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Factors influencing household-level positive and negative solid waste management practices in rapidly urbanizing cities: insights from Santa Cruz de la Sierra, Bolivia

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Ethical statement: During the development of the research protocol, we followed best practices proposed by different organizations. All participants were provided extensive explanation about the research (and how the results would be used), oral consent was required to be part of the study, and it was clear that participants could decline to be part of the study at any point. Furthermore, the information was anonymized in order to prevent the location of the households.

Abstract

Household solid waste management (HSWM) practices are a critical aspect of municipal solid waste management (MSWM) systems. Despite efforts to implement source separation and recycling at the household level in developing countries, negative practices such as illegal dumping and backyard burning remain ubiquitous, particularly in rapidly urbanizing cities. Source separation and recycling behaviors have been rarely studied in such cities. Moreover, studies on illegal dumping and backyard burning using robust tools and frameworks are practically non-existent. This study aims to (a) estimate the prevalence of "negative" and "positive" behaviors for different HSWM practices, and (b) identify their observable and non-observable influencing factors. The focus is Santa Cruz, a rapidly urbanizing city of Bolivia. Household surveys (n=305) are used to establish the connections between latent constructs (e.g. awareness, satisfaction), and observable variables (e.g. location, socio-demographic characteristics) with each behavior. This is achieved through the combination of exploratory factor analysis to validate the constructs to be included in the analysis, and structural equation modeling to identify the most influential factors. Two causal models are developed, one for the positive behaviors (i.e. source separation, recyclables donation, recyclables selling, and use of drop-off facilities), and the other for the negative behaviors (i.e. illegal dumping and backyard burning). Results indicate that, satisfaction with the MSWM service has a negative and significant influence on the prevalence of illegal dumping and backyard burning behaviors, while the remoteness of the household (i.e. distance to the city center) has a positive significant effect on the prevalence of these behaviors. Source separation and recyclable donation are influenced positively by latent constructs such as attitudes, knowledge, and awareness. For recyclables

selling and use of drop-off stations, income and location are the most relevant factors, although with smaller effects.

Keywords: illegal dumping; backyard burning; source separation; recycling; municipal solid waste management; developing countries

1 Introduction

At the global level, municipal solid waste management (MSWM) has been shifting its focus from managing waste to managing resources, emphasizing the importance of upstream activities (e.g. waste reduction, product design) and the implementation of circular economy approaches (Bartl, 2015; Wilson et al., 2015). However, this paradigm change has been challenging to implement effectively in developing countries, which in most cases are still struggling with basic service provision aspects such as waste collection coverage, collection quality and environmentally controlled disposal (Brunner and Fellner, 2007; Guerrero et al., 2013).

This observed underperformance has been associated to a combination of problems in both the "hard" (e.g. machinery, equipment, facilities) and "soft" elements (e.g. policies, regulation, institutions) of the MSWM system (Savino et al., 2018). However, while the hard elements used to be considered as the priority, the soft elements and particularly aspects related to community involvement, have started gaining more attention recently (JICA, 2005; Ma and Hipel, 2016; Rodić and Wilson, 2017). In this sense, many gaps have been identified in the relevant research on the social dimension of MSWM systems, seeking to understand the factors affecting solid waste management (SWM) individual participation, particularly related to attitudes and behaviors (Ma and Hipel, 2016).

Negative household SWM practices such as backyard burning and illegal dumping are still relatively common in many developing cities (Karija and Lukaw, 2013; Tadesse et al., 2008). Such practices have negative impacts on the environment and human health, generating also additional costs for municipalities (Estrellan and Iino, 2010; Reyna-Bensusan et al., 2018). The prevalence of backyard burning has been estimated through household surveys (Reyna-Bensusan et al., 2018) and observation following transect sampling (Nagpure et al., 2015), respectively providing estimates of the proportion of households engaging in backyard burning or the number of incidents per area. For example, studies have estimated that the proportion of households practicing backyard burning can range between 5% and 70% in urban and peri-urban areas of various cities (Adzawla et al., 2019; Akpinar-Elci et al., 2015; Israel, 2010; Reyna-Bensusan et al., 2018; Tadesse et al., 2008). Similar studies for illegal dumping have estimated the proportion of households to range from around 4% to 46% (Adzawla et al., 2019; Babayemi and Dauda, 2010; Sekito et al., 2013; Sujauddin et al., 2008). However, these statistics are not comparable in most cases, or might underestimate the ubiquity of these practices by considering household SWM practices (e.g. discharge to collection service, container use, backyard burning, illegal dumping) to be mutually exclusive, when in fact, households usually combine two or more of them.

Conversely some of the positive household SWM practices such as source separation and recycling have increased in developing countries in recent decades to improve environmental management. This is mainly due to the implementation of recycling programs and the emergence of an informal sector dedicated to the recovery of recyclable material for income generation (Majeed et al., 2017; Wilson et al., 2009). Studies have found that the proportion of households engaging in source separation ranges between 17% and 76% across cities (Babayemi and Dauda,

2010; Padilla and Trujillo, 2018; Tadesse, 2009; Vassanadumrongdee and Kittipongvises, 2018). Other studies have found that approximately 24-61% of households can engage in recyclable selling, and 22-33% in recyclables donation (Nguyen et al., 2015; Vassanadumrongdee and Kittipongvises, 2018). Few studies have also explored the participation in drop-off recycling programs, but mostly in developed countries (Dahlén and Lagerkvist, 2010; Sidique et al., 2010).

Factors influencing separation and recycling behaviors – as a whole – have been mostly studied in industrialized countries (Amini et al., 2014; Desa et al., 2011; Mamady, 2016; Oztekin et al., 2017), however factors influencing negative behaviors such as waste burning, and dumping have not received much attention (Tadesse et al., 2008) or have focused predominantly on rural areas (Wang et al., 2018).

Studies analyzing the factors influencing either positive or negative household SWM behaviors have used different theoretical frameworks such as the List of Value (LOV) (McCarty and Shrum, 1994), the Theory of Reasoned Action (Amini et al., 2014; Park et al., 1998), the Theory of Planned Behavior (TPB) (Oztekin et al., 2017; Pakpour et al., 2014; Ramayah et al., 2012), and the "Knowledge, Attitudes, Practices" (KAP) (Babaei et al., 2015; Mamady, 2016; Tatlonghari and Jamias, 2010). Such theoretical frameworks have been directly applied or expanded with additional elements to formulate hypotheses regarding the possible latent constructs (i.e. non-observable variables) influencing recycling or source separation behaviors. However, to the best of our knowledge, no study has used such frameworks to explore negative SWM behaviors such as backyard burning and illegal waste dumping. Furthermore, most studies using these frameworks have focused on developed countries, with robust studies in developing contexts being rather scarce (Heidari et al., 2018; Vassanadumrongdee and Kittipongvises, 2018; Zhang et al., 2015; Zhang et al., 2016).

Some of the studies on positive and negative behaviors towards SWM practices have focused solely on observable variables such as socio-economic characteristics (e.g. household education, income, size, and distance to facilities) (Padilla and Trujillo, 2018; Tadesse et al., 2008). The most common data analysis methods in such studies have included descriptive statistics and correlations (Sekito et al., 2013), regression analysis (Padilla and Trujillo, 2018; Tadesse et al., 2008; Wang et al., 2018) and Structural Equation Modeling (SEM) (Loan et al., 2017; Mosler et al., 2008; Ramayah et al., 2012; Wu et al., 2017).

The aim of this study is to determine (a) the prevalence of different SWM practices at the household level, (b) identify the observable and non-observable factors influencing these practices. This includes "negative" (e.g. waste dumping and burning) and "positive" behaviors (e.g. source separation), as well as the factors influencing engagement in each type of behavior. To achieve this, we combine the Theory of Planned Behavior, Exploratory Factor Analysis (EFA) and Structural Equation Modeling (SEM), focusing on Santa Cruz de la Sierra, which is the largest city of Bolivia. The city is characterized by rapid/unplanned growth that has influenced negative SWM behaviors and a lack of resources/capacity that has precluded the wide implementation of sustainable SWM practices in large parts of the city (Lozano and Gasparatos, 2019).

Overall, this study seeks to contribute to closing three major knowledge gaps in the current literature: (a) identify factors affecting negative solid waste management behaviors, which are quite prevalent in many developing cities, (b) provide further evidence about factors affecting positive behaviors (i.e. recycling) in developing cities, (c) comprehensively address similar but different recycling behaviors, which should be analyzed separately in order to be adequately understood. All of these are major gaps in the academic literature concerning positive and

negative household waste management behaviors, especially in rapidly urbanizing developing contexts.

Section 2 outlines the research framework, study site, and data collection and analysis methods. Section 3 presents the results about the prevalence of positive/negative behaviors (and the factors affecting them), while Section 4 synthesizes and discusses the main findings and implications for environmental management.

2 Methodology

2.1 Research Approach

This study combines the Theory of Planned Behavior (TPB) as the guiding conceptual framework to understand the aspects dictating SWM behaviors, with Structural Equation Modeling (SEM) to establish the connections between reflective indicators (i.e. latent constructs), formative indicators (i.e. observable variables) and the MSW behaviors themselves. The TPB framework is essentially the base for the research design, which is then validated and analyzed through an approach that combines Exploratory Factor Analysis (EFA) and Structural Equation Modeling (SEM). We investigate six SWM behaviors, namely backyard burning, illegal dumping, source separation, recyclables donation, recyclables selling and use of drop-off stations, all of which occur at the household level, which is considered the unit of analysis for this study.

The TPB is one of the most utilized frameworks in behavioral studies (Zhang et al., 2016), and assumes that there are three main abstract constructs influencing behavioral intentions, namely: (a) attitudes (i.e. degree of positive or negative opinion about a given behavior), (b) subjective norms (i.e. perceived social pressure to engage or not in a given behavior), and (c) perceived behavioral control (i.e. ease or difficulty in engaging in a given behavior). The latter of these

abstract constructs has an additional effect in the materialization of the intention into the actual behavior (Ajzen, 1991).

Various studies have applied the TPB framework in the waste management field and have had mixed outcomes. For example some studies have successfully identified relevant factors influencing source separation and recycling practices at the household level (Oztekin et al., 2017; Pakpour et al., 2014; Wang et al., 2016; Xu et al., 2017), while others could not establish the hypothesized connections (Wu et al., 2017) or established a weak influence (Knussen et al., 2004; Tonglet et al., 2004). Studies have addressed some of the limitations of the TPB, suggesting possible reasons for the failing to establish the significant influence of some constructs, and the need to consider additional variables when explaining the behaviors (Soltani et al., 2015; Stoeva and Alriksson, 2017).

Structural Equation Modeling (SEM) has been one of the preferred analytical techniques to deal with abstract constructs, due to its capacity to model complex interactions between multiple dependent and independent variables in more powerful ways compared to conventional regression analysis (Rahman et al., 2017; Zhang et al., 2015). SEM consists of two stages: a measurement model and a structural model. The measurement model, also referred to as Confirmatory Factor Analysis (CFA), tests the validity of the indicators (i.e. items/questions) that are expected to reflect a latent abstract construct. Following the measurement model, the structural model is used to estimate the effects of constructs and observed variables on the dependent variables of the model in a similar manner to multivariate analysis techniques (Schumacker and Lomax, 2016; Wu et al., 2017).

When using SEM in factor analysis studies, it has been suggested testing the measurement validity of new data capturing instruments (i.e. questionnaires) or even existing instruments when applied in new contexts (Fabrigar et al., 1999; Mardani et al., 2017). This validation process can be performed through an Exploratory Factor Analysis (EFA), which is carried out prior to the SEM (Rahman et al., 2017; Wang et al., 2016). The EFA seeks to identify latent structures by "grouping" similar items through iterative statistical processes, which would become the groups that are subsequently included in the SEM. During this process those items considered to not be sufficiently related to the various latent constructs, are discarded in order to have a "cleaner" dataset for the SEM analysis (Nikolaou et al., 2020).

In this study, we investigate two negative SWM behaviors: (a) backyard burning, and (b) illegal dumping. The backyard burning behavior refers to the act of burning any type of waste generated by the household, whether it occurs inside the dwelling or outside (e.g. on the curbside). For this study, "illegal dumping" will refer to the act of taking any type of household waste to any place that is not the household curbside or waste deposit, where it is collected by a waste collection service (depending on the geographical context). Common types of household waste illegal dumping include discharging the waste to other neighbors' waste containers (Guitard, 2015), abandoned fields (Boadi and Kuitunen, 2003; Buenrostro et al., 2001), green spaces (Girma et al., 2019), or water canals (Boadi and Kuitunen, 2003; Zapata Campos and Zapata, 2013).

The positive SWM behaviors investigated in this paper include (a) source separation, (b) recyclables donation, (c) recyclables selling, and (d) recyclables drop-off. "Source separation" refers to the act of separating at least some types of materials from the waste, regardless of the posterior use of this material. Households can engage in this behavior to use the materials themselves, to deliver the recyclable materials to the separate collection service, to donate the

material to stakeholders that can process it (e.g. informal waste pickers) or just to deliver it in separate bags to the regular collection service. In this sense, households engaging in "recyclables donation" purposefully give away the recyclable material to any stakeholder engaging in waste recovery activities. "Recyclables selling" refers to those households engaging in the separation of recyclables from their waste, as a means of generating household income. Households that "use drop-off stations" essentially give away their recyclables in any of the drop-off stations existing in the city.

2.2 Study site

Santa Cruz de la Sierra (hereinafter called Santa Cruz) is the largest city in Bolivia, and its economic center. After being a small town for centuries, with a population below 50,000 until the 1950s, due fossil fuels exploitation and commercial agriculture, the city received an important inflow of foreign and domestic migrants, surpassing the 1 million inhabitants before the end of the 90s decade (UNDP, 2015). Currently, the city has an approximate population of 1.7 million inhabitants in the city (INE, 2012) and around 2.3 million including neighboring urban areas of the metropolitan region (Canedo Velasco, 2018; Suarez Subirana, 2018). Similarly, the area of the city increased from 47 km2 in 1969 (Mazoni, 2005), to 428 km2 in 2018 (Suarez Subirana, 2018). This rapid growth was mostly unplanned, leading to the deficient provision of public services in the outskirts of the city (Lozano Lazo and Gasparatos, 2019).

Waste burning and dumping practices in the city have not been quantified properly, except for some modest attempts through a couple of questions included in the national census and relevant surveys. However, according to the public perception both practices have intensified in the past years. This has generated public criticism and calls for the municipality to implement emergency

collection activities, as a means of eliminating illegal dumpsters and establish sanctions for waste burning. However, the effective implementation of these sanctions is questionable, due to the limited regulation enforcement capacities of the local government (Lozano Lazo and Gasparatos, 2019).

Source separation has been formally implemented in Santa Cruz in the past only as pilot programs with limited duration. In the last few years, it has also been implemented through a separate collection service in specific neighborhoods of the city, which collects only the recyclable material. However, even within the limited scope of these programs, various stakeholders have questioned their effectiveness. Conversely, a large number of informal waste pickers operate in the city, independently or in small associations, using recyclables collection from the unsorted waste to generate income. Additionally, the municipality has implemented two "eco-points" or "eco-stations" in the city, where residents can drop-off the recyclable materials on their own (Lozano Lazo and Gasparatos, 2019).

2.3 Data Collection

2.3.1 Survey design

The questionnaire seeking to capture positive/negative SWM behaviors and the factors affecting them was designed based on a literature review of similar studies (Section 1), the constituents of the TPB framework (see below), and the researchers' knowledge of the local context. Due to the possible limitations of TPB (Section 2.1), we included items for measuring additional constructs related to knowledge, satisfaction, and habits (Table S1, Supplementary Electronic Material), as well as observable variables related to socio-economic aspects of the household and characteristics of the neighborhood.

It is expected that the positive (i.e. source separation, recycling, use of drop-off facilities) and negative behaviors (i.e. dumping, burning) would be affected by common factors. For this reason, we conducted the analysis separately for these two groups of behaviors (Section 2.4): (a) Group 1 (Negative Behaviors), (b) Group 2 (Positive Behaviors).

The variables related to the latent constructs were measured through a 6-point Likert type scale (range from 1 = "Strongly disagree" to 6 = "Strongly agree"), with the exception of six items relating to knowledge and attitudes. For these six items it is more sensible to use a dichotomous scale (i.e. Yes/No). Although enumerators were instructed to avoid its use as much as possible, an option of "No Response/Non applicable" was contemplated in case it was needed during the application of the questionnaire.

2.3.2 Sampling

As outlined in multiple other studies, it is expected that further to the latent constructs, the SWM behaviors are influenced by observable factors such as socio-economic (e.g. education, income) and geographical characteristics (e.g. household location, neighborhood characteristics) (Chung and Lo, 2004; Struk, 2017; Tadesse et al., 2008). As a result, when conducting such studies, it is important to adopt a sampling approach that allows for a high degree of randomization and geographical representation, in order to avoid potential biases.

In this study we adopt a systematic sampling consisting of (a) 30 randomly generated points throughout the city (through ArcGIS), and (b) at least 10 households per point randomly selected through a systematic rule (Figure 1). Following this approach, a total of 348 households were surveyed between August and September 2019 by trained enumerators using tablets to capture

the data. In each household, the household head or spouse were the preferred respondent, although other adult members with knowledge about SWM practices were also accepted.

Thirty-eight respondents did not accept to participate in the survey or argued lack of sufficient knowledge about the household SWM practices. Following data screening, five households were discarded due to a high proportion of unanswered questions, resulting in a final sample of 305 households with valid answers. This sample size is considered to be appropriate for the EFA-SEM methodological approach (Section 2.3.3), which is usually estimated to be above 200 participants (Weston & Gore, 2006) or at least 5 subjects per variable (Musil, Jones, & Warner, 1998).

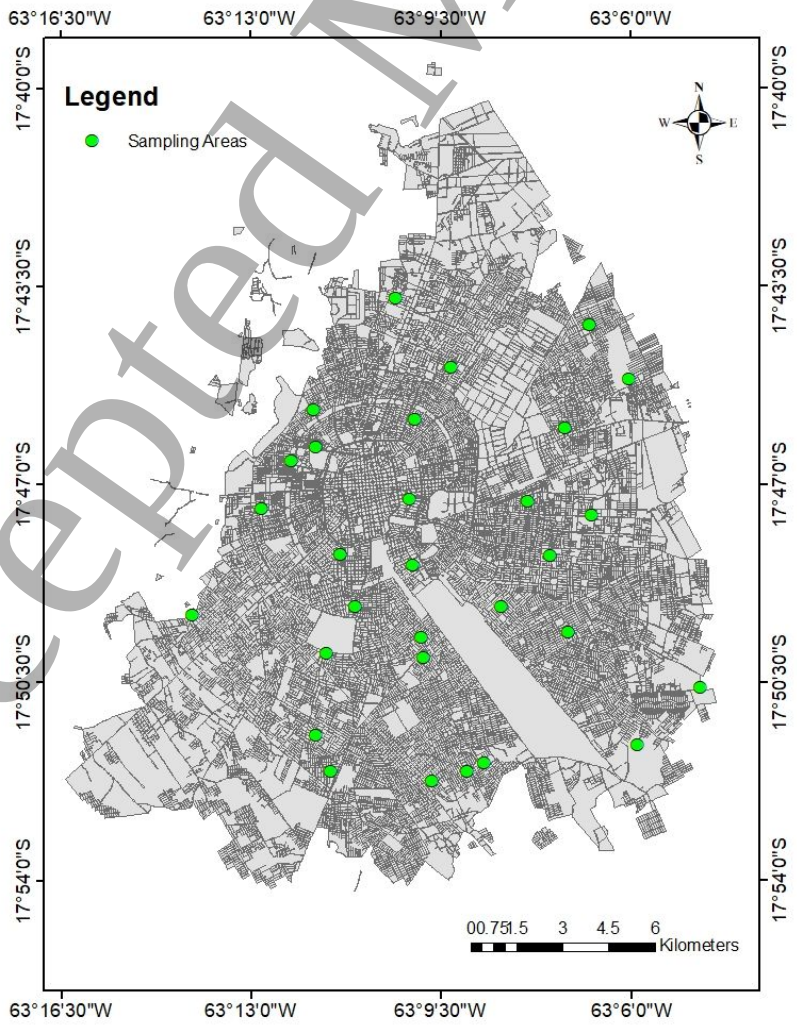

Figure 1. Locations of sampling areas across Santa Cruz de la Sierra

2.4 Data Analysis

During the data screening, each item was checked to confirm the level of missing data, which was below 5% for more than 90% of the items. For the remaining 10% of items, the missing data was below 30%, which is considered common in behavioral studies (Dong and Peng, 2013). For the factor analysis, it has been suggested that if less than 30% of data is missing, there is no need for the use of advanced imputation methods such as linear trends (Chen et al., 2012; Dong and Peng, 2013; Enders, 2003). Therefore, in this study we follow a simpler approach, which entails the substitution of missing values in the dataset with (a) the sample mean for continuous variables, and (b) sample median for categorical and dichotomous variables (Huang and Zhu, 2002; Jönsson and Wohlin, 2006).

As mentioned in Section 2.1, the EFA is used to confirm the validity of the measurement instrument and, if necessary, discard those items that might not be adequately reflecting the

latent constructs. In order to achieve that, we analyze separately the items for each group of behaviors (Section 2.3.1) in SPSS, using the factor analysis tool. The Principal Axis Factoring is used as the extraction method, as it is one of the most widely used such methods (Hinkin, 1998), due its flexibility for application in any type of sample distribution and the lower probability of producing distorted results in case of non-normality (Fabrigar et al., 1999). Varimax is the adopted rotation method, which is the preferred type of rotation in applied social sciences research, due to its simplicity for the interpretation of the results (Brown, 2015; Fabrigar et al., 1999).

The process to determine the factors is iterative, providing a number of factors (latent constructs) after each iteration, and classifying each item ideally in only one factor. Each item presents a "loading factor" (which should be >0.3 or >0.4 depending on the literature), representing the "correlation strength" with the factor (Brown, 2015; Watkins, 2018). Additionally, overall indicators of adequacy such as KMO>0.5 suggest that the factor analysis is suitable for all the items included (Nikolaou et al., 2020). Variables below the cut-off value should be removed from the analysis, and the number of factors should be adjusted accordingly before starting a new iteration. This procedure is continued until all of the variables included in each factor are above the cut-off value (Brown, 2015; Hinkin, 1998). Once the final factor structure is achieved, then the internal reliability is validated. In this study we use the Cronbach's Alpha test as the validation test, which according to literature should result in values ideally >0.7 (Bonett and Wright, 2015; Stoeva and Alriksson, 2017). Dependent variables such as intention and behavior were analyzed separately due to the possibility of results' distortion, considering the expected strong relation between items measuring these variables with influencing factors (Brown, 2015).

During the EFA analysis, it was found that the measurement instrument did not reflect completely and adequately all of the TPB constructs for either of the two groups of behaviors. For this reason, there was a need to modify the original approach in order to use factors that reflect more appropriately the empirical outcome of the EFA (see (Helfrich et al., 2007; Ruslan et al., 2018; Wu et al., 2017; Zheng et al., 2011) for similar modifications). Additionally, considering that the recyclables donation, recyclables selling, and use of drop-off facilities behaviors were detached from the separation behavior, and that each of them is only measured by one item, they were not considered for the first stage of SEM. Thus, they are just included directly in the second part (see below).

Following the constructs measurements validation through the EFA, the SEM analysis is done to estimate the effect of the reflective indicators (i.e. latent constructs), and formative indicators (i.e. observable variables) on behaviors. The first part of SEM consists of the measurement model (Section 2.1) and serves to confirm the results obtained in the previous step through the use of more advanced statistical tools. For this analysis, the data from SPSS is directly imported to the AMOS module. During this stage, various indices are estimated to confirm the model fit, convergent validity, and composite reliability for both groups (Tables S3-S4, Supplementary Electronic Material).

For the second part of the SEM, we create a causal model that includes the latent variables and the observable variables in order to test possible influences in the behavior variables previously mentioned. Table 1 shows the observable variables included in this last step. For each variable we establish the hypothesized influences in the model, which is then run to estimate the standardized coefficients for each of the variables and verify the model fitness indices. As long

as acceptable fitness is not achieved, the non-significant paths are deleted, and ultimately the variables that do not have any significant path (Gallagher et al., 2008; Weston and Gore, 2006).

Table 1: Observable variables

Variable	Description	Group 1	Group 2
Income per capita	Monthly per capita income (BOB/person)	✓	✓
Household head education	Number of years of education of the household head (Years)	✓	✓
Distance to the city center	Concentric ring location of the household (dummy values from 1 to 9)	✓	✓
Stray animals prevalence	Prevalence of stray animals in the neighborhood [1= No stray animals observed, 2 = Some stray animals observed (1-3 daily); 3= Many stray animals observed (>3 daily)]	✓	
Collection frequency	Number of days per week that the collection truck passes by the neighborhood (Days)	✓	
Household collection service	Door-to-door waste collection (1=Yes; 0=No)	✓	
Separate Collection	Separate waste collection service in the neighborhood (1=Yes; 0=No)		✓
Waste pickers frequency	Frequency of wastepickers visits in the neighborhood (1 =Never; 2=Every 2 months; 3=Once per month; 4=Once per week; 5=Few times per week; 6=Many times per week)		✓

3 Results

3.1 Sample characteristics

Most of the respondents are women and household heads (Table S2, Supplementary Material). The education level of the household head reflects the generally low education levels in Santa Cruz (INE, 2013), with approximately 40% of respondents not having finished high school. Income per capita is quite low, with at least 66% of households reporting below 1800 BOB/capita, which is lower than the national minimum wage (2122 BOB = ~300USD). However, income was the socio-economic variable with the highest rate of not answer (19%), presumably due to suspicions over the use of this information, as is common in the context of developing countries (Hoang et al., 2017; Parizeau et al., 2006).

Figure 2a) displays some of the most relevant neighborhood characteristics. According to the results, 67% of the households are located in a paved street, 96% of the households have a waste collection service in the neighborhood, and 18% have the separate collection service in the neighborhood. Approximately 46% of the households have some type of waste container in their curbside, with the rest of the households depositing it directly on the ground. Furthermore 72% of the households mentioned that waste pickers regularly visit their neighborhood.

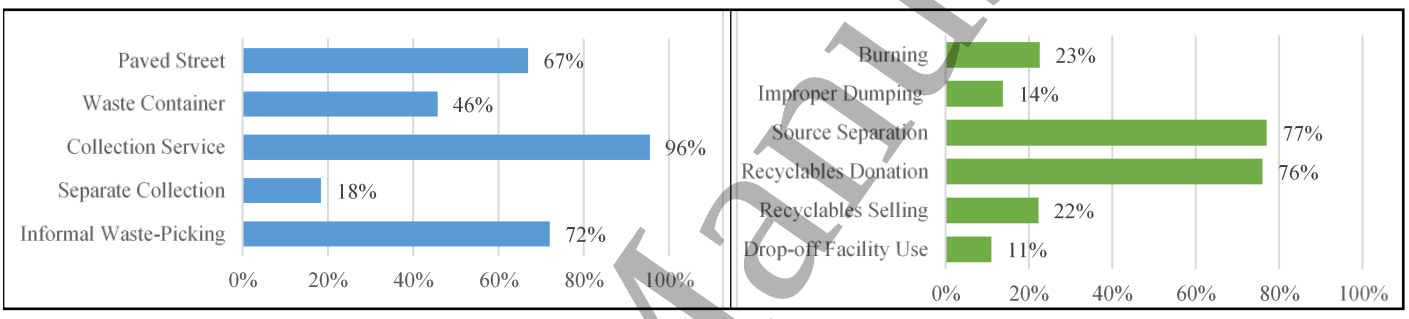

Figure 2: General neighborhood characteristics (a); and prevalence of waste management practices (b)

In terms of the investigated negative SWM behaviors (Figure 2b), 23% engage in waste burning and 14% in inappropriate dumping practices, to some extent. In terms of positive behaviors, approximately 77% of the households conduct some type of waste separation, 76% donate some of the materials recovered to other stakeholders (that re-use it or commercialize it in the recyclable market), 11% use a recyclables drop-off facility, and 22% sell the recyclables they gathered from their own waste.

3.2 Latent constructs in solid waste management behaviors

Table 2 contains the factors identified after the EFA for both positive and negative behaviors. In the case of negative behaviors (i.e. backyard burning, inappropriate dumping), five factors were

identified, and the Chronbach's Alpha test conducted for each construct. The results are within the recommended value of >0.7 (Section 2.4), which suggests satisfactory internal reliability for all constructs.

Based on the items included in each factor, the factors are denominated as "general awareness", "general satisfaction", "dumping impact awareness" and "burning impacts awareness". General awareness refers to the knowledge and perception of the importance of good SWM practices, and the possible impacts of inadequate practices. General satisfaction refers to the satisfaction with the various aspects of the municipal waste management service in the city, and particularly for the collection service. Dumping impacts awareness and burning impact awareness refer to the knowledge and perception of the possible impacts of dumping practices and burning practices, respectively. The burning behaviors and dumping behaviors are factored together (but separately from other constructs) and are analyzed separately following the results of EFA.

Regarding the factors tested for positive SWM behaviors, eight factors were identified after the EFA. General awareness refers to the knowledge and perception of the importance of source separation and recycling in various positive impacts. General satisfaction has a similar definition to the one used above for negative behaviors, but here we also include satisfaction with recycling initiatives. Local context knowledge refers to the knowledge about existing activities related to formal and informal recycling. Satisfaction with the education and communication of waste management services includes items such as the communication of changes in collection service, and satisfaction with educational campaigns on SWM conducted either by the municipality or the private cleansing company. Attitude refers to positive or negative perceptions/feelings associated to the behavior itself. Facilities knowledge and concrete knowledge refer to the specific knowledge required to use the drop-off facilities and conduct the source separation,

respectively. Separation intention refers to the willingness to engage in the respective behavior in the future, regardless of the current behavior. Each behavior is measured through only one item, in which case the factor loading and Cronbach's alpha are not applicable.

As Table 2 shows, constructs related to attitudes and knowledge about facilities are slightly below the recommended cut-off values for the reliability test (0.59) (Section 2.4). However, it was decided to include them to further explore their influence during the next stage of the analysis. This is because the literature highlights that there is no universal acceptable minimum value for Cronbach's alpha, with researchers judging the pertinence of allowing values as low as 0.5, particularly for exploratory research (Bonett and Wright, 2015; Brown, 2015; Gallagher et al., 2008).

Table 2: Constructs for behaviors after the EFA

Group	Item	Factor Loading	α
Group 1 – Negative Behaviors	***General Awareness***		0.81
	Inadequate SWM practices cause pollution	0.84	
	Inadequate SWM practices cause health problems	0.87	
	Importance to take out the garbage only in the designated days and times	0.52	
	General Satisfaction		0.76
	Satisfaction with collection frequency	0.80	
	Satisfaction with SWM infrastructure	0.77	
	Satisfaction with SWM quality	0.56	
	General satisfaction with the SWM in the city	0.51	
	Dumping Impacts Awareness		0.78
	Illegal dumping practices affects neighborhood's aesthetics	0.73	
	Illegal dumping practices contribute to urban flooding	0.64	
	Illegal dumping practices contributes to pollution	0.78	
	Burning Impacts Awareness		0.75
	Backyard burning contributes to pollution	0.66	
	Backyard burning can cause health problems	0.84	
	Satisfaction with Education and Communication		0.85
	Satisfaction with received education about SWM activities	0.91	
	Satisfaction with communication about SWM activities	0.65	
	Burning Behavior		0.86
	Household engages in waste burning practices	0.95	
	Household has burnt waste frequently this year	0.90	
	Household has traditionally engaged in waste burning practices	0.59	
	Dumping Behavior		0.81
	Household engages in illegal dumping practices	0.94	

	Household has dumped waste frequently this year	0.96	
	Household has traditionally engaged in waste dumping practices	0.43	
	General Awareness		0.85
	Source separation improves wastepickers' working conditions	0.69	
	Source separation can reduce pollution	0.91	
	Source separation reduces the amount of waste landfilled	0.89	
	Recycling is important	0.50	
	General Satisfaction		0.78
	Satisfaction with collection frequency	0.78	
	Satisfaction with SWM infrastructure	0.74	
	Satisfaction with SWM quality	0.56	
	Satisfaction with formal recycling initiatives	0.51	
	General Satisfaction with SWM in the city	0.61	
	Local Context Knowledge		0.78
	Knowledge about existence of recycling industry in the city	0.61	
	Knowledge about existence of informal waste picking sector in the city	0.97	
	Educ. and Comm. Satisfaction		0.75
	Satisfaction with education about SWM received	0.75	
	Satisfaction with communication about SWM activities	0.70	
	Attitude		0.59
	Ease to carry out source separation	0.38	
	Time to carry out source separation (R)	0.44	
	Source separation is a waste of time (R)	0.45	
	Family thinks source separation is not necessary (R)	0.56	
	Family does not care much about recycling (R)	0.48	
	Facilities Knowledge		0.59
Group 2 –	Knowledge about recyclables dropping point existence in the city	0.95	
	Knowledge about materials accepted in dropping points	0.49	
Positive	***Concrete Knowledge***		0.72
	General knowledge about waste types (organic/inorganic)	0.74	
Behaviors	Knowledge about materials that can be recycled	0.64	
	Separation Intention		0.90
	Willingness to carry out full source separation	0.89	
	Willingness to separate at least some recyclable materials	0.92	
	Separation Behavior		0.73
	Household engages in source separation practice	0.76	
	Household has never engaged in source separation (R)	0.76	
	Recyclables Donation Behavior		NA
	I usually give away recyclable material	NA	
	Recyclables Selling Behavior		NA
	I usually sell recyclable material	NA	
	Use of Drop-off Facilities Behavior		NA
	I usually take recyclable material to the drop-off facilities	NA	

Note: (R) = Reversed Scale; NA = Non Applicable

After the EFA, the CFA was run in AMOS software (Section 2.4). In the positive behaviors model, the factors related to attitudes and knowledge about facilities, continued to interfere with the model fitness. For this reason, we discard the entire factor related to the knowledge of facilities, and one item from the attitudes factor. Following these changes, the fitness of both the

positive behavior model and the negative behaviors model (which did not require modifications) was judged to be good across multiple indices (Table S3, Supplementary Electronic Material).

Besides the model fit, the literature also recommends testing the composite reliability (CR), as well as the convergent validity through the average variance extracted (AVE) of all model constructs (Raykov and Grayson, 2003; Wang et al., 2016; Zhang et al., 2015). The former relates to the internal consistency of constructs, with values >0.6 considered acceptable (Bagozzi and Yi, 1988; Wang et al., 2016), while the latter refers to the amount of variation explained by the model, with recommended values >0.5, although values as low as 0.4 have been accepted if good reliability indexes exist (Bagozzi and Yi, 1988; Fornell and Larcker, 1981). Thus, this test present acceptable results for all the constructs, except for "Attitude", which displays an AVE of only 0.25 (Table S4, Supplementary Electronic Material).

3.3 Factors affecting waste management behaviors

The second part of the SEM identifies the factors affecting the behaviors, by adding the selected observable variables to the latent constructs and making the necessary changes to run the causal model (Section 2.4). During this process, the constructs models for the negative behavior remained unchanged, while for the positive behavior we dropped the separation intention for not presenting any significant path. Dropping this construct contributed to the improvement of the model fitness (Table 4). The graphical representation of both models can be found in Figure S1, in the Supplementary Electronic Material.

The latent construct that affects the most burning and dumping behaviors is the satisfaction with SWM services in the city (Table 3). However, for waste burning, observable variables such as the education of the household head and the location of the household play more important roles.

For the waste dumping practices, some constructs such as the impact awareness, and the satisfaction with education and communication – and the observable variable related to the collection frequency – seem to have counterintuitive effects, displaying a small but positive and significant influence on the dumping behavior. While there is no clear explanation for these results, in the case of the satisfaction with education and communication, this could imply that people that engage more on dumping practices have lower expectations regarding education and communication activities, leading to higher satisfaction levels. Regarding the collection frequency, its positive effect on dumping could be related to a vicious cycle occurring from implementation of additional collection rounds in areas with significant dumping levels (pers. commun.: Project Officer, Empresa Municipal de Aseo Urbano Santa Cruz). In these cases, additional rounds do not always reach all households but rather focus on collecting dumped waste in specific areas of the neighborhood, which would encourage households to continue dumping in these areas instead of waiting for the door to door collection.

The latent constructs that seem to play the most important role for the positive behaviors are concrete knowledge (for separation) and attitudes (for the separation and recyclables donation). However, these results should be considered carefully, given the issues presented in the attitudes factor during previous stages of the analysis. For the recyclables selling and use of drop-off stations, it is observable variables such as income and location that are more important, although with smaller effects in both cases.

Table 3: Effects on behaviors in causal model

Group	Outcome	Predictor	Estimate	Sig.
Group 1 – Negative Behaviors	Backyard	Distance to city center	0.358	***
		Household head education	-0.12	*
	Burning	General Satisfaction	-0.114	†
		Educ. and Comm. Satisfaction	0.085	

		Household collection service	-0.072	
		Income per capita	-0.067	
		Collection frequency	0.061	
		Burning Impacts Awareness	-0.001	
		General Awareness	-0.01	
	Illegal Dumping	General Satisfaction	-0.333	***
		Distance city center	0.255	***
		Dumping Impacts Awareness	0.197	***
		Collection frequency	0.151	**
		Educ. and Comm. Satisfaction	0.135	*
		General Awareness	-0.119	†
		Household head education	-0.077	
		Household collection service	-0.067	
		Stray animals prevalence	-0.053	
		Income per capita	-0.036	
Group 2 – Positive Behaviors	Separation Behavior	Concrete Knowledge	0.568	***
		Attitude	0.566	***
		Local Context Knowledge	0.329	***
		General Awareness	0.195	***
		General Satisfaction	0.116	***
		Distance city center	0.017	
		Separate Collection	0.011	
		Educ. and Comm. Satisfaction	-0.059	***
		Income per capita	-0.012	
		Waste pickers frequency	-0.006	
	Recyclables Donation	Attitude	0.357	***
		General Awareness	0.216	***
		Local Context Knowledge	0.143	**
		Waste pickers frequency	0.141	**
		Educ. and Comm. Satisfaction	0.079	
		Satisfaction	-0.078	
		Distance city center	-0.057	
		Separate Collection	0.054	
	Recyclables Selling	Distance city center	0.162	**
		Income per capita	-0.137	*
		Waste pickers frequency	-0.089	
		Separate Collection	0.081	
		Attitude	-0.066	
	Use of drop-off station	Educ. and Comm. Satisfaction	0.169	**
		Waste pickers frequency	-0.118	*
		Distance city center	0.112	†
		Attitude	0.11	†
		Income per capita	0.097	†
		Local Context Knowledge	-0.072	

Note: *** p<0.001; ** p<0.01; * p<0.05; † p<0.1

Table 4 displays the model fit statistics for both positive and negative behaviors, with a good fit in both cases. It includes the various statistical tests used to assess the model fitness, and their comparison with minimum recommended values from the literature. The Standardized Root Mean Square (SRMR) represents a summary of the difference between the observed data and the

model, with smaller values indicating better fit. The Root Mean Square of Error Approximation (RMSEA) reflects the model's complexity, meaning that when different models explain the observed data equally well, a simpler model will have a better RMSEA value (Weston and Gore, 2006). While a RMSEA of 0.08–0.1 is considered acceptable, values of 0.06 or less suggest good fit (Brown, 2015). The Probability of Close Fit (PCLOSE) represents RMSEA's p-value. χ^2/df, and the Goodness of Fit Index (GFI), and Adjusted Goodness of Fit (AGFI) are measures of absolute fitness, indicating how well the model fits the data. While χ^2/df has been criticized by being excessively affected by sample size, the GFI and AGFI are considered to be less sensitive to this aspect (Gallagher et al., 2008). The Normed Fit Index (NFI), Tucker-Lewis Index (TLI) and Comparative Fit Index (CFI) assess the model in comparison to a baseline or "null" model. While sample size affects the first, the others perform rather well even with small samples (Gallagher et al., 2008; Weston and Gore, 2006).

Table 4: Fit statistics for the causal model

Fit Statistics	Description	Recommended fit		Negative Behaviors Model	Positive Behaviors Model
		Value	Reference		
χ^2/df	Minimum Discrepancy	<3.0	(Gallagher et al., 2008)	1.04	1.61
RMSEA	Root Mean Square of Error Approximation	< 0.06	(Brown, 2015)	0.01	0.05
PCLOSE	Probability of Close Fit	>0.5	(Brown, 2015)	0.66	0.58
GFI	Goodness of Fit Index	>0.9	(Weston and Gore, 2006)	1.00	0.99
SRMR	Standardized Root Mean Square	0.0 - 1.0	(Brown, 2015; Weston and Gore, 2006)	0.01	0.02
AGFI	Adjusted Goodness of Fit	>0.85	(Gallagher et al., 2008)	0.95	0.92
CFI	Comparative Fit Index	>0.9	(Brown, 2015; Gallagher et al., 2008)	1.00	0.99
TLI	Tucker-Lewis Index	>0.9	(Brown, 2015; Gallagher et al., 2008)	1.00	0.96
NFI	Normed Fit Index	>0.9	(Gallagher et al., 2008)	1.00	0.98

4 Discussion

4.1 Applicability of theory of planned behavior for household waste management practices

Our study identified the factors influencing various positive and negative behaviors related to household SWM in Santa Cruz, Bolivia. We used the TPB framework as the basis of the questionnaire design and analysis, but mindful of its limitations we took various precautions to adapt it, and better explain the empirical results, both in the questionnaire design and the EFA (Section 2.1).

The EFA found that items related to subjective norms and perceived behavioral control were not reflecting adequately the constructs in either of the two models (Group 1 and Group 2), resulting in their complete removal or integration into other constructs. Attitudes and intention constructs were also discarded during this stage in the model for Group 1 (Section 3.2), while in the case of Group 2 the intention construct was discarded during the SEM stage, remaining only the attitudes construct (Section 3.3).

The failure of one or more of the TPB constructs to predict behaviors has been discussed in multiple studies (Armitage & Conner, 2001; Knussen, Yule, MacKenzie, & Wells, 2004; Sniehotta, Presseau, & Araújo-Soares, 2014; Wu, Yu, & Shen, 2017). For example, Wu, Yu & Sen (2017) used the TPB as the basis for a theoretical model to investigate the determinants of construction waste dumping in China. Similar to our results, the SEM process conducted in their study rendered a final model that did not include any of the TPB constructs initially theorized, which was attributed to issues in applying the framework to explain the "collective behavior" (instead of an individual behavior) of construction companies. Similarly, Knusen et al (2004) found that subjective norms did not influence recycling behaviors in Scotland. Similar to other

scholars they have attributed this to issues in understanding the ways in which respondents identify themselves with the normative groups (i.e. family, neighbors, colleagues) in the context of the study (Armitage and Conner, 2001; Knussen et al., 2004; Terry et al., 1999). Furthermore, they suggested that in contexts where the norms that are supposed to influence the behavior are not sufficiently established within the normative groups, then the pressures to engage in a given behavior are not strong enough to account for any effect (Knussen et al., 2004).

When it comes to the perceived behavioral control construct some studies have found that it has an insignificant effect on behaviors, attributing this to (a) issues related to the construct's measurement or (b) the behavior's characteristics and context (Davies, Foxall, & Pallister, 2002; Tonglet, Phillips, & Read, 2004; Warner & Åberg, 2006; Zhou, Romero, & Qin, 2016). For instance, Tonglet et al (2004) and Davies et al (2002) investigated the determinants of recycling behavior in UK, attributing the differences in the accounted effects to the choice of using "perceived control variables" (e.g. ease, opportunity) or "facilitating/inhibiting variables" (e.g. knowledge, resources) to measure this construct, with the latter being the preferred option according to their research. Conversely, studies have pointed to characteristics of the practice that would make the "control" aspect irrelevant in the act of engaging in the behavior, as possible reasons for the insignificant effect of the construct (e.g. people living in areas with long-standing recycling schemes in the determination of recycling behavior; able-bodied people in the determination of pedestrian crossing violation behavior) (Tonglet et al., 2004; Zhou et al., 2016).

Davies et al (2002) suggest eliminating the intention construct, arguing that it is not a significant predictor (in the case of recycling behavior), but rather a mere indication of support to the practice. Instead, they suggest including other constructs such as "affective evaluation", and finding ways to measure behavior choices between different alternatives within the framework.

Other scholars assessing the overall validity and utility of the construct (in any field) share similar concerns by highlighting issues of (a) "inclined abstention" where individuals who form an intention actually fail to act accordingly (Sniehotta et al., 2014), and (b) a failure of the measures to reflect the construct properly when participants suspect the way in which they are supposed to respond according to the framework, and fall into inconsistencies (Trafimow, 2015). The latter issue has also been discussed for the attitudes construct (Trafimow, 2015)

The multiple issues discussed above could have influenced the results of our study in Santa Cruz. Currently, the city lacks comprehensive approaches to address illegal dumping and backyard burning, although the local government has attempted to implement punitive initiatives in the past. In this sense, for the case of subjective norms for negative behaviors, participants might have feared possible sanctions for them or their normative groups (i.e. family, friends, neighbors), leading to inconsistent answers. Indeed, during the data collection activities we identified that some respondents seemed to be distrustful and reluctant to reply, possibly due to this fear (Section 2.2). These issues have been observed in other studies dealing with negative behaviors such as texting while driving, and excessive food waste generation (Bazargan-Hejazi et al., 2017; Visschers, Wickli, & Siegrist, 2016), and this is possibly reflected by the fact that some of the items related to subjective norms for negative behaviors have the largest proportion of missing data (Section 2.4).

Conversely, positive behaviors such as source separation and all types of recycling are still not included in formal policies or programs in Santa Cruz (Lozano and Gasparatos, 2019) (Section 2.2). Thus, while some respondents might be aware of their importance, these SWM practices are probably not normally discussed within their normative groups, further contributing to inconsistent replies among respondents on the perceptions of these groups.

It is also worth discussing the specific issues regarding the perceived behavioral control construct in our study. Earlier in this section, we described how issues related to the construct´s measurement and the behavior´s characteristics have led to insignificant effects in other studies. In our study, and particularly for negative behaviors, the expected "control" over them might not have been clear enough for participants. For instance, one of our questions for this construct addressed the "ease/difficulty to take out the garbage bags only during the designated days and times" (Table S1, Supplementary Material). However, if the local MSWM system does not provide the sufficient information to guarantee that the waste collection schedule is clear to the households, this could have contributed to inconsistencies in the answers. Conversely, for positive behaviors, the EFA demonstrated that the questions reflected the construct appropriately, but suggested to divide it into a few subcomponents. For this reason, we decided to substitute the "perceived behavioral control" by a few constructs related to different types of "knowledge" (Table 2).

Overall, in our study the negative behaviors model was more challenging in terms of applicability of the TPB framework compared to the positive behavior model. As mentioned in Section 1, to the best of our knowledge no study has used the TPB framework (or other behavioral frameworks) to determine backyard burning or household illegal dumping, so it is difficult to infer the general applicability of the TPB framework for negative household waste management behaviors. However, we suspect that the issues discussed above might be related, at least partially, to the already mentioned wariness of respondents to openly admit that they (or their normative groups) engage in these negative behaviors, as it has been identified in other studies of negative behaviors unrelated to waste management (Bazargan-Hejazi et al., 2017; Zhou et al., 2016).

4.2 Household waste management practices and their influencing factors

According to our results, the socio-economic and location characteristics are the most influential factors for negative SWM behaviors. Household location has a moderate positive effect both for backyard burning (0.358) and illegal waste dumping (0.255), while the education of the household head has a weak negative effect only for backyard burning (-0.12). The strongest predictor of waste dumping behavior is the general satisfaction with the waste management services, which has a moderate negative effect (-0.333) (Table 3). In other words, the lower the satisfaction with the waste management services and the more remote the location of the household, the higher is the prevalence of these negative SWM behaviors. Other studies focusing only on socio-economic characteristics through the use of regressions, have found that higher levels of education of the household head (Adzawla et al., 2019; Wang et al., 2018) and the location in more urbanized areas (Adzawla et al., 2019) reduce waste burning and dumping. As mentioned in Section 1, to the best of our knowledge no studies have explored the influence of service satisfaction on negative SWM behaviors. However, some studies have found a moderate (but not significant) influence on SWM satisfaction and willingness to conduct separation (Sekito et al., 2013), and that the lack of satisfaction with waste management services decreases the willingness to pay for the service (Babaei et al., 2015). The results of this study suggest that regardless of socio-economic conditions, efforts to increase the satisfaction of the urban residents with waste management could motivate them to improve their SWM practices. Additionally, it provides evidence on the importance of adequately addressing the SWM needs of residents in the outskirts of the city, who might not be adequately served under the current SWM system.

For the positive SWM behaviors, in general, the latent constructs had a stronger influence than socio-economic variables. The strongest predictors were identified for the separation behavior,

and include a positive influence from the concrete knowledge to conduct waste separation (0.568), positive attitudes towards waste separation (0.566), and knowledge of the local context (0.329) (Table 3). For recyclable donations, the strongest predictor is a positive attitude towards the behavior (0.357), followed by general awareness (0.216) and knowledge of the local context (0.143) (Table 3). Other studies have found that different types of knowledge and convenience for recycling are some of the most relevant factors influencing waste separation and recycling behaviors (Barr et al., 2001). Regarding convenience, an interesting finding from our study is that the frequency of wastepickers' activities has a significant effect on recyclable donation that is higher (0.141) than the existence of separate waste collection in the neighborhood (0.054) (Table 3).

For recyclables selling, the estimated factors have a relatively weaker effect compared to the other SWM behaviors, with income and household location being the main influencing factors (portraying income generation as a driver of the behavior). Finally, for the use of drop-off facilities, it seems logical that the satisfaction with education and communication activities is positively related to engagement in this SWM practice (0.169). This suggests that the respondents exposed to more educational campaigns are probably more aware of the existence of these facilities, which are relatively new in the city (Lozano and Gasparatos, 2019). It also seems reasonable that respondents in areas with more frequent wastepicker operations prefer to give them the recyclable material, instead of taking it to the drop-off facility, resulting thus in a negative effect for this predictor (-0.118).

As suggested by our results, in the positive behaviors group there are considerable differences among the factors identified for each behavior (Table 3), which demonstrates the need of distinguishing between them during the analysis. As indicated by Knussen et al (2004), issues

might arise when combining various behaviors with similar but different characteristics into a single variable (e.g. the act of separating the waste vs. the act of delivering it to a recycling point).

4.3 Implications and future research

Our study has various implications for policy and practice, both for Santa Cruz, as well as other rapidly urbanizing cities of the developing world. First, this study is an important step towards identifying the prevalence of positive and negative SWM behaviors, and their influencing factors. The combination of EFA and SEM in our study tested the validity of the instrument to reflect the theorized constructs, and identified the influencing factors through a tool (i.e. SEM) which is considered to be more robust than other commonly used methodologies such as regression analysis (Musil et al., 1998; Nusair & Hua, 2010).

Through the EFA we identified issues in the measurement of the initially theorized constructs, and conducted the necessary changes to assure a proper factor identification through the SEM. Although relatively few studies have followed this comprehensive approach in the past, recent literature highlights the benefits of following this procedure to improve the quality of results (Asparouhov & Muthén, 2009; Liu, Zhao, Zhou, & Tang, 2018).

Furthermore, the results suggest that negative SWM behaviors might be more influenced by a "motivational" aspect related to dissatisfaction with the SWM services, than by other commonly attributed factors such as awareness, income, and education (Adzawla, Tahidu, Mustapha, & Azumah, 2019; Chung & Lo, 2004). Furthermore, the strong effect of the household location (regardless of income or education) suggests that there are unobserved factors related to this

aspect, despite our best attempts to account for them in the survey (e.g. prevalence of stray animals). Nevertheless, these findings indicate that municipal cleansing companies or local governments should find ways and invest effort and resources in (a) improving the relationship with local communities, and (b) identifying the unattended SWM needs from communities in peri-urban areas. Both of the above seem to be contributing to the pervasiveness of these negative behaviors, and point to the need to find adequate solutions.

For positive waste management behaviors, the results provide further support to already established ideas regarding the importance of awareness, knowledge, and attitudes for reinforcing recycling behaviors (Almasi et al., 2019; Bhawal Mukherji, Sekiyama, Mino, & Chaturvedi, 2016). Furthermore, the results provide evidence about additional factors influencing each of the behaviors such as (a) the role of convenience (i.e. effect of waste picking frequency) in the recyclable donation and use of drop-off facilities; and (b) the economic motivations (i.e. effect of income) for recyclables selling. Similar to the negative behaviors discussed above, these results can provide some guidance for local government initiatives in Santa Cruz and other rapidly urbanizing cities. In particular they point to the need to carefully consider the actual location of drop-off stations or establish community-based recycling initiatives in areas where economic motivations can affect positively recycling behavior.

Finally, the study points to multiple avenues for future research. First, the analysis showed that the use of TPB might present several challenges in the context of solid waste management behaviors, at least in the context of our research. However, given the lack of consensus in the existing literature about the causes and solutions for the challenges outlined in Section 4.1 (Sniehotta et al., 2014; Trafimow, 2015), it is still valuable to extract some of the lessons learnt from our study. While the sample size of our study is considered sufficient for our

methodological approach, and the sampling procedure guaranteed that the characteristics of the different areas of the city are well represented, it is important to conduct similar studies to contrast the results obtained in our research both in Santa Cruz and other developing cities with similar characteristics. Furthermore, as household location was found to be an important determinant for negative behaviors, future studies should expand the number of variables associated to household location, to identify the specific mechanisms that lead to these outcomes.

5 Conclusions

This study estimated the prevalence of different SWM practices at the household level, including various "negative" and "positive" behaviors, as well as the factors influencing each of these behaviors in Santa Cruz, Bolivia. The studied negative SWM behaviors consisted of illegal dumping and backyard burning, while the positive behaviors included source separation, recyclables donation, recyclables selling and use of drop-off facilities. The tested factors included very diverse observable (i.e. location, socio-demographic characteristics) and non-observable (latent constructs) variables analyzed through a combination of EFA-SEM. Collectively the results bridge many gaps for SWM practices in developing countries, and are particularly novel for the research on negative household waste management practices, as no study has currently explored these behaviors through robust approaches as the one we present in this research. As such they can provide very useful insights to guide environmental management in the waste sector in rapidly urbanizing contexts of the developing world.

The results indicate that factors such as the level of satisfaction with the waste management service and the distant location of the household from the city center have the greatest influence

for both negative SWM behaviors, with the level of education also influencing backyard burning behaviors. For positive SWM behaviors, waste separation and recyclable donation are mostly influenced by latent constructs such as attitudes, knowledge, and awareness. The most relevant predictors for recyclables selling and the use of drop-off stations are observable variables such as income and location, although with smaller effects in both cases. Such findings can contribute to the development and implementation of more effective policies by the local government to reduce negative and promote positive SWM practices.

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