The drivers and barriers to battery pack drop-off intention perceived by Belgian households

S. Lizin[1], M. Van Dael[1], R. Hoogmartens[1], and S. Van Passel

[1]Centre for Environmental Sciences, Hasselt University, Belgium

Abstract. This research aims to investigate the drivers and barriers to battery pack drop-off intention perceived by Belgian households. It is the first study looking specifically at this specific type of recycling. A standardized online survey, extending the framework provided by the Theory of Planned Behaviour by incorporating measures on objective knowledge, the perception of the consequences, moral norms, end-of-life habits and the perceived effectiveness of BEBAT's actions, has been made. Data was collected during the 11/2014-01/2015 period and processed using partial least squares structural equation modelling. A moderate to strong R^2 of 0.62 was found, signalling that our model predicts the drop-off intention well. Based on the size of the path coefficients we can conclude that perceived behavioral control, moral norm, and consequences have the largest influence on the intention to drop-off battery packs as soon as they become unnecessary.

1 Introduction

We are increasingly mobile, and therefore, so are our devices. Consequently, to feed our increasing energy hunger the use of portable batteries has been firmly rising (Li et al., 2013). Unfortunately, batteries may have a negative impact on the environment if they are not properly collected and recycled (Karnchanawong and Limpiteeprakan, 2009). The collection of portable batteries, both primary and rechargeable, in Europe is mandated by Directive 2006/66/EC which requires Member States to achieve a collection rate of 25% in 2012 and 45% in 2016 (EU, 2006). Therefore, OVAM, which is a Flemish institution responsible for waste management related policy, has highly committed to the proper management of used batteries by enforcing a take-back scheme. Battery producers and importers, intermediaries, and the final seller are legally obliged to accept used batteries. To meet the legal obligation to collect 45% of used batteries by 2016 producers and importers have created BEBAT, which is the single nonprofit organization responsible for collecting, sorting, and recycling of portable batteries in Belgium. Having a longstanding tradition in separate waste collection, Belgium has passed this cap prior to this date achieving a collection rate of over 50% in 2012 (Perchards/Sagis, 2013). With such a collection rate, we are amongst the

frontrunners in battery recycling in Europe. However, despite the efforts of both agents (i.e. OVAM and BEBAT), 45% of used batteries and accumulators are not properly collected. 27% of used batteries and accumulators are hoarded at home, whereas the remaining 18% end up in the incorrect bin. In absolute terms, a regular family has on average 107 batteries in its possession, be it used, new, or in use (OVAM, n.d.). According to prior market research ordered by BEBAT, used batteries are brought to a collection point on average 2-3 times a year. Furthermore, it was revealed that about 96% of the population is aware of BEBAT's collection system's existence (Coonen and Peeters, 2014). Seeing the environmental impact of the eluding batteries that may contain heavy metals and the issue of resource scarcity, it is important to identify the reasons for this recycling gap and how to bridge it.

Whereas the current collection rate is worthy of praise, it should be noted that it does not differentiate between types of portable batteries. One can differentiate batteries according to the type in: (l) loose batteries, (2) button cells, and (3) battery packs. According to personal communication with BEBAT the lowest collection rates in Belgium for households are currently found for battery packs. The latter are batteries which are used to power, for example, mobile phones, digital cameras, portable game consoles, and power tools (see Figure 1). A low collection rate is troublesome given that time literally is money. Battery packs that were hoarded for a long period of time are less valuable and hence more costly as the recycling industry has moved on to a recycling process optimized for other battery content. For instance, the amount of cobalt in lithium-ion driven battery packs is decreasing which causes the costs of recycling to increase. Hence, to minimize the costs of avoiding external costs people are to be stimulated to drop off used battery packs as quickly as possible. For these reasons, this research aims to investigate the drivers and barriers to battery pack drop-off intention perceived by Belgian households.

Figure 1. Examples of battery packs

Our research can be situated within the wide branch of literature analysing pro-environmental behavior. The latter refers to behaviors that either harm the

environment as little as possible or benefit the environment (Steg and Vlek, 2009). The stimulation of such conduct is necessary as many environmental problems, such as heavy metal leaching, are rooted in human behavior, such as not sorting correctly (Vlek and Steg, 2007). Our focus will be on a specific type of pro-environmental behavior, i.e. recycling, being the act of collecting, sorting, and depositing waste to a suited waste management provider. This is one of the most studied forms of environmentally responsible behavior because it mostly involves simple and economically feasible actions (Huffman et al., 2014). However, to the best of our knowledge, only a single study has explored recycling behavior concerning spent batteries. Hansmann et al. (2006) found that recycling knowledge, self-organization of recycling, and disagreement with justifications for non-recycling were positively related to recycling behavior, while attitudes towards ecological waste disposal and trust in waste disposal authorities were not directly related to respondents' self-reported battery recycling behavior. We add to the literature in this domain by looking at battery packs specifically. We argue that this is a specific type of battery, mostly used to power products in the higher end of the consumer electronics market and therefore different drivers and barriers may be at play. Different products may have different preferred end-of-life strategies.

The remainder of this report contains the following sections. First, we discuss the methodology used. In the next section we describe the survey and the collected sample. Section 4 contains an overview of the results of the different analyses. In section 5 we will discuss these results and in section 6 we will present the main findings of our work.

2 Methodology

To investigate the drivers and barriers on the intention of dropping off battery packs at a BEBAT collection point, we have decided to use the framework provided by the Theory of Planned Behavior (TPB) as a starting point. As recommended in literature, additional variables -besides attitude, subjective norm, perceived behavioral control, and past behavior- are included to be able to adequately explain intentions or behavior (Tonglet et al., 2004). Hence, an integrative (structural) model is being estimated (Bamberg and Möser, 2007). A standardized online survey was made in Dutch and French to collect data on the influence of (1) attitudes, subjective norms, perceived behavioral control, and past behavior after Ajzen (1991), extended with (2) the objective knowledge on how to recycle after Aertsens et al. (2011), (3) the perception of the consequences and moral norms after Tonglet et al (2004), (4) end-of-life habits after Knussen et al. (2004), and (5) the perceived

effectiveness of BEBAT after Wan et al. (2014) on the intention to drop-off battery packs at a BEBAT collection point. Data was collected during the 11/2014-01/2015 period via a market research company. An overview of the analysed model and hypotheses is provided in Figure 2.

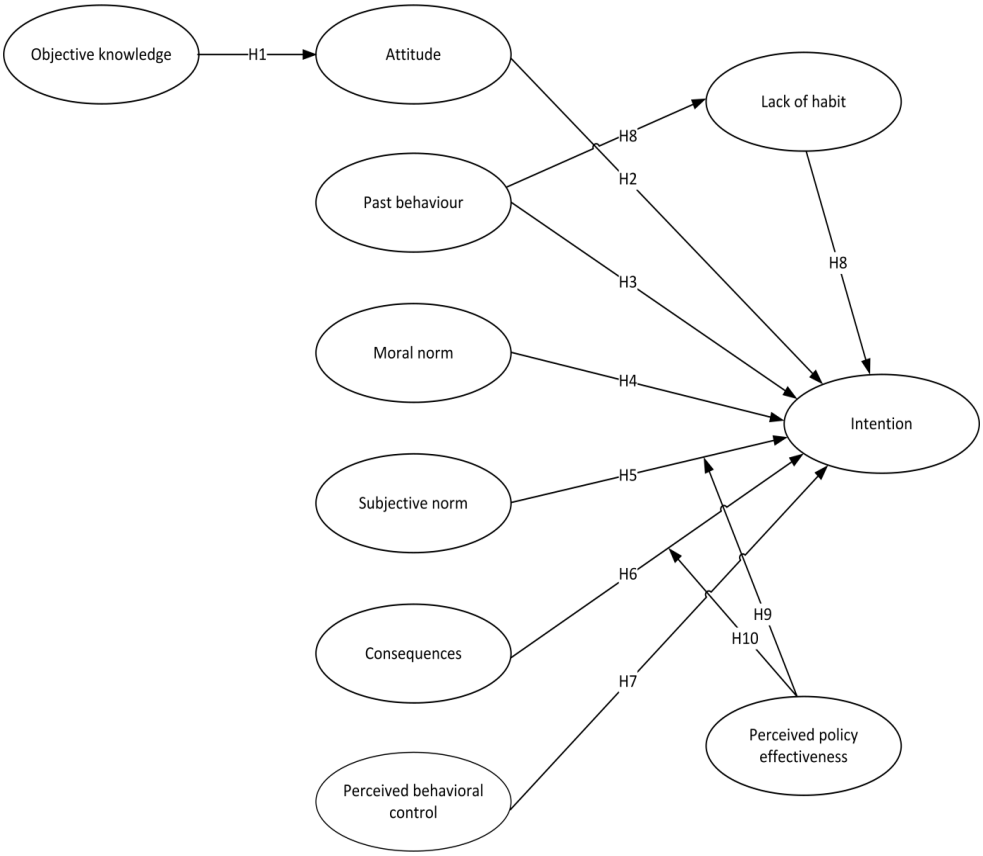

Figure 2. Overview of the general model and hypotheses

The hypotheses, H1 to H10, can be described as follows:

H1: The **higher** one's objective knowledge on recycling battery packs, the **more positive** the attitude towards dropping off used, removable battery packs at a BEBAT collection point as soon as possible. (+)

H2: The **more positive** one's attitude, the **higher** the intention of dropping off used, removable battery packs at a BEBAT collection point as soon as possible. (+)

H3: The **more** one has properly recycled electronic waste streams in the past, the **higher** the intention of dropping off used, removable battery packs at a BEBAT collection point as soon as possible. (+)

H4: The **more** one feels morally obliged to recycle battery packs, the **higher** the intention of dropping off used, removable battery packs at a BEBAT collection point as soon as possible. (+)

H5: The **more** one perceives recycling battery packs as a socially desirable action by peers, the **higher** the intention of dropping off used, removable battery packs at a BEBAT collection point as soon as possible. (+)

H6: The **more** one perceives the positive consequences of recycling battery packs as being present, the **higher** the intention of dropping off used, removable battery packs at a BEBAT collection point as soon as possible. (+)

H7: The **more** one feels in control of the process of carrying out battery pack recycling, the **higher** the intention of dropping off used, removable battery packs at a BEBAT collection point as soon as possible. (+)

H8: The lack of a habit of dropping off battery packs at a BEBAT collection point mediates the influence of past behavior on the intention of dropping off used, removable battery packs at a BEBAT collection point as soon as possible. (-)

H9: The **more** people think that BEBAT is highly effective in stimulating people to recycle battery packs, the **lower** the influence of subjective norms on the intention of dropping off used, removable battery packs at a BEBAT collection point as soon as possible. (-)

H10: The **more** people think that BEBAT is highly effective in stimulating people to recycle battery packs, the **lower** the influence of perceiving the positive consequences of recycling battery packs as being present on the intention of dropping off used, removable battery packs at a BEBAT collection point as soon as possible. (-)

Using structural equations modelling (SEM) the underlying relationships between latent variables, measured indirectly by indicator variables can be

assessed. The term "structural equation model" most commonly refers to a combination of two things: a "measurement model" that defines latent variables each being measured by one or more observed indicator variables, and a "structural model" that links the latent variables together. The two parts of a structural equation model are linked together by a system of simultaneous regression equations. Within SEM one of two approaches can be chosen depending on the objectives of the research. Covariance based SEM is used to confirm or reject theories, whereas PLS-SEM is used when theory is less developed. In this research, PLS-SEM is chosen, because no former study has been executed. Additionally, PLS-SEM offers the following advantages: (1) it can handle formative, reflective, and single-item measurement scales, (2) it makes virtually no assumptions about the distribution of the data, (3) it does not require large sample sizes, (4) it allows for estimating higher order models, and (5) it works better for complex models, i.e. when the focus is on the interrelationships among a large set of factors and in case of many manifest variables (Chin and Newsted, 1999, Chin, 2010). PLS-SEM is an ordinary least squares (OLS) regression based method. The estimation procedure estimates the structural path coefficients that maximize the R^2 values of the target endogenous latent variables while accounting for measurement error. The sequence of latent variables in a SEM-model is based on theory, logic, or practical experiences observed by the researcher. Typically measurement approaches are used that are validated by prior research. Besides, explaining target latent variables, PLS-SEM also allows testing for differences between identical models for different subsamples divided using a categorical variable (Hair et al., 2013). Hence, the goal of this research is not only to find out the latent drivers and barriers to battery pack drop-off intention, but also to reveal if and where heterogeneity in relationships is present. All estimations and tests are performed using the statistical software program IBM SPSS version 22.0 and SmartPLS 2.0.

3 Data collection and sampling

In order to collect the necessary input to perform the PLS-SEM analyses, first, an online survey was designed by the authors of this report. The survey consisted of an opening page and five different sections, being:

(1) **Screening & profiling**: In this section it was decided whether or not to allow respondents to participate in the survey. Hereafter, the respondents were profiled based on socio-demographic characteristics.

(2) **Introduction**: in a second section the respondents were carefully explained what the desired behavior entails. In this study the desired

behavior was defined as: dropping off unnecessary, removable battery packs to a BEBAT collection point as soon as possible. To assure full understanding, it was verified whether the provided definitions of 'unneccesary and 'removable' were memorized by the respondents. In case they did not reveal full understanding of the desired behavior, the definitions provided earlier were repeated once more, before being able to continue.

(3) **Opinion**: In a third section the respondents were asked to fill in several previously validated 7-point Likert scales, whose scores give rise to the indicator variables (see rectangular shapes in Figure 3) that shape all of the latent variables under revision (see circles in Figure 3), except for objective knowledge and past behavior.

(4) **Knowledge and past behavior**: In a fourth section, respondents' objective knowledge on recycling battery packs was verified. Based on the responses a knowledge index was created, which was used as a single-item measurement. Additionally, respondents past recycling behavior of all types of batteries was assessed. The scores on this series of questions gives rise to the indicator variables measuring the latent variable past behavior.

(5) **Environment**: In the final section, respondents' pro-ecological worldview was assessed using a previously validated scale (Dunlap et al., 2000).

Next, in order to obtain a sample of the Belgian population, a marketing research company was hired to carry out the data collection and survey translation into French. The online survey was taken from their panel of respondents during the 11/2014-01/2015 period. In total 1638 respondents aged between 18 and 64 participated in the survey. The primary sampling goal was to collect data that would subsequently allow investigating whether heterogeneity was an issue. We hypothesized that observed heterogeneity could be present in the following features: (1) whether the majority of battery packs was brought back to a BEBAT collection point (yes/no), (2) whether the living area is a rural or urban environment, and (3) what lifestage the respondent is in (young adult; family -12; family +12; medior; senior). As guidelines dictate that the minimum sample size is obtained by multiplying the maximum amount of arrowheads pointing at a latent variable times 10, 70 respondents are required per subgroup in our study. An overview of the obtained subgroup sample sizes is given in Table 1.

Table 1. Subgroup sample sizes (# respondents)

Battery pack = No			**Battery pack = Yes**		
	Living area			**Living area**	
Lifestage	*City*	*Rural*	**Lifestage**	*City*	*Rural*
Young adult	98	85	*Young adult*	69	73
Family -12	73	87	*Family -12*	54	67
Family +12	102	87	*Family +12*	100	94
Medior	86	88	*Medior*	93	91
Senior	50	62	*Senior*	89	90

The respondents' mean age is 45. The percentage of Dutch speaking respondents is 57%, the remaining respondents are French speaking. The majority (i.e. almost 42 %) of the respondents' households consists of 2 people. The percentage of respondents with a family size of 1, 3, 4 and 5 respectively amounts to about 19%, 18%, 14% and 6%. Only 2% of respondents indicate to have a family size of over 5 members. Almost 60% of respondents had no kids. Only 17% of respondents has kids under the age of 12 and 23% has kids older than 12. The number of respondents living in the city and rural area are equally divided. Also the number of respondents that brought battery packs back to a BEBAT collection point are roughly the same. From the respondents, 60% is living in Flanders, 32% is living in the Walloon part of Belgium and 8% is living in Brussels. In Table 2 and 0 the distribution of respondents' education level and income can be found. Almost 46% has a more than part-time job, whereas 7% has a part-time job. The percentage of respondents on retirement is equal to 21%. The percentage of students, housewives/men, unemployed and disabled is respectively 9%, 7%, 5% and 5%.

Table 2. Education level respondents

Category	**Percentage**
Primary school	3.1%
Secondary school (general)	23.3%
Secondary school (technical and art)	28.3%
Higher education	31.6%
University	13.7%

Table 3. Income level respondents

Income (€/month)	Percentage
0	3.4%
<500	0.7%
500-1499	21.3%
1500-2499	31.0%
2500-3499	24.4%
3500-4499	14.2%
4500-6000	4.0%
>6000	1.1%
Missing	19.0%

4 Results

PLS-SEM is performed to gain understanding of the relationship between the different latent variables or constructs (i.e. unobservable variables). PLS-SEM allows to simultaneously estimate the structural and measurement model. The structural model describes the relationships between the latent variables, whereas the measurement model describes the relationship between the indicators and the latent variables. Note that the indicators measure the latent variables.

The latent variables 'Past behavior', 'Consequences', and 'Perceived behavioral control' are assumed to be formative, whereas the latent variables 'Attitude', 'Subjective norm', 'Moral norm', Intention', and 'Objective knowledge' are defined as being reflective. Formative indicators are multidimensional in nature (i.e. a change in one indicator is not necessarily associated with a change in another indicator of that latent variable), whereas reflective indicators are unidimensional and thus highly correlated. An overview of the characteristics of reflective and formative latent variables is provided by (Jarvis et al., 2003). It is crucial to correctly define the relationship between the latent variables and its indicators in order to avoid biased parameter and standard error estimates for the structural model and inflated type II errors (MacKenzie et al., 2005).

An overview of the structural equation model is provided in 0. The model is first estimated without moderating effects. These effects are tested after the structural and measurement model are estimated and confirmed and mediation is verified. A mediator is a variable that influences the strength or even the sign of a path coefficient which depends on the predictor variable. A

moderator is a variable that influences the strength or even the sign of a path coefficient which does not depend on the predictor variable. Path coefficients are standardized values and represent the strength of the relationship between latent variables.

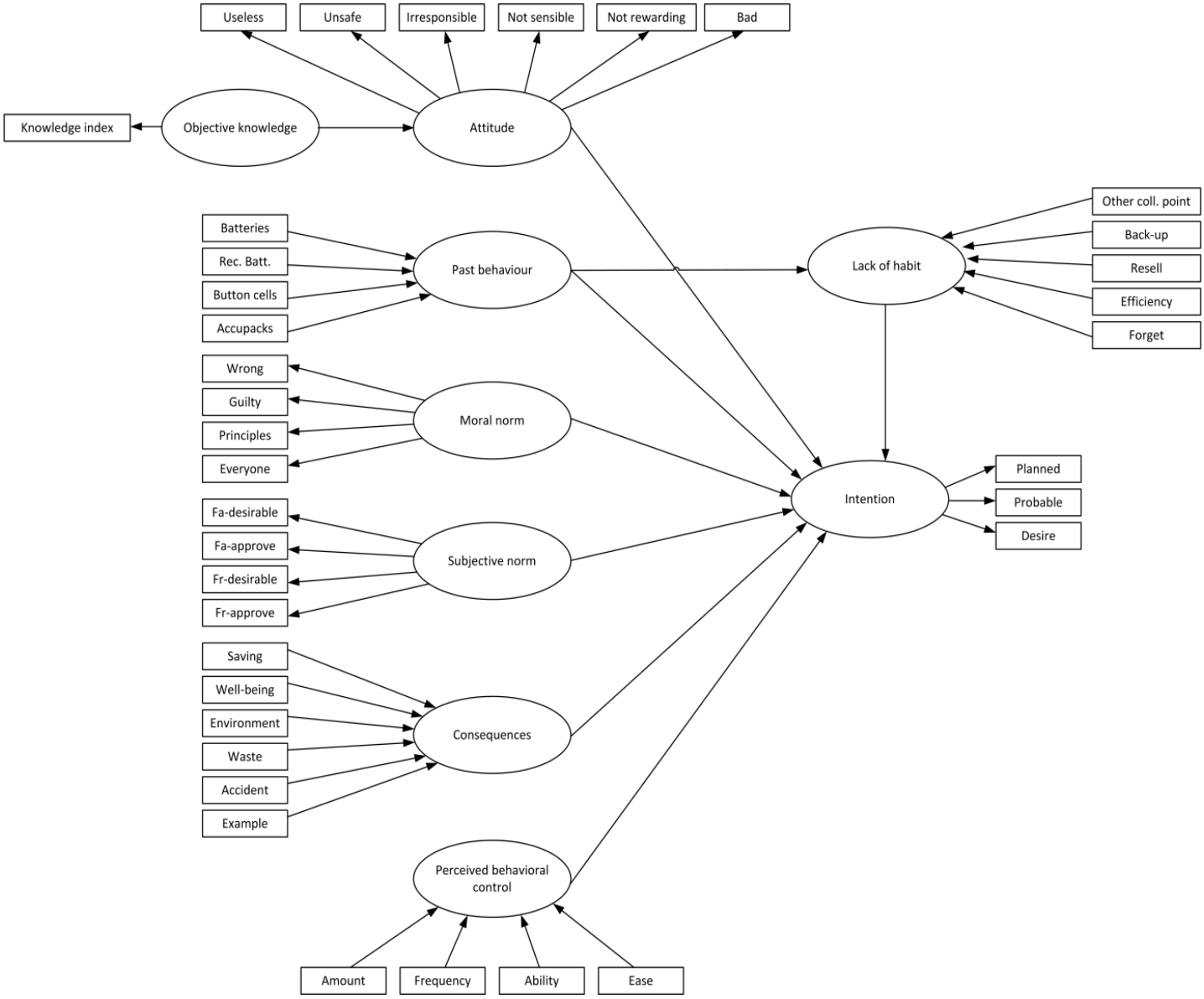

Figure 3. Structural equation model

The results of the structural equation model are provided in Figure 4. However, these result cannot be interpreted yet. First, it should be tested whether the measurement and structural model are adequate and only then can one turn to verifying the significance of the obtained results. In the next sections, we will hence first discuss the results of the evaluation of the reflective measurement models. After that, we will show the results of the formative measurement models. Section 0 will contain the evaluation of the structural model and mediating effects. Afterwards, when the model is confirmed, we will evaluate the moderating effects in section 0. Finally, observed heterogeneity will be tested in section 0.

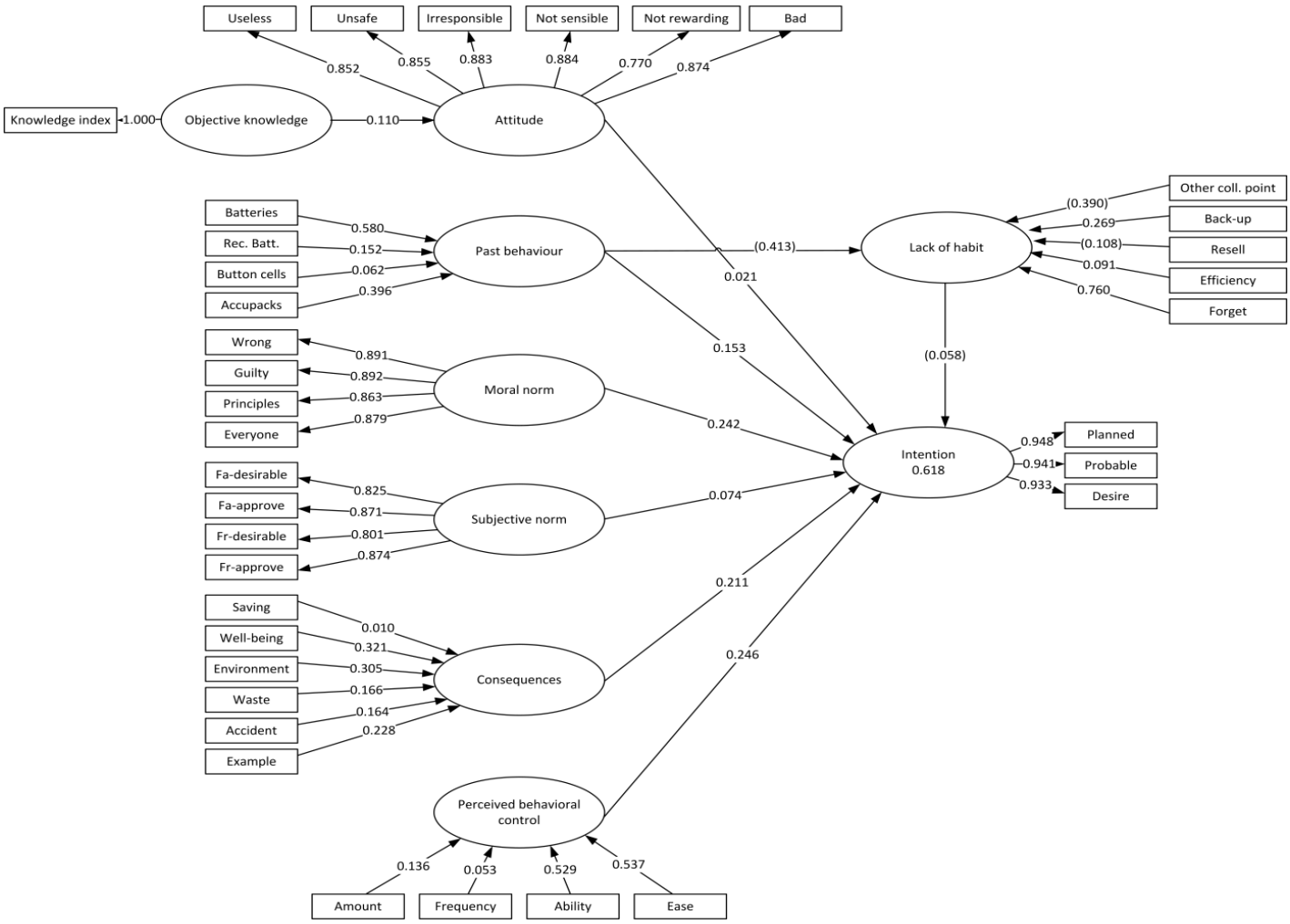

Figure 4. Structural equation modeling results

4.1 Evaluation of reflective measurement models

When evaluating reflective measurement models, different aspects have to be tested, being: (1) indicator reliability, (2) construct reliability, (3) convergent validity, and (4) discriminant validity.

The indicator reliability specifies the part of an indicator's variance that can be explained by the underlying latent variable. At least 50% of an indicator's variance should be explained by the latent variable (i.e. loading above 0.70). For the construct reliability the composite reliability is used. Cronbach's alpha could also be used, but this measure is sensitive to the number of items in the scale and is more conservative. Values for the composite reliability above 0.60 are acceptable for exploratory research. The convergent validity measures the extent to which a measure correlates positively with alternative measures of the same construct. Both the outer loadings and average variance extracted (AVE) can be used to test this. The outer loadings should be higher than 0.70. The AVE is calculated as the sum of the squared loadings divided by the number of indicators. An AVE of less than 0.5 is considered insufficient, because more variance is due to error variance than to indicator variance. Finally, the discriminant validity represents the extent to which a construct is distinct from other constructs, i.e. unique. The cross loadings may not exceed the indicators' outer loadings and the Fornell-Larcker criterion has to be met. The latter compares the square root of the AVE values with the latent variable correlations.

It can be concluded that all criteria are met. An overview of the results of the overall reflective measurement model is provided in Table 4.

Table 4. Estimation results and psychometric properties of reflective measurement models

Latent variable	Indicator	Loadings	Indicator reliability	Composite reliability	AVE	Discriminant validity
Attitude	Useless	0.852	0.726	0.942	0.729	yes
	Unsafe	0.855	0.731			
	Irresponsible	0.883	0.780			
	Not sensible	0.884	0.781			
	Not rewarding	0.770	0.593			
Moral norm	Bad	0.874	0.764	0.933	0.776	yes
	Wrong	0.891	0.794			
	Guilty	0.892	0.796			
	Principles	0.863	0.745			
	Everyone	0.879	0.773			
Subjective norm	Fa-desirable	0.825	0.680	0.908	0.711	yes
	Fa-approve	0.871	0.759			
	Fr-desirable	0.801	0.642			
	Fr-approve	0.874	0.764			
Intention	Planned	0.948	0.898	0.958	0.885	yes
	Probable	0.941	0.886			
	Desire	0.933	0.870			

4.2 Evaluation of formative measurement models

Formative latent variables require a different evaluation of the measurement model as indicators are not supposed to be correlated. For formative measures we assessed the indicator reliability. Convergent and discriminant validity do not have to be evaluated since indicators do not have to be strongly interrelated.

Indicator reliability is examined by verifying whether high correlations exists between indicators. The variance inflation factor (VIF) is used to check whether multicollinearity poses a problem. The VIF should not exceed a value of 10. Using a bootstrapping procedure it is also evaluated which indicators are significant and relevant. The null hypothesis, stating that an outer weight equals zero (i.e. has no significant effect), is rejected when the interval does not include zero. When it seems that indicators are not significant, these are further investigated. In case the outer loadings of these indicators are significant, it can be opted to keep the indicator in the model.

The results of the overall formative measurement models are provided in Table 5. Based on the results, it is decided to keep all indicators within the model.

In order to check for construct reliability it is suggested to use a general question, which might be considered reflective, related to each of the formative constructs in order to evaluate formative measurement model's external validity. However, no question is taken into account in our survey as the questionnaire is already perceived as being quite long. As a consequence, the external validity of the formative constructs was not evaluated.

Table 5. Results bootstrapping procedure

Latent variable	**Indicator**	**Outer weights (outer loadings)**	**Significance level (* .10 ** .05 ***.01)**	**Confidence interval (10%)**
Past behavior	Batteries	0.580 (0.905)	***	[0.493;0.667]
	Rec. Batt.	0.152 (0.732)	***	[0.072;0.232]
	Button cells	0.062 (0.733)	NS	[-0.023;0.147]
	Accupacks	0.396 (0.804)	***	[0.313;0.479]
	Saving	0.010 (0.296)	NS	[-0.043;0.063]
Consequences	Well-being	0.321 (0.925)	***	[0.196;0.446]
	Environment	0.305 (0.917)	***	[0.174;0.436]
	Waste	0.166 (0.795)	***	[0.079;0.253]
	Accident	0.164 (0.597)	***	[0.092;0.236]
	Example	0.228 (0.839)	***	[0.121;0.335]
Perceived behavioral control	Amount	0.136 (0.461)	***	[0.079;0.193]
	Frequency	0.053 (0.875)	*	[0.004;0.102]
	Ability	0.529 (0.868)	***	[0.446;0.612]
	Ease	0.537 (0.319)	***	[0.458;0.616]
Lack of habit	Other coll. Point	-0.390 (0.648)	***	[-0.472;-0.308]
	Back-up	0.269 (0.648)	***	[0.170;0.368]
	Resell	-0.108 (0.193)	**	[-0.191;-0.025]
	Efficiency	0.091 (0.512)	NS	[-0.004;0.186]
	Forget	0.760 (0.889)	***	[0.664;0.856]

4.3 Evaluation of the structural model

The main focus of a structural model in PLS-SEM analysis is on the predictive power in terms of variance explained, as well as on the significance of all path coefficients. To assess the hypotheses accompanying the various path coefficients, a bootstrapping procedure is again used to obtain the standard errors. The results of this procedure are shown in Figure 5.

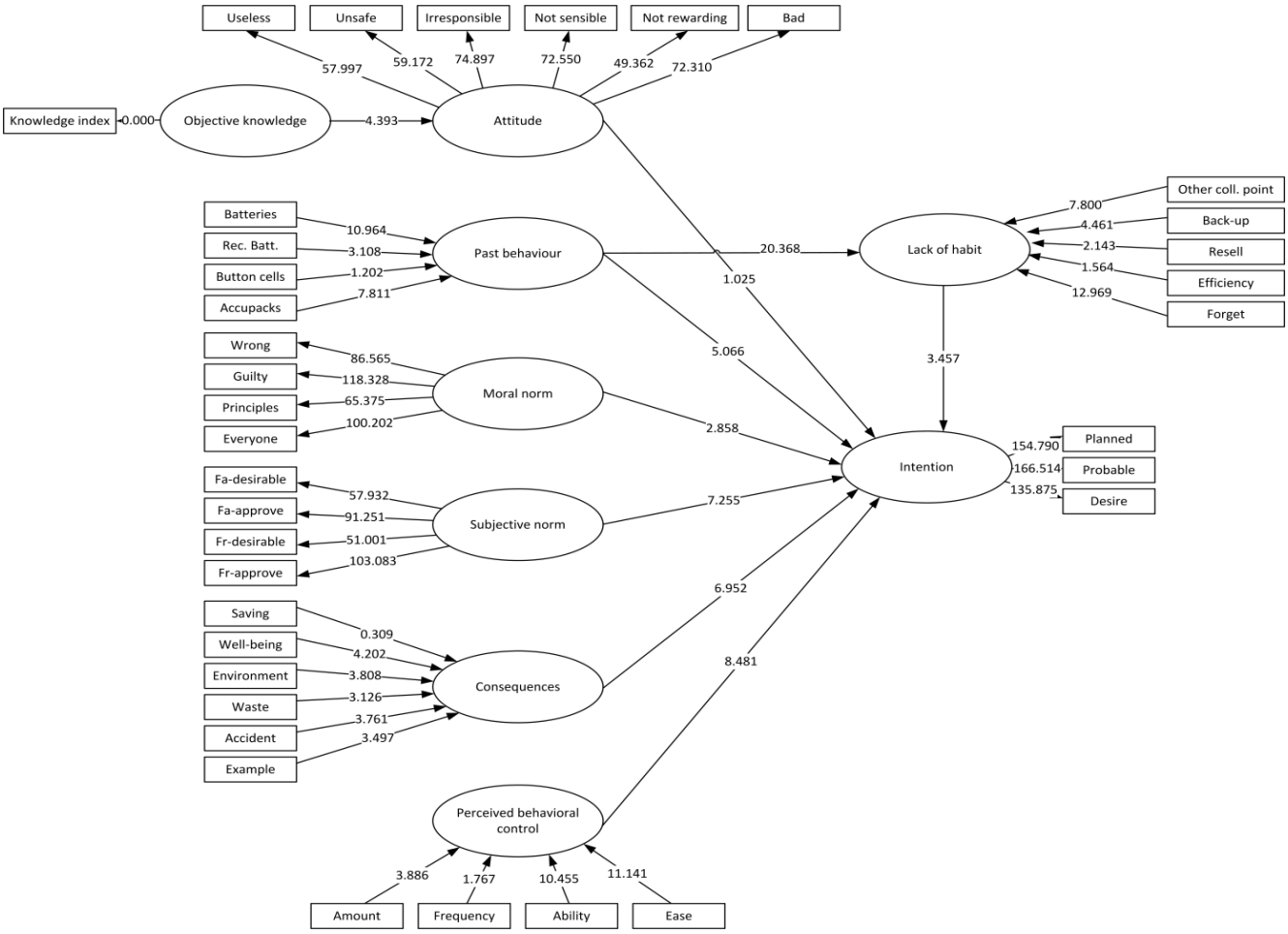

Figure 5. Structural equation modeling bootstrapping results

In order to evaluate the structural model, the predictive accuracy is estimated, the relationships between latent variables is analysed, the effect size f^2, and the predictive relevance of the path model is interpreted, as well as the effect size q^2.

The model's predictive accuracy is evaluated using the R^2 values of the endogenous construct (i.e. intention). There is a lot of discussion about rules of thumb for acceptable R^2 values because they depend on the model's complexity and the research discipline. According to (Chin, 1998), R^2 values of 0.67, 0.33 and 0.19 can be considered as respectively strong, moderate and weak. It can be concluded that the R^2 value in our study (i.e. 0.62) is moderate to strong. To test for the R^2's significance, a bootstrap confidence interval is calculated by using the equation described in (Tenenhaus et al., 2005). The R^2 90% bootstrap confidence interval amounts to [0.39,0.74].

The significance of the relationship between the latent variables is analyzed using a bootstrapping procedure. All relationships are significant and positive, except for the relationship between 'attitude' and and 'intention'. Hence, the hypotheses H1 and H3 to H7 are confirmed.

The impact of omitting an exogenous construct on the R^2 value of the endogenous constructs can be evaluated. As such, the contribution of each exogenous construct in terms of explanatory power can be compared. The measurement is referred to as the f^2 effect size, with values of 0.02, 0.15 and 0.35 indicate the latent exogenous variable's weak, moderate or substantial influence on the latent endogenous variable (Cohen, 2013). It is concluded that the exclusion of one of the exogenous variables has no or only a weak effect on the R^2 value of intention.

In the following step a blindfolding procedure is run to have an idea of the predictive relevance of the path model. From the procedure in SmartPLS the Stone-Geisser's Q^2 value is obtained (Geisser, 1974). The Q^2 value for intention amounts to 0.54 which means the model has predictive relevance for intention. The relative impact of exogenous constructs can be compared by means of the q^2 effect size. Similarly, the q^2 effect size is lacking or weak for all exogenous variables.

4.4 Evaluation of moderating effects

A continuous moderator is a continuous variable that influences the strength or even the sign of a path coefficient. In this work the effects of the perceived policy effectiveness of BEBAT on consequences and subjective norms were investigated by means of the two-stage approach. The results of the estimation procedure on the model used in the second step of the approach are shown in Figure 6. Similarly, bootstrapping is performed to allow making statements about the path coefficients' significance. This led to the conclusion that the only significant moderating effect is that of the perceived policy effectiveness on the weight of the subjective norms. Hence, only hypothesis H10 is confirmed.

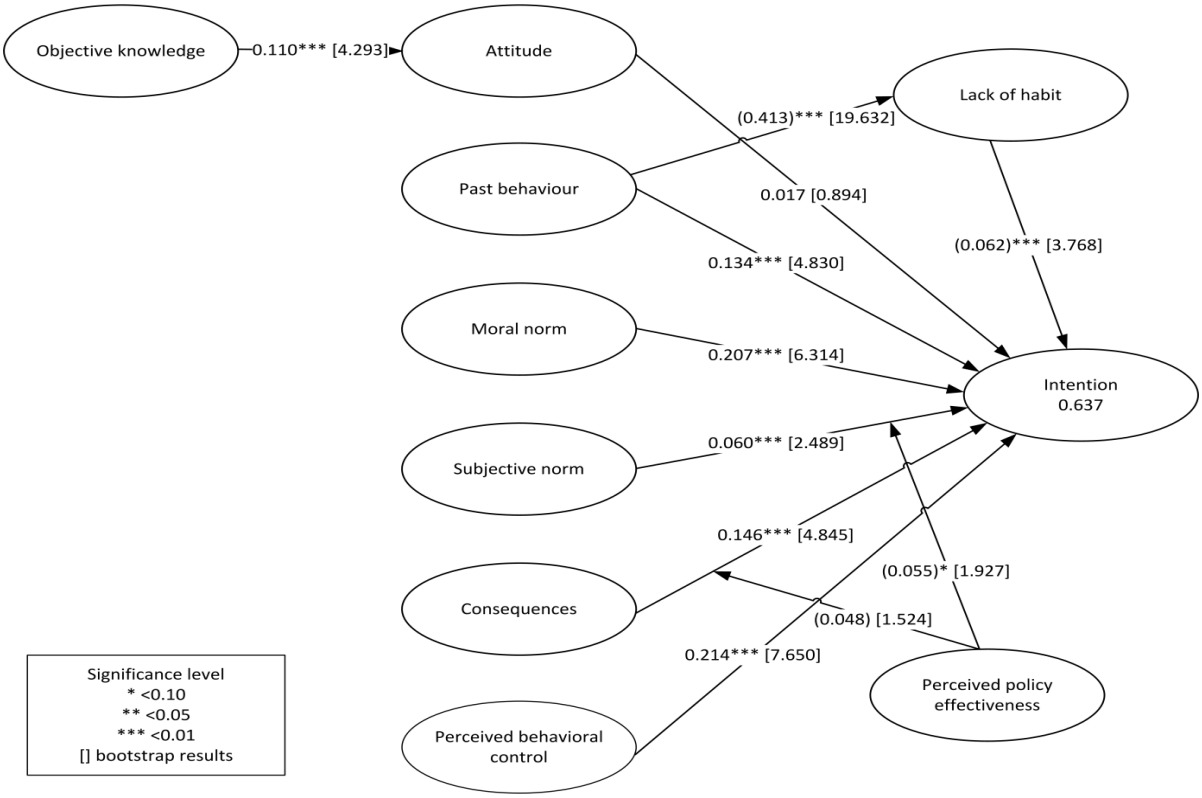

Figure 6. Structural equation modeling with moderating effects

4.5 Evaluation of observed heterogeneity

A multi-group analysis (MGA) is used to assess the impact of observed (categorical) variables, such as lifestage, living area, and past drop-off behavior, on the estimated path coefficients. Observed heterogeneity exists when significant differences are found between path coefficients when dividing the dataset into subgroups based on observed features. Seeing that PLS-SEM does not make any distributional assumptions, a non-parametric approach is used to test for differences between subgroups (Henseler, 2012). Such an analysis is meant to reveal the pitfalls of relying solely on the full sample's results. Nevertheless, it assumes measurement invariance, i.e. we assume that the subgroups do not require a different measurement model. In Table 6 we first present the results of the MGAs when dividing the dataset in subgroups based on a single feature. The p-value expresses the probability that the second subgroup has a larger population parameter than the first subgroup. Hence, if the path coefficient is positive a p-value smaller than 0.10 signals that the first subgroup has the largest impact, whereas a value larger

than 0.90 indicates the opposite. In case the path coefficient is negative a p-value smaller than 0.10 signals that the first subgroup has the smallest absolute impact, whereas a value larger than 0.90 indicates the opposite.

Table 6. Results MGA single feature based subgroups

Observed variable	Subgroup	Number	Significant difference	Sign	p-value
Accupack	Minority	818	Subjective norm -> Intention	+/NS	0.004
	Majority	820	Lack of habit -> Intention	NS/-	0.015
			Objective knowledge -> Attitude	+/+	0.050
Education	Low	895	Attitude -> Intention	+/NS	0.049
	High	743			
Ecological worldviev	Low	835	Moral norm -> Intention	+/+	0.991
	High	803	Past behavior -> Intention	+/+	0.082
			Lack of habit -> Intention	-/NS	0.965
			Objective knowledge -> Attitude	+/NS	0.000
Gender	Female	822	Moral norm -> Intention	+/+	0.090
	Male	816	Objective knowledge -> Attitude	NS/+	0.985
Language	Dutch	940	Subjective norm -> Intention	+/NS	0.025
	French	698	Past behavior -> Intention	+/+	0.0924
			Objective knowledge -> Attitude	+/+	0.993
Living area	City	814	/	/	/
	Rural	824			
Lifestage	Young adult	325	Subjective norm -> Intention	+/NS	0.081
	Familiy -12	281	Moral norm -> Intention	+/+	0.042
			Consequences -> Intention	+/+	0.982
			Objective knowledge -> Attitude	+/+	0.969
Lifestage	Young adult	325	/	/	/
	Family +12	383			
Lifestage	Young adult	325	Subjective norm -> Intention	+/NS	0.066
	Medior	358	Lack of habit -> Intention	NS/-	0.019
			Objective knowledge -> Attitude	+/NS	0.04
Lifestage	Young adult	325	Subjective norm -> Intention	+/NS	0.014
	Senior	291			
Lifestage	Family -12	281	Subjective norm -> Intention	NS/+	0.926
	Family +12	383	Moral norm -> Intention	+/+	0.904
			Consequences -> Intention	+/+	0.044

Observed variable	Subgroup	Number	Significant difference	Sign	p-value
			Objective knowledge -> Attitude	+/+	0.013
Lifestage	Family -12	281	Consequences -> Intention	+/+	0.037
	Medior	358	Lack of habit -> Intention	NS/-	0.075
			Objective knowledge -> Attitude	+/NS	0.000
Lifestage	Family -12	281	Moral norm -> Intention	+/+	0.965
	Senior	291	Consequences -> Intention	+/+	0.025
			Objective knowledge -> Attitude	+/NS	0.009
Lifestage	Family +12	383	Subjective norm -> Intention	+/NS	0.059
	Medior	358	Lack of habit -> Intention	NS/-	0.010
			Objective knowledge -> Attitude	+/NS	0.032
Lifestage	Family +12	383	Subjective norm -> Intention	+/NS	0.007
	Senior	291			
Lifestage	Medior	358	PBC -> Intention	+/+	0.090
	Senior	291	Lack of habit -> Intention	-/NS	0.952

From the above the following trends can be derived additionally:

- There are only 2 groups without significant differences: city-rural and young adult-family+12.

- Differences are most common in the susceptibility towards objective knowledge, subjective norms, the lack of habit, moral norms, and consequences.

- Objective knowledge significantly differs between many subgroups. However, the attitude -> intention path coefficient is not significant for all of these subgroups.

- Subjective norms have a stronger impact on intention for people not bringing back more than 50% of their battery packs to a BEBAT collection point, for Dutch-speaking people, and for young adults and for families with kids older than 12 compared to families with kids younger than 12.

- Lack of habit has a stronger impact on intention for people not bringing back more than 50% of their battery packs to a BEBAT collection point, for people with a low pro-ecological worldview, and

for mediors compared to young adults, families with kids older than 12, and families with kids younger than 12.

- Moral norms have a stronger impact on intention for people having a high pro-ecological worldview, for females, for young adults, for families with kids older than 12, and for seniors compared to families with kids younger than 12.

- Consequences have a stronger impact on intention for families with kids younger than 12 compared to all other lifestage categories.

- The features causing most heterogeneity are: ecological worldview and lifestage (family -12 <-> family +12 & family -12 <->family +12).

- Only the lower educated respondents display a positive relationship between attitude and intention, whereas the other display an insignificant relationship.

- The influence of perceived behavioral control on intention is larger for mediors than for seniors.

5 Discussion

In this study we have verified what the drivers and barriers to battery drop-off intention are and have located which observed characteristics cause significant heterogeneity using an integrative structural model based on the TPB. This implies that the study results presented here are based on self-reported statements. The latter do not necessarily have a high correlation with observed behavior. The strength of the relationship has been found to depend on the product under study, but typically one overestimates the degree to which one displays the desired behavior when self-reporting (Huffman et al., 2014). Hence, further study based on objective measurements of actual behavior is needed to verify whether our findings hold in such a context. The importance of such a study is supported by the following conclusions that could be drawn from the survey. Almost 78% of the respondents said to bring back the majority of their battery packs to a BEBAT collection point in the past. This might be true, as there is no indication included here of the speed with which the battery packs are brough back. However, at the same time we found that (1) about half of the respondents are unaware that BEBAT collects

all types of portable battery packs, (2) almost all respondents struggle to identify the devices that contain removable battery packs, (3) about half of the respondents admit to having the habit of bringing electric and electronic devices and their battery packs to another collection point, and (4) respondents do not perceive themselves as being guilty of hoarding devices including the battery pack or of forgetting to take battery packs with them to a collection point.

Additionally, we are faced with the rather uncommon finding for TPB models that attitude does not significantly influence intention, except for the lower educated subgroup, if combined with other latent variables. On its own the path coefficient is significant with the expected positive sign. When combined with the other latent variables its significance disappears, however, not due to multicollinearity issues. Hence, further research should explore other types of theories that allow attitude to take on the role of a partial mediator.

6 Conclusion

This research aims to investigate the drivers and barriers to battery pack drop-off intention perceived by Belgian households. It is the first study looking specifically at this specific type of recycling. The gathered information may serve as guidance for the communication strategy of BEBAT, which is the single non-profit organization responsible for collecting, sorting, and recycling of portable batteries in Belgium. To this end, a standardized online survey, which extends the framework provided by the Theory of Planned Behavior (TPB) by incorporating measures on the objective knowledge, the perception of the consequences, moral norms, the lack of habits, and the perceived effectiveness of BEBAT's actions, was made. Data was collected during the 11/2014-01/2015 period and processed using partial least squares structural equation modelling (PLS-SEM). After verifying the adequacy of the measurement and structural model, it allowed verifying the following hypotheses: (H1) objective knowledge - attitude (+), (H3) past behavior - intention (+), (H4) moral norm - intention (+), (H5) subjective norm - intention (+), (H6) consequences - intention (+), (H7) perceived behavioral control – intention (+), (H8) lack of habit mediates, in this case weakens, the influence of past behavior on intention (-), (H9) perceived policy effectiveness negatively moderates the effect of subjective norm on intention (-). Based on the size of the path coefficients we can conclude that perceived behavioral control, moral norm, and consequences have the largest influence on the intention to drop-off battery packs as soon as they become unnecessary. However, a multi-group analysis has revealed that significant differences exist between subgroups made by dividing the full

sample based on an observed characteristic. Subgroups were made using the following features: bringing back the majority of battery packs (yes/no) education (high/low), pro-ecological worldview (high/low), gender (male/female), language (Dutch/French-speaking), living area (city/rural), and lifestage (young adult/family -12/family +12/medior/senior). The characteristics causing most heterogeneity are: ecological worldview and the lifestage: family -12. Moreover, statistically significant differences in path coefficients are regularly found for the latent variables: objective knowledge, subjective norms, the lack of habit, moral norms, and consequences. However, it should be noted that whereas the relationship between objective knowledge is generally significant, the relationship between attitude and intention is not. This is an unusual finding for a model based on the Theory of Planned Behavior. Nevertheless, as the direct effect is significant on its own and there is no multicollinearity issue future research might look into models in which attitude takes on the role of a partial mediator.

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