direct or indirect) for the desired use (Fielding et al., 2019; Jefferson et al., 2004), and according to the quality of greywater collected (Shaikh & Ahammed, 2020). However, previous studies have shown that the public acceptability of water reuse is one of the most important barriers that must be overcome to achieve success, longevity and reliability of reuse schemes (Garcia-Cuerva et al., 2016; Hurlimann et al., 2008; Smith et al., 2018).

Acceptability and consumer behaviour are clearly influenced by implementation and usage costs and by the benefits arising from reduced mains water use (Wilcox et al., 2016). This is in line with a "rational" view of human behaviour, where undesirable characteristics (e.g. increased costs) reduce the appeal and hence the likelihood of choosing a product, with the opposite applying for desirable characteristics. However, acceptance of a new technology is, at least in part, driven by subjective psychological constructs that determine what is desirable and what is not for each individual (cf. Oteng-Peprah et al., 2020; Yang & Yoo, 2004); the outcome might appear irrational from an economic perspective. For example, even though technology can remove every contaminating microscopic particle from water at an acceptable cost, this does not imply that all users can eliminate the mental association of treated greywater with impure water (Ching, 2015). Clear evidence of this comes from the fact that even though the most common residential water uses (toilet flushing, garden irrigation) do not require direct water-skin contact, the disgust factor still remains a significant effect on acceptability (Garcia-Cuerva et al., 2016; Leong, 2016).

Mental associations in the water reuse context are thus clearly linked to perceptions and attitudes. These are psychological phenomena that have attracted much attention in behavioural research in recent years (Bahamonde-Birke et al., 2017; Wester et al., 2016). Both concepts can contribute to how the characteristics of a good or service are viewed in terms of being desirable or undesirable by individual decision makers, and also to how overall intentions of approval or disapproval can be driven by wider attitudes to life, society, etc. (Yang & Yoo, 2004; Aitken et al., 2014). There is empirical evidence to support the relevance of this work in a greywater reuse (GWR) context. For example, Domnech & Saurí (2010) studied perceptions about greywater reuse for toilet flushing, which has been in widespread use in a municipality in Barcelona (Spain) since 2004. There was clear evidence of heterogeneity in the perception of the colour of the water, and what constituted a desirable colour. Similarly, in a wider environmental setting, the empirical benefit of giving due consideration to the role of attitudes is clear (cf. Hoyos et al., 2015).

The analysis of human behaviour is a complex undertaking, and this is further amplified when attempting to capture the role of attitudes and other psychological constructs. Past studies in greywater research found important differences in preferences across individual households (Amaris et al., 2020; Fielding et al., 2019), but a key question then is to what extend these differences relate to variations in underlying attitudes and perceptions. That is an important objective of the present paper.

To obtain useful and reliable results requires a careful approach that separates out the many potential and simultaneous influences on behaviour. This rules out simplistic approaches, such as basic tabulations (or correlation analysis) of answers to attitudinal questions and stated willingness-to-adopt greywater reuse. In the literature, particular attention has been paid to two approaches: the use of the *Theory of Planned Behaviour (TPB)* and of *Discrete Choice Models* (DCMs). TPB (Ajzen, 1985) is focused on explaining behavioural intentions through attitudes, subjective norms and perceived behavioural control. The behavioural intention can then be used, again together with perceived behavioural control, to explain actual behaviour. For example, one recent study in greywater reuse developed by Oteng et al. (2020) found that the impact of beliefs from personal norms such as, moral obligation, feeling of guilt and better feelings, had the greatest impact on household's willingness to adopt a greywater treatment and reuse system. While TPB focusses primarily on attitudinal intentions, DCMs have become a popular tool to quantify the influence of different product/service characteristics on choices

(Saldias et al., 2016; Tchetchik et al., 2016; Amaris et al., 2020), as well as to measure the heterogeneity across decision makers (cf. Ortúzar & Willumsen, 2011, Chapters 7–9; Train 2009; and Hess & Daly, 2014 for a coverage of application areas). A key advantage of DCMs is their suitability for modelling behaviour in a multi-alternative multi-attribute setting rather than simply explaining willingness to adopt or not, for example. In a GWR context, Amaris et al. (2020) use DCMs to explain the influence on preference of the qualitative appearance of the treated water, the intended use, and the monetary savings. They found extensive heterogeneity in preferences across households but linked this exclusively to observed household characteristics.

Tchetchik et al. (2016) go further than this by allowing for the influence on behaviour of "unobserved" heterogeneity in preferences across people. They also link some of this heterogeneity to answers to attitudinal questions concluding, for example, that more pro-environmental people are more likely to adopt GWR. The work by Tchetchik et al. (2016) groups answers to attitudinal questions together using factor analysis, and then use the resulting factors as error free measures of attitudes. However, there is now a growing recognition that attitudes and perceptions can never be observed with certainty by an analyst, and that answers to attitudinal questions are thus not error free and should not be used as explanatory variables in a model (cf. Ben-Akiva et al., 2002). This has led to the development of an advanced group of DCMs, known as *Hybrid Choice Models* (HCMs), which treat attitudes as latent (i.e. unobserved) variables and use the answers to attitudinal questions as "indicators" of attitudes, rather than "measures". HCMs allow an analyst to understand the role of the characteristics of the decision makers in the formation of attitudes, and then use them in the computation of substantive model outputs, such as elasticities and willingness-to-pay measures, as well as in forecasting (Abou-Zeid & Ben-Akiva, 2014).

To know where efforts should be focused to achieve greater acceptability in the management plans of waters, it is important to both understand the sources of heterogeneity for greywater allocation in different uses and to know how important these factors are in the preferences. Most studies have focused on measuring the correlation of reuse preferences and the socioeconomic characteristics of the individual (Ryan et al., 2009; Garcia-Cuerva et al., 2016), while others have more recently concluded that attitudes are also influential (Etale et al., 2020; Yuriev et al., 2020; Oteng-Peprah et al., 2020). However, these two sources of heterogeneity are not mutually exclusive, and the missing piece is to quantify the weight that both aspects exert on reuse choices. Such a decomposition of heterogeneity is a crucial potential use of HCMs, as we illustrate in the present paper.

This study considers the scenario of a large metropolitan area, Santiago de Chile, where greywater reuse is legally permitted but does not take place at present. Santiago is affected by water scarcity problems that are common to many cities around the world. More importantly, Santiago has been experiencing an ongoing draught, further increasing the need for new water supply measures and making it a very topical case study. Given the complexity of measuring perceptions in a context where the market is unknown, the study focused on a longer-term underlying pro-GWR attitude, while at the same time allowing for heterogeneity in preferences as a function of the characteristics of the treated greywater. The estimated model finds statistical support for the role of this attitudinal construct in shaping the heterogeneity of preferences for different greywater reuse options within a home.

One of the most important contributions of the present study is that it is, to the best of our knowledge, the first application to GWR of a HCM, an approach that has become increasingly popular across disciplines, including environmental science (cf. Mariel & Meyerhoff, 2016). As highlighted by Vij & Walker (2016), many applications of HCMs, however, use inferior specifications leading to potential misattribution of heterogeneity, notably an overestimation of the role of attitudes. A second highly relevant contribution is the full decomposition of the sources of heterogeneity, which allows pinpointing what share of the heterogeneity in GWR preferences can, in fact, be linked to underlying attitudes.

While many of our findings are in line with past work, the methods used are more robust than past work, avoiding the potential confounding between different influences and exposure to endogeneity bias. This provides reliable results and important insights for policy makers, indicating the scope to which changes in attitudes may help with increasing the uptake of GWR. In addition, the work demonstrates the benefit of the approach in general, opening up scope for using the models -and in particular the analysis of sources of heterogeneity- in a wider water reuse context, and also to study the influences of more specific attitudes, including the disgust factor.

2. DATA

2.1. Study area

Santiago is the most populated urban centre in Chile (40% of the Chilean population), with 7.1 million inhabitants (INE, 2017). This Metropolitan Region has water deficit problems and is predicted to become the area with the highest deficit in Chile by 2025 (Valdés-Pineda et al., 2014), with periods between one to four weeks of very low flows (Vicuña et al., 2018). 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). Mains water is supplied by traditional sources of fresh water mainly from the *Maipo River*, supported by the *Mapocho River*, the *El Yeso reservoir* and some groundwater wells (Meza et al., 2014). Almost 90% of the population receives water supply and sewage services from a private company called *Aguas Andinas*. Although designed to be robust and maintain high levels of service (considering both continuity and quality), the supply system is quite fragile in the face of significant threats due to climate variability, climate change and population growth (Vicuña et al., 2018).

2.2.Sample

The survey was carried out face to face in 29 of the 37 municipalities that form the city, and only household heads or their partners over 18 years of age were interviewed. The information was collected by a private survey company with experience in this type of tasks. Municipalities were selected from the areas of the city with drinking water and sanitation services provided by *Aguas Andinas*. In each municipality, the survey was carried out in different non-neighbouring blocks and the households participating in the survey were randomly selected. 606 interviews were conducted but only 510 of them were retained for the analysis, where 65.3% of respondents 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 water reuse.

2.3.Survey Overview

A carefully designed survey was applied in order to understand how the acceptability of GWR could be associated with qualitative and quantitative attributes of greywater after treatment, and how acceptability could vary as a function of characteristics of the individuals and their attitudes. This was built on earlier work by Amaris et al. (2020), and in what follows, the most relevant aspects of the survey considered for modelling are described. For more information on the experimental design of the survey, the reader is referred to Amaris et al. (2020).

The questionnaire was made up of four different parts:

- ***Section 1:*** Schematic representation of greywater reuse, configuration, and operation of the system inside the dwelling (houses and apartments).

- ***Section 2:*** Personal greywater reuse choices (stated choice experiment).
- ***Section 3:*** Questions about reactions, attitudes, and confidence in treated greywater reuse within the home.
- ***Section 4:*** Characterization of household (age, gender, income).

Sections 2 and 3 of the survey provide the core information for the model proposed in this paper.

2.3.1. *Stated choices*

Given the interest of this study in qualitative attributes and currently inexistent reuse situations, we relied on a *stated choice* (SC) experiment, a widely used tool across different research areas – for a comprehensive introduction, see Louviere *et al*. (2000). In SC surveys, respondents make hypothetical choices between mutually exclusive options, requiring an analyst to decide on the choice setting, alternatives, and attributes of these alternatives. The situations studied were based on real experiences of water reuse (Domnech & Saurí, 2010; Ilemobade et al., 2013; Wester et al., 2016), arriving at the following setup.

Greywater treatment in general mainly seeks to remove suspended solids, organic materials and microorganisms (Li et al., 2009). Several investigations carried out in the last two decades (Jefferson et al., 2004; Li et al., 2009, Fountoulakis et al., 2016; Wu, 2019) suggest that biological processes combined with solids separation, filtration and disinfection practices, configure the most appropriate approach in greywater treatment, allowing its reuse even for drinking purposes. For that reason, some of the information provided in the hypothetical situation was based on the existing equipment in Latin America called *Hydro4*, which includes biological water treatment, pumping equipment, pipe sections, filtration, and a disinfection system (see Appendix 1).

The choice options were framed around a hypothetical scenario where respondents had to assume that the technology is already installed in their property, is as easy to use as a standard appliance (e.g. washing machine) and the water after treatment has high quality standards. In this way, the implementation costs of the greywater reuse technology were intentionally eliminated to remove their biasing impacts on acceptability, allowing the focus on the characteristics of the water as these could impact respondents' likes and dislikes.

In the choice scenarios, respondents were presented with three mutually exclusive alternatives. The first two implied greywater reuse for a single purpose within the home (and mains water for all other uses), while the third was a *status quo* option, implying the use of mains water for all purposes. The greywater options were described on the basis of usage, quality, and also water bill savings, with the following levels:

(1) Usage: six different types of reuse, namely *Toilet flushing, Garden irrigation, Washing clothes, Washing hands, Shower/tub,* and *Drinking*.

(2) Quality: quality was considered in terms of water appearance through three levels of colour (*Transparent, Light blue* and *Dark blue*) and three levels of odour caused by the treatment (*No odour, light chlorine odour* and *Strong chlorine odour*). Such a difference in the appearance of greywater (compared to mains water) could be caused by the type of device[1], and treatment (e.g. water purification tablets), or could be introduced deliberately to indicate to users that the removal of contaminants had been successful, in line with reuse laws (Domnech & Saurí, 2010).

(3) Savings: a mains water savings attribute was included to reflect the lower use of mains water at home due to the reuse of greywater. Previous experiences show that water savings can vary between 10 and 50% (Chen, et al., 2017; Fountoulakis et al., 2016; Guthrie et al., 2017; Lambert & Lee, 2018). In the absence of local experience, an intermediate range were used, with levels of savings of 10%, 20%, and 30% of the current mains water consumption.

[1] https://www.theguardian.com/lifeandstyle/2014/jul/21/greywater-systems-can-they-really-reduce-your-bills

In the choice scenarios the savings attribute was monetised as a function of current consumption, with two reference groups: (i) group 1 (T1, with 290 households) having a monthly water consumption bill below 20,000 Chilean Pesos (CLP) (approximately US $ 28.8 at the time of data collection) and (ii) group 2 (T2, with 220 households) having a monthly water bill above CLP 20,000.

Alternatives 1 and 2 differed from each other in their attributes (colour, smell and use of treated greywater), in such a way that respondents had to make trade-offs between the different characteristics to select the alternative of their preference. An example of a choice task is shown in Appendix 2. Our SC survey faced respondents with multiple scenarios, with the combinations of attributes varying on the basis of a D-efficient experimental design (cf. Rose & Bliemer, 2014) produced using NGENE (ChoiceMetrics, 2012). To reduce respondent burden, only six scenarios per person were used (Caussade et al., 2005). For a better understanding of the fundamentals considered in the modelling process see the schematic representation in Figure 1.

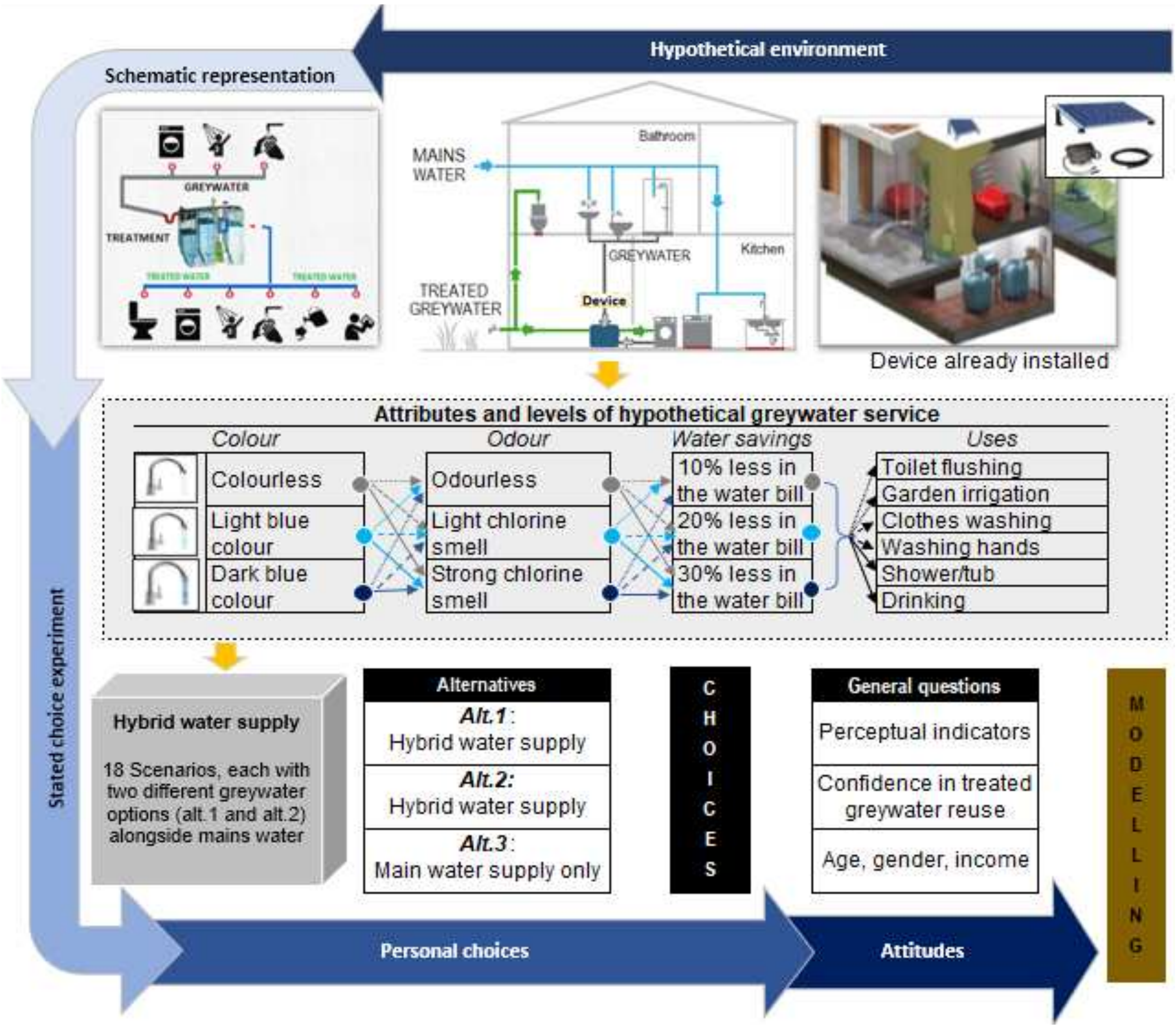

Figure 1. Context of the choice experiment

2.3.2. *Questions on attitudes and acceptability*

The calibration of the role of the attitudinal constructs required additional information at the level of each respondent. For this purpose, respondents were first asked to indicate their level of agreement with eleven statements (Table 1), which were in part informed by previous studies on environmental attitudes carried out by Hoyos et al. (2015). To reduce the risk of fatigue and potentially biased responses (Ampt, 2003), the number of these "indicators" of underlying attitudes was limited. The survey also collected (1) six binary responses (yes/no scale) to questions about willingness-to-accept greywater reuse for different uses inside the house, and (2) three sequential questions about willingness-to-install technology for greywater reuse in a respondents' dwelling if: (a) they should cover for the costs themselves, (b) the costs were partially covered by someone else, and (c) the costs were fully covered by someone else. Note that as the questions were sequential, question (b) was only asked if the respondents answered no to question (a), and question (c) was only asked if they answered no to question (b). Before the last set of questions, respondents were shown the dimension of the device (i.e. 1.1 m^2, similar to the space occupied by a washing machine) and its cost (i.e. one million CLP, equivalent to 1170 US$). This information was taken from Ferguson, (2014) and the Hydro4 web page[2].

3. MODELLING WORK

3.1. Selection of attitudinal statements

Initially a factor analysis was conducted to explore which of the statements were related to each other. The most consistent findings were obtained when using a single factor, which loaded strongly onto six of the statements (with loadings larger in absolute value than 0.3, marked in bold in Table 1). As can be seen, these six statements were split into two groups, where people who agree with the first four (A, B, C, F) were more likely to disagree with the final two (G, H), and vice versa.

Table 1: Attitudinal statements and loadings in factor analysis (retained statements shown in bold)

	Attitudinal question	Loading
A	**Water protection will provide a better world for me and my family**	**0.66**
B	**Water and the environment must be protected for the well-being of the entire population**	**0.77**
C	**We must worry more about protecting water than about economic growth**	**0.47**
D	Water service companies limit my choice and personal freedom in terms of water uses	-0.14
E	In case of water cuts, people should worry more about taking their own measures	0.15
F	**Everyone can contribute by saving water**	**0.67**
G	**The claims that there is a drought are exaggerated**	**-0.51**
H	**If the government does not take care of water problems, why should I?**	**-0.38**
I	When I wash crockery, I let the water run, I accumulate it in a bowl and wash the crockery with this	-0.24
J	When I take a shower, I let the water run for more than one minute	-0.15
K	I do everything possible to reduce my water consumption	0.14

[2] http://hydro4.com.ar/linea-ingenieria/reciclado-de-aguas-grises/

3.2. Overall model structure

Econometric methods belonging to the family of discrete choice models were used, and specifically those based on random utility theory, to help disentangle the different influences on choice. In these models, the probability of choosing a specific option amongst mutually exclusive alternatives increases in the presence of desirable characteristics and decreases in the presence of undesirable characteristics (Train, 2009).

HCMs are an advanced type of DCM that treat attitudes as unobserved and represent them through latent variables (LV). These have a deterministic component, linking the latent attitude to observed decision maker characteristics such as socio-demographics, and a random component, accounting for noise across individual decision makers. The LV are used to explain the answers to attitudinal questions, and also part of the heterogeneity across individuals in the utilities for different alternatives in the choice model.

A HCM thus consists of a number of individual components, namely: (a) a structural equation for each latent variable, (b) a structural equation for the utility function of each alternative in the choice model, where at least some of these utilities are affected by the latent variables, (c) a measurement model for each indicator (e.g. attitudinal question), where each of these uses at least one of the LV as an explanator, and (d) a choice model component to explain the observed choices on the basis of the utilities (the choice model is a measurement model for the choice data). For a general introduction about HCMs the reader is referred to Abou-Zeid & Ben-Akiva, (2014).

The estimated model is complex due to the number of components to be analysed. However, in contrast with other approaches used in past work, HCMs have two key benefits. First, they do not treat the answers to attitudinal questions as error free measures of attitudes; instead they see them simply as “indicators” of underlying attitudes which are latent. The answers to the attitudinal questions are thus treated as dependent variables rather than explanatory variables. Second, a careful specification allowing the full level of flexibility, as done in this paper, allows an analyst to pinpoint what share of heterogeneity in preferences can be linked back to the attitudinal constructs. HCMs are now seen as a reliable tried and tested tool across fields, and this paper brings this technique to the important area of GWR. Figure 2 shows our model schematically. The model is made up of:

- One latent variable, where its structural equation uses five socio-demographic characteristics of the respondent (z_n).
- Three structural equations for the utilities in the choice model; these are a function of attributes of the alternatives in the SC scenarios for respondent *n* (X_n), and vary across alternatives (*j*) and across choice tasks (*t*).

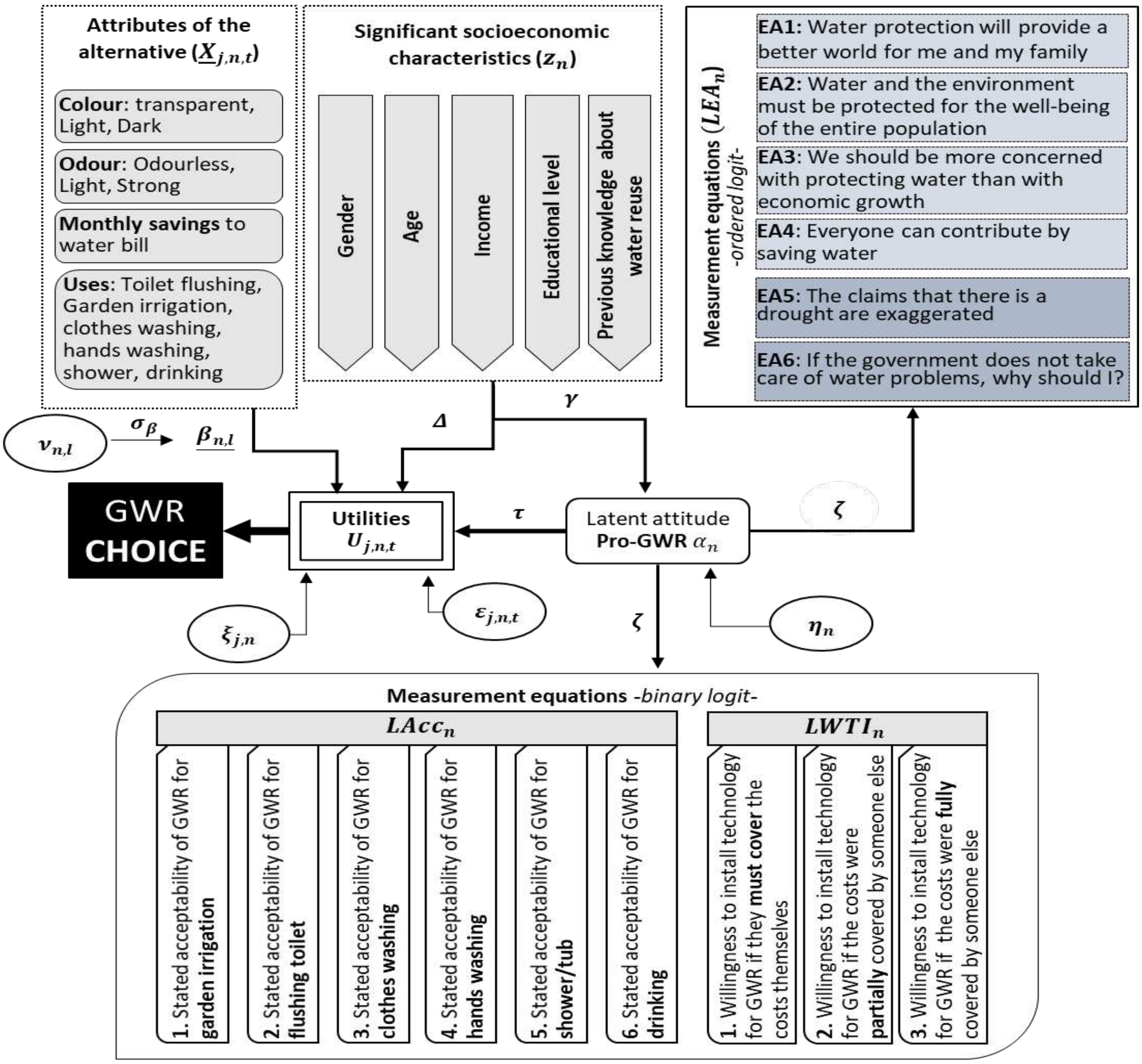

Figure 2. Greywater reuse (GWR) hybrid choice model (Greek symbols are explained in the text)

The latent variable and the utilities are then used in several separate model components:

- A choice model for the choices (C_n) of respondent n (answers to T_C= 6 tasks with three alternatives each).
- Six measurement models for the answers to attitudinal questions (EA_n: set of T_{EA}= 6 questions, 5-point Likert scale – a standard approach for testing agreement in psychology).
- Six measurement models for the stated willingness to accept different uses (Acc_n: set of T_{Acc}= 6 questions, binary yes/no, one per use).
- Three measurement models for the stated willingness to install technology questions (WTI_n: set of T_{WTI}= 3 sequential questions, binary yes/no).

3.3. Structural equations

3.3.1. *Structural equation for the latent variable*

The structural equation for the single latent variable α_n is given by (1):

$$\alpha_n = \gamma z_n + \eta_n, \quad (1)$$

where z_n is a vector of socio-demographic characteristics of person *n*, γ is a vector of estimated parameters, and η_n is a random error that distributes $N(0,1)$.

3.3.2. *Utilities in the choice model*

The choice model has three alternatives, the utilities of which differ across scenarios and respondents as a function of the characteristics of both the alternatives and the respondents. In particular, the utility of alternative j in task t for person n is given by:

$$U_{j,n,t} = \delta_j + \underline{\beta}_n \underline{X}_{j,n,t} + \xi_{j,n} + \varepsilon_{j,n,t}, \quad (2)$$

where δ_j is a constant for alternative *j*, which is only estimated for the left-most alternative (i.e., for *j*=1) and $\underline{\beta}_n$ is a vector of parameters associated with the impact of the different explanatory variables for respondent n. In particular, the utility component for attribute l (which could be either the continuous *savings* attribute or one of the levels of a categorical variable, i.e., usage type, colour and odour) is given by one of the elements in $\underline{\beta_n}$, say $\beta_{n,l}$, as follows:

$$\beta_{n,l} = \beta_l + \Delta_{hc,l} z_{n,hc} + \sum_{m=1}^{4} z_{n,m} (\Delta_{\mathrm{m,l}} + \Delta_{\mathrm{m,l,hc}} z_{n,hc}) + \sigma_l \nu_{n,l} + \lambda_l \alpha_n \qquad (3)$$

The sum over m refers to the four characteristics other than water expenditure level (gender, age, education and previous greywater experience). The different terms in (3) are as follows:

- β_l captures the value of the parameter for attribute l for a respondent in the base category for all socio-demographic variables.
- $\Delta_{hc,l}$ captures a shift in this base value for respondents in the high water expenditure group (T_2), where the socio-demographic variable $z_{n,hc} = 1$ if respondent n falls into that group (and 0 otherwise);
- The remaining four socio-demographic characteristics are captured by the indicators $z_{n,m}$, where, for example, $z_{n,1} = 1$ if respondent n is female (and zero otherwise). $\Delta_{\mathrm{m,l}}$ captures the shift in the sensitivity to attribute l for a respondent who has the socio-demographic characteristic $z_{n,m}$, while $\Delta_{\mathrm{m,l,hc}}$ captures an additional additive shift if that respondent also belongs to the high water expenditure group (T_2).
- σ_l is the standard deviation for the random heterogeneity in the sensitivity $\beta_{n,l}$ across respondents; this is standard normal distributed, such that $\nu_{n,l} \sim N(0,1)$, and is only incorporated for the six types of uses (i.e. and not for the qualitative attributes or the savings attribute).
- λ_l captures the impact of the latent variable α_n (from equation 1) on the value of $\beta_{n,l}$, where these impacts are only captured for the six different uses (i.e. again, not for the qualitative attributes or the savings attribute).

The utility function in (2) also contains two error terms. The first, $\xi_{j,n}$, is identically and independently distributed (IID) across alternatives and respondents according to a Normal $N(0, \sigma_\xi)$ distribution; σ_ξ is estimated and serves to treat the pseudo panel effect inherent to SC data (Ortúzar and Willumsen, 2011, chapter 8). The second term, $\varepsilon_{j,n,t}$, is IID across alternatives and observations, and follows a type I extreme value distribution, leading to a logit type probability of choice (Train, 2009).

The discussion above has been very technical and detailed with the aim of ensuring that readers who seek to adopt a similar specification for other applications recognise the inter-play between the different component. A key feature of the specification used in this paper is that the heterogeneity in preferences in the utility function (i.e. Equation 3) is not limited to either heterogeneity linked to attitudes or heterogeneity not linked to attitudes. Rather, it does both at the same time. This avoids the issue highlighted by Vij & Walker (2016) of models misattributing all heterogeneity to attitudes. It also sets the scene for the analysis of the sources of heterogeneity in Section 4.4.

3.4. Measurement models and joint likelihood

The model jointly explains the values of 16 different dependent variables; namely, the answers to six attitudinal questions, six willingness-to-accept questions, up to three willingness-to-install questions, and the SC component (with six observations per respondent). The estimation of the model parameters involves the maximisation of the joint log-likelihood (LL) of all model components, given by:

$$LL = \sum_{n=1}^{N} log \int_{\eta} \int_{\xi} P_{C_n} \cdot LEA_n \cdot LAcc_n \cdot LWTI_n d\xi d\eta \qquad (4)$$

The data for each individual *n* contributes to this overall *LL* in the form of the likelihood of the observed sequence of stated choices (P_{C_n}), the likelihood of the stated agreement with the environmental statements (LEA_n), the likelihood of the stated willingness-to-accept greywater reuse ($LAcc_n$), and the likelihood of the stated willingness-to-install technology ($LWTI_n$). All four components depend on the latent variable α_n, while the choice model component also makes use of the random panel effect term (ξ). Thus, (4) incorporates an integral over the distribution of the two random components in the model. As this integral does not have a closed form solution, it was approximated through numerical simulation, using 500 Modified Latin Hypercube Sampling (MLHS) draws per random component and per individual (Hess et al., 2006). All models were coded and estimated in Apollo v.0.1.0 (Hess & Palma, 2019).

The remainder of this section now looks at the functional form of the four separate model components included in (4).

3.4.1. *Choice model component: P_{C_n}*

Given the IID extreme value assumption for $\varepsilon_{j,n,t}$ in (2), the probability of the sequence of six choices is given by:

$$P_{C_n} = \prod_{t=1}^{6}\sum_{i=1}^{3}(c_{nt} == i)\left(\frac{e^{\delta_i+\underline{\beta}_n\underline{x}_{i,n,t}+\xi_{i,n}}}{\sum_{j=1}^{3}e^{\delta_j+\underline{\beta}_n\underline{x}_{j,n,t}+\xi_{j,n}}}\right) \quad (5)$$

where c_{nt} identifies the alternative chosen by respondent *n* in task *t*, and where the term $(c_{nt} == i)$ will be equal to 1 if and only if respondent *n* chooses alternative *i* in task *t*. This probability is conditional on the random component (η_n) within the latent variable α_n (which influences β_n) as well as the random panel effect term ($\xi_{j,n}; j = 1,2,3$).

3.4.2. *Attitudinal statements: LEA_n*

To model the response to the six attitudinal statements (see Table 1), an ordered logit model (Train, 2009) was used, with likelihood given by:

$$LEA_n = \prod_{t=1}^{6}\sum_{p=1}^{5}(EA_{nt} == p)\left(\frac{e^{\tau_{EA_t,p}-\zeta_{EA,t}\alpha_n}}{1+e^{\tau_{EA_t,p}-\zeta_{EA,t}\alpha_n}} - \frac{e^{\tau_{EA_t,p-1}-\zeta_{EA,t}\alpha_n}}{1+e^{\tau_{EA_t,p-1}-\zeta_{EA,t}\alpha_n}}\right) \quad (6)$$

where the term $(EA_{nt} == p)$ will be equal to 1 if and only if respondent *n* answers with level p to question EA_t, where *p=1,…,5*. The $\tau_{EA_t,p}$ parameters are thresholds to be estimated (with the normalisation that $\tau_{EA_t,0} = -\infty$ and $\tau_{EA_t,5} = +\infty$); furthermore, as no respondents chose the lowest level (i.e. strong disagreement) in the case of the first two statements (i.e., *t=1,2*), we also set $\tau_{EA_t,1} = -\infty$. The estimated parameter $\zeta_{EA,t}$ measures the impact of latent variable α_n

on EA_{nt}. If the parameter is significantly different from zero, the latent attitude α_n has a statistically significant impact on the answers provided to the attitudinal question EA_{nt}.

3.4.3. *Stated acceptability questions: $LAcc_n$*

To model the answers to the six acceptability of use questions, where $Acc_{nt} = 1$ if use *t* was acceptable to person *n*, and 0 otherwise, a simple binary logit model was used, with likelihood:

$$LAcc_n = \prod_{t=1}^{6} \frac{\left(e^{\delta_{\mathrm{Acc}_t}+\zeta_{\mathrm{Acc}_t}\alpha_n}\right)^{Acc_{nt}}}{1+e^{\delta_{\mathrm{Acc}_t}+\zeta_{\mathrm{Acc}_t}\alpha_n}}, \quad (7)$$

where the exponent Acc_{nt} ensures that the numerator takes the appropriate value depending on the answer provided by the respondent (noting that Acc_{nt} is either 0 or 1); δ_{Acc_t} is an estimated constant that explains the average rate of respondents answering yes, while $\zeta_{\mathrm{Acc_t}}$ captures the impact of the latent attitude.

3.4.4. *Willingness-to-install questions: $LWTI_n$*

Finally, the response to the sequential willingness-to-install questions were modelled. These were, at most, three sequential binary answers. So, three binary logit models were used, but with the latter stages only applying if the previous ones were answered negatively, with the likelihood given by:

$$LWTI_n = \frac{\left(e^{\delta_{\mathrm{WTI}_1}+\zeta_{\mathrm{WTI}_1}\alpha_n}\right)^{WTI_{n1}}}{1+e^{\delta_{\mathrm{WTI}_1}+\zeta_{\mathrm{WTI}_1}\alpha_n}} \cdot \left(\frac{\left(e^{\delta_{\mathrm{WTI}_2}+\zeta_{\mathrm{WTI}_2}\alpha_n}\right)^{WTI_{n2}}}{1+e^{\delta_{\mathrm{WTI}_2}+\zeta_{\mathrm{WTI}_2}\alpha_n}}\right)^{1-WTI_{n1}} \cdot$$

$$\left(\frac{\left(e^{\delta_{\mathrm{WTI}_3}+\zeta_{\mathrm{WTI}_3}\alpha_n}\right)^{WTI_{n3}}}{1+e^{\delta_{\mathrm{WTI}_3}+\zeta_{\mathrm{WTI}_3}\alpha_n}}\right)^{(1-WTIc_{n1})\cdot(1-WTI_{n2})} \quad (8)$$

where WTI_{nt}=1 if and only if the respondent answered yes to the question in stage *t*. The values for WTI_{nt} was automatically set to zero if the answer to $WTI_{nt-1} = 1$. Therefore, these exponents ensure that the second and third components in (8) are simply equal to one when a positive answer was given in an earlier stage. The estimated parameters have the same definition as for the binary acceptability questions.

4. RESULTS AND DISCUSSION

In this section, the results corresponding to each of the components of the model are described and analysed. Firstly, the directionality of the impacts of the nature of the latent variable is investigated, followed by the socio-demographic drivers of the attitudes, and finally the role of the latent attitude in the choice model. For each model component, ρ^2 is presented as a goodness of fit measure[3]. The results show the estimate for each parameter, the associated robust standard error and its t-ratio (i.e., the ratio of the two). The latter is used to test the null hypothesis (H_0) that the parameter is equal to zero[4].

4.1. Results for the measurement models for indicators

Table 2 shows the results for the six ordered logit models estimated to explain the answers to the six attitudinal questions considered in our study. For each model, all the estimated thresholds ($\tau_{EA_t p}$, discussed in 3.4.2) show the required increase i.e., utility needs to be larger for a stronger agreement with a statement. The distances between thresholds reflect the uneven distribution of answers in the data – a bigger gap between two thresholds means that more answers fall into that area.

The additional parameter ζ_{EA_t} in each model is the marginal utility of the latent variable α_n in the ordered logit model. A positive estimate means that, as the latent variable α_n increases, respondents are more likely to agree more strongly with the statement that the model seeks to explain, with the opposite applying for a negative estimate.

Looking at the statements in Table 2, two opposite effects are highlighted, namely:

[3] ρ^2 would be zero for a model with equal shares for all outcomes and one for a deterministic (perfect) model. In choice modelling, this is used as a goodness of fit measure especially for multi-alternative choice models, with values between 0.2 and 0.4 often considered to provide a satisfactory fit (McFadden, 1974).

[4] The critical value to reject H_0 at a 95% confidence level is 1.96 in a two-sided test (i.e., when the expected sign of the parameter is unknown); if the sign is known, a one-sided test is applicable and the critical value in that case is 1.64.

a. Results for the first four statements show that the ζ_{EA_t} estimate is positive and highly significant. Thus, a more positive value for the latent variable increases the probability of stronger agreement with the attitudinal statements. These four attitudinal statements relate to water protection and the public good nature of water. The actual size of the impact varies across statements and is especially strong for environmental protection.

b. For the remaining two statements, the impact of the latent variable as captured by ζ_{EA_t} is negative and highly significant. This implies that people with a more negative latent attitude are more likely to agree with these attitudinal statements. The impact varies across these two statements and is especially strong for droughts being exaggerated. These two statements relate much more to water shortage scepticism, and thus go in the opposite direction of the first four, so the opposite signs for ζ_{EA_t} in both groups are entirely reasonable.

The goodness of fit measures implies much higher performance for the first four indicators. The lower fit statistics for the final two are simply a result of the shares for the five levels being very similar for these last two indicators, meaning that no model can offer substantial improvements in fit over an equal-shares model. The more important finding is, of course, that the estimated parameters are statistically significant across all indicators.

Table 2: Ordered logit models results for answers to attitudinal questions

Statements for measurement equations (ordered logit)	**Estimate**	**Robust. std. err.**	**t-ratio**
1. Water protection will provide a better world for me and my family			
… Threshold $\tau_{EA_1 1}$	-∞	fixed	fixed
… Threshold $\tau_{EA_1 2}$	-7.272	0.959	-7.59
… Threshold $\tau_{EA_1 3}$	-4.553	0.589	-7.73
… Threshold $\tau_{EA_1 4}$	-2.133	0.412	-5.17
… ζ_{EA_1}(impact of LV)	1.555	0.342	4.55
Goodness of fit for model component (ρ^2)	0.550		
2. Water and the environment must be protected for the well-being of the entire population			
… Threshold $\tau_{EA_2 1}$	-∞	fixed	fixed
… Threshold $\tau_{EA_2 2}$	-8.013	1.109	-7.23

Statements for measurement equations (ordered logit)	Estimate	Robust. std. err.	t-ratio
… Threshold $\tau_{EA_2 3}$	-4.683	0.838	-5.59
… Threshold $\tau_{EA_2 4}$	-2.645	0.646	-4.09
… ζ_{EA_2} (impact of LV)	2.610	0.555	4.70
Goodness of fit for model component (ρ^2):	0.450		
3. We should be more concerned with protecting water than with economic growth			
… Threshold $\tau_{EA_e 1}$	-6.469	0.764	-8.47
… Threshold $\tau_{EA_3 2}$	-4.734	0.386	-12.25
… Threshold $\tau_{EA_3 3}$	-2.021	0.240	-8.43
… Threshold $\tau_{EA_3 4}$	-0.738	0.200	-3.69
… ζ_{EA_3} (impact of LV)	1.009	0.154	6.56
Goodness of fit for model component (ρ^2):	0.340		
4. Everyone can contribute by saving water			
… Threshold $\tau_{EA_4 1}$	-7.592	0.996	-7.62
… Threshold $\tau_{EA_4 2}$	-6.060	0.702	-8.63
… Threshold $\tau_{EA_4 3}$	-3.365	0.475	-7.09
… Threshold $\tau_{EA_4 4}$	-1.391	0.356	-3.91
… ζ_{EA_4} (impact of LV)	1.744	0.307	5.68
Goodness of fit for model component (ρ^2)	0.370		
5. The claims that there is a drought are exaggerated			
… Threshold $\tau_{EA_5 1}$	-0.098	0.183	-0.54
… Threshold $\tau_{EA_5 2}$	0.452	0.204	2.21
… Threshold $\tau_{EA_5 3}$	1.538	0.248	6.20
… Threshold $\tau_{EA_5 4}$	2.913	0.301	9.69
… ζ_{EA_5} (impact of LV)	-1.023	0.179	-5.71
Goodness of fit for model component (ρ^2)	0.080		
6. If the government does not take care of water problems, why should I?			
… Threshold $\tau_{EA_6 1}$	-1.160	0.141	-8.22
… Threshold $\tau_{EA_6 2}$	-0.619	0.137	-4.53
… Threshold $\tau_{EA_6 3}$	0.777	0.157	4.97
… Threshold $\tau_{EA_6 4}$	2.135	0.204	10.45
… ζ_{EA_6} (impact of LV)	-0.655	0.127	-5.14
Goodness of fit for model component (ρ^2)	0.080		

* Recall that thresholds $\tau_{EA_1 1}$ and $\tau_{EA_2 1}$ were fixed to -∞ as nobody selected them in the survey.

In the case of the six binary logit models for the stated acceptability of greywater use (Table 3), an estimate for a constant in each case was obtained, capturing the baseline utility (δ_{Acc_t}), and another for the impact of the latent variable (ζ_{Acc_t}). A positive value for δ_{Acc_t} would imply that net of the effect of the latent variable, a larger share of respondents would be willing to accept greywater reuse for that specific usage. The estimated constants decrease across uses, showing that the stated acceptability gets progressively lower with the more direct uses, as expected. The impact of the latent variable is positive across all categories, and the ζ_{Acc_t} estimates are highly significant. The positive signs imply that respondents with a more positive value for the latent variable are more likely to indicate that they would be willing to use greywater for these uses.

Table 3. Results for binary logit models for acceptability of use

Measurement equations (binary logit)	**Estimate**	**Robust. std. err.**	**t-ratio**
Stated acceptability of greywater reuse for flushing toilet			
…Constant δ_{Acc_1}	1.943	0.250	7.79
…ζ_{Acc_1} (impact of LV)	1.349	0.248	5.43
Goodness of fit for model component (ρ^2)	0.150		
Stated acceptability of greywater reuse for garden irrigation			
…Constant δ_{Acc_2}	1.003	0.145	6.92
… ζ_{Acc_2} (impact of LV)	0.648	0.136	4.75
Goodness of fit for model component (ρ^2)	0.070		
Stated acceptability of greywater reuse for clothes washing			
…Constant δ_{Acc_3}	0.048	0.158	0.30
… ζ_{Acc_3} (impact of LV)	0.895	0.198	4.52
Goodness of fit for model component (ρ^2)	0.020		
Stated acceptability of greywater reuse for hands washing			
…Constant δ_{Acc_4}	-1.144	0.183	-6.25
… ζ_{Acc_4} (impact of LV)	1.148	0.329	3.49
Goodness of fit for model component (ρ^2)	0.270		
Stated acceptability of greywater reuse for shower/bath			
…Constant δ_{Acc_5}	-1.759	0.245	-7.20
… ζ_{Acc_5} (impact of LV)	1.435	0.408	3.52
Goodness of fit for model component (ρ^2)	0.420		
Stated acceptability of greywater reuse for drinking			
…Constant δ_{Acc_6}	-3.051	0.280	-10.89
… ζ_{Acc_6} (impact of LV)	1.011	0.366	2.76
Goodness of fit for model component (ρ^2)	0.760		

The actual impact again varies across the six categories, but it is strongest for *Shower/tub* (1.435) followed by *Hand washing* (1.148), and lowest for *Garden irrigation* (0.648). The goodness of fit measures again implies a varied picture across the six indicators, and those cases where ρ^2 is lower, simply reflect the fact that the binary split in the data is very close to 50-50. The more important point, again, is that the impact of the LV is statistically significant across the six indicators.

Finally, the three binary logit models for the sequential questions about willingness to install new technology in the house to treat and to reuse greywater were analysed (Table 4). In the first two models, a negative value for δ_{WTI_t} was obtained (-1.565 and -1. 423), representing the lower number of respondents that would be willing to invest their money, totally or partially, to fit a new technology for reusing treated greywater at their homes. By contrast, the positive value of δ_{WT3} (1.462) implies an overall positive response in the third stage. Note that across the three stages, the positive and significant estimate of ζ_{WTI_t} implies that increases in the latent variable would lead to increases in the stated willingness to fit the new technology. In terms of the goodness of fit, once more the lower fit for the final component is due to its shares being much closer to 50-50 than for the other components.

Table 4. Binary logit models' results for acceptability of installing greywater reuse technology

Measurement equations (binary logit)	**Estimate**	**Robust. std. err.**	**t-ratio**
Willingness to invest their money in a new device for GWR			
…Constant δ_{WTI_1}	-1.565	0.136	-11.48
…ζ_{WTI_1} (impact of LV)	0.521	0.160	3.25
Goodness of fit for model component (ρ^2)	0.390		
Willingness to invest partially their money in a new device for water reuse			
…Constant δ_{WTI_2}	-1.423	0.144	-9.87
…ζ_{WTI_2} (impact of LV)	0.311	0.158	1.97
Goodness of fit for model component (ρ^2)	0.330		
Willingness to accept a new device for water reuse but without investment			
…Constant δ_{WT3}	1.576	0.254	6.21
…ζ_{WT3} (impact of LV)	0.989	0.244	4.05
Goodness of fit for model component (ρ^2)	0.100		

4.2. Structural equation for the latent variable

Section 4.1 shed some light on the role and interpretation of the latent variable α_n. In particular, a more positive value for α_n correlates with stronger agreement with water conservation statements, stronger disagreement with the statements expressing scepticism about water shortage claims, and a greater willingness to accept greywater reuse and to install greywater reuse technology. This suggests that the attitudinal construct can be interpreted as a ***pro-greywater reuse attitude***.

The next step consists of seeking to understand how this latent attitude varies across our sample. Table 5 shows the estimates for the parameters γ explaining the influence of the socio-demographic characteristics on the latent variable. Here, it is important to remember the presence of the additional standard Normal disturbance term, meaning that there is also random variation in the attitudinal construct. Our model estimates show that female respondents, those younger than 55 years and those with low education, have a lower value for the latent variable than men, respondents over 55 years, and people with high education. In contrast, prior knowledge and being in the lowest income category has a positive influence on the latent variable. The largest estimate is for people with low income.

Table 5. Results for structural equation for latent variable (deterministic part)

Impact of socio-demographics on α_n (γ parameters)	**Estimate**	**Robust. std. err.**	**t-ratio**
Female	-0.199	0.113	-1.75
Age below 55	-0.323	0.108	-3.00
Low income (less than 200.000 CLP)	0.509	0.290	1.75
Low education	-0.367	0.115	-3.20
Previous knowledge	0.299	0.131	2.28

The findings that previous knowledge and higher education lead to respondents being more pro-greywater reuse is not surprising. However, the finding that low income and older respondents appear to be more pro-greywater reuse is not necessarily in line with *a priori* expectation and provides important new insights. Note that the use of attitudinal constructs allows us to detect situations where a group of people can be more pro-greywater reuse without necessarily being in a position to turn this attitude into reality due to other constraints on their behaviour. This is a greywater reuse analogue to an occasional finding in transport research, that women and lower income people may actually be more pro-car than men and higher income people (Hess et al., 2018), but represent a smaller share of car travellers due to other constraints on their behaviour (namely income).

4.3. Choice model component

Finally, the results of the choice model component (Table 6) first show a reduced rate of choosing the left-most option (δ_1=-0.697) and a strong pseudo-panel effect, that is, correlation across choices for the same respondent (σ_ξ=1.945). The goodness of fit of the choice model component is 0.28, exceeding the value of 0.25 found by Amaris et al. (2020). This shows that adding the latent variable and additional random terms on top of the components linking attribute preferences to socioeconomic characteristics allows for a better understanding of the heterogeneity in choices of greywater reuse, giving valuable insights for establishing acceptability strategies.

The utilities include seven socio-demographic effects which are not significantly different from zero at the 95% confidence level (three in the *Toilet flushing* attribute, one for *Garden irrigation*, two for *Washing clothes* and one for *Shower/tub*), plus the standard deviation σ_2. They were kept in the model because they had the expected sign and were the best estimates, we could get with our sample size (cf. Ortúzar and Willumsen, 2011, page 278).

Table 6. Results for choice model component

Attribute	General description	Estimate	Robust. std. err.	t-ratio
	Constant for left most alternative ($\boldsymbol{\delta_1}$)	-0.697	0.125	-5.58
Colour	**Clear or light blue**	**0**	***-Fixed-***	
	Dark blue (β)	-0.651	0.123	-5.28

Attribute	General description	Estimate	Robust. std. err.	t-ratio
Odour	**Odourless**	**0**	***-Fixed-***	
	Light chlorine (β)	-0.517	0.138	-3.74
	Strong chlorine (β)	-1.480	0.158	-9.39
	Savings on water bill (β)	0.189	0.040	4.70
	… shift for high-water water expenditure group (Δ)	-0.106	0.040	-2.66
Toilet flushing	**Mean for utility** $\boldsymbol{\beta}$ ($\boldsymbol{\mu_1}$)	3.172	0.552	5.75
	Standard deviation for $\boldsymbol{\beta}$ ($\boldsymbol{\sigma_1}$)	1.846	0.375	4.92
	… λ_1 (impact of LV)	2.565	0.322	7.95
	… shift for female (Δ)	0.751	0.482	1.56
	… shift for female and high-water expenditure group (Δ)	-0.861	0.594	-1.45
	… shift for low education (Δ)	-1.457	0.471	-3.09
	… shift for low education and high-water expenditure (Δ)	0.707	0.629	1.12
Garden irrigation	**Mean for utility** $\boldsymbol{\beta}$ ($\boldsymbol{\mu_2}$)	2.615	0.414	6.31
	Standard deviation for $\boldsymbol{\beta}$ ($\boldsymbol{\sigma_2}$)	0.432	0.299	1.45
	… λ_2 (impact of LV)	1.972	0.288	6.84
	… shift for female (Δ)	0.445	0.323	1.38
	… shift for female and high-water expenditure (Δ)	-1.827	0.473	-3.86
	… shift for low education (Δ)	-1.617	0.348	-4.65
	… shift for low education and high-water expenditure (Δ)	1.246	0.452	2.76
Washing clothes	**Mean for utility** $\boldsymbol{\beta}$ ($\boldsymbol{\mu_3}$)	2.095	0.415	5.05
	Standard deviation for $\boldsymbol{\beta}$ ($\boldsymbol{\sigma_3}$)	1.847	0.325	5.68
	… λ_3 (impact of LV)	1.872	0.345	5.43
	… shift for female and high expenditure (Δ)	-0.758	0.418	-1.82
	… shift for age below 55 and high-water expenditure (Δ)	0.521	0.403	1.29
	… shift for low education (Δ)	-0.819	0.347	-2.36
Washing hands	**Mean for utility** $\boldsymbol{\beta}$ ($\boldsymbol{\mu_4}$)	1.092	0.343	3.18
	Standard deviation for $\boldsymbol{\beta}$ ($\boldsymbol{\sigma_4}$)	0.878	0.280	3.14
	… λ_4 (impact of LV)	1.572	0.261	6.02
Shower/ Tub	**Mean for utility** $\boldsymbol{\beta}$ ($\boldsymbol{\mu_5}$)	1.728	0.400	4.32
	Standard deviation for $\boldsymbol{\beta}$ ($\boldsymbol{\sigma_5}$)	1.530	0.275	5.57
	… λ_5 (impact of LV)	1.973	0.327	6.03
	… shift for female and high-water expenditure (Δ)	-1.117	0.365	-3.06
	… shift for low education (Δ)	-0.478	0.322	-1.48
Drinking water	**Mean for utility** $\boldsymbol{\beta}$ ($\boldsymbol{\mu_6}$)	-1.066	0.463	-2.30
	Standard deviation for $\boldsymbol{\beta}$ ($\boldsymbol{\sigma_6}$)	-1.366	0.452	-3.02
	… λ_6 (impact of LV)	1.152	0.258	4.46
	… shift for female (Δ)	0.870	0.443	1.96
	… shift for female and high-water expenditure (Δ)	-2.153	0.592	-3.64
	… shift for age below 55 and high-water expenditure (Δ)	0.985	0.460	2.14
	… shift for previous knowledge and high-water expenditure (Δ)	1.928	0.587	3.28

Attribute	General description	Estimate	Robust. std. err.	t-ratio
	Standard deviation of error component (σ_ξ)	1.945	0.144	13.51
	Goodness of fit for model component (ρ^2)	0.280		

4.3.1. *Appearance*

The negative signs show that an increase in the level of odour and colour, negatively affects the choice of reusing water; but there is no difference between clear and light blue in the case of colour. This is consistent with other investigations (Domnech & Saurí, 2010; Ilemobade et al., 2013, Amaris et al., 2020).

4.3.2. *Savings in the water bill*

Monetary savings is a relevant attribute in the decision to reuse greywater. However, we found that it had different weights according to the household's water expenditure. The marginal utility (i.e. the per-unit value) is larger for people whose households have lower water expenses (0.189) compared to those who have higher expenses (0.189 + (-0.106) =0.083), as expected.

4.3.3. *Uses*

The respondents' utility for reusing greywater varies across uses and needs to be interpreted relative to using mains water only for each type of use (where that utility was set to zero for normalisation). In each case, we have a mean utility, along with random and deterministic heterogeneity, and the impact of the latent variable.

a) Mean utility and deterministic heterogeneity not linked to LV: Results show that the mean utility (μ) is positive for all uses except for drinking. These estimates, however, only relate to the base socio-demographic group (male, highly educated, aged over 55 and not in the lowest income group). *Gender* is the common characteristic that influences most purposes. In the low water expenditure group, we see a more positive utility for reusing greywater for toilet flushing, garden irrigation, and drinking in the case of women. In contrast, women in the high expenditure group have lower utility (than men) for all uses, except for washing hands, which is the only use without any direct sociodemographic interactions (i.e. net of the latent attitude). Another finding is that *Prior knowledge* has a direct (as opposed to via the latent attitude) positive influence only in the utility of reusing treated greywater for drinking. This is in contrast with the strong positive influence of *Prior knowledge* on the pro-greywater reuse attitudes, which suggests that prior knowledge is more likely to have an indirect (i.e., through the attitude) rather than direct impact on choices, supporting the theoretical points of Ajzen & Fishbein (1975) .

b) <u>Random heterogeneity not linked to LV</u>*:* There is extensive random heterogeneity around the above values with a larger magnitude in the greywater reuse for *Toilet flushing*, *Washing clothes* and *Shower/tub* (σ_{toilet}: 1.846, $\sigma_{clothes}$: 1.847, σ_{shower}: 1.530), meaning that there is a non-trivial probability of negative values throughout these uses. For the remaining three uses, the random heterogeneity is less extensive, but with the estimated standard deviations remaining statistically significant.

c) <u>Impact of LV</u>*:* Additionally, our estimates show that the utility of using greywater for all uses increases for respondents with a more positive value for the latent variable. The impact of this pro-greywater reuse attitude is different in magnitude according to the use. The strongest impact of the attitudinal construct is observed for the utility of greywater reuse for *Toilet flushing* ($\lambda_{toilet} = 2.565$), followed by *Shower/tub* ($\lambda_{shower} = 1.973$), *Garden irrigation* ($\lambda_{garden} = 1.972$), *Washing clothes* ($\lambda_{clothes} = 1.872$), *Washing hands* ($\lambda_{hands} = 1.572$), and finally *Drinking* ($\lambda_{drinking} = 1.152$). This is a first indication that for some uses, especially the most direct ones, there is less scope for changes in attitudes leading to changes in behaviour.

4.4. Analysis of sources of heterogeneity

A more detailed analysis of the heterogeneity in the model, with a focus on the importance of the latent attitude is described in this section. In particular, a situation where the greywater is clear and odourless but has no financial savings associated with it, was analysed. Results indicate that the mean monetary valuation is positive for all uses except *Drinking*, where a strong monetary incentive would be required (figure 3a). Across uses, the willingness to pay of users decreases as uses involve more direct contact. Note the strong heterogeneity in the monetary valuations across individuals, reflected in the wide confidence interval of the valuations. Heterogeneity comes mainly from the utility associated with the various uses rather than from the sensitivity to the monetary incentive (where only a shift for the high expenditure group was captured, cf. Table 6).

Given the careful and detailed specification used in this paper, the model allows the separation of four sources of heterogeneity: (i) deterministic heterogeneity, not linked to the latent variable; (ii) deterministic heterogeneity in the latent variable itself and, finally, two types of random heterogeneity: (iii) net of the latent attitude, and (iv) through the latent attitude. In what follows, components (i) and (iii) are labelled as “direct” by not entering the utility through the latent variable.

The results first show that a large share of heterogeneity is random across uses (Figure 3Figure 3b). The main exception is the case of *Drinking*, where just over a third of the total heterogeneity can be linked to observed respondent characteristics, driven by the strong influence of *Gender*, *Age* and *Previous knowledge*. These effects are primarily direct, rather than being captured through the latent attitude. In terms of random heterogeneity, it can be observed that a larger share of this variation can be linked to the attitudinal construct (size of λ) rather than being unrelated random heterogeneity (size of σ) for all uses except *Washing* *clothes* (where the two sources are roughly equal in importance) and *Drinking* (where the direct random heterogeneity is larger than that through the latent attitude).

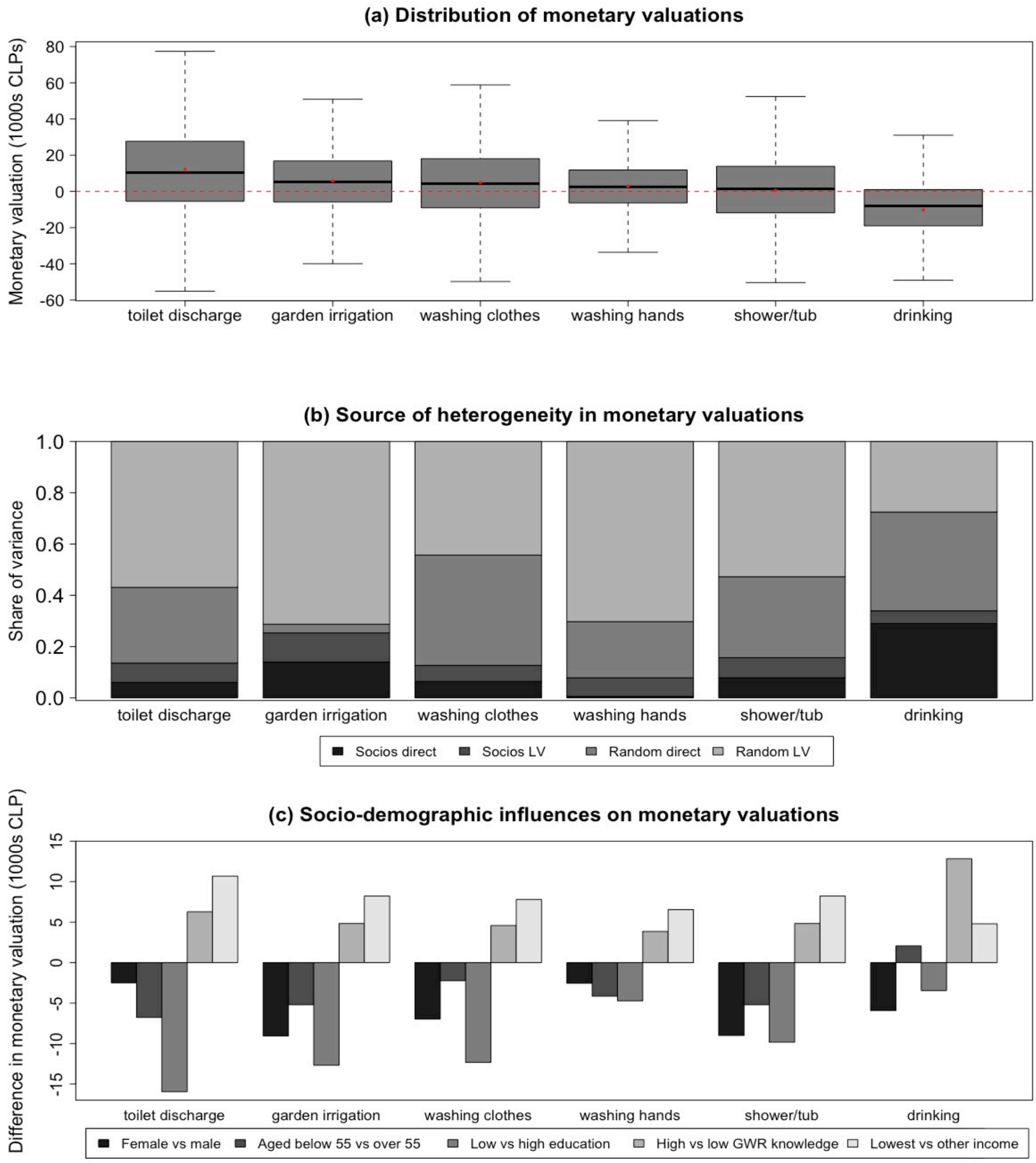

Figure 3: Analysis of heterogeneity in monetary valuations. Note that for the box-plots, the "box" is bounded by the lower and upper quartile limit (25% and 75%), the horizontal line is at the medium, the mean is represented by a dot, and the whiskers are situated 1.5 times the interquartile range below the lower quartile and above the upper quartile limit.

Finally, Figure 3c looks at the influence of respondent characteristics on monetary valuations, given by the combined effects of direct influences or through the latent attitude. A key point to note is that all the λ parameters are significant and have the same sign (positive). As a result, if a socio-demographic variable has an impact on the latent attitude, it will have an impact (although of different magnitudes) on the six utilities, and its effect will be in the same direction across all uses. However, this can be counteracted or in fact strengthened by the direct effects (i.e. the inclusion of the socio-demographics in the utilities, net of the impact of the latent attitude). For *Gender*, the latent attitude for women is more negative, leading to a reduced utility across all six uses. In the case of *Toilet flushing*, this reduction is party cancelled out by a positive direct shift (-4.17+1.67), while for all other uses (except *Washing hands*), there is a further negative direct effect. For respondents aged below 55, the latent attitude is again more negative, but this impact is reduced by a positive direct effect for *Washing clothe*s (-4.95+2.70), while the direct effect is so positive as to change the overall utility difference compared to older respondents in the case of *Drinking* (-3.04+5.11). *Low education* leads to a lower (or negative) monetary valuation, with the opposite applying for *Previous knowledge*. Finally, the positive shift in the monetary valuation for the lowest income group, is driven entirely by the strong positive latent attitude estimated for that group.

4.5. Role of attitudes in behaviour

A more in-depth account of the role of attitudes in the potential preferences for greywater reuse is possible by analysing the relative importance of the latent attitude and the qualitative appearance of greywater. The results in Figure 4 show that any change away from the best possible qualitative appearance (i.e., clear colour and no odour) will lead to a loss in utility. The underlying attitude varies across the sample population, while its impact on utility varies across the six uses.

A positive latent attitude can compensate for the loss of utility resulting from a deterioration of the qualitative appearance. Of course, this is only possible for positive values of the latent attitude, and the share of respondents where the attitude is strong enough decreases as the qualitative appearance becomes worse. There are also differences across uses, and the share is the lowest for *Drinking*; note that this is not because this type of use has the lowest utility across uses, but rather because the role of the latent attitude is the weakest in the utility of greywater reuse in this case (λ_6). The effects are identical for *Garden irrigation* and *Shower/tub*, given the near identical λ for these two uses.

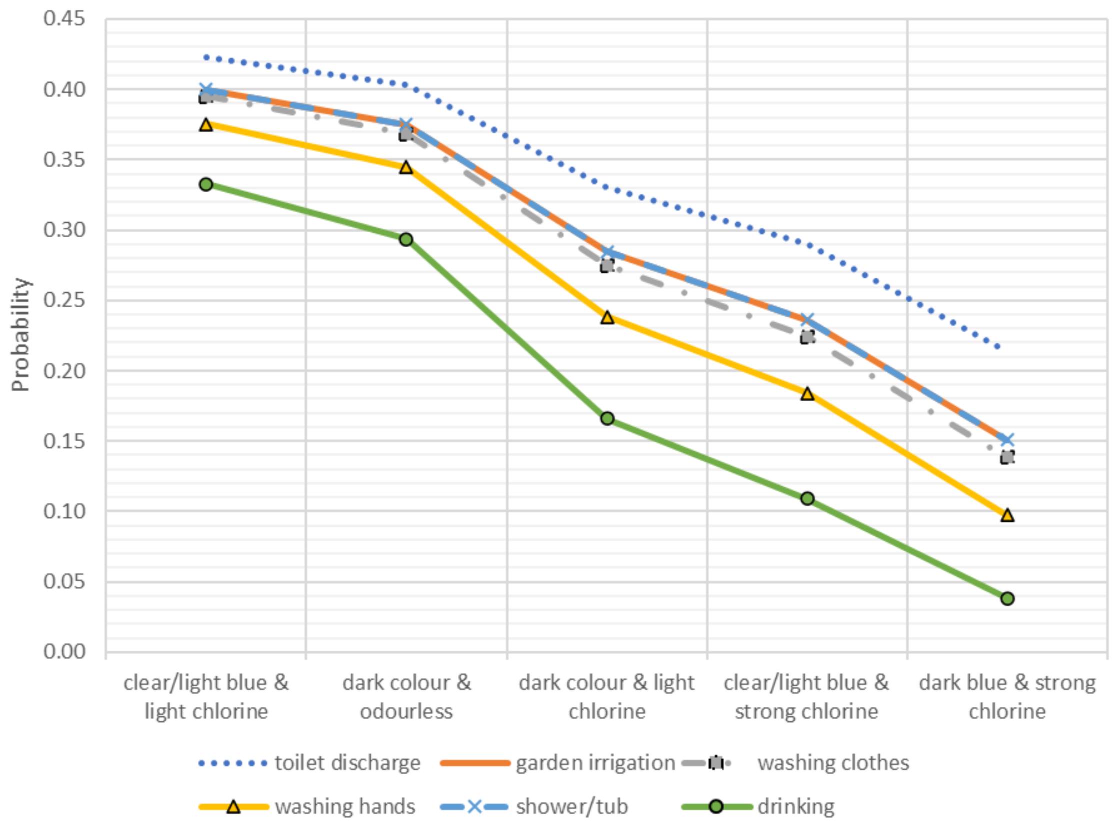

Figure 4: Probability of latent attitude compensating for inferior appearance for different treated greywater uses

Figure 5 looks at a different type of trade-off, namely how increased savings can cancel out the negative impact on utility for GWR for the share of the population with anti-GWR attitudes. As expected, the probability of increased savings cancelling out the negative impact are linked with the amount of the savings. In particular, for the use where the impact of the latent attitude is strongest (i.e., *Toilet flushing*), even the highest incentive would only compensate for 47% of the negative attitude in the population. In the case of *Drinking* this is much higher (79%), given the lower role of the latent attitude in that use ($\lambda_6 = 1.152$, is the smallest of the λ

parameters). So, even though drinking is the least attractive use overall, the further decrease in its utility for respondents with the most negative attitudes is smaller than for other uses.

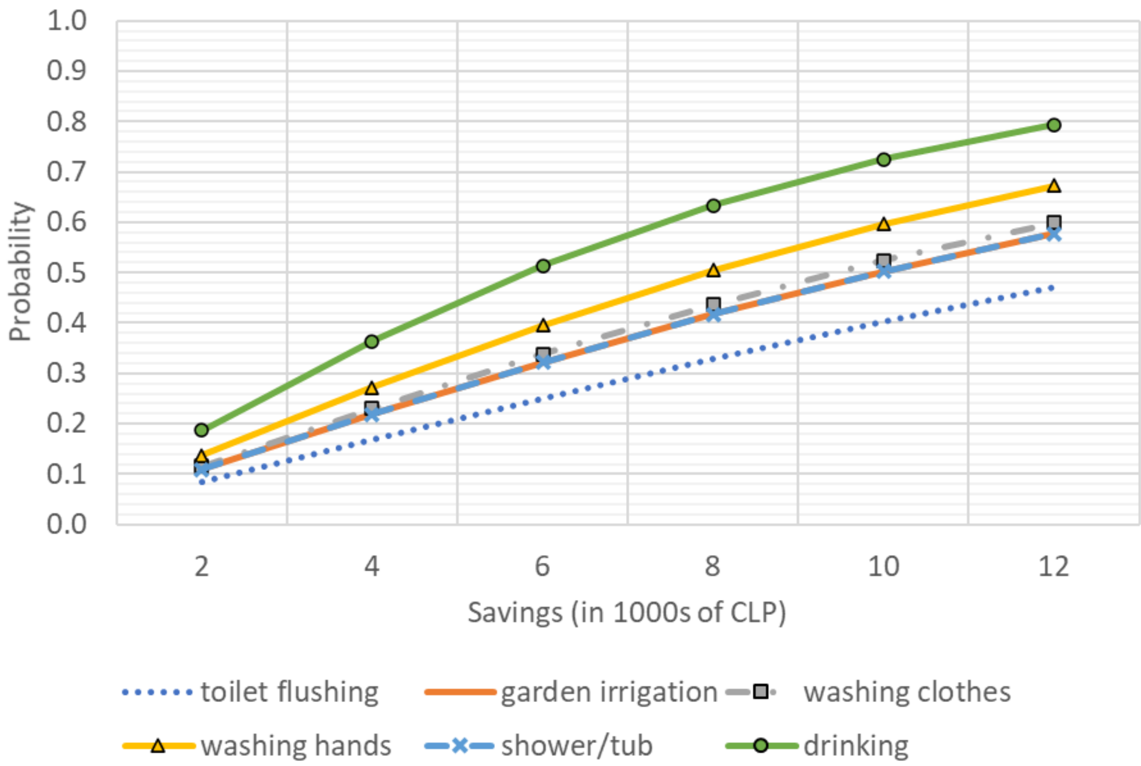

Figure 5: Probability of savings compensating for negative attitude

Of course, a key interest in studying the role of attitudes is to try and understand how behaviour might change if attitudes change. As discussed by Chorus & Kroesen, (2014), the cross-sectional nature of typical data and the arbitrary scale of the latent attitudes, mean that it is not meaningful to look at the impact of a given percentage change in attitudes. Instead, we focus on studying the best possible outcome of a policy that would uplift the negative (or less strong positive) attitudes in the population, to those of the segment with the most positive attitude. Again, the analysis was carried out considering the best qualitative appearance scenario (i.e., clear and odourless), but for the case of having no financial savings. The outcome of this is shown in Figure 6, which shows the binary probabilities of a given type of greywater reuse being preferred to using mains water, for all uses.

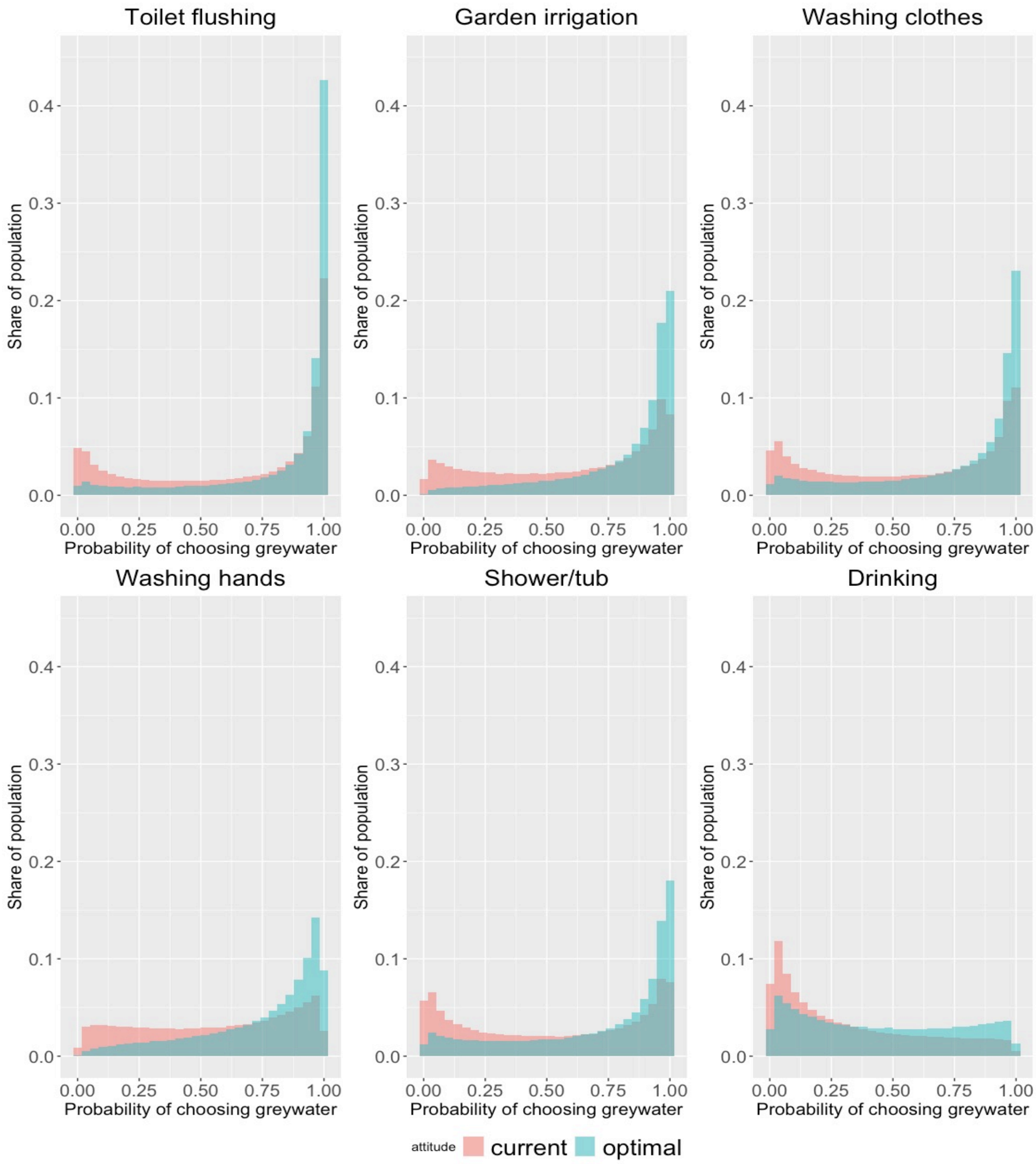

Figure 6. Potential change in acceptability of different uses after change in attitudes

Of course, the probabilities vary across individuals as a function of both deterministic and random heterogeneity, some of it linked to the latent attitude. As a result, each panel in Figure 6 shows two distributions. The first, labelled as *current*, shows the probabilities for the current attitudes, while the second, labelled as *optimal*, shows the probabilities in a situation where all attitudes are at the level of the most positive individuals in the sample. This represents an upper bound on what can be achieved (on the basis of our results and for our sample), and shows clear shifts in the shape of the distribution (and hence also in the means and median probabilities of accepting greywater reuse).

5. CONCLUSIONS, LIMITATIONS AND FUTURE RESEARCH DIRECTIONS

There is growing interest in the possibility of treating greywater at the source (i.e. in individual residences) and reducing the demand for mains water in urban areas with water scarcity problems. The success of any policy related with promoting GWR clearly relies on a good understanding of the potential response by households to this new type of service. A growing number of studies are considering econometric models to understand household preferences in this context, and how they may vary across individual households. An emerging body of empirical work has also attempted to link this heterogeneity to underlying attitudes. This paper follows in the footsteps of such work but makes two important novel contributions. First, it is so far the only application of a HCM to investigate the impact of pro-greywater reuse attitudes in households' preferences for different types of uses. The advantage of this method is that it correctly recognises that attitudes can never be observed by an analyst and that the use of answers to attitudinal questions as error free measures of attitudes (as done in past work) thus leads to endogeneity bias and measurement error. Second, the paper has demonstrated how a careful specification of a HCM allows an analyst to separate out the different sources of heterogeneity, and thus being able to determine what share of the heterogeneity can be linked to the attitudinal constructs.

The results provide a variety of insights into the drivers of preferences in the context of greywater reuse decisions. These preferences vary as a function of the characteristics of the greywater option (i.e. quality, type of use, and savings), showing for example that uses requiring more direct contact are less popular, and that the appeal of GWR reduces as the qualitative appearances becomes worse. In addition, however, we highlight how preferences vary across individuals for the same product configuration. Although part of this heterogeneity can be linked back to the individuals' characteristics (e.g., gender and age), a remaining part is random heterogeneity. Importantly, parts of both the deterministic and random heterogeneity are linked to the pro-greywater reuse attitude incorporated in the HCM.

The results indicate that the utility of using greywater, for all uses, increases for respondents with a more positive value of the latent attitude. The share of the heterogeneity that can be linked back to the attitude however varies across uses and is by far the lowest for drinking. This could suggest that there are other sources of heterogeneity when it comes to the acceptability of using greywater for drinking; for example, other attitudes - linked more to disgust or safety concerns - than towards water resources in general. For other uses, the share of heterogeneity linked to the attitudes is much higher, reaching over 80% for garden irrigation, and over 50% for all uses except drinking.

A crucial next step would be to use the results from analyses such as those presented here in practice. Currently, the Chilean regulations about water reuse establish that greywater must be treated inside the dwelling (Law 21 075). However, even if the water quality is good enough, the lawful uses are only toilet discharge and garden irrigation, which together only account for a maximum of 36% of the mains water consumption. This study provides evidence that additional types of water uses could contribute substantially to water reuse (recovery of up to 50% of the mains water). Indeed, the results find that in the best scenario examined, the adoption of pro-water reuse attitudes can cause the acceptability of indirect uses to increase by between 16.3% and 18.7%, and between 13.8% and 18.9% for direct uses.

While the work in this paper is largely technical in its nature, there are clear real world benefits to it. With a decentralised system such as home-based greywater treatment, it is clear that household-level preferences will drive uptake, and our work helps policy makers understand which consumers are more likely to accept the technology, and where incentives may be needed. A key issue is, of course, how to shift attitudes. One possibility is the use of diffusion strategies that can focus, initially, on persuading individuals through messages about the direct (i.e. water saving) and indirect (environmental benefits, water security, autonomy) benefits associated with greywater reuse. Looking at the combined effect of socioeconomic characteristics, direct and through the attitudes, we note that diffusion strategies about reusing greywater could start by targeting women, given that they have the most negative latent attitude. Our results also show that monetary incentives can compensate for the negative impact of attitudes on acceptability, especially when there is also a deterioration of the qualitative appearance.

While the work presented in this paper relates to one specific application area (i.e. the city of Santiago de Chile), the methods themselves are almost directly transferable to other locations. The results of this work highlight the benefits of the method in terms of exploring sources of heterogeneity and how this can be linked to underlying attitudes. Thus, the work serves as an important blueprint for repeating the application in other cities. Conducting similar surveys in other areas will only require tailoring the attributes to a local context, while the methods themselves can be transferred directly subject to new specification searches for the utility functions. The extent to which the current empirical results are transferable to other cities is unclear without empirical testing. However, the large role played by attitudes in this case study would make it unlikely for such a role to not exist elsewhere.

As with any study, there are limitations to highlight and opportunities for future research to explore. Firstly, this work includes only the perception of uses but does not consider the costs of installing and operating/maintaining the technology. The results thus provide an approximation about individual acceptability and could be useful in explaining the interest in greywater reuse for new properties equipped with the technology or for a situation where there is a subsidised installation in existing properties. Future work needs to incorporate the additional cost elements to obtain insights into their impact on the decision to treat and reuse greywater. Secondly, it should be noted that, with treated greywater reuse not yet being in operation in the study city, this work has relied on hypothetical settings. Stated choice experiments are an established tool for contributing to the planning process which allow us to gain insights into the behaviour of the population regarding a non-existent good or service (Bennett & Blamey, 2001). However, the survey-based presentation of tangibles attributes (e.g. savings in potable water bill) as well as capturing of intangible elements associated with users' perceptions and attitudes could be influenced by survey artefacts. There is thus, as ever, a need for future studies to validate these results using new data, including, when possible, data on real world choices. Third, future studies should investigate the role of more specific attitudinal factors, including feelings of disgust. This requires including additional attitudinal questions. Fourth, it would be beneficial to combine the quantitative work with further qualitative work in future studies, allowing the analysts to fine tune the questions used for probing for underlying attitudes, for example. Finally, for use in actual policy work, the results would need to be reweighted to bring the data in line with the socio-demographic distribution of the target population.

Despite these gaps, this paper presents a wealth of new results and, more importantly, provides a useful template for future research using Hybrid Choice Models in a recycling context in general, and GWR in particular.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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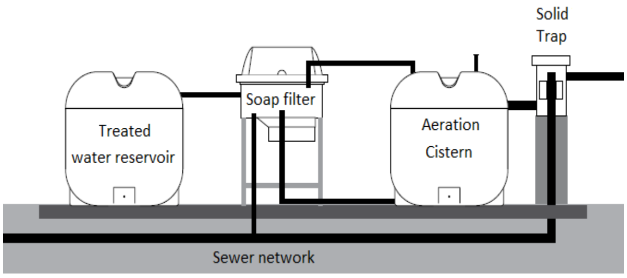
7. APENDIX

Appendix A - 1. Technical specifications of water recycling technology (Hydro4)



Equivalent inhabitants	*Daily flow [L/day]*	*Electrical consumption [kWh/day]*
30 max.	3000	22
60 max.	6000	35
120 max.	12000	70

	Guiding Values	
Control in treated water	**Greywater entry**	**Greywater recovered exit**
Turbidity [NTU]	22 - 100 NTU	< 2
E. Coli [CFU / 100 ml]	10-10000 UFC/100 ml	No detected
DBO5 [mg/Lt]	90 - 100	< 20
pH if chlorine is added		7.0 - 8.0

Appendix A – 2. Example of hypothetical scenario card. Individuals must choose one of three alternatives

Attributes	Alternative A TREATED GREYWATER	Alternative B TREATED GREYWATER	Alternative C TAP WATER – ALL USES
Colour caused by treatment	Light blue	Dark blue	Transparent
Odour caused by treatment	Soft chlorine odour	Odourless	Odourless
Uses of treated greywater	Garden irrigation	Washing clothes	
Monthly savings expected on the water bill	Saving US$ 3.00	Saving US$ 8.00	Saving US$ 0.00
	I prefer alternative A ☐	*I prefer alternative B* ☐	*I prefer alternative C* ☐