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Predicting intention to adopt solar technology in Canada: The role of knowledge, public engagement, and visibility

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A R T I C L E I N F O

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A B S T R A C T

Solar power (i.e., solar photovoltaic) accounts for about 0.3% of total electricity production in Canada. To enhance this contribution to energy supply from solar power, financial incentives and technological breakthroughs alone may not guarantee change. Drawing on a national survey of 2065 Canadian residents, we identify the determinants of technology adoption intention with the exemplary case of rooftop solar. Using a combination of latent and observed variables within a non-linear structural equation model, our analysis quantifies how a set of individual and community level factors affect adoption intention. Analysis reveals that the visibility of solar technology has a particularly strong effect on intention, lending support to social learning and social network theories of diffusion of innovation. Our findings also show that the perceived knowledge of energy systems and being publicly engaged in energy issues significantly increases adoption intention. These conclusions encourage policy options that enhance public engagement and the visibility of solar technology within neighborhoods and communities.

1. Introduction

Globally, electricity systems are undergoing significant transformation in response to energy and climate change policy and shifting cost structures for energy technologies like photovoltaic systems. Worldwide, installed solar capacity is reported to be 228 gigawatts (International Energy Agency, 2016), with utility-scale solar and distributed photovoltaic (PV) expanding "100% and slightly over 900%, respectively, between 2009 and 2015" (Energy Information Administration, 2016). In Canada, a country best known for its fossil fuel resources, investments in solar technology are growing steadily, particularly in the Province of Ontario where feed-in tariffs encourage adoption at commercial and household scales. Solar capacity in Ontario accounts for about 4.5% of total installed electricity capacity (National Energy Board, 2016). Yet, at the national level, solar capacity is hardly significant at approximately 1.0% of total capacity in 2014 (National Energy Board, 2016, p. 81). In reporting these numbers, the Canadian National Energy Board states that solar adoption across Canada is likely to depend on "local solar potential, costs and incentives, ease of integration with the existing grid, and further technological breakthroughs" (National Energy Board, 2016, p. 25). Although the contribution of solar technology to generation capacity remains low, this trend may change as federal and provincial governments push for renewable energy transition with 2016 commitments to phase out coal-fired power and to establish a national benchmark for carbon pricing (Government of Canada, 2016).

In addition to economic and technological issues that dominate public debates over renewable energy transition (Morton, 2006), social scientists identify a wider range of potential challenges to the broader adoption of renewable technology, and solar installations in particular. These challenges include individual factors such as knowledge, attitudes and political beliefs (Arkesteijn and Oerlemans, 2005), as well as system-wide factors, such as the blocking tactics of incumbent electricity producers (Hess, 2013). Moreover, well-documented public resistance to wind energy installations in Canada (Fast et al., 2016) underscore that financial incentives and technological breakthroughs alone are no guarantee of transition to a low-carbon future.

This paper contributes to the renewable energy policy and adoption literature using the exemplary case of rooftop solar in Canada. Our empirical analysis draws broadly on value-belief-norm theory (Wolske et al., 2017) to quantify the extent to which previously neglected latent individual and community level factors, plus informational and value orientations influence pro-environmental behavior. In particular, our contribution is centered on the role of visual exposure to solar technology adoption, as well as more generalized forms of knowledge about the energy system in Canada and public engagement in energy issues.

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Investigations into the role of attitudes, knowledge, and engagement are commonplace in technology adoption studies, but our non-linear structural equation model quantifies these latent variables in the generalized context of the whole energy system, rather than the technology-specific context of previous studies (e.g. Balcombe et al., 2014).

This study employs data from a national survey of 2065 Canadian residents who self-report adoption intentions as a proxy for future adoption behavior. We explicitly address a frequent empirical problem involving measurement error in complex latent constructs (e.g. environmental values) (Train et al., 1987). Our non-linear structural equation model (SEM) produces unbiased and efficient estimates in the presence of multiple simultaneous categories of latent factors (e.g. Daly et al., 2012).

Two research questions guide our analysis. First, is there a link between knowledge about energy systems, public engagement in energy issues and adoption intention? Second, is there a link between visual exposure to solar technology and adoption intention? Our empirical findings reveal that the combined experience of perceived knowledge, public engagement, and visual exposure to renewable energy technology significantly influences adoption intention, and through this cluster of community level variables, we make policy recommendations to enhance solar adoption through neighborhood and community level visibility of solar technology.

Before presenting analytical results, the following sections provide a review of literature and related theoretical concepts that give rise to our analysis as well as the methodological approach employed in the empirical analysis. We then discuss the empirical results and the paper concludes with a discussion of implications for research on solar adoption and policy options to enhance solar adoption.

2. Literature review: factors affecting solar adoption

Research on pro-environmental behavior is ubiquitous (Klöckner, 2013), but studies are more limited regarding the drivers of adoption of renewable energy technology at the household level. Solar adoption literature includes a study of factors influencing green electricity adoption in Dutch households (Arkesteijn and Oerlemans, 2005), the motivators and barriers related to the adoption of microgeneration technologies in the UK (Balcombe et al., 2014), social-psychological factors associated with solar power system adoption intentions in Taiwan (Chen, 2014), and socio-psychological patterns of photovoltaic investment in Austria and Italy (Braito et al., 2017). Common to these studies is their focus on internal and external drivers of behavior ranging from values, attitudes and knowledge to the mitigation of rising energy costs in specific jurisdictions; and a shared conclusion that aspects of cognition, social position, and communities of like-minded individuals appear to explain more of the variability in adoption intentions than standard socio-economic variables (e.g., income). For instance, Chen (2014) finds that environmental values are a significant predictor of adoption intention, and Arkesteijn and Oerlemans (2005) find that knowledge and visibility are important predictors of adoption.

From a theoretical and conceptual perspective, these studies range from straightforward claims about the link between environmental values and consumer decisions (Chen, 2014) to complex models integrating value-belief-norm (VBN) theory, diffusion theory, and theory of planned behavior (Wolske et al., 2017). We ground our analysis broadly in VBN theory, holding that "the root cause of pro-environmental behavior lies in values and emphasizes the importance of altruism directed at" human and non-human entities (Wolske et al., 2017, p. 137). As such, our study focuses directly on norms and information as social influences that inform attitudes towards a targeted intention or behavior (Fornara et al., 2016).

2.1. Environmental attitudes & values

VBN theory makes a strong claim regarding the assembly of cognitions and experiences that lead to observable environmental behaviors. Addressing the norms component later in this section, values are taken up within this study through the new ecological paradigm scale (Dunlap et al., 2000). Similarly, Clark et al. (2003), utilizing the new ecological paradigm scale as a measure of environmental concern, shows that such attitudes predict participation in a green electricity program. Poortinga et al. (2004) also offer empirical evidence that measures of environmental concern can explain variance in "intent-oriented measures of environmental behavior that directly or indirectly influence environmental qualities" (p. 88). Along these lines, Gadenne et al. (2011) find that consumers who are concerned about the environment are more likely to pay higher prices and to act to reduce emissions. Specific to solar adoption, using a green consumer values scale Chen (2014) finds that environmental values have a positive impact on ecological lifestyle and solar power system intentions. Consistent with this stream of literature, we expect latent environmental values to have a positive effect on adoption intention.

2.2. Knowledge

The role of knowledge in technology adoption behavior and decisions is a consistent focus in the literature dating back several decades (Labay and Kinnear, 1981). The claim here is that more knowledgeable consumers are more likely to understand the environmental concerns associated with carbon-intensive electricity generation systems and are more likely to appreciate the environmental benefits of investments in alternative renewable energy systems, including residential rooftop solar technology. Drawing on diffusion of innovation theory, Faiers and Neame, (2006, p. 1789) note that "adopters need to be knowledgeable of a product, and then be motivated to raise their awareness about it." They also clarify that early innovators tend to display more education and more knowledge about a technology, particularly the attributes of the technology that are attractive. Consistent with this theory, Arkesteijn and Oerlemans (2005) show a positive correlation between knowledge of energy systems and related adoption behavior.

Although these findings are consistent with classical adoption theory (Faiers and Neame, 2006), analysts are often skeptical of the role that knowledge plays in behavior change. The Knowledge Deficit Model (KDM), assumes that individuals are generally ignorant of facts (e.g. the economic and environmental benefits of solar technology). Therefore, according to the KDM, increasing factual knowledge will lead rational individuals to make better decisions. Yet, Árvai, (2014, p. 1246) notes that "decades of research in the decision sciences have shown that, in many contexts, better information and more education are largely disconnected from improved decision-making." Furthermore, it can be difficult to define what might constitute "improved decision-making" for different individuals. Those who are more fiscally focused, less altruistic, or less environmentally focused could make a knowledgeable decision not to adopt rooftop solar panels. In the context of this debate, we model the relationship between knowledge (perceived and factual dimensions outlined below) and adoption intention with attention to knowledge of energy systems, broadly defined. Given ongoing debates between diffusion theorists and critics of the KDM, we make no prior assumptions about the relationship between knowledge and adoption intention.

2.3. Engagement

Scholars point to the need for public engagement on energy-related issues to increase understanding, community support and sustainable pathways for a successful energy system transition. This focus on public engagement is described by Devine-Wright (2007) as a form of 'energy citizenship' that follows a tradition of scholarship in deliberative democracy (Gastil and Dillard, 1999) and environmental governance (Baber and Bartlett, 2005). The general claim here is that deeper levels of engagement in political life is desirable, and is expressed through formal institutions (e.g. voting), as well as a myriad of informal institutions (e.g. a public engagement). Public engagement may not result in predicted or desirable outcomes (thus avoiding critics of the KDM), but a more engaged citizenship is thought to lead to broad-based support for public policy decisions that are in line with broader public interests (Schmid et al., 2016). Similar to the often ambiguous effect of knowledge on adoption intentions, engagement may also involve support for the fossil fuel industry (a significant source of economic activity and employment across Canada) or support for the renewable energy industry. For instance, the Canadian Association of Petroleum Producers (2015) launched their Energy Citizens campaign to promote public engagement with the energy system, presumably to garner support for the petroleum industry. We therefore cannot assign *a priori* a clear direction of effect between engagement and adoption intention.

2.4. Seeing and experiencing renewable energy infrastructure

Extending the focus of this paper beyond attitudinal, knowledge and engagement variables, we explicitly consider an individual's experience at the community level as a potentially important contributor to adoption intention and subsequent behavior. This community context involves social norms, defined as rules and standards that exist within a community that influence behavior (Cialdini and Trost, 1998). Our focus here is the extent to which visible renewable energy infrastructure in the community results in spillover effects associated with solar adoption (Schmid et al., 2016). We highlight the potential importance of 'seeing solar technology' as a predictor of adoption intention with three supporting theories. First, social learning theory emphasizes the importance of innovation that extends beyond specific physical aspects of the technology in question. Im et al. (2007. p. 64) define social learning as "cognitive activities and behavioral patterns [that] are modified as the person observes and attends to stimuli in the social environment." Research on information technologies (e.g. Williams et al., 2005) emphasizes the roles social interaction can play in peer-to-peer learning processes about users and uses of new technologies within a community. Similarly, Im et al. (2007) draw on the idea of vicarious innovativeness and the role of *modeling* – the process of observing other people with a similar background – as a form of social learning, which is in turn provides *social proof* that a technology is worthy and desirable.

Second, social network approaches to innovation adoption and diffusion emphasize the importance of friendship, advice and support within social networks that can stimulate innovative behavior (Valente, 1996, p. 70). Valente's threshold model of innovation through social networks suggests that individuals engage in innovative behavior when a proportion of individuals within the social system already engage in the behavior. In other words, the adoption of solar technology may depend to some degree on the observed adoption behavior within an individual's social network. With attention to consumer behavior, Festinger's (1954) social comparison model underlines the human inclination to compare one's behavior with others in a group, thus further supporting the likely influence of social networks on energy technology adoption (e.g. Petkov et al., 2011).

Third, with reference to the phenomena of epistemic distance, Carolan (2007, p. 1273) calls for reconnecting individuals to the sensory environment around them as a way to enhance environmental commitments by nurturing connections between "people, social structures, and the environment." These broad areas of innovation theory offer clear support to our hypothesis that seeing and experiencing renewable energy infrastructure may foster adoption intention. Furthermore, existing research on solar technology adoption is providing empirical support for the above hypothesis. Arkesteijn and Oerlemans (2005, p. 184) show that "adoption is closely related to social and product visibility" and Braito et al. (2017, p. 150) indicate a "neighborhood effect to be a significant motivation for individual photovoltaic investors".

2.5. Government regulation

Although the impact of government regulations on adoption behavior is not a focus in this paper, several studies on solar adoption identify that regulation matters. For instance, Chen (2014, p. 952) quotes Kaplan (1999) who "provided empirical evidence suggesting government initiatives and institutional finance are important influencers of the decision to adopt PV power supply systems in India." Simpson and Clifton (2015) also talk about the role of government policy in adoption decision regarding solar microgeneration systems. Based on evidence from these studies, we also capture regional variation among Canadian provinces that offer divergent incentives for the adoption of residential renewable energy technology.

3. Empirical advances in predicting behavior

Attitudes, values, knowledge, and engagement are examples of latent variables, which means they have hidden realizations and must be inferred from one or more observed variables (Skrondal and Rabe-Hesketh, 2004). In survey-based research, latent variables are typically measured using Likert scales, which consist of a series of statements or questions with an ordinal response format (DeVellis, 2003). Many studies employing Likert scales rely upon two-step modeling techniques, where factors are scored using one of several methods (see DiStefano et al., 2009) and specified as observed covariates in a single equation model. However, specifying latent variables as observed variables results in biased parameter estimates when modeling discrete dependent variables that require non-linear estimation procedures (Train et al., 1987).

SEM provides a solution to these problems by allowing for joint estimation of latent variables and the discrete dependent variable of interest (Temme et al., 2008), such as solar adoption intention. However, SEM analyses typically specify ordinal Likert-type responses as continuous variables which can also result in biased parameter estimates (Horrace and Oaxaca, 2006). To overcome these problems with empirical models, recent advances in SEM, software, and computing abilities allow researchers to simultaneously estimate multiple latent factor constructs as explanatory variables within a non-linear model that accounts for measurement error and thus produces unbiased and efficient parameter estimates (Daly et al., 2012).

Much of the advancement in modeling methodology pertaining to our study was developed in the context of hybrid and integrated choice latent variable models (Ben-Akiva et al., 1999). The approach integrates a multiple indicators multiple causes (MIMIC) model (Jöreskog and Goldberger, 1975), relating latent variables to their indicators and observed traits of an individual, with a choice model that estimates the effect of each latent and observed variable on an individual's decision. This approach not only reduces bias and improves consistency of estimates, but it also allows latent variables to mediate the effects of observed variables on the outcome, providing greater explanatory power (Bollen and Noble, 2011). By specifying the latent variables as mediators, we can estimate the total effect of the observed characteristics on adoption intention, rather than the effect of each observed variable while controlling for the effects of latent variables. Further, we can parse out the degree to which each latent variable explains the total effect of an observed variable on adoption intention; for example, the degree to which a respondent's age reduces the intention to adopt solar due to a lower influence of being engaged in energy dialogue. Fig. 1 provides a simplified diagram of our SEM approach. In summary, our national dataset and non-linear SEM modeling approach allows us to examine the simultaneous influences of individual and community components that are linked to a person's intention to adopt solar technology.

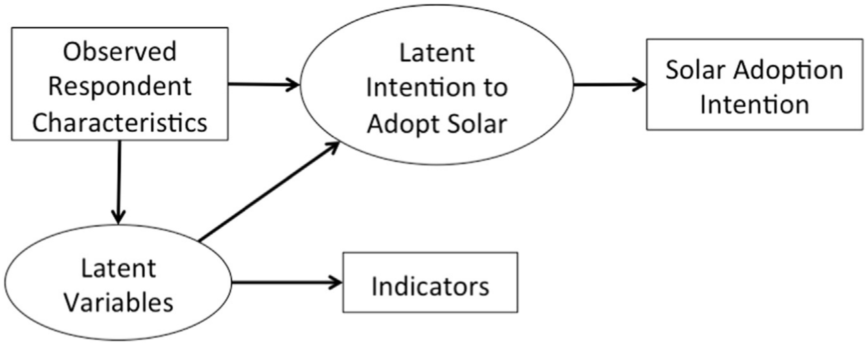

Fig. 1. Simplified path diagram of the effects of observed variables (boxes) and latent variables (ovals) on the intention to adopt rooftop solar technology, where arrows indicate causality between variables.

4. Methods

4.1. Questionnaire design and data

Survey data was collected in October of 2014 by Corporate Research Associates, a market research provider. From the firm's pool of 450,000 panel members, 3851 participants started the survey for a completion rate of 78% (3000 survey responses). The survey assessed Canadians' perceptions, preferences, and behavior relating to an array of energy issues as part of a larger research project examining energy citizenship and literacy across Canada (Reference withheld for blind review). The survey encompassed a wide range of variables categorized around the drivers of adoption of renewable energy technology at the household level, including environmental values, relevant factual and subjective knowledge, public engagement, as well as existing experiences with solar technology at the community level. Additional questions elicited important socio-demographic control factors, including residential and geographical data.

To understand an individual's intention to adopt residential solar technology, respondents were asked how likely they were to install rooftop solar technology to heat water and/or generate electricity over the next three years using four ordered-categorical options: *definitely not, probably not, probably,* and *definitely*, as well as *not applicable.* Those who stated solar panel installation was not applicable and those who were not homeowners were excluded from the analysis, resulting in a subset of 2065 useable survey respondents.

Descriptive statistics from the survey are summarized in Table 1. Survey response quotas for age, gender, language, income, education and regional distribution assure nationally representative demographics of our data align with the 2011 Canadian census, with the exception of higher educational attainment of survey respondents (Statistics Canada, 2013). Table 1 also provides first insights into our respondents' political orientations, with 40% stating liberal leanings compared to 29% claiming conservative leanings. Almost 36% of respondents indicate regularly seeing solar technology.

We developed a series of scales to measure key latent individual and community factors of engagement, subjective knowledge, factual knowledge, and environmental values. The items forming each scale and their response formats used are listed in Table 2. Items measuring engagement asked respondents whether they had taken part in a range of activities with a specific focus on energy in the past three years, such as joining a group, writing to a politician or newspaper, or attending meetings or hearings regarding energy projects. Subjective knowledge was assessed by asking respondents to rate their perceived knowledge of a range of Canadian energy sources, such as oil, hydroelectricity, or biomass. Factual knowledge was measured by a series of five multiple-choice questions relating to energy production and systems. To avoid false positives when measuring factual knowledge, respondents were asked to state how certain they were of their response to each question, and responses which were, "not at all certain" (the least certain category) were recoded as incorrect answers. Last, environmental attitudes were measured using items from the new ecological paradigm scale (Dunlap et al., 2000) and statements developed to represent biocentrism.

Table 1
Descriptive statistics of the population sample.

Variable	Description	Mean: Sample	Mean: Population
Female	1 = Female	0.50	0.51
Age (/10 years)	Age in years divided by 10	4.91	4.76
Income[*,a]	Annual household income (thousands)	51.00 – 76.00	78.87
University Degree	1 = University degree attained	0.43	0.26
Other Post-Sec	1 = Attended post-secondary institution other than university	0.24	0.33
Urban	1 = Lives in urban area	0.40	0.60
Suburban	1 = Lives in suburban area	0.24	–
Small City	1 = Lives in small city	0.13	0.09
Small Town	1 = Lives in small town	0.12	0.12
Rural	1 = Lives in rural or remote area	0.12	0.19
Atlantic	1 = Resident of New Brunswick, Newfoundland, Nova Scotia, or Prince Edward Island	0.08	0.07
Prairies	1 = Resident of Alberta, Manitoba, or Saskatchewan	0.19	0.18
British Columbia	1 = Resident of British Columbia	0.13	0.13
Quebec	1 = Resident of Quebec	0.22	0.24
Ontario	1 = Resident of Ontario	0.38	0.38
Liberal	1 = Politically liberal leaning	0.40	–
Conservative	1 = Politically conservative leaning	0.29	–
Regularly Sees Solar Panels	1 = Regularly sees solar panels	0.36	–

N = 2065.
[*] N = 1747.
[a] Median values are presented, rather than means. Population data from Statistics Canada (2012a, 2012b, 2013, 2016).

4.2. Statistical methods

Our modeling approach largely follows that of Gibson and Burton (2014), using multiple equations to simultaneously estimate respondents' latent traits and solar adoption intention. The empirical model of individuals' intentions to adopt rooftop solar technology was specified as a function of observed traits (e.g. socio-demographics) and the four latent factors of interest described in Table 2 within a generalized structural equation modeling (SEM) framework. We assume that the intention to adopt rooftop solar technology is driven by an unobserved function, A^*, from which an individual's observed solar adoption intention, A, may be predicted. This was specified as the following ordered probit model:

$$A^* = \beta X + \Lambda\eta + \varepsilon \quad (1)$$

Table 2
Descriptions of scales used to measure latent traits.

Scale, *Indicator*	Question Text	Response Format
Engagement	Have you engaged in any of the following, with a specific focus on energy issues, in the last three years?	1 = Have done it; 2 = Haven't, but willing; 3 = Haven't, unwilling
E1	Attended either an information meeting or hearing that approves projects or sets prices.	
E2	Attended a rally.	
E3	Joined either a group or became a member of an advisory committee.	
E4	Done any of the following: Written to a politician, written a Letter to the Editor, posted online comments in response to media stories, signed a petition, and/or used a toll-free telephone number to register your point of view.	
E5	Gave a presentation in formal public meetings.	
Environmental Values	Please indicate whether you agree or disagree with the following statements:	1 = Strongly disagree; 2 = Disagree; 3 = Neither agree nor disagree; 4 = Agree; 5 = Strongly agree
EV1	I believe that humans are members of the earth's community of life along with all other living things.	
EV2	I believe that humans, along with all other species, are dependent on the environment and one another to live well.	
EV3	When humans interfere with nature it often produces disastrous consequences.	
EV4	We are approaching the limit to the number of people the earth can support.	
Factual Knowledge	The next few questions explore what facts you know about energy (correct response in brackets).	Multiple choice with 6 options, including "don't know". Respondents were also asked to state how certain they were of each answer. Analyzed as binary (1 = correct), with "not at all sure" responses recoded as incorrect.
FK1	What percentage of the total electrical supply does hydroelectricity provide to your province/territory? (varies by province)	
FK2	Which of the following requires the least energy in the average Canadian home in one year? (lighting the home)	
FK3	To the best of your knowledge, it is impossible to (build a machine that produces more energy than it uses)	
FK4	Which one of the following statements best describes "renewable energy resources" to you? (resources that are in continuous supply or can be replenished by nature in a short period of time)	
FK5	What does it mean to you if an electric power plant is 35% efficient? (for every 100 units of energy that go into the plant, 35 units are converted into electrical energy)	
Subjective Knowledge	How much do you believe you know about the following energy sources in Canada?	1 = Nothing; 2 = Not much; 3 = A medium amount; 4 = Quite a bit; 5 = A lot.
SK1	Oil from oil sands/tar sands	
SK2	Wind	
SK3	Hydroelectric	
SK4	Nuclear	
SK5	Bioenergy	

$$A = \begin{Bmatrix} 1 & if & & & A^* \leq \kappa_1 \\ 2 & if & \kappa_1 & < & A^* \leq \kappa_2 \\ 3 & if & \kappa_2 & < & A^* \leq \kappa_3 \\ 4 & if & \kappa_3 & < & A^* \end{Bmatrix} \tag{2}$$

where X is a vector of observed characteristics, η represents latent traits of an individual, while β and Λ are parameters to be estimated and ε is a mean-zero, normally distributed error term. In Eq. (1), X includes demographics, political orientation, and characteristics of one's built environment, and η includes subjective and factual knowledge, environmental values, and engagement in energy dialogue. Three thresholds, κ_i, are estimated to predict the observed categorical response from the underlying response function (Eq. (2)).

Eqs. 3–5 represent the MIMIC model, which consists of two components. Eqs. 3 and 4 represent the measurement model, which estimates the relationships between the i indicators belonging to latent variable j, as listed in Table 2 (Skrondal and Rabe-Hesketh, 2004). Similar to Eq. (1) and 2, it is assumed that an underlying response function, y_{ij}^*, predicts one's response to the c-category indicator question, y_{ij}, by estimating a series of *c-1* thresholds, τ. The relationship between each latent variable and the responses to its indicators is represented by:

$$y_{ij}^* = \Gamma_i \eta_j + v_{ij}, \quad \Gamma_1 = 1 \tag{3}$$

$$y_{ij} = \begin{bmatrix} 1 & if & & y_{ij}^* \leq \tau_{ij,1} \\ 2 & if & \tau_{ij1} & < y_{ij}^* \leq \tau_{ij,2} \\ & & \vdots & \\ c & if & & \tau_{ij,c-1} < y_{ij}^* \end{bmatrix} \tag{4}$$

where Γ_i is a matrix of coefficients and v_{ij} is a matrix of mean-zero, normally distributed error terms. We assume that indicators for a scale do not impact the measurement of the other scales, restricting these parameter estimates to zero. For identification of the latent variables, the measurement parameter between each latent variable and one of its indicators is restricted to equal one (Skrondal and Rabe-Hesketh, 2004). In Eq. (4), four thresholds were estimated for indicators of the subjective knowledge and environmental values scales, two thresholds for indicators of the engagement scale, and one threshold for each indicator of factual knowledge. All equations were specified as probit models: binary for factual knowledge, and ordinal for the other latent variables.

The second component of the MIMIC model is the structural model, which relates each latent variable (η_j) to the observed respondent-specific variables (X) as follows:

$$\eta_j = \lambda_j X + w_j, \quad w_j \sim N(0, \varphi) \tag{5}$$

where λ_j is a vector of parameters and w_j is a vector of residuals. For identification purposes, the mean of each latent variable is fixed at zero

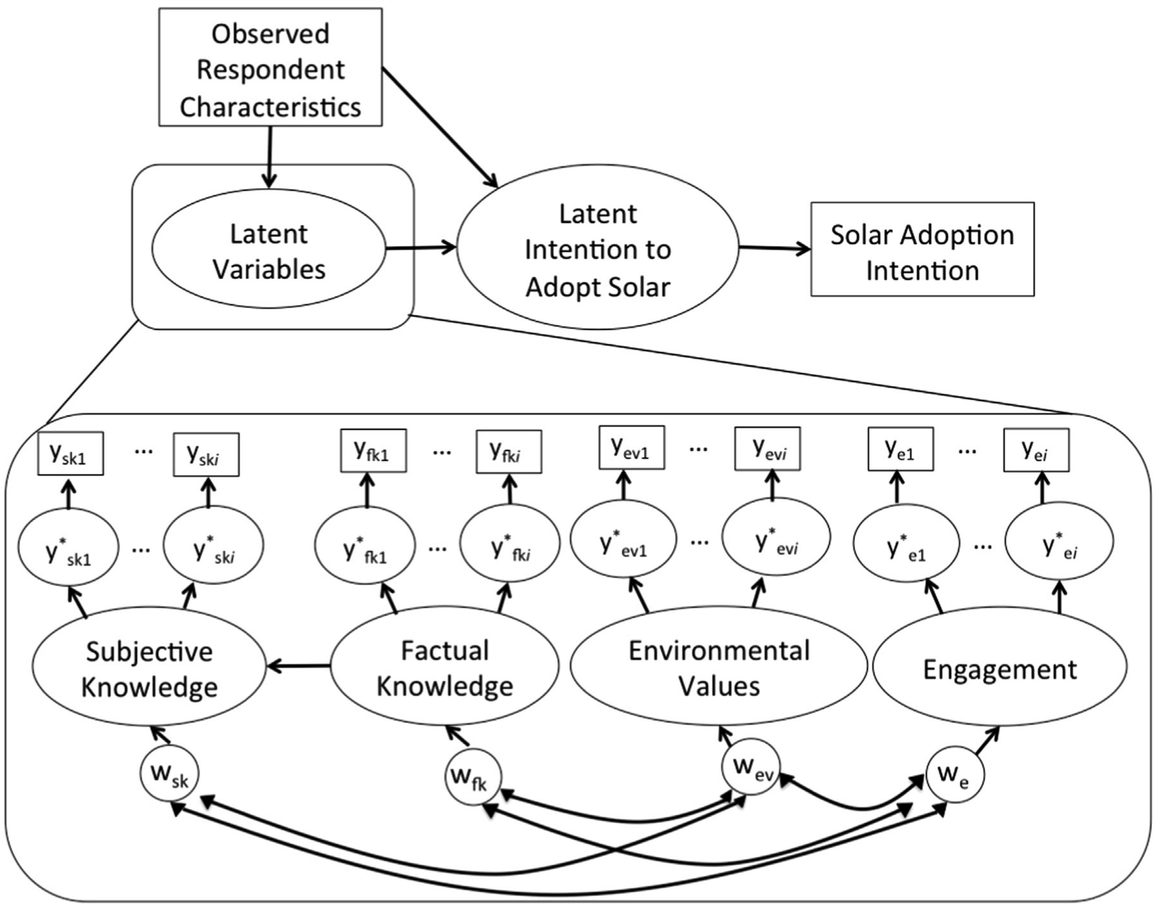

Fig. 2. Path diagram estimating the effects of observed and latent variables on the intention to adopt rooftop solar technology with a detailed representation of causality between latent and indicator variables. In the diagram, boxes represent observed variables, ovals represent latent variables, circles represent error terms, single-ended arrows signify causal relationships, and double-ended errors signify correlations.

and residual variances are estimated. Fig. 2 illustrates the system of Eqs. (1) to (5) to be estimated and their linkages. Arrows represent causal relationships between variables, double-ended arrows represent correlations, rectangles denominate observed variables, and ovals correspond to latent variables.

We estimated Eqs. 1 to 5 simultaneously, where Eqs. 1 to 4 were specified as binary or ordered probit models depending on the number of response categories, and Eq. (5) was specified as a series of four linear regressions. Given the required four dimensions of integration in estimating the model, Monte Carlo integration was used to approximate the likelihood function. The system of equations was estimated in Mplus 7.0 (Muthén and Muthén, 2012) using 8000 Monte Carlo integration points.

5. Results

Before further interpretation of SEM model estimates we make the following remarks. First, as typical model fit statistics are not available, using Monte Carlo integration, model fit was assessed by examining the residuals of all dependent variables. No residuals had absolute values greater than 0.018, and none of the standardized residuals had an absolute value greater than 1.96, implying an accurate overall model fit. The Monte Carlo simulation results with 500 replications also produced favorable results. For the 158 coefficients and standard errors estimated, the absolute mean relative bias was 2.98% and 4.22%, respectively.

Overall, our empirical model results suggest that major determinants of solar technology adoption are not found among standard socio-demographic characteristics. Instead, other than age and some geographical variation, stated political orientation, exposure to solar, active engagement in energy issues and environmental values are significant predictors of adoption intention.

As a first step in the analytical process we list the results of the measurement model in Eq. (3) (Table 3), estimating the relationships between latent variables and predictors as listed in Table 2. All loadings are highly significant, implying a high convergent validity and reliability of each indicator and scale. The ordinal alpha scores (see Gadermann et al., 2012) range from 0.72 for factual knowledge to 0.90 for engagement, implying internal consistency of each scale.

Table 4 presents the effects of individual's observed traits on their latent traits (Eq. (5)). In line with the findings of previous studies, we find significant linkages between a respondent's observable socio-demographics and their latent traits. Environmental values are positively affected by female gender (coef. = 0.432) (Xiao and McCright, 2014), age, educational attainment and suburban or small city demographics (Huddart-Kennedy et al., 2009). Also, we find liberal political orientation, relative to neutrality, and past exposure to solar technology to positively affect environmental values. Looking at predictors of public engagement, however, many of the same demographics factors predict negative outcomes. Only liberal political orientation, coastal geographical location, and exposure to solar technology are positively correlated with engagement. Respondents in French speaking Quebec are less likely to engage in energy issues.

Several observable traits explain latent subjective and objective knowledge scores. Negative results for females on both knowledge categories underscore the gendered differences in interest and background. As expected, factual knowledge is carried by an older higher educated suburban population already exposed to renewable energy

Table 3
Measurement model results relating latent variables to their indicators.

Latent Variable	Indicator	Coefficient	S. E.
Engagement	E1	1.000	0
(α = 0.90)	E2	1.055***	0.080
	E3	1.226***	0.098
	E4	0.797***	0.051
	E5	0.968	0.081
Environmental Values	EV1	1.000	0
(α = 0.89)	EV2	1.346***	0.178
	EV3	0.511***	0.040
	EV4	0.266***	0.025
Factual Knowledge	FK1	1.000	0
(α = 0.72)	FK2	0.748***	0.085
	FK3	1.947***	0.229
	FK4	1.801***	0.225
	FK5	2.173***	0.254
Subjective Knowledge	SK1	1.000	0
(α = 0.89)	SK2	1.277***	0.087
	SK3	0.936***	0.066
	SK4	1.096***	0.070
	SK5	0.905***	0.063

*** Significant at the 1% level.

Table 4
Linear model estimates with latent traits as the dependent variables.

	Latent Dependent Variable			
	Engagement	Enviro. Values	Subjective Knowledge	Factual Knowledge
Independent Variable	Coefficient	Coefficient	Coefficient	Coefficient
Female	−0.294***	0.432***	−0.545***	−0.301***
Age (/10 years)	−0.081***	0.248***	−0.028	0.056***
University Degree	0.115	0.260**	0.121*	0.287***
Other Post-Sec	0.053	0.147	0.017	0.079*
Suburban	−0.203***	0.283***	−0.203***	0.140***
Small City	0.024	0.258*	−0.093	0.061
Small Town	0.196	0.183	−0.123	0.046
Rural	0.220*	0.206	−0.102	0.161***
Atlantic	0.329**	0.082	0.067	0.137**
Prairies	−0.014	0.063	−0.091	0.133***
BC	0.246**	−0.030	0.025	0.085*
Quebec	−0.321***	−0.068	0.137	−0.054
Liberal	0.297***	0.493***	0.061	0.110***
Conservative	0.127	0.012	0.148**	0.059
Regularly Sees Solar Panels	0.228***	0.218**	0.223***	0.177***
Factual Knowledge			0.971***	
McKelvey Zavoina R^2	0.072	0.096	0.288	0.263

* Significant at the 10% level, ** Significant at the 5% level, *** Significant at the 1% level.

infrastructure. Factual knowledge also strongly relates to subjective knowledge (coef. = 0.971), which interestingly, is also significantly associated with conservative political views (coef. = 0.148). To appropriately capture the direct and indirect effects of latent individual and community level factors on decision-maker's intentions to adopt rooftop solar technology Table 5 presents estimates of direct, indirect, and total variable effects. In Table 5, indirect effects indicate the effect an observed variable has on the intention to adopt solar technology mediated through latent variables.

Our findings strongly suggest that the intention to adopt rooftop solar technology among Canadian households is not driven by standard socio-demographic characteristics. Instead, other than age and some geographical variation, individuals' stated political orientation, exposure to solar, active engagement in energy issues, and environmental values are significant predictors of renewable energy adoption.

Although female gender was a factor in predicting environmental values and knowledge (Table 4), it is not significantly linked to adoption intention. Similarly, educational attainment and income are not predictors of adoption intentions. However, modest and negative effects of age (coef. = −0.133), conservative political views (coef. = −0.165) and suburban residential location (coef. = −0.128) remain significant.

In line with previous literature, we find that the drivers (or barriers) to more widespread positive intentions towards the adoption of renewable technology lie in latent individual and community factors, including perceived knowledge and understanding (coef. = 0.129), attitudes towards energy transition as expressed in biocentric (environmental) values (coef. = 0.047) and related public engagement (coef. = 0.154) (Arkesteijn and Oerlemans, 2005). Most prominent, however, is the visual effect of seeing solar (coef. = 0.310). This finding is consistent with evidence from Europe, where the neighborhood effect (i.e., "a photovoltaic plant in my close environment has increased my motivation to have my own photovoltaic plant") was found to be a significant predictor of individual adoption intentions (Braito et al., 2017, p. 146).

6. Discussion and conclusions

Returning to the guiding questions for this study. Is there a link among cognitions, political engagement and adoption intention? We confirm evidence in the literature (e.g. Chen, 2014) that values play an important role in predicting solar adoption intention. Our results also directly confirm Arkesteijn and Oerlemans (2005) in that certain kinds of knowledge are crucial to the adoption process. In so far as general factual knowledge of the energy system was not a predictor of solar adoption intention, our results sustain criticism of the knowledge deficit model. Factual knowledge of energy systems is not a predictor of solar adoption intention. Our results indicate, however, that perceived knowledge of the energy system (i.e., confidence about what it is and what it represents to a person rather than the science behind it) predicts adoption intentions. Moreover, public engagement in energy issues was linked with adoption intention.

These insights hold important policy implications, showing the extent to which general improvements in civic engagement on energy issues can enhance the transition to renewable energy sources. Contrasting our findings with studies on renewable energy adoption (e.g. Wolske et al., 2017), the differences in our policy implications are nuanced yet powerful. Rather than pushing citizen engagement and information about specific renewable energy options, governments can achieve a level of openness to adopting renewable energy by encouraging people to think and learn about the energy system in general. While our results are distinct from past studies, they also provide confirmation of persistent uncertainties. With conventional thinking on diffusion of innovation, initial phases of adoption intention involve interest, engagement, and knowledge seeking behavior (Rogers, 2003). For this reason, it is difficult to make causal inferences about the role of knowledge and engagement on adoption behavior because these factors are confounding. Those who are more willing to adopt have likely sought knowledge on the subject. To avoid these confounding effects in this study, however, there are many reasons why one may be more engaged in or feel more knowledgeable about the energy system, including reasons that could represent opposition to renewable energy initiatives. Thus, our conclusions add insight into the role of knowledge and engagement as a predictor of adoption. A more engaged citizenship that is more confident in their knowledge of the energy system is more willing to adopt renewable energy technology.

Is there a link between visual exposure to solar technology and adoption intention? The answer to this question is clearly yes, where

Table 5
Direct, indirect, and total effects of all variables on individuals' intention to adopt rooftop solar panels at home, as estimated by an ordinal probit equation.

	Direct Effect		Sum of Indirect Effects		Total Effect	
Variable	Coef.	S. E.	Coef.	S. E.	Coef.	S. E.
Female	0.028	0.058	−0.028	0.037	0.000	0.051
Age (/10 years)	−0.116***	0.018	−0.017**	0.009	−0.133***	0.018
University	−0.071	0.063	−0.018	0.032	−0.089	0.062
Other Post-Sec	−0.029	0.065	0.000	0.023	−0.029	0.066
Suburban	−0.053	0.065	−0.075***	0.027	−0.128**	0.064
Small City	0.020	0.081	−0.010	0.026	0.010	0.083
Small Town	−0.158*	0.086	0.013	0.030	−0.145*	0.087
Rural	−0.038	0.081	−0.005	0.034	−0.043	0.083
Atlantic	0.210**	0.095	0.033	0.033	0.243***	0.093
Prairies	0.151**	0.074	−0.040	0.028	0.111	0.076
BC	0.160**	0.077	0.021	0.028	0.181**	0.080
QC	0.074	0.070	−0.023	0.028	0.050	0.070
Liberal	−0.085	0.058	0.069**	0.024	−0.016	0.059
Conservative	−0.191***	0.064	0.026	0.023	−0.165**	0.066
See Solar	0.264***	0.054	0.046	0.023	0.310***	0.054
Engagement	0.154***	0.024			0.154***	0.024
Biocentrism	0.047**	0.022			0.047**	0.022
Factual Knowledge	−0.222**	0.103	0.143***	0.039	−0.097	0.091
Subjective Knowledge	0.129***	0.032			0.129***	0.032
Threshold 1	−1.762***	0.132				
Threshold 2	−0.331***	0.126				
Threshold 3	0.625***	0.125				
McKelvey-Zavoina R^2	0.137					

* Significant at the 10% level, ** Significant at the 5% level, *** Significant at the 1% level.

proximity to solar technology at the community level can make a difference. Our empirical findings lend further support to diffusion of innovations theories that emphasize social interaction (Williams et al., 2005), modeling (Im et al., 2007) and social networks of like-minded adopters (Valente (1996). Moreover, we find evidence for a group of community factors that are uniquely influential in this study. These factors include regional effects (i.e., living in Atlantic Canada), age, engagement on energy issues, and visual exposure to solar technology infrastructure that are relevant here. The inclusion of community factors in concert with individual-level adoption characteristics is one of the empirical contributions of this analysis that allows us to provide a deeper understanding of how adoption behavior is incentivized – a key factor in today's political energy transition agenda.

While our results on key indicators of adoption, such as values and knowledge are consistent with previous studies (e.g. Arkesteijn and Oerlemans, 2005), the existing renewable energy policy literature has often neglected social norms and community factors as predictors of technology adoption. The work of scholars such as Carolan (2007) who seek to reconnect individuals with sensory environments or Im et al. (2007) who emphasize the importance of modeling behavior remind us of the ways that individual actors are embedded within social networks of influence. These insights resonate with our empirical work, suggesting that other researchers may want to include measures of visibility and exposure to energy technologies as a factor in shaping perceptions around technology and subsequently acceptance and adoption decisions.

From a policy perspective, these community-level perspectives are significant. Within quantitative models in the social-psychological literature, like the SEM model presented in this paper, adoption decisions are often linked to specific human characteristics such as gender, education or income. Although marketing and educational campaigns can form around these individual characteristics, such individual-level characteristics are much less salient in this study. Instead of finding that predictors of adoption are within the domain of these individual characteristics, what we identify as community factors are amenable to a wider range of public policy scenarios. For example, installing solar panels in public spaces like community centers where people can see them, or making available venues for public engagement are clear policy choices. In fact, these community-level approaches are consistent with policy choices currently under consideration across the country. A strategic plan for renewable energy development in the City of Edmonton, capital of the fossil energy rich province of Alberta, states that the city should "support and initiate community projects that demonstrate and promote renewable energy" (City of Edmonton, n.d., p. 2). Community projects represent promising policy choices that our data suggests could make a difference in adoption intention. Part of this focus on community projects is also recognized in other research where such projects can act as a catalyst for change, improve the social image of a place, and encourage development of social norms (Busch and McCormick, 2014). Work within Germany on the "peer effect" also notes that "propensity to install PV [photovoltaic] increases with the number of previously installed systems in spatial proximity" (Müller and Rode, 2013. p. 532). In addition to seeing solar panel community projects, public engagement is also within the realm of public policy. To the extent the governments can facilitate dialogue and public engagement on energy development issues, this policy tool is positively linked to solar adoption intention.

Finally, there are several avenues for future research. First, our understanding of the role of knowledge in adoption behavior remains incomplete. This study attempts to untangle the differential roles that factual and subjective knowledge variables play in behavior, but the direct and indirect effects of factual knowledge cancel out the total effects. Future research on the role of knowledge, with questions about the energy system, the technology in question, the governance and regulatory context can provide further insights into this persistent and complex area of adoption behavior. Second, given the strong positive effect between seeing solar technology and adoption intention, it is important to validate this relationship in future studies. To what extent does seeing solar, and other community factors, contribute to adoption intention, and more importantly, how does this expressed intention translate to the actual adoption of solar panels? One possible explanation is that those who are more inclined to adopt solar technology are also more likely to pay attention to existing solar technology infrastructure in their immediate environment. Although simulations revealed minimal endogeneity bias in our parameter estimate (1.6%), future research should attempt to further disentangle the causal structure of observed variable and latent traits to gain a more complete picture of renewable energy adoption intentions. These areas for research will extend our understanding of the possibilities for solar adoption in Canada, and the public policy choices that can hasten the transition to a lower carbon future.

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