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Rethinking the forecasting of innovation diffusion: A combined actor- and system approach☆

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ABSTRACT

Technological forecasting has significantly expanded over the last decades, leading to widespread use of forecasting models for explaining technology adoption and diffusion of innovation. While these models are broadly used, they have faced criticism for narrowing the explanatory components of adoption, focusing on adopters, innovation characteristics, or environmental factors, but seldom combine these to address complex problems holistically. This paper aims to combine actor- and system perspectives on innovation diffusion with the intention to broaden the explanatory power of traditional forecasting models. The study focuses on the case of solar photovoltaic (PV) diffusion in Sweden, surveying 46,507 residential PV adopters that applied for the capital subsidy program between 2009 and 2021 about their adoption satisfaction. Findings suggest that traditional models primarily account for direct effects on adoption satisfaction, whereas incorporating system-level factors captures indirect effects, providing a more comprehensive understanding of technology adoption. This highlights the interplay between actor- and system-level factors and acknowledging the holistic nature of innovation diffusion, which can inform future forecasting practices.

1. Introduction

The field of technological forecasting has grown extensively over the last 50 years, which has led to an increased use of forecasting models and a larger research output from an international community (Roca et al., 2023; Sarin et al., 2020). This is reasonable, since risk- and uncertainty management is a central concern of both companies and policymakers (Kerr and Phaal, 2020). Forecasting methods are used with various purposes. Historically, but still relevant in present times, forecasting has been used to anticipate technological progress and the development of technological features (Albright, 2002). At present, forecasting methods are often used to predict market development and dynamics, such as national production needs, technology and material prices and sales, market demand and technology diffusion (Bridgelall, 2023; Manickavasagam et al., 2020; Nasir, 2020; Ren et al., 2023; Tripathy et al., 2023). In the future, with the increased numbers of complex global problems such as climate change, pandemics, or crises, it is expected that forecasting methods and theories will focus more on socio-technical systems and transition contexts (Sarin et al., 2020).

Forecasting methods have also been used to a large extend in order to understand why and under what circumstances large-scale diffusion of technology takes place (Valor et al., 2022). Innovation diffusion research has built on a variety of theoretical perspectives spanning sociology, psychology, and information systems, to elucidate the forecasting of technology diffusion across diverse domains. As a result, explanatory models have been developed that mainly focus on individual adopters to predict the diffusion of innovation. In particular, well-established models developed in the 1960s (and improved over time), such as those by Rogers (Rogers, 1962) or Bass (1969) have been used extensively (Turk and Trkman, 2012). While these models mainly focus on explanatory factors at the actor level, over the last two decades, the importance of understanding the broader context of diffusion has been emphasized in technological forecasting research (Sarin et al., 2020; Savin, 2023). In particular, in new complex settings where diffusion needs to be accelerated (e.g., a transition to clean technology), it is important to consider additional explanatory factors in forecasting models, such as institutions, infrastructure, cultural meaning and market dynamics (Geels, 2005; Negro et al., 2012).

Still, it may be acknowledged that forecasting studies that actually combine a broader approach considering several levels of influence on

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diffusion are more the exception than the rule (exceptions include e.g., Biswas et al., 2022). Consequently, current forecasting research seldom takes a broader system perspective, including not only actors and their perception of the innovation, but also the environment where both actors and the innovation interact.

In this paper, our point of departure is that models of diffusion forecasting are indeed useful, but that they would gain in explanatory power by considering, not only an actor perspective, but also a system perspective. Hence, the aim of this paper is to combine actor- and system perspectives on innovation diffusion with the intention to broaden the explanatory power of traditional forecasting models. In this study, actor-level factors include adopters' perceptions about the innovation, i.e., its relative advantage, compatibility, complexity, and observability. Meanwhile, system-level factors encompass factors relative to the context of actors, i.e., the economic environment, social influences, policies as well as the geographic location where the innovation is used. To test this combined forecasting model, we focus on the case of solar photovoltaic in Sweden. We surveyed the entire population of adopters (46,507 households) in Sweden that applied for the subsidy that existed between 2009 and 2021.

In the following section, we start by reviewing existing literature on forecasting technology adoption and then lay the groundwork for the development of our model, i.e., introducing factors affecting adoption satisfaction, as well as factors emerging from the context where diffusion takes place. After that, the methods used in the paper are described and results are presented. These results are later discussed and compared with previous studies and theoretical understanding of innovation diffusion. We end the paper by drawing key conclusions, suggesting policy implications and providing suggestions for future research.

2. Theoretical framework and hypotheses

2.1. Forecasting technology adoption

In a context where competition, crises and societal changes make it extremely difficult – yet, very well needed – to predict the future, researchers, companies and policymakers have devoted energy and resources to develop tools and methods to forecast technology development and diffusion. Methods developed for that purpose include scenario building, modeling/simulations, Delphi studies and road mapping. They all have some key characteristics in common: 1) they involve (or rely on) practitioners' expertise and visions of the future (Park et al., 2020), 2) they rely on patterns of the past in order to predict the future (Fernández-Durán, 2014; Meade and Islam, 2006), 3) they provide tools for companies or policymakers aimed at facilitating decision-making, planning and strategy development (Kraus et al., 2023).

Forecasting methods can be used for various purposes, e.g., technology assessment, policy decision-making, R&D strategy development, and understanding future technological trends. Forecasting methods have also been used to a large extend in understand circumstances of large-scale diffusion of innovation (Valor et al., 2022). Innovation diffusion research has built on a variety of theoretical perspectives spanning sociology, psychology, and information systems, to elucidate the forecasting of technology diffusion across diverse domains. As a result, explanatory models have been developed that mainly focus on individual adopters to predict the diffusion of innovation. In particular, well-established models developed in the 1960s (and improved over time), such as those by Rogers (1962) or Bass (1969) have been extensively used (Turk and Trkman, 2012). Among the explanatory variables included in these models, adopters' characteristics, including desire to innovate, need to imitate others, education, social status and income are predominant (Meade and Islam, 2006).

While these models predominantly emphasize actor-level factors, over the years, studies have advocated for the importance of considering system-level– sometimes called socio-technical or environmental – factors such as social trust, support, growth and price. Authors have indeed highlighted that some innovations are important and valuable, not only from the perspective of the adopter, but also from the perspective of society as a whole (e.g., sustainable innovations, green technologies) (Javed et al., 2024; Yun and Lee, 2015). For these innovations, considering social and environmental driving forces in addition to the relative advantage or visibility/status, is crucial (Flores, 2024; Torma and Aschemann-Witzel, 2023; Yun and Lee, 2015). In many cases, technology is also dependent on the context where it will be used; hence, aspects such as technical facilitating conditions, technological legitimacy and acceptance are determinant for diffusion (Claudy et al., 2011; Negro et al., 2012; Yun and Lee, 2015).

In recent years, authors have started to underline that forecasting innovation diffusion cannot solely based prediction on measuring intention, likelihood, or willingness to adopt in a pre-adoption phase (e.g., Claudy et al., 2024; Parkins et al., 2018; Peñaloza et al., 2022; Roy and Mohapatra, 2022). Instead, they advocate for the importance of considering also the confirmation stage, when the satisfaction of the adoption is established and when a suitable use of the innovation is confirmed (Cho and Koo, 2012; Eriksson and Nilsson, 2007; Turk and Trkman, 2012). As Turk and Trkman (2012) put it "[from a societal perspective] no benefits can be realized if the consumer stops using the technology soon after having adopted it" (p86). Adoption satisfaction is key for sustained diffusion, since it requires that individual adopters participate in spreading a positive word about the innovation within their network (Ferreira and Lee, 2014; Yeon et al. Yeon et al., 2006).

In this paper, we intend to enrich forecasting research by proposing a model that considers both actor- and system-level factors to explain (and forecast) diffusion. Additionally, we operationalize diffusion prediction based on adopter satisfaction, rather than limiting it to intention to adopt.

2.2. Actor perspective on diffusion of innovation

To forecast the diffusion of an innovation, the role of individual adopters and the influences that shape their decisions to adopt have been central components in classical models (e.g., Bass, 1969; Davis, 1989; Rogers, 2003). Rooted in the sociological discipline, Rogers (2003) highlights that adopters' perceptions matter for the diffusion of innovation, and that these can be influenced by characteristics of the innovation itself, social systems surrounding the adopters, communication channels, and time. Forecasting practices have, however, mostly referred to the technological characteristics of the focal technology, for which the technology is perceived to be valuable and affordable by adopters (e.g., Rogers, 2003). According to diffusion of innovation theory, these characteristics consist of relative advantage, compatibility, complexity, trialability, and observability. To forecast technology adoption, the more prominent these characteristics are (with the exception of complexity), the faster the diffusion is predicted to be (e.g., Rogers, 2003; Yuen et al., 2020). Yet, for some technologies, such as solar PVs, the factor trialability (i.e., the degree to which an innovation may be experimented with before adoption) may be difficult to assess due to lack of possibility to try the technology before investing in it. Although extant research has often regarded these characteristics from the technology alone, they cannot be fully understood without considering adopters' perceptions of them (Davis, 1989; Venkatesh et al., 2003). Thus, the actor and the technology are interrelated for the forecasting of a technology.

Relative advantage, defined as the extent to which an innovation is perceived to surpass existing practices (Rogers, 2003), stands out as a significant predictor for adoption (Labay and Kinnear, 1981; Vasseur and Kemp, 2015). It is posited to exert influence on the perceived value of innovation, encompassing economic, functional, hedonic, and social advantages (Yuen et al., 2020). The prominence of relative advantage varies depending on the nature of the innovation, with some innovations exhibiting greater economic salience.

From a behavioral economics perspective, individuals are considered rational decision-makers who meticulously weigh the perceived benefits and costs of an innovation (e.g., Kahneman and Tversky, 1979). The concept of relative advantage aligns with this principle, exerting a direct impact on the perceived value of an innovation. Innovations that offer clear advantages in terms of efficiency, cost-effectiveness, or functionality are more likely to be perceived as valuable, thereby contributing to their adoption and potential satisfaction of it.

H1. Relative advantage is positively related to adoption satisfaction.

Compatibility pertains to the extent to which an innovation is perceived as aligning with existing values, practices, and routines (Rogers, 2003). The greater the perceived compatibility of an innovation with established values and practices, the higher the likelihood of its adoption. Consequently, if the innovation does not require significant shift in e.g., routines, the perceived value of it would increase and it is more readily adopted (Jansson, 2011; Wolske et al., 2017). Furthermore, a high level of compatibility reduces the effort required to integrate the innovation into everyday life and routines and would hence increase adoption satisfaction (Chan et al., 2010; Oliveira et al., 2016).

H2. Compatibility is positively related to adoption satisfaction.

Complexity refers to the extent to which an innovation is perceived as challenging to use or comprehend (Rogers, 2003). In essence, innovations are more likely to be adopted if they are perceived as simple to understand and use. Lower complexity reduces the cognitive load on adopters, making them more comfortable and confident with the technology. By minimizing frustration or confusion, which could otherwise lead to dissatisfaction, lower complexity may ultimately increase satisfaction.

However, the significance of complexity in technology adoption and diffusion varies depending on the specific technology. For certain innovations, complexity can significantly influence adoption, as the time and cost required for understanding may diminish the perceived value of the innovation. Research indicates that complexity negatively impacts adoption across various innovations, including autonomous vehicles (Yuen et al., 2020), mobile payments (Liébana-Cabanillas et al., 2018), and renewable energy technologies (Jager Yeon et al., 2006; Labay and Kinnear, 1981).

H3. Complexity is positively related to adoption satisfaction.

Observability denotes the extent to which the outcomes of an innovation are visible to others (Rogers, 2003). The adoption of an innovation can be expedited if its results are easily observable and communicable. This is attributed to the notion that when an innovation or its outcomes are readily observable, it can stimulate peer discussions, thereby enhancing the likelihood of adoption (Rogers, 2003) by highlighting its value. If others see the benefits and speak positively about it, it also boosts the adopter's confidence in their choice, further enhancing satisfaction (Mundaca and Samahita, 2020; Singh et al., 2020). Consequently, enhanced observability may provide time and cost savings for adopters and contribute to the perception of its functionality (Yuen et al., 2020). Additionally, it has the potential to instigate a favorable disposition toward the technology, thereby increasing the probability of future adoption (Palm, 2020).

H4. Observability is positively related to adoption satisfaction.

2.3. Systemic perspective on diffusion of innovation

Broadening the perspective of innovation diffusion from the adopter level to the system level, theoretical perspectives with roots in socio-technological transitions and innovation system theories have been important contributions to make sense of what explains the extent of the diffusion of innovations or the rate at which innovation diffuse (Bergek et al., 2008a; Edquist, 2013; Geels, 2002). While acknowledging the important role that users or adopters have for the diffusion of innovation, these theoretical perspectives also stress that adoption (like innovation) does neither happen in isolation nor is context-independent, and they instead highlight the importance of system-level factors inducing or hampering innovation diffusion. Among these system-level factors, institutions, networks, culture, economy, or geography are aspects, within the environment, that differ from one innovation to the other, and that in turn impact the diffusion (Carlsson and Stankiewicz, 1991; Grübler, 1996; Mignon and Bergek, 2016; Negro et al., 2012).

Despite a clear consensus among scholars that systemic factors are determinant for the diffusion of innovation, one remaining problem is diffusion theory often fails to consider such factors and as a consequence, established forecasting models of diffusion do not give them sufficient attention (Palm, 2022). In this paper, we propose that there are specifically four factors emerging from the environment and that should be considered in forecasting models, namely economy, social networks, policy, and geography:

Before the socio-technological or the technological transition perspectives on diffusion of innovation had even emerge, economic scholars put forward the importance of the *economic environment* as a crucial factor explaining innovation and its diffusion (Griliches, 1957; Mansfield, 1961). Since then, the economic perspective to explain diffusion has been problematized, nuanced and complemented by socio-technological perspectives (e.g. Dosi et al., 1988), but it is undeniable that the economic context plays a fundamental role in explaining why innovations diffuse at a slow or rapid pace (Karshenas and Stoneman, 1992; Wang et al., 2020). This explains e.g., why innovations diffuse at a faster pace in developed countries, under times of economic growth, and when there are favorable credit conditions, while in times of financial crisis or economic instability, diffusion is slower (Bundgaard-Nielsen, 1976; Graham and Senge, 1980; Karshenas and Stoneman, 1992; Law et al., 2018; Wang et al., 2020).

At a macroeconomic level, governmental policies and central bank decisions shape the state of the economy, for instance, by influencing interest rates. Interest rates, specifically, have been identified as exerting a substantial impact on the economic viability of innovations (Zainali et al., 2023) and are also presumed to influence the purchasing power of adopters. Lower interest rates make funding more accessible, reducing the financial burden of adopting new technologies. This affordability may enhance adopters' confidence in their decision, by minimizing regret or stress associated with high costs, which can lead to greater adoption satisfaction (e.g., Singh et al., 2020). Similarly, a stable or growing economy increases the likelihood that adopters will view their investment as financially sound, further boosting satisfaction and reinforcing long-term commitment to innovation.

H5. Interest rate is positively related to adoption satisfaction.

H6. The state of the economy is positively related to adoption satisfaction.

Numerous studies over the years have illustrated the pervasive impact of *social influence* on the diffusion of innovation (e.g., Lee et al., 2023; Palm, 2017; Valente, 1996). In particular, diffusion rate is very sensitive to changes in adoption per contact and word of mouth (Sharma et al., 2023), and social networks and peer influence are considered as critical factors in the decision-making process related to innovation adoption (Lee et al., 2023). These elements serve to mitigate perceived technological barriers (Palm, 2017; Rai et al., 2016) and expedite the diffusion process (Jager Yeon et al., 2006), especially in the early stages of diffusion process (Graziano and Gillingham, 2015).

Empirical evidence has documented the influence of social networks and peer effects in the adoption of a broad spectrum of technologies, spanning diverse domains such as electric vehicles (Axsen et al., 2013; Li et al., 2017), urban air mobility (Lee et al., 2023), mobile payment (Dahlberg et al., 2015; Liébana-Cabanillas et al., 2018), and renewable energy technologies (Jager Yeon et al., 2006; Palm, 2017; Yun and Lee, 2015). With only a few exceptions (e.g., Vasseur and Kemp, 2015), social influence (peer effects) has consistently predicted intentions to adoption and has operated as a confirmatory mechanism, enhancing the perceived value of and satisfaction with the innovation (e.g., Palm, 2017; Singh et al., 2020).

H7. Social influence is positively related to adoption satisfaction.

In some contexts, e.g., when a technological shift is urgent for society, government intervention is needed to accelerate diffusion. For instance, the diffusion of sustainable energy and transportation technologies often require legislative, infrastructural, and entrepreneurial changes and activities (Mignon and Bergek, 2016). In these settings, *policies* can contribute to addressing different system failures (Klein Woolthuis et al., 2005; Smith, 2000; Weber and Rohracher, 2012). Alongside with failures related to infrastructure, soft and hard institutional, interaction or network, capability, etc., policies have the potential to lower lock-in failures, which are associated with barriers created by the prevalence of incumbent technology or system, and can be tackled e.g., by creating incentives to invest in the new technology (Negro et al., 2012).

As policies are developed and implemented, the characteristics of the innovation change. For instance, from an adopter perspective, the creation of policy incentives can increase the innovation's attractivity (due to economic premium created by policies and to economy of scale) (Andersson and Jacobsson, 2000; Rydehell et al., 2024). Meanwhile, as policy measures contribute at making the innovation more attractive, user networks expand, which in turn contribute to increased visibility and increased experience in the innovation (Bergek et al., 2008b; Hillman and Sandén, 2008). As more adopters engage with the innovation, users benefit from shared knowledge and reduced uncertainty, leading to higher confidence and satisfaction with their decision (Groß, 2016; Oliveira et al., 2016; Palm, 2017). There is therefore an undeniable link between policy and adopters' perceptions of innovation, particularly when it comes to relative advantage, complexity and observability. As a matter of fact, in other fields of research using forecasting methods to predict technological transition, e.g. the energy (or innovation) policy research, or research on forecasting of climate change, policy as a factor is central to most of the models (e.g. Jiang and Xu, 2023; Liang et al., 2022; Nicolini and Tavoni, 2017; Raven and Walrave, 2020; Wu et al., 2023), positively influencing adoption. These studies highlight how policy interventions, such as financial incentives (subsidies), can reduce adopters' perceived risks while enhancing the relative advantage of the innovation. By fostering a sense of security and perceived benefit, policies can contribute to greater satisfaction with the decision to adopt.

H8. Policy incentives, specifically subsidies, are positively related to adoption satisfaction.

Lastly, geography has received attention for its role in the diffusion of innovation. In his seminal work (and building on the work of e.g., Hägerstrand (1953)), Grübler (1996) showed that innovations do not diffuse randomly across space. Instead, through the lens of historical diffusion processes, it is possible to distinguish spatial patterns of diffusion. In particular, Grübler identified that diffusion is more intense in spatial areas that are nearer to the source of the innovation (i.e., its node of origin) and that different attributes of regions or geographic areas are more or less predisposed to innovation diffusion. For instance, the density of population (e.g. Doshi and Narwold, 2018; Müller and Rode, 2013; Neshat et al., 2023), the means of communication (e.g., transport and communication infrastructure) (e.g. Grübler, 1990, 1996) and the sociodemographic characteristics of the population (e.g. Goldenberg et al., 2000; Young, 2009) are aspects that explain why the diffusion rate and density (i.e., number of adopters) of the diffusion.

More recently, the innovation system and socio-technological transition literatures have highlighted the centrality of geography for the understanding of technological transformations (Asheim and Gertler, 2006; Coenen et al., 2012; Hansen and Coenen, 2015). In particular, they emphasize that technological transitions (which incorporate the emergence and diffusion of technological innovations) are in fact geographic processes; they do not happen everywhere simultaneously, but instead consecutively (and in parallel) in concrete locations (Hansen and Coenen, 2015). In highly dense areas for instance, factors such as infrastructure, institutional frameworks, natural endowments, industrial specialization, and networking structures may either hamper or facilitate the diffusion processes (Alipour et al., 2020; Bollinger and Gillingham, 2012). These dense regions often provide adopters with increased access to support networks, peer feedback, and institutional resources, that can foster an informed and confident adoption process (Palm, 2016). Moreover, the interaction in such areas can create positive reinforcement and validation among adopters, enhancing satisfaction with the adoption decision. Some special areas have similarities that are important to account for, e.g., cities, Nordic countries, rural areas, and recognizing the distinct local attributes inherent in each diffusion context is essential for a comprehensive understanding of why transitions occur at varying paces. In Sweden, where population distribution is highly uneven with concentration in a few large cities and coastal areas (Statistics Sweden, 2024), total population size serves as a practical proxy for understanding technology adoption. While population density varies, population size may provide a more direct measure of the scale and potential impact of technology exposure, particularly in regions with significant geographic disparities.

H9. Population size is positively related to adoption satisfaction.

2.4. Analytical model

To sum up, in the theoretical review above, we found that current forecasting frameworks have underscored the significance of exogenous variables, notably social influence, in shaping individuals' intentions to adopt. Rogers' (2003) seminal work further accentuates the role of social networks and communication channels in the diffusion of innovations. In line with this perspective, population size, particularly in densely urban areas, is suggested to facilitate greater visibility and exposure to innovations within communities, fostering communication and knowledge-sharing among peers (Alipour et al., 2020; Bollinger and Gillingham, 2012; Müller and Rode, 2013; Neshat et al., 2023). In areas with larger population size, innovations are more likely to be observable due to increased interactions and communication among individuals (Neshat et al., 2023), thereby enhancing awareness and familiarity with new technologies, ultimately facilitating their adoption as well as improving satisfaction with the adoption process.

However, while traditional models emphasize external impact of factors, such as social influences on adoption, they often overlook broader systemic influences like policy incentives and economic conditions. Lower interest rates and a stable economy can increase the affordability and attractiveness of adopting new technologies (Lindahl et al., 2022; Zainali et al., 2023), making them more compatible with the socio-economic context. Additionally, subsidies and other policy incentives can further promote compatibility by reducing financial barriers and incentivizing adoption among potential users (Polzin et al., 2019; Sadorsky, 2021). Integrating these linkages between internal and external factors into forecasting models enriches our understanding of adoption dynamics.

Finally, adding an additional layer to the direct effects of actor- and system-level influences, transition scholars have also highlighted the interplay between system-level dynamics and individual actors in shaping adoption patterns (Fuenfschilling and Truffer, 2016). More specifically, authors have stressed that transitions do not only take place through interactions between technology and institutions, but instead, through actions and decisions made by actors that are embedded within more or less institutionalized environments. In other words, depending on their institutional environment, actors will be more or less prone on making certain decisions regarding technologies, e.g., adopting a technology and continuously using it (Fuenfschilling and Truffer, 2016). In order to account for this mediating effect, we developed the following analytical model to answer our research questions (Fig. 1).

3. Methodology

To reiterate, the research model (Fig. 1) incorporates the perspectives of actors' perception of the technology and the systemic factors for forecasting technology adoption and innovation diffusion. To test how well this model is appropriate to explain (and forecast) diffusion, we use the case of solar PV adoption in Sweden. As a renewable energy technology, solar PVs possess substantial market potential (Andersson et al., 2021; Sandén et al., 2014), and with the industry growing into becoming global in the last decades, the technology adoption has grown exponentially over the years (IEA, 2022; Palm, 2017). From a diffusion life cycle perspective (Rogers, 2003), the Swedish market is current in an early phase and transitioning into an early majority of adopters (Sommerfeldt et al., 2022). The Swedish PV market has been reliant on economic incentives from the government, with direct capital subsidy programs (IEA, 2022) available to expedite the adoption and diffusion of the innovation. During this program, adopters (including private households, companies, public organizations and associations) have had the opportunity to apply to receive a subsidy to finance a part of the investment (for more information about the subsidy program and its conditions, see Rydehell et al., 2024). As a result, the large majority of organizations and individuals that have gone through the whole adoption process for solar PV have applied to the subsidy program between 2009 and 2021, which represents an exceptional source of data to test factors influencing adoption over time.

Given these circumstances, the case of solar PV in Sweden is deemed suitable for testing the research model, allowing for the examination of diffusion from multiple perspectives rather than a singular one on a very large group of adopters, which can be considered to approach the total population of adopters.

3.1. Survey design and data collection

The survey designed consisted of four sections. The first section introduced the participants to the motivation and objective of the study. The second section collected demographic information about the respondents, not included in the dataset, such as gender, educational level, and income. This section also encompassed questions regarding PV adoption status, including whether the respondent had installed a PV system, was in the process of doing so but had not completed installation, or had no intent to install a PV system. The third section included the measurement items related to the pre-decision phase of adoption (i.e., technological characteristics and social influence). The last section included the measurement item adoption related to the post-decision phase of adoption satisfaction.

The first version of the survey was pilot tested in two steps to identify ambiguities and assess functionality, as well as to reduce common method bias. First, it was tested with an expert panel consisting of researchers and professionals in the industry sector. Second, we tested the survey with a small number of PV adopters to make sure the terminology and structure worked. In the latter case, adopters included in the dataset of subsidy applicant were removed from the final sample. Based on feedback from the pilot-testing we adjusted some questions due to language and made some changes in the order of questions to reduce common method bias.

The final survey was created in the online tool Qualtrics and distributed through the tool to the entire population of private households in Sweden (adopters) that had applied for the subsidy during the program period, and for which there was data available about emails (or phone numbers). Due to missing data about contact details, the final sample consisted of 46,507 adopters.

The survey was active for two months during summer of 2023 and reminder was sent out after half the time. Data was collected in Qualtrics as a majority answered online. For those respondents who for any reason did not want to answer the survey online, we provided additional assistance by phone or sending it by post. In total we received 16,888 responses (36 % response rate).

3.2. Measurement items

To operationalize the constructs related to actor-level (e.g., innovation diffusion theory) – relative advantage, compatibility, complexity, observability – we adapted and refined the measurements items informed by extant research and grounded in well-established literature. These are shown in Table 1. We also included items related to social influence and adoption satisfaction of solar PV based on previous research. These were all measured on a 7-point Likert scale.

Data on the independent variables related to system perspective of innovation diffusion (i.e., economy, policy, and population size) were extracted from databases.[1] For economy, the economic environment was measured through interest rate (INT) and state of the economy (ECS). With state of the economy, we refer to the aggregated economic sentiment of households as measured by the Economic Tendency Survey (Konjunkturinstitutet, 2023), specifically focusing on their expectations regarding personal finances, the general economic situation, and intentions to make major purchases. For the study period, we based these variables on monthly data, which was sourced from Ekonomifakta (2023) and the Economic Tendency Survey compiled by the Swedish National Institute of Economic Research (NIER) (Konjunkturinstitutet, 2023), respectively.

For policy incentives, we included the subsidy level (SUB) of direct capital subsidy program in effect from 2009 to 2021, as this was the primary incentive for PV adopters. Data about the subsidy levels during the time when the program was active, was obtained based on a combination of governmental reports and official documentation (i.e., IEA, 2022; Swedish Energy Agency, 2018).

Based on a dataset provided by the Swedish Energy Agency about adopters applying for direct capital subsidy between 2009 and 2021,[2] data could be acquired about the geographic location (i.e., municipality) of adopters. Population size (POP) was added as independent variable to consider variations in the availability of networks (e.g., distance to peers) and infrastructure across different regions, subsequently influencing the facilitation or hindrance of social learning (e.g., Alipour et al., 2020; Bollinger and Gillingham, 2012). This variable was based on the population size of the municipality (Statistics Sweden, 2023) for which the adopters had stated in their application for subsidy.

Moreover, we added sociodemographic variables of age (AGE), education (EDU) and gender (GEN) as control variables for households (see e.g., Ruokamo et al., 2023). The two latter were collected through the survey explained in section 3.2. Age of adopters were sources from the dataset from the Swedish Energy Agency about applications for direct

[1] Other system-level variables that were considered but excluded in the study were time, technology price (i.e., PV module price), and electricity price. The reason for not adding the first two was due to previous research showing how these variables create endogeneity and multicollinearity with subsidy level. The latter variable was excluded since the electricity price for the study period was relatively stable and extremely low.

[2] The dataset included information provided by the adopters when applying for the subsidy, including day of application, geographic location (municipality and county), contact details of adopter (address, email, phone number), size of PV system, installation costs, type of PV modules and placement of the system, etc. The data also consist of different groups of adopters: private households, sole proprietorship, companies (including housing associations, economic associations, limited and incorporated companies), foundations, municipalities, regions, and authorities. In total the dataset consists of 79,336 (individual) applications, of which the largest group belong to private households (57,525 applications).

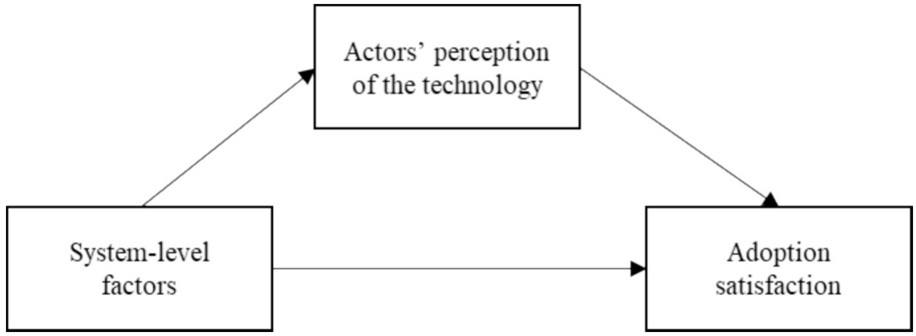

Fig. 1. Analytical model.

capital subsidy.

3.3. Data analysis

To ensure representativeness of the data collected, nonresponse analysis proceeded the data analysis. The analysis of nonresponse was carried out in two steps. First, we compared responders to non-responders based on key demographic variables: home county, type of building, application year, the amount applied for, and the age of the applicant at the time of application (applicable only to households). We used chi-squared tests to analyze categorical variables and *t*-tests for quantitative variables. Second, we conducted a qualitative analysis to explore the reasons non-responders gave for choosing not to participate. This qualitative data was gathered from multiple sources, including phone calls, emails, and letters. Although detailed findings are presented in the results section, preliminary analysis indicates that nonresponse bias is unlikely to have a significant impact on the sample's representativeness. To address concerns about common method bias, we conducted a Harman's single-factor test using all aggregated factors. The factor accounted for 15.0 % of the variance, well below the 50 % threshold commonly used to indicate significant common method bias. These results suggest that common method bias is unlikely to significantly influence the findings. Additionally, Cook's Distance values were examined to identify potential influential observations. The values were all below 0.012, that is, well below the threshold of 1. This indicates that no observations were identified as influential outliers that could unduly affect the model.

We began our data analysis with confirmatory factor analysis (CFA) to validate our hypothesized factor structure. In this process, we focused on two key aspects: convergent validity, ensuring each factor is adequately represented by its respective items (Hair et al., 2010), and discriminant validity, confirming that the factors are distinct from each other (Fornell and Larcker, 1981). After that, we tested our hypotheses using structural equation modeling with maximum likelihood estimation. Finally, we included indirect effects of actor-level variables on the relationships between system-level variables and Adoption to explore mediating effects. Collinearity diagnostics were conducted to ensure the predictors were sufficiently independent. Variance Inflation Factors (VIFs) for all predictors ranged from 1.02 to 2.11, and all tolerance values exceeded the threshold of 0.2. These results indicate no significant multicollinearity, supporting the reliability of the regression model. All data analyses were conducted using Jamovi version 2.2.8.

4. The Swedish case

As one of the leading countries in the global energy transition, Sweden has set a target of achieving 100 % renewable energy production by 2040 (The Governmental Offices of Sweden, n.d.). However, despite ambitious policy goals, solar PV currently accounts for only 1.2 % of the country's electricity production (IEA, 2023). With a potential to reach up to 15 % of electricity production (Svensk Solenergi, 2024), this relatively low penetration highlights the critical need to accelerate the diffusion of solar PV to ensure that Sweden can meet its renewable energy targets. Besides large PV investments from traditional adopters (i.e., governments and energy utilities), it has been highlighted that adoption from private households are important for the transition (Palm and Eriksson, 2018).

Though the Swedish solar PV market is still in an early stage of development, it has grown significantly in recent years. This growth has been shaped by government policies (see Fig. 2) and changing actors' perceptions and motivations. The journey of which this study took departure began in 2009 when the government introduced a direct capital subsidy program to reduce the upfront costs of solar PV installations. At that time, PV module prices were still high but had started to decrease gradually (Palm, 2018; Palm and Tengvard, 2011). Despite the subsidy, there were rather high interest rates and uncertain support timelines. As a result, mainly environmentally conscious and technology interested early adopters were investing at that time and there was a slow but steady growth in solar PV installations between 2009 and 2012 (see Fig. 2).

Between 2013 and 2016, solar PV adoption conditions improved noticeably. PV module prices dropped significantly, while interest rates fell, hence making solar systems more financially attractive for households. The subsidy program remained in place, though the level of subsidy decreased somewhat in line with the falling prices. Additionally, an important change occurred in mid-2016: a reform to the energy tax allowed households to install larger systems and produce electricity for self-consumption without being taxed on that production. This made solar energy a more attractive option for many households.

Despite these highly favorable system-level conditions—dropping PV module prices, low interest rates, and continued subsidy support—there was no exponential growth in applications for solar subsidies during this period. Adoption was steady but did not spike dramatically. Geographic patterns also revealed that the majority of applications were coming from the southern regions, where population size (and density) is highest. However, when accounting for population size, some central regions in Sweden demonstrated higher rates of adoption per capita, indicating that local factors, such as community networks or infrastructure, may have influenced these adoption patterns.

A major turning point came between the years 2017 and 2018, when solar PV adoption increased considerably. Several factors contributed to this change. First, in mid-2017, another energy tax reform further incentivized households to produce and sell their electricity, and the subsidy level was increased at the start of the year, increasing the attraction of investments in solar even more. These system-level improvements occurred while PV module prices continued to drop, providing stronger financial incentives for households to adopt solar technology.

Another key development in 2017 was the launch of a nationwide campaign aimed specifically at homeowners. Previous studies have shown that this campaign had a significant effect on adoption rates by

Table 1
Constructs and measurement items.

Construct	ID	Measurement items	Adapted source
Relative advantage		From 1 = *strongly disagree* to 7 = *strongly agree*	Labay and Kinnear (1981), Vasseur and Kemp (2015), Wolske et al. (2017), Yuen et al. (2020)
	RLA1	Installing solar PVs could be economically beneficial in the short term	
	RLA2	Solar PVs could provide a good long-term return on investment	
	RLA3	Solar PVs could help protect my family from rising electricity prices	
	RLA4	Having solar panels on my home could help meet my family's needs	
	RLA5	Solar PVs could protect my family from power outages	
	RLA6	Solar PVs could increase the value of my house	
Compatibility		From 1 = *strongly disagree* to 7 = *strongly agree*	Labay and Kinnear (1981), Yuen et al. (2020)
	COM1	Solar PVs were in line with my values	
	COM2	Solar PVs fit well with my routines	
	COM3	Solar PVs were compatible with my electricity needs	
	COM4	Solar PVs suited me well	
	COM5	Solar PVs fit well into my daily life.	
Complexity		From 1 = *strongly disagree* to 7 = *strongly agree*	Labay and Kinnear (1981), Vasseur and Kemp (2015), Wolske et al. (2017)
	CPL1	Installing solar PVs was complicated	
	CPL2	A lot of paperwork was required to install solar PVs	
	CPL3	Installing solar PVs took a lot of time	
Observability		From 1 = *strongly disagree* to 7 = *strongly agree*	Labay and Kinnear (1981), Wolske et al. (2017)
	OBS1	I had seen solar PVs installed on many properties	
	OBS2	Many in my area had recently installed solar PVs	
	OBS3	I knew many people who had installed solar PVs	
	OBS4	It was very common to have solar PVs on properties in my residential area	
	OBS5	I had several times spoken to someone who had already installed solar PVs	
Social influence		From 1 = *strongly disagree* to 7 = *strongly agree*	Venkatesh et al. (2012), Roy and Mohapatra (2022)
	SOC1	People who were important to me thought I should invest in solar PVs	
	SOC2	People who influenced my behaviour thought I should invest in solar PVs	
	SOC3	People whose opinions I valued preferred that I invested in solar PVs	
Adoption satisfaction		From 1 = *strongly disagree* to 7 = *strongly agree*	Yuen et al. (2020)
	ADP1	I would recommend friends and acquaintances to install solar PVs	
	ADP2	I would encourage others to invest in solar PVs	
	ADP3	Overall, I have positive things to say about solar PVs	

increasing the information about the technology (Palm and Lantz, 2020). This campaign, adding to the other economic incentives, may have broadened the appeal beyond early adopters, moving into an early majority of adopters (see e.g., Sommerfeldt et al., 2022). During this last period, the geographic data showed that the southern regions continued to lead in terms of absolute numbers of applications due to their larger populations, enhancing for example PV visibility. However, central Sweden—despite its lower population size (and density)—maintained a higher rate of applications per capita. This pattern underscores the probability that a combination of both system-level factors (like subsidies, prices, and tax reforms) and actor-level dynamics (perception, motivations, and visibility) may have contributed to driving adoption over time.

5. Results

5.1. Nonresponse analysis

In the first phase of our nonresponse analysis, we compared demographic variables between responders and non-responders. Although statistically significant differences emerged due to the large sample size (Lantz, 2013), effect sizes were generally small or within acceptable limits. Specifically, Cramér's V for home county was 0.092, indicating small effects. For the type of building, Cramér's V was 0.087. Regarding the application year, responders applied significantly later than non-responders, but effect sizes were small-to-medium (Cohen's d = 0.271). Additionally, responders applied for smaller amounts than non-responders, although effect sizes were below the benchmark for a small effect (Cohen's d = 0.152). Lastly, the age of applicants was higher among responders than non-responders, with a low effect size (Cohen's d = 0.093).

In the second phase, we examined reasons cited by non-responders for abstaining from participation. Reasons such as survey length and disinterest in surveys appeared unrelated to biases concerning the study's focal issues.

Our overall conclusion from these analyses is that nonresponse bias is unlikely to have a significant impact on the sample's representativeness, hence, we proceeded with the tests related to the research model.

5.2. Descriptive statistics

The initial part of this results section provides an overview of the descriptive statistics for the participating households (see Table 2).

5.3. Factor analysis

An exploratory factor analysis (EFA) was initially conducted to evaluate the factor structure of the variables under study. The extraction method used was based on minimum residuals with an Oblimin rotation to allow for factor correlation, guided by parallel analysis for determining the number of factors. Bartlett's test of sphericity was significant,

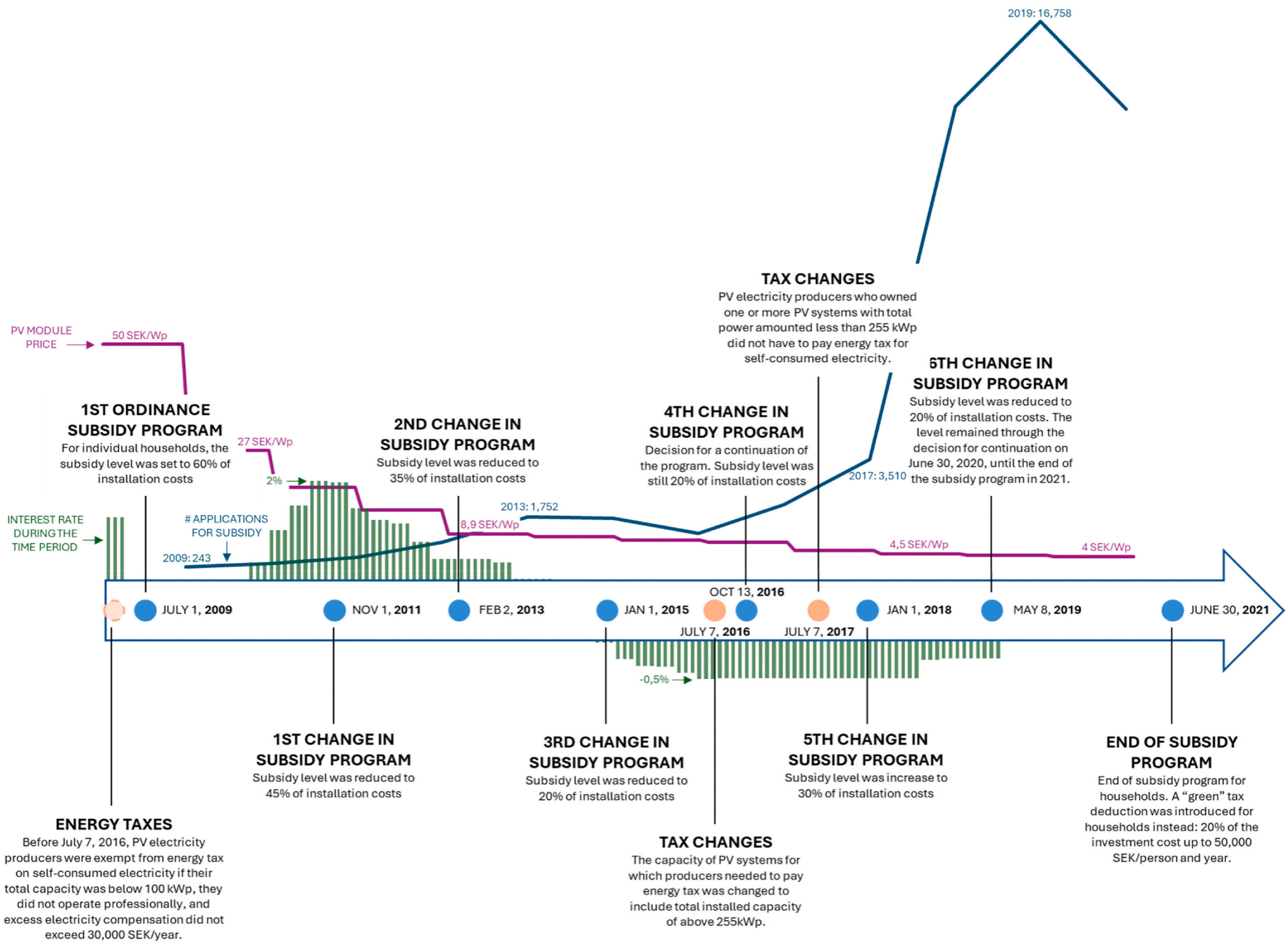

Fig. 2. Timeline of system-level factors for PV adoption in Sweden 2009-2021

Table 2
Descriptive statistics.

	Households		
Variable	N	Mean	S.D.
RLA1	14,920	3.20	2.09
RLA2	14,963	5.83	1.45
RLA3	14,324	4.42	1.96
RLA4	14,547	4.64	1.92
RLA5	14,370	1.86	1.54
RLA6	14,539	5.03	1.73
COM1	14,515	6.19	1.30
COM2	14,737	4.66	1.91
COM3	14,691	4.90	1.75
COM4	14,982	6.06	1.20
COM5	14,476	4.96	1.81
CPL1	14,830	2.36	1.57
CPL2	14,822	2.89	1.70
CPL3	14,192	2.68	1.64
OBS1	14,641	3.69	1.98
OBS2	14,738	2.16	1.56
OBS3	14,463	2.03	1.38
OBS4	14,710	1.65	1.15
OBS5	14,946	2.55	1.91
SOC1	14,906	2.39	1.87
SOC2	14,881	1.96	1.53
SOC3	14,840	2.32	1.79
ADP1	14,253	6.59	0.95
ADP2	14,208	6.54	1.02
ADP3	14,231	6.64	0.87

confirming the appropriateness of factor analysis for our dataset, and the Kaiser-Meyer-Olkin (KMO) measure verified the sampling adequacy with satisfactory values above 0.80, indicating that a substantial amount of variance might be explained by underlying factors. The EFA results initially suggested a solution where the factor loadings for RLA were notably dispersed, with several items loading significantly on multiple factors or failing to load adequately on the intended factor. As a result, RLA was excluded from subsequent analyses to enhance construct clarity and focus on the remaining five factors, which aligned well with the hypothesized structure.

Following the EFA, a confirmatory factor analysis (CFA) was conducted, excluding the Relative Advantage factor. The CFA results supported the revised five-factor structure, with factor loadings after minor item refinement (removal of COM1 and OBS1) due to low factor loadings (see Kline, 2016) showing substantial contributions to their respective factors, ranging from 0.621 to 0.958 (see Table 3). Model fit indices suggested an excellent fit (CFI = 0.963; TLI = 0.954; RMSEA = 0.052; SRMR = 0.037), indicating that the model adequately represents the data.

Table 3
CFA factor loadings.

Factor	Indicator	Estimate	SE	Z	p	Stand. Estimate
COM	COM2	1.410	0.016	90.2	< 0.001	0.740
	COM3	1.158	0.015	79.2	< 0.001	0.661
	COM4	0.795	0.010	78.2	< 0.001	0.660
	COM5	1.275	0.015	85.1	< 0.001	0.704
CPL	CPL1	1.245	0.012	100.6	< 0.001	0.793
	CPL2	1.199	0.014	88.9	< 0.001	0.706
	CPL3	1.336	0.013	102.2	< 0.001	0.813
OBS	OBS2	1.183	0.012	96.2	< 0.001	0.758
	OBS3	1.188	0.011	112.0	< 0.001	0.857
	OBS4	0.788	0.009	83.8	< 0.001	0.685
	OBS5	1.184	0.016	76.4	< 0.001	0.621
SOC	SOC1	1.543	0.013	118.3	< 0.001	0.826
	SOC2	1.358	0.010	130.7	< 0.001	0.886
	SOC3	1.538	0.012	124.6	< 0.001	0.857
ADP	ADP1	0.911	0.006	152.0	< 0.001	0.958
	ADP2	0.953	0.007	144.8	< 0.001	0.932
	ADP3	0.730	0.006	121.3	< 0.001	0.835

Reliability assessments (see Table 4) revealed strong internal consistency for each construct, with Cronbach's alpha (α) and composite reliability (CR) values well above the 0.7 threshold (Hair et al., 2014). The Average Variance Extracted (AVE) for each construct, ranging from 0.485 for COM to 0.837 for ADP, indicated good convergent validity.

These AVE values were compared against the squared inter-factor correlations, as recommended for assessing discriminant validity (Fornell and Larcker, 1981). For example, the highest inter-factor correlation was between SOC and OBS (0.311), which when squared (0.097) is less than the AVE values for SOC (0.734) and OBS (0.517), confirming that each construct shares more variance with its indicators than with other constructs (see Table 5).

5.4. Direct effects

In the structural model, the hypothesized direct relationships between the latent constructs and the outcome variable, Adoption satisfaction (ADP), were tested. The model included additional independent variables based on secondary data (population size, subsidy level, state of the economy, and interest rate) and control variables (age, educational level, and gender). The analysis showed significant paths from COM, CPL, OBS, and SOC to ADP, with standardized coefficients of 0.324, −0.158, −0.091, and 0.054 respectively, all $p < .001$ (see Table 6). This suggests that Compatibility and Social Influence positively influence Adoption, while Complexity and Observability exert negative effects.

The other system-level variables displayed varied influences, with the population size showing a small but significant effect ($\beta = 0.025$, $p = .004$), whereas the effects of subsidy level and state of the economy were not statistically significant at the $p < .05$ level. Control variables also significantly influenced Adoption satisfaction. Age and educational level positively affected Adoption satisfaction, whereas being of male gender was negatively related to Adoption satisfaction, indicating differences in Adoption satisfaction across demographic groups.

The standardized beta coefficients provide insights into the relative strengths of direct effects. For example, a one-standard-deviation increase in perceived complexity ($\beta = -0.158$) is associated with a 0.158-standard-deviation decrease in adoption satisfaction, reflecting a small negative effect. Similarly, compatibility ($\beta = 0.324$) demonstrates a medium effect, indicating that a one-standard-deviation increase results in a 0.324-standard-deviation rise in satisfaction (Fey et al., 2023). In contrast, population size ($\beta = 0.025$) has a very small direct effect, suggesting its limited standalone influence. These results underscore that while actor-level variables exert stronger direct impacts, system-level variables like population size may have broader implications through indirect pathways.

Robustness was assessed by running various model configurations, focusing separately on actor perception variables, system-level variables, control variables, and combinations thereof. All models supported the primary analysis, underscoring the stability of the findings across different model specifications.

5.5. Indirect effects

To deepen the analysis, the next step was to extend the SEM model to examine the potential mediating effects of actor-level variables on the

Table 4
Analysis of convergent validity.

Factor	α	CR	AVE
COM	0.774	0.784	0.485
CPL	0.814	0.815	0.595
OBS	0.792	0.806	0.517
SOC	0.890	0.892	0.734
ADP	0.932	0.938	0.837

Table 5
Analysis of discriminant validity.

	COM	CPL	OBS	SOC	ADP
COM	0.485	0.003	0.011	0.018	0.092
CPL		0.595	0.004	0.006	0.034
OBS			0.517	0.097	0.004
SOC				0.734	0.004
ADP					0.837

Table 6
SEM analysis: parameters estimates.

Dependent	Predictor	Estimate	SE	β	z	p
ADP	COM	0.209	0.007	0.324	30.54	< 0.001
ADP	CPL	−0.115	0.007	−0.158	−15.84	< 0.001
ADP	OBS	−0.072	0.008	−0.091	−8.71	< 0.001
ADP	SOC	0.031	0.006	0.054	5.30	< 0.001
ADP	POP	0.000	0.000	0.025	2.87	0.004
ADP	SUB	−0.003	0.002	−0.020	−1.84	0.066
ADP	ECS	0.002	0.001	0.024	1.88	0.061
ADP	INT	0.005	0.034	0.002	0.14	0.890
ADP	AGE	0.003	0.001	0.038	4.23	< 0.001
ADP	EDU	0.028	0.008	0.032	3.58	< 0.001
ADP	GEN	−0.083	0.025	−0.030	−3.38	< 0.001

relationships between system-level variables and Adoption satisfaction. The results, shown in Table 7, indicate that nine of the fifteen indirect paths were significant, demonstrating mediating effects of actor-level variables on the relationship between system-level variables and Adoption satisfaction. However, the nature of these effects varied. For example, COM acts as a complementary mediator between SOC and ADP but as a competitive mediator between POP and ADP. Additionally, CPL fully mediated the relationship between SUB and ADP (Hair et al., 2021).

Despite their small direct effects, system-level variables demonstrate meaningful indirect impacts through actor-level perceptions. For instance, subsidies influence adoption satisfaction indirectly by affecting perceived complexity, highlighting the importance of addressing technical and bureaucratic barriers to enhance satisfaction. Similarly, the very small direct effect of population size ($\beta = 0.025$) contrasts with its broader role in influencing compatibility and complexity, which are critical drivers of satisfaction. These findings emphasize that even small coefficients can significantly shape outcomes through mediating pathways, illustrating the nuanced interplay between system- and actor-level factors.

6. Discussion

6.1. Direct effects of internal and external factors on adoption

As presented in Section 5.4, our analysis reveals that actor-level variables have a stronger impact on adopter satisfaction than system-level variables. More specifically, all actor-level factors[3] related to adopters' perception of the technology (i.e., technology characteristics) have a significant impact on satisfaction with solar PV adoption. Yet, while results show support for the fact that compatibility positively influences adoption satisfaction (H2) and that complexity negatively influences adoption satisfaction (H3), the analysis did not provide support for the fact that relative advantage (H1) and observability (H4) have a positive effect on adoption satisfaction. As a matter of fact, in contrast to expectations, observability negatively affected the satisfaction with solar PV adoption. To explain this result, we can relate to previous research on solar PV, where it has been suggested that some adopters perceive the aesthetics of solar PV as rather negative and that, for some adopters, the technology may lack observable advantages (Sánchez-Pantoja et al., 2018). Meanwhile, the significant direct effects of technology characteristics such as compatibility, complexity, and observability on adoption demonstrate their independent influence on adopters' perceptions and decisions, confirming previous research (e.g., Bao et al., 2017; Jager, 2006; Liébana-Cabanillas et al., 2018; Vasseur and Kemp, 2015).

When it comes to system-level factors, only social influence and geographic location (population size) had significant positive effects on adoption, supporting H7 and H9. These findings are consistent with prior diffusion of innovation research and traditional forecasting models, even if, in these streams of research, the two factors are traditionally assimilated with actor characteristics (e.g., Davis, 1989; Rogers, 2003; Venkatesh et al., 2003). Indeed, social influence is usually associated with adopters' networks (which is sometimes considered as a resource which adopters have or lack (see e.g., Rogers, 2003)) and population size is associated as adopter's specific location (Assunção et al., 2019; Westin et al., 2018).

Surprisingly, in contrast with e.g., innovation system, policy, and transition research, our results did not reveal any direct effects of other system-level factors, i.e., the economic environment and policy incentives. As explained in section 2.4., these results were difficult to interpret, and it led us to deepen the testing for indirect effects of system-level factors. Nevertheless, some explanations can be provided regarding the absence of a direct effect of subsidy level on adoption satisfaction. During the period of the subsidy program (see section 4), uncertainties about the program's continuity, concerns over whether the subsidy would cover all applicants, and the complexity of the application process created barriers for adopters (Swedish Energy Agency, 2018). These challenges likely contributed to a disconnection between the subsidy level and satisfaction with adoption outcomes.

6.2. Indirect effects of system-level factors on adoption

To deepen the analytical model, after focusing on the direct effect of actor- and system-level factors, we examined the indirect effects of system-level factors on adoption satisfaction. Interestingly, the results revealed that all system-level factors have an effect on satisfaction with adoption decision indirectly, through adopters' perceptions of the technology. As underlined in previous research within the fields of socio-technological transitions and innovation systems, these results highlight the importance of adopters' surrounding system on their decision to adopt and the confirmation of that decision after its implementation.

As expected, social influence does not only directly influence adoption, but it also indirectly affects adoption satisfaction by influencing adopters' perception of the technology. This means that adopters' networks do not only influence satisfaction with adoption decision, but also their perception of the technology, including e.g., their perceptions of complexity and compatibility. In line with e.g., Palm (2017), Singh et al. (2020), these findings emphasize the interplay between technology characteristics, social influence, and technology adoption and satisfaction with the former operating as confirmatory mechanisms. In a similar fashion, our results show that population size has both a direct and indirect effect on adoption satisfaction. Yet, while the direct effect of population size has a positive impact on adoption satisfaction, the indirect effect points at the other direction. In other words, adopters' perceptions of technology compatibility and complexity are influenced by the geographic location where they are situated, which may indicate for instance that access to infrastructure, architecture and local policies may have an impact on adopters' perceptions. The indirect effect of both social influence and population size therefore demonstrates the embeddedness of actors in the institutional environment and its importance for technological transitions (Fuenfschilling and Truffer, 2016).

[3] As motivate din Section 5.3, relative advantage was excluded from this specific analysis due to methodological considerations. This does not mean that it should not be considered in future studies, on the contrary.

Table 7
Indirect effects.

Path	Estimate	SE	β	z	p	Mediation
SOC ⇒ COM ⇒ ADP	0.0269	0.0022	0.046	12.331	< 0.001	Partial, complementary
SOC ⇒ CPL ⇒ ADP	−0.0084	0.0011	−0.014	−7.515	< 0.001	Partial, competitive
SOC ⇒ OBS ⇒ ADP	−0.0170	0.0021	−0.029	−8.185	< 0.001	Partial, competitive
POP ⇒ COM ⇒ ADP	−0.0001	0.0000	−0.011	−3.281	0.001	Partial, competitive
POP ⇒ CPL ⇒ ADP	−0.0001	0.0000	−0.010	−5.653	< 0.001	Partial, competitive
POP ⇒ OBS ⇒ ADP	0.0000	0.0000	0.001	0.625	0.532	Direct only
SUB_ ⇒ COM ⇒ ADP	−0.0005	0.0006	−0.003	−0.727	0.467	No effect
SUB ⇒ CPL ⇒ ADP	−0.0008	0.0003	−0.005	−2.406	0.016	Full mediation
SUB ⇒ OBS ⇒ ADP	0.0001	0.0002	0.001	0.692	0.489	No effect
ECS ⇒ COM ⇒ ADP	0.0000	0.0003	0.001	0.124	0.902	No effect
ECS ⇒ CPL ⇒ ADP	−0.0002	0.0002	−0.002	−0.954	0.340	No effect
ECS ⇒ OBS ⇒ ADP	0.0009	0.0001	0.013	6.643	< 0.001	Full mediation
INT ⇒ COM ⇒ ADP	−0.0048	0.0128	−0.002	−0.374	0.709	No effect
INT ⇒ CPL ⇒ ADP	−0.0057	0.0063	−0.002	−0.905	0.365	No effect
INT ⇒ OBS ⇒ ADP	0.0074	0.0033	0.002	2.254	0.024	Full mediation

Interestingly, while both policy incentives and the economic environment do not have a direct impact on adoption satisfaction, when examining the indirect effects on satisfaction with adoption decision, we found that both factors exhibit clear indirect effects on adoption satisfaction. Our results further demonstrate that, in general, the effect sizes are small for many of the relationships. For example, subsidy has a marginal negative effect on adoption satisfaction when mediated by complexity. Thus, despite the presence of subsidies incentivizing adoption, the negative fully mediating effect of complexity suggests that perceived technical challenges associated with the technology may outweigh the potential positive impact of financial incentives. This indicates the importance of addressing perceived complexities through simplified processes, clear guidance, and effective support mechanisms, such as intermediaries (e.g., Bergek, 2020; Gliedt et al., 2018), to overcome adoption barriers. Nonetheless, alternative explanations for this negative and counterintuitive effect of subsidies warrant further investigation to enhance our understanding.

Moreover, by influencing adopters' perceptions of the technology, policy incentives and the economic environment may lead to different perceptions on the adoption decisions. For instance, an adopter that perceives the technology as non-aesthetic, may change this perception in a context of favorable economic environment. It may seem logical from a policy perspective, since one goal of incentive policies is to lower adoption challenges or technology drawbacks. Nevertheless, it demonstrates the importance of considering indirect relationships between system- and actor-level factors, which is most often neglected in forecasting models.

6.3. Implications for forecasting research and practice

To start with, it is important to acknowledge that actor-level factors indeed are important for explaining variation in adopter satisfaction. As introduced in Sections 1 and 2.1, previous forecasting research and models used for forecasting innovation diffusion have considered a number of factors (i.e., actors' perceptions of the technology, as well as the impact of social influence and, to some extent, the geographic location (see e.g., Bridgelall, 2023; Tripathy et al., 2023)), whose direct effects on adoption, and the confirmation of the decision, are indeed confirmed in our study.

Nevertheless, in order to broaden the understanding of adopter satisfaction, our study indicates that it is also important to consider system-level factors, which both have some direct and indirect impact. To our knowledge, this study is the first of its kind demonstrating the indirect impact of system-level factors on adoption satisfaction. Our results make sense in several ways. To start with, given the lack of direct impact of factors such as the economic environment and policy incentives, it is not surprising that they have been overlooked in previous models. Indeed, it is not given that forecasting models have the possibility (or the ambition) to include indirect factors in already rather complex models. Moreover, it can be argued that the list of indirect factors potentially affecting innovation diffusion is inexhaustible, and that the limit should be set somewhere. In this study, among system-level factors, we only included the economic environment (i.e., interest rate and state of the economy), policy incentives, population size in addition to social influence (which has already traditionally been included in most forecasting models).

Many more system-level factors may potentially be included, e.g., competing technologies, market structure, access to knowledge and funding, influence of the media, etc. Nevertheless, our study reveals that the system where adopters (co)exist indeed influences the diffusion of innovation, and that it should therefore not be overlooked. System-level influences, such as policy incentives and the economic environment, may therefore add to the interpretation of forecasting results (e.g., when predictions are not in line with the factual development of markets or diffusion results). Alternatively, in some contexts where major changes have taken place in adopters' system, e.g., a major change in the economic context such as a sudden increase in the inflation rate or in interest rates, or the creation (or the termination) of a policy incentive, forecasting models should enlarge their perspective to include system-level factors. If not, there is a significant risk that they will be disconnected from the real context and that their results will be inaccurate.

To end this section on implications, it is important to mention a few key learnings for the solar PV industry and its actors. For instance, the study highlights the importance of a combination of actor- and system-level factors incentives, not only for the decision to invest in solar PV, but also for the satisfaction of actors after their decision to invest. Traditionally, in the context of renewable electricity investments, economic policies have been the dominant explanatory factor put forward in policy literature (e.g., Alolo et al., 2020; Faúndez, 2008; Rydehell et al., 2024; Wu et al., 2023). Combining such perspective with the forecasting research hence gives the possibility to underline the importance of actor-level factors (including actor perceptions on the technology). Likewise, in a context where not only investments, but also continuous use of clean technology is crucial in order to limit the impact of climate change, our study provides a better understanding of factors determining adoption satisfaction of households over time. Given that households represent an investor group that is drastically growing in the market for solar PV (Westerberg and Lindahl, 2024), the results of the study provide potential inputs for companies selling and installing solar PV in Sweden.

7. Conclusion

The aim of this paper was to combine actor- and system perspectives on innovation diffusion with the intention to broaden the explanatory power of traditional forecasting models. More specifically, the paper strived to answer the question of how the explanatory power of models forecasting the diffusion of innovation can be increased through the combination of actor- and system-level factors. By incorporating both levels of explanatory factors, it becomes apparent that traditional forecasting models primarily account for direct effects on perceptions of adoption decision, whereas indirect effects require a system-level forecasting approach. Thus, acknowledging the indirect effects that system-level factors have on actors and, consequently, on satisfaction with technology adoption, can enhance the explanatory power of forecasting models.

This study provides insights into the complex interplay between actor- and system-level factors influencing adoption satisfaction, informing forecasting practices to recognize the holistic nature of these influences and offer a more comprehensive understanding of the drivers and barriers to technology adoption.

Despite these advancements, the study acknowledges certain limitations. The model presented may not encompass all potentially relevant system-level factors, particularly those specific to certain technologies or contexts. Future research could explore other technologies, whether capital-intensive or not, to validate and extend these findings, adding other system-level factors related to the context of the chosen technology. Understanding the context-specific dynamics will be crucial in refining and enhancing forecasting models.

In conclusion, this paper highlights the importance of combining actor- and system-level factors in innovation diffusion forecasting. By doing so, it opens new pathways for more holistic and accurate forecasting models, thereby contributing valuable knowledge to both academic research and practical applications in technology adoption.

CRediT authorship contribution statement

Hanna Cardol: Writing – original draft, Visualization, Validation, Methodology, Data curation, Conceptualization. **Ingrid Mignon:** Writing – original draft, Validation, Project administration, Funding acquisition, Conceptualization. **Björn Lantz:** Writing – original draft, Validation, Methodology, Formal analysis.

Declaration of competing interest

None.

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Data availability

The authors do not have permission to share data.

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