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Role of the social factors in success of solar photovoltaic reuse and recycle programmes

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By 2050, the cumulative mass of end-of-life photovoltaic (PV) modules may reach 80 Mt globally. The impacts could be mitigated by module recycling, repair and reuse; however, previous studies of PV circularity omit the consideration of critical social factors. Here we used an agent-based model to integrate social aspects with techno-economic factors, which provides a more realistic assessment of the circularity potential for previously studied interventions that assesses additional interventions that cannot be analysed using techno-economic analysis alone. We also performed a global sensitivity analysis using a machine-learning metamodel. We show that to exclude social factors underestimates the effect of lower recycling prices on PV material circularity, which highlights the relevance of considering social factors in future studies. Interventions aimed at changing customer attitudes about used PV boost the reuse of modules, although used modules can only satisfy one-third of the US demand during 2020–2050, which suggests that reuse should be complemented by recycling.

Soaring global deployment of solar photovoltaics (PV) could mitigate problems related to energy generation, but may exacerbate other issues. PV manufacturing depletes scarce resources, such as silver, tellurium and copper[1,2]. For instance, silver production could peak by 2030, with a risk of demand outstripping supply around 2075[3]. Although minerals and metals are essential for the transition to a low-carbon society, increased use could aggravate social and ecological problems[4]. Large-scale PV deployment also will produce substantial amounts of end-of-life (EOL) PV materials. By 2050, a cumulative 80 Mt of PV modules are expected to reach EOL globally, with 10 Mt in the United States alone[5].

Outcomes associated with increased PV deployment depend on the economic approach applied. In today's predominantly linear economy, resources are extracted to manufacture goods, which are later discarded. The alternative circular economy (CE) model could mitigate resource and ecological challenges[6] by encouraging dematerialization and the recovery and reuse of products and materials[6,7]. Challenges to a PV CE include low recycling rates[3,8], non-specialized PV recycling[9], which results in low material recovery rates and profits[8], difficult separation of module components[3] and product reuse limited by consumer awareness and attitude towards used products as well as to the current policy[10].

Adopting a social viewpoint to complement other perspectives could increase the effectiveness of circularity-promoting interventions. Social behaviours could play a critical role in developing secondary PV markets and managing EOL PV, because psychological and behavioural traits often undermine the viability of technical solutions[11–14]. Sovacool and Griffiths, for instance, report that culturally rooted driving behaviours influence the adoption of fuel-efficient vehicles and ride-sharing services[14]. However, current studies of material circularity (that is, the degree to which materials are recirculated in the economy) are limited to the technical and economic material efficiency potentials and do not account for consumer behaviour[13,15]. This assessment means that major changes in the way CE is analysed need to be undertaken[12,16,17].

We help fill this gap by incorporating social considerations into an exploration of the techno-economic, market and policy conditions that may improve the material circularity of the dominant crystalline-silicon (c-Si) PV module technology. We applied an agent-based model (ABM) to represent multiple actors involved with the PV life cycle as well as social factors (attitude and peer influence) that constrain CE strategies, and built a machine-learning (ML) metamodel (that is, a model of a model) to conduct a global sensitivity analysis. An ABM is well-suited to a study of the CE transition because it considers temporal aspects, adopts a systemic view, accounts for human decisions and interactions between actors[16], and exploits recent advances in behavioural economics and psychology[16,18–20]. ABMs are used to study CE scenarios in relation to waste management[21–24], but no previous model has included secondary market dynamics that underlie the reuse CE strategy. Many ABM studies have addressed PV adoption[19], but the method has not been used to investigate renewable technologies through EOL. By integrating social considerations, we not only analyse the factors that affect PV CE scenarios more comprehensively than previous studies have, but we also explore types of CE interventions—such as strengthening warranties for used PV modules and 'seeding' used modules to encourage secondary-market development—that cannot be assessed using techno-economic analysis alone. The result is a fuller picture of the options available to promote PV circularity and a fuller picture of the potential effectiveness of those options separately and in combination. However, given the exploratory nature of our work, the results should be viewed as estimates of how CE principles could affect EOL management of PV modules in the future, rather than robust predictions.

ABM of PV circularity

In our ABM, four types of agents (PV owners, installers, recyclers and manufacturers) and five EOL management options (repair, reuse, recycling, landfilling and storage) are defined (Supplementary Fig. 1), with a focus on CE strategies that have been proposed by stakeholders as likely to contribute most to the CE in the future[25]. Landfilling and storage are included because those options are reported in the United States[26,27]. Two purchasing options are also modelled: the purchase of new or of used PV modules. For each type of agent, behavioural rules are defined to model the adoption of CE strategies. For instance, for PV owners, the ABM

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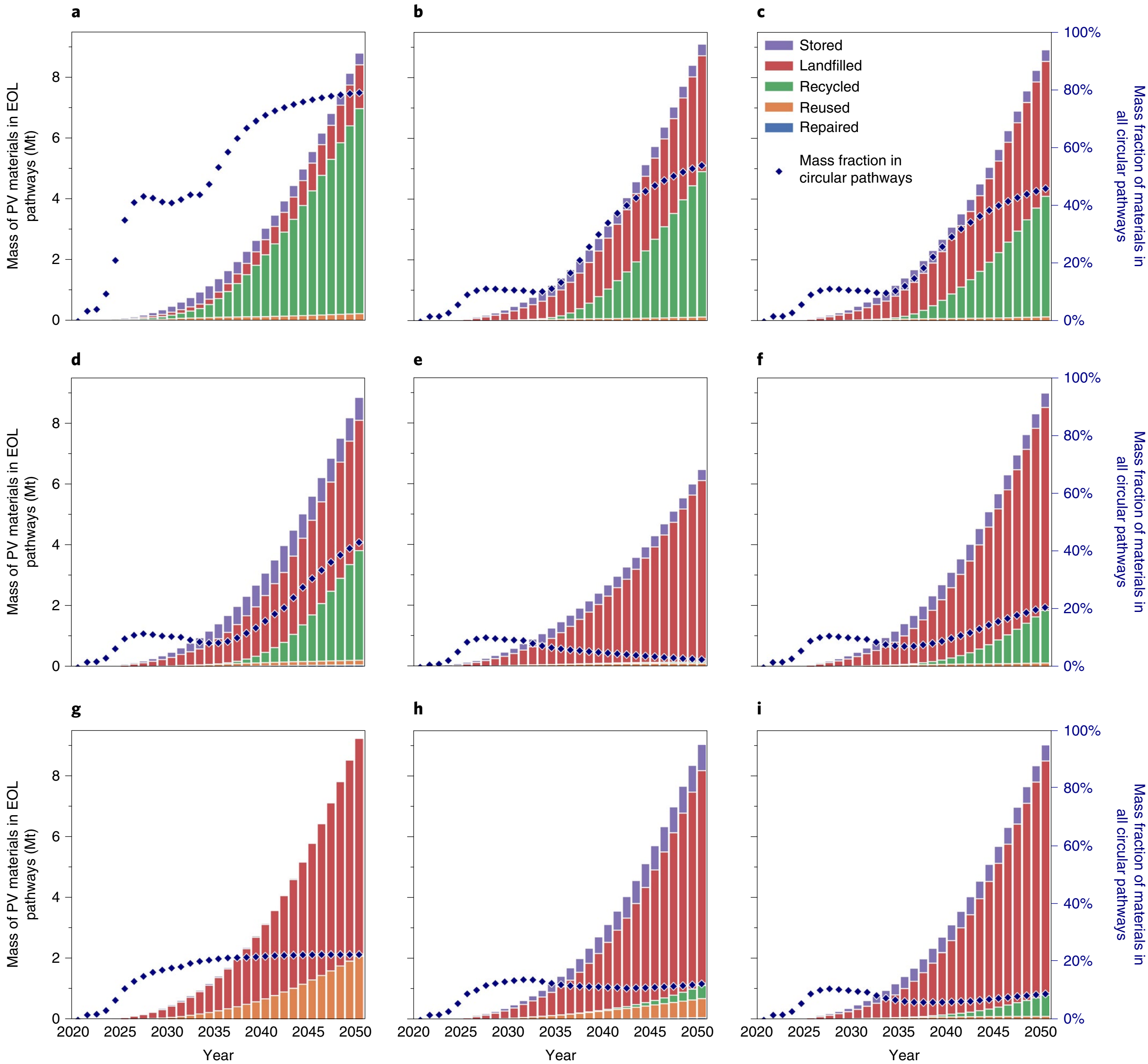

Fig. 1 | Various interventions could improve material circularity in the PV sector. a–i, Landfill ban (**a**), high material recovery (96%) and US $18 per module recycling costs (**b**), lower recycling costs (US $18 per module) (**c**), higher landfill costs (US $2.75 per module) (**d**), improved learning (from 30 to 60 yr in 2050) (**e**), improved learning effect (learning parameter = 0.6) (**f**), reuse warranties (equal new/used attitude) (**g**), seeding reuse (5% of population per year) (**h**) and baseline (**i**). Some interventions, which include improved warranties (**g**) and seeding used modules (**h**), particularly boost module repair and reuse. Other interventions, such as lower initial recycling costs (**c**) and higher landfill costs (**d**), boost recycling.

projects the cumulative amount of PV modules in use as well as the waste generated at their EOL. Then, the PV owner agents make decisions about whether to comply with a particular CE strategy according to the theory of planned behaviour (TPB), which is one of the most influential theories used to explain human behaviour[13] and accounts for various factors that affect human decisions, such as economics and peer influence. Details are presented in Methods and Supplementary Table 1.

Our ABM simulates the current US conditions, although changing several rules and other parameters would enable it to simulate EOL decisions for PV modules anywhere in the world. The European Union, where PV modules must be recycled at the EOL based on waste electrical and electronic equipment (WEEE) regulations, is the most constrained region because only a few pathways are allowed. The United States is projected to have the second-largest amount of EOL modules by 2050[5], and landfilling is considerably cheaper than recycling[26]. In this challenging environment for a PV CE, it is vital to identify the most effective and cost-efficient strategies or combinations of strategies to improve material circularity. To do so, we assessed not only the fraction of EOL mass that avoids being landfilled (and stored), but also societal costs (that is, the net costs of manufacturers, recyclers and installers) and recyclers and installers net revenue, because these metrics are relevant to assuring the sustainability of the CE. The dynamic factors considered include the PV module failure rate and the learning effect for module recycling—that is, the decrease in

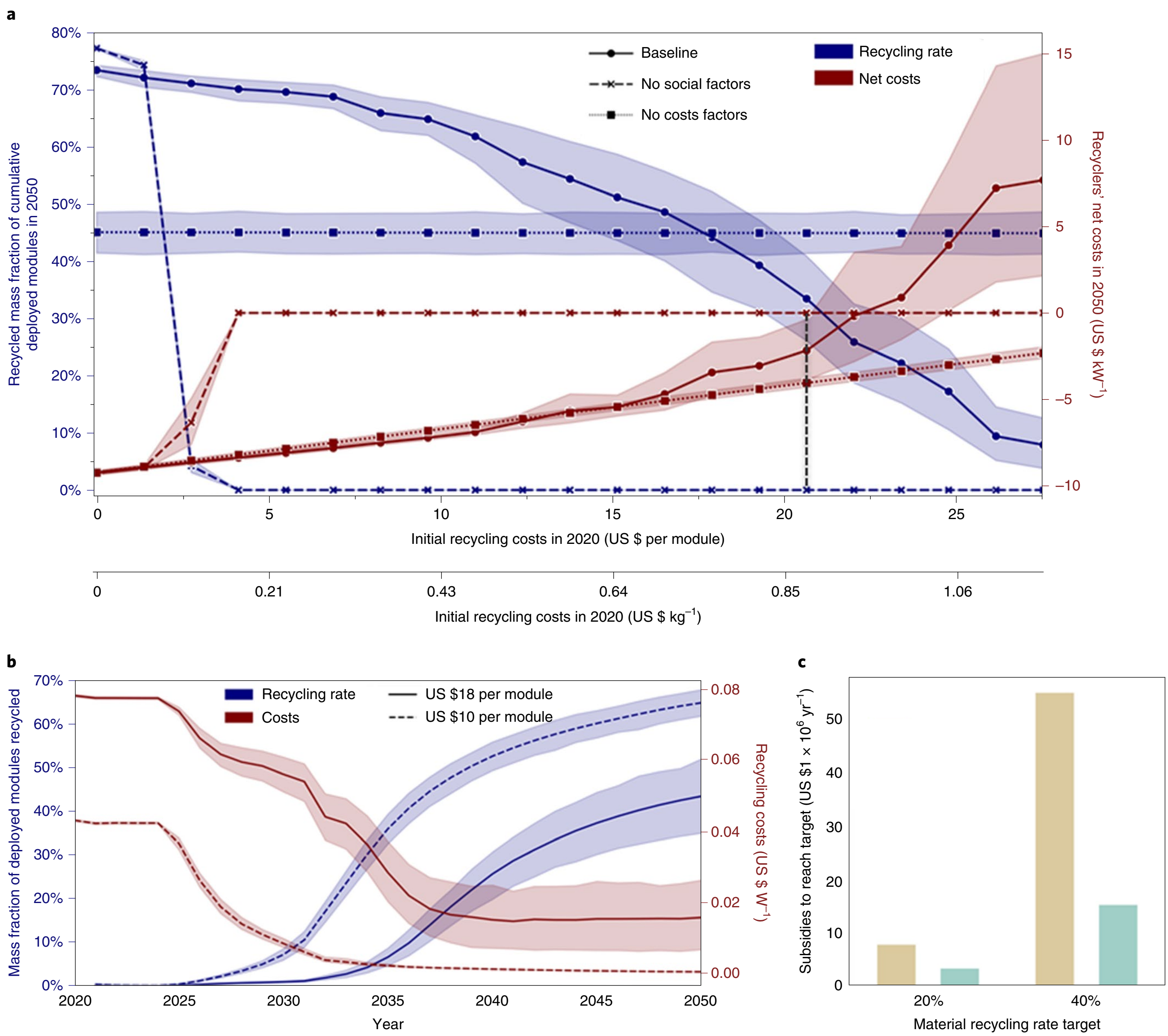

Fig. 2 | The influence of recycling costs on the material recycling rate. **a**, In the baseline scenario, the volume of materials recycled (cumulative total in 2050) quickly increases with falling initial recycling costs until it reaches a plateau. Not accounting for economic factors (costs of recycling for PV owners) and social factors (attitude and peer influence) misrepresents the effect of lower initial recycling costs on the volume of materials recycled. Recycling is profitable (provides negative net costs, that is, recycling costs minus value of recovered materials) by 2050 for initial recycling costs of US $21 per module or less (black dashed line). Shaded areas represent 95% confidence intervals, blue and red lines correspond to the left and right *y* axes, respectively. **b**, Recycling costs (without accounting for the value of recovered materials) decrease with the amount of PV modules being recycled. Shaded areas represent 95% confidence intervals, blue and red lines correspond to the left and right *y* axes, respectively (see Supplementary Fig. 7 for a *y* axis in US $ kg^{-1}). **c**, High initial subsidies (initial recycling costs of US $10 per module, yellow) boost recycling and help recyclers be profitable (due to the learning effect) more quickly than low subsidies do (initial recycling costs of US $18 per module, green), which results in lower overall costs for the subsidy provider (US $16 million per year instead of US $56 million per year to reach a 40% recycling rate).

recycling costs with increasing recycled volumes due to factors such as economies of scale and technological advancement[28]. Our ABM is also stochastic to account for variability in some parameters, such as landfill costs, and to enable advanced sensitivity and uncertainty analysis (Supplementary Table 1). We ran 30 simulations for each scenario from 2020 to 2050 and present the means in this article; we selected the number of simulations based on a stability analysis reported in Supplementary Fig. 2. The ABM differs from similar waste-management models as it includes decisions related to the demand and supply sides of reuse, accounts for technical factors, such as the recycling learning effect, and extends the reported metrics[21–24]. Our approach also differs from current literature on PV EOL management in that behavioural aspects are captured to better characterize the CE transition. We start by providing an overview of CE scenarios, and show that many interventions besides regulations could promote circularity (Fig. 1, Supplementary Table 2 and Supplementary Figs. 3 and 4). In the subsequent sections, we further explore several of the interventions from Fig. 1.

The baseline scenario reflects the current US conditions, calibrated to the available evidence (through iterations of full factorial

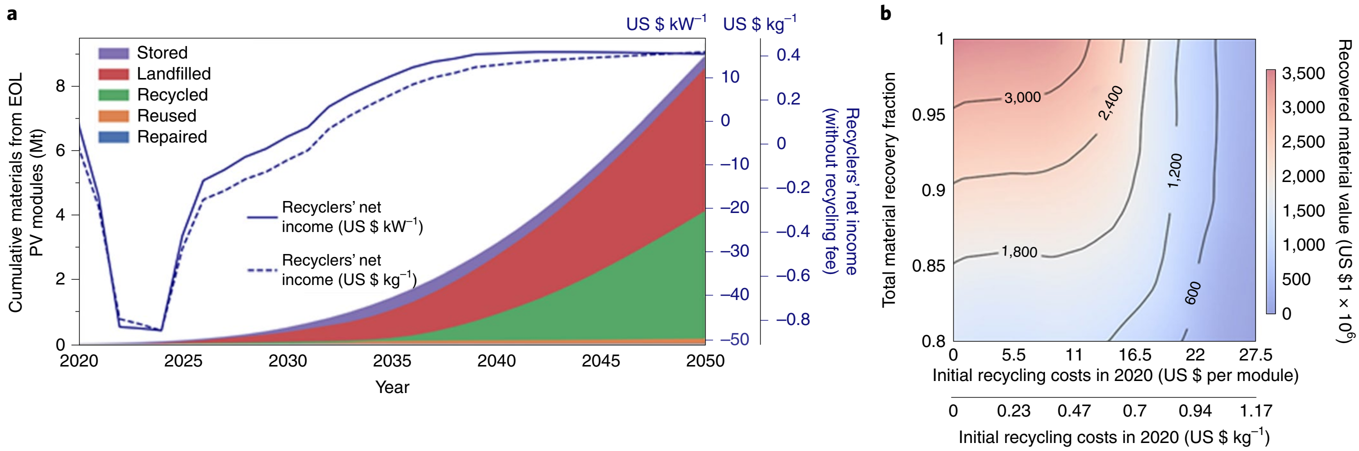

Fig. 3 | The effect of the material recovery rate and initial recycling costs on material circularity and recyclers' net income. a, Cumulative materials from EOL PV modules and recycler net income assuming the use of the FRELP process and an initial recycling cost of US \$18 per module; in this scenario, the recycler cumulative net income reaches US \$1.6 billion and the net income is US \$0.42 kg^{-1} in 2050. **b**, Cumulative recovered material value in 2050 as a function of the material recovery rate and initial recycling costs; high materials recovery and low initial recycling costs have a synergistic effect on value generation.

experiments, the unknown PV owners' attitudes towards CE behaviours were set to values that reproduced today's low recycling and reuse rates[8,29]). The baseline scenario also reproduces projected cumulative PV capacity and EOL modules based on the literature[5]. In this scenario, 500 GW of PV will be installed in the United States between 2020 and 2050, which generate 9.1 Mt of PV waste during the same period (Supplementary Fig. 5). The average initial recycling costs are US \$28 per module, the average repair costs are US \$65 per module, the used module prices are 36% of the new module prices on average and the average landfill costs are US \$1.38 per module (Supplementary Table 1). In this scenario, most modules are landfilled (83%), with 1.2% reused and 9.5% recycled (here, the percentages are mass fractions of the total generated waste). Only 80% of a given module's materials is recovered through recycling in the baseline scenario, because the assumed recycling process entails simple mechanical separation, which recovers only the aluminium frame and glass sheets from EOL modules[9]. Thus, the material recycling rate is 7.7%, equivalent to 0.7 Mt cumulatively through to 2050 (Fig. 1i). In the following, we express all the EOL rates as the mass percentage of materials and represent cumulative amounts in 2050 unless otherwise specified. In this baseline scenario, recycling is not profitable in any year, even when the learning effect and the revenue from recovered materials is accounted for, so PV owners must pay a recycling fee (Supplementary Fig. 5).

Techno-economic interventions could improve PV materials circularity. Research and development in recycling technologies could yield lower costs (Fig. 1c), better performance or both (Fig. 1b,f). Research and development to improve module durability would lower the amount of PV EOL materials generated (Fig. 1e). Market interventions, such as better warranties for recovered modules (Fig. 1g), higher landfill costs (Fig. 1d), 'seeding' of used modules to encourage secondary market development (Fig. 1h) and existing regulatory policies, such as a landfill ban[11] (Fig. 1a) could also increase circularity. We also examined two existing business models of PV module manufacturers: extended producer responsibility and waste-generator responsibility (Supplementary Fig. 6). In Fig. 1, the reuse of EOL PV modules is limited by customer willingness to purchase used modules, which explains the circularity rate decline around 2035 in some scenarios, as EOL PV modules move from the reuse pathway to other EOL pathways. Although the simulations start in 2020, the generation of EOL PV modules is assumed to start from modules installed in 2000.

Effect of lower recycling costs on the recycling rate

One barrier to recycling EOL PV modules is the lack of profitability[11,26,30]. Module materials are difficult to separate and, for the most part, have low values[30]. For example, silver accounts for half of the material value but represents less than 1% of the module mass[5]. Thus, recycling costs are not offset by revenues from recovered materials in the current simple mechanical processes of glass and metal recyclers in the United States, which leads to recycling fees of US \$25–30 per module that PV owners or installers must bear in the absence of enhanced product responsibility or take-back programmes[26]. Some states, such as Maryland and Washington, have proposed tax incentives to overcome this issue[31,32].

Figure 2a (blue line with circles) shows the effect of varying the initial (year 1) recycling costs in the ABM. The percentage of recycled EOL modules increases steeply with the falling initial recycling costs before it plateaus and reaches 73% recovery at zero cost. The plateau is due to several factors: part of the materials from recycled modules is still landfilled (for example, silicon), for some PV owners storage costs are null, so storage competes with free recycling and some cliques of agents reinforce each other into non-recycling behaviours through peer influence (these agents are tightly connected in the social network and therefore strongly influence each other's decisions). Owing to the learning effect (Fig. 2b), recycling is profitable by 2050 for each value of the initial recycling costs below US \$21 per module (Fig. 2a, red line with circle markers). With the current PV installed capacity and volumes of EOL modules, module recycling can still be considered in its infancy, and the learning effect will probably drive recycling costs down during 2020–2050. For instance, at an initial recycling cost of US \$18 per module (similar to the processing costs of high-recovery mechanical processes reported in the literature[30]) instead of US \$28 per module in the baseline scenario, the recycling rate increases from 7.7 to 44% (or 4.0 Mt) in 2050 (Fig. 1 and Supplementary Fig. 3). With the learning effect, this initial recycling cost enables recycling to be profitable by 2050 with a net income of US \$0.09 kg^{-1}. The material recycling rate is also higher when recycling processes recover more materials, for example, with the full-recovery end-of-life photovoltaic (FRELP) process. In this process, 94% of the silver and 97% of the silicon in c-Si PV modules are recovered[26], which greatly enhances the value of the recovered materials (Fig. 3a, blue lines, and Supplementary Fig. 4).

When costs alone are included in the model, the recycling rate is always null as long as recycling is more expensive than landfilling

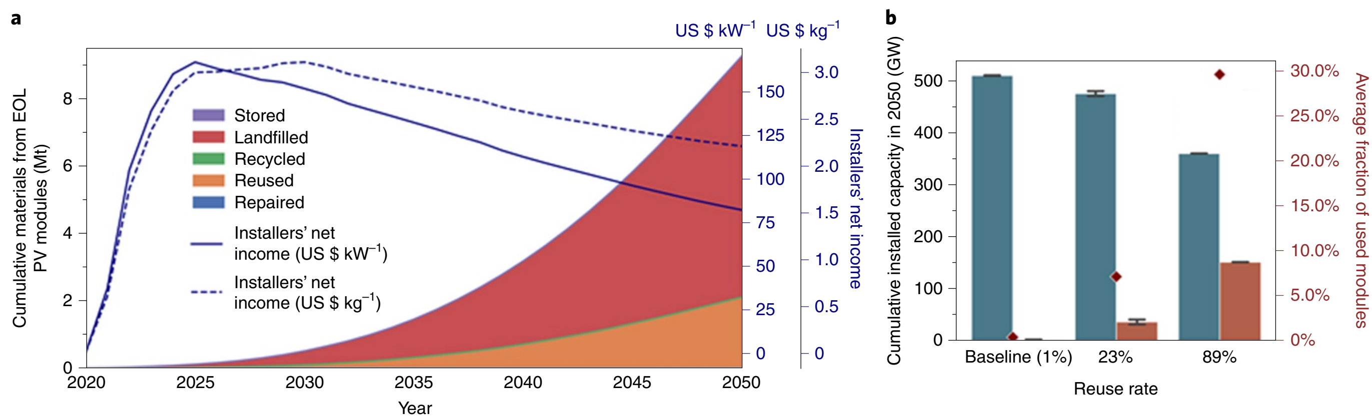

Fig. 4 | Reuse rate under different scenarios and the resulting displacement of new modules. a, Cumulative materials from EOL PV modules and installer net income assuming that improved warranties give PV owners an equivalent attitude towards used and new modules shows substantial module reuse. Installer cumulative net income is US $3.5 billion and net income is US $2.2 kg^{-1} in 2050. After 2025, the net income per module decreases as innovation reduces the PV module costs. **b**, Cumulative installed capacities of used (brown) and new (blue) modules in 2050 for various reuse rates obtained with our simulations; red diamonds (correspond to the right *y* axis) represent the average fraction of used modules. In an ideal reuse case (the 89% reuse bars), modules landfilled after their second life represent almost 10% of the cumulative EOL PV modules in 2050. Error bars are 95% confidence intervals.

(that is, when the initial recycling costs are above US $3 per module)—see the 'No social factors' line in Fig. 2a. However, when social factors that influence the PV owner decisions, such as peer influence and attitude towards recycling, are included, the recycling rate increases with falling recycling costs. When social factors alone are included (the 'No costs factors' line in Fig. 2a), the recycling rate is overestimated or underestimated. These results demonstrate the relevance of accounting for social aspects in the techno-economic analysis, because they may explain how and why a technology or behaviour is adopted. In our case study, the positive effect of social factors on circularity when the initial recycling costs are high shows the potential importance of nurturing early adopters of recycling behaviours who create a trend for other PV owners to follow.

One strategy to increase recycling is to provide a subsidy until the recycling rate target is achieved. Our simulations indicate that a larger initial subsidy can be less costly than a smaller subsidy, because it engages more PV owners to recycle earlier (Fig. 2c). Moreover, the learning effect supports recycling behaviours by lowering costs further, which leads to more PV owners adopting the recycling pathway. Overall, if the stream of EOL modules that reaches recyclers keeps increasing (which is likely), the learning effect could spur profitable recycling without subsidies. In our simulations, a 20% recycling target can be reached earlier with an US $18 per module subsidy (12 years) than with a US $10 per module subsidy (18 years), which limits the period over which subsidies must be provided. The simulations show that a yearly recycled volume above 15,000 t of EOL modules could make recycling profitable owing to the learning effect, a threshold value in line with the literature[33]. High subsidies to encourage recycling and exploit the learning effect are a relevant strategy, but the results depend strongly on the presence of a sufficient learning effect. Thus, a subsidy programme could benefit from establishing performance targets that verify the continuous improvement of recycling processes, which ensures that recycling costs do not return to original levels once subsidies stop.

Economic benefits of a higher material recovery

Recycling profitability could be increased through research and development in technologies that enable the recovery of more valuable materials—such as silver, copper and silicon—from EOL modules. High-recovery mechanical processes can enable a higher material recovery, up to 97% of the total mass using the FRELP process[26]; however, in contrast with thermal recycling processes, such mechanical processes typically recover lower-quality materials with less value and usefulness than they had in the original module[3]. Figure 3a shows shares of modules in each EOL pathway and recycler net income assuming materials recovery fractions from the FRELP process[26] and an initial recycling cost of US $18 per module[30]. FRELP recovers 20% more materials per module than that in the baseline scenario and substantially increases the recovered material value owing to the silver and silicon recovery (Supplementary Table 1). This economic benefit is likely to weaken in the future, however, as innovation causes silver and silicon to constitute progressively smaller mass fractions in c-Si PV modules[5]; our analysis does not consider this trend because of the high associated uncertainty.

Recycler cumulative net income in 2050 increases from US $296 million in the simple mechanical process scenario to US $1.6 billion in the FRELP scenario. Moreover, recycling becomes profitable earlier (2032 instead of 2037), with recycler net income reaching US $0.42 kg^{-1} in 2050 (the dip in recycler net income in Fig. 3a (blue lines) is due to initially unprofitable recycling). Figure 3b shows the synergistic effect on the recovered material value of lower initial recycling costs (which spur recycling among PV owners) and higher total material recovery fractions. For instance, at an initial recycling cost of US $16 per module, a 13% increase from an 80% material recovery fraction roughly doubles the recovered material value. The synergy between the two factors diminishes as the initial recycling costs are very high or very low. Our simulations also show that some EOL modules are stored for a short period, which leads to the small, relatively constant share of stored modules in Fig. 3a (purple wedge) as PV owners and installers wait for cheaper and more accessible recycling options or the accumulation of quantities that are more economical to ship and recycle[26].

Strategies to improve PV module reuse

Improved warranties for used modules could promote secondary markets[11]. The reuse rate increases from 1.2 to 23% (by 2.1 Mt) when it is assumed that warranties give PV owners an equivalent attitude towards used and new modules[10] (Figs. 1g and 4a). However, this assumption also decreases the recycling rate from 7.7% to less than 1%. Figure 4b shows that a 23% reuse rate (that is, the result from Fig. 4a) only covers a small portion of projected PV demand. Even with an ambitious 89% reuse rate—set by removing all the constraints to reuse except that modules can only be reused

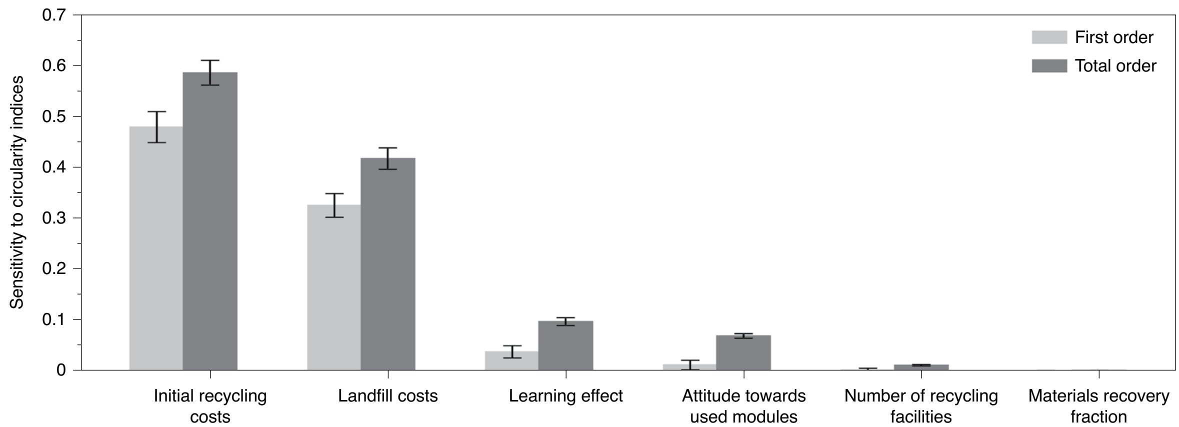

Fig. 5 | Parameter importance for EOL PV module circularity in the ABM. Categorical parameters, such as the landfill ban, are excluded. The *y* axis shows the first- and total-order Sobol indices on the effect of a parameter on the EOL PV module circularity. Error bars are 95% confidence intervals.

once in the ABM—only one-third of PV demand is met with used modules, which highlights the reuse strategy's limitation. This result is explained by the projected growth of PV demand and the imperfect substitution of used modules for new modules (due to a lower power efficiency and lifetime[34]) (see Supplementary Table 1). Once reused, modules still must be managed at the end of their second life, so developing other circular pathways, such as recycling or lifetime extension, is critical.

In practice, improved warranties may be insufficient to improve PV owner attitudes towards used modules, because other factors, such as safety concerns or aesthetic preferences, may intervene. Thus, other strategies to promote secondary markets should be considered. For instance, short-term 'seeding'—providing free modules and installation to some PV owners—has proved to be an effective strategy[35] that could develop secondary markets for PV through the peer effect (Fig. 1h). Such a seeding strategy applied to 5.0% of PV owners (that is, at least 5.0% of PV owners have used modules each year) enhances the reuse rate from 1.2 to 6.9% but lowers the recycling rate from 7.7 to 4.8% (Fig. 1 and Supplementary Fig. 3). A similar strategy, in which 10% of PV owners pay a lower initial recycling fee (US $18 per module), increases the material recycling rate to 21% (Supplementary Fig. 8).

Sensitivity analysis and combined interventions

We used a ML metamodel of the ABM to conduct a variance-based sensitivity analysis and explore the ABM parameter space at a higher speed. In this approach, the ABM is used to generate both the training and cross-validation data of the ML metamodel, whereas the latter provides expected outputs of the ABM for a given parameter combination. Figure 5 presents the first- and total-order Sobol indices (which measure the main effects and interaction effects, respectively) for some parameters that underlie the techno-economic and social interventions presented thus far. Initial recycling costs, landfill costs and the learning effect are most important to the module circularity rate, with contributions of 48, 33 and 4% to the total variance in results, respectively (Supplementary Table 3). The attitude towards used modules has a smaller but notable effect. Although some parameters present higher-order effects, the parameters rank similarly. However, the rankings change when examining output metrics other than the material circularity rate, such as the reuse rate or societal costs (Supplementary Table 3 and Supplementary Figs. 9–11). Finally, notable second-order interactions exist between the initial recycling costs and other parameters (Supplementary Table 4).

Figure 6 presents the interaction effects between the initial recycling costs and four other parameters: landfill cost, attitude towards used modules, learning parameter and number of recycling facilities. Increments of the landfill cost and learning parameter boost the effect of decreasing the initial recycling costs on the material circularity (Figs. 6a,c, respectively). For instance, with initial recycling costs of US $10 per module, raising the landfill cost from US $1.38 to 2.76 per module increases the material circularity rate from about 60 to 70% (Fig. 6a). As the reuse and recycling pathways compete, combining a more positive attitude towards used modules with lower recycling costs does not enhance the volume of PV materials diverted from landfills and storage (Fig. 6b). Transportation costs are negligible compared with recycling costs, so having fewer facilities increases the material circularity rate slightly owing to an enhanced learning effect (Fig. 6d). Finally, as with the sensitivity indices (Fig. 5), the results are different when examining other output metrics (Supplementary Figs. 12 and 13).

Figure 6 also highlights that different intervention combinations may yield the same results (that is, equifinality). For instance, initial recycling costs of US $18 per module combined with landfill costs of US $2 per module yield a 45% circularity rate, as do initial recycling costs of US $13 per module combined with 48 recycling facilities. Using the ML metamodel, we designed an experiment to identify the parameter combinations that maximize the circularity rate while minimizing societal costs (Supplementary Table 5). Overall, combining low recycling costs, high landfill costs and a high learning effect yields the best result in the ABM, which suggests that combining interventions might be the most promising strategy to increase PV circularity at the lowest costs.

Discussion

Our results should be understood as estimates of how applying CE principles could affect the EOL management of PV modules, and not as robust predictions. The ABM uses various sources as inputs, which include some outside the PV sector (for example, electronic waste literature) owing to the limited availability of primary data. For instance, the initial recycling and reuse rates are dated to 2016, and more recent estimates could yield slightly different results. Moreover, as some data variability is unknown, we approximate it using probability distributions, which adds uncertainty to the results (Supplementary Table 1). In practice, there are regional geopolitical and demographic differences, which could lead to various degrees of adoption of CE practices. Although we use the TPB to better represent human decisions related to EOL management, factors not included in the theory may affect stakeholder decisions. The parameters of the TPB model were also taken from a meta-analysis on recycling behaviours, which may not directly apply to the PV context (Supplementary Table 6). In addition, we simplify stakeholders as constituting four broad categories (PV owners,

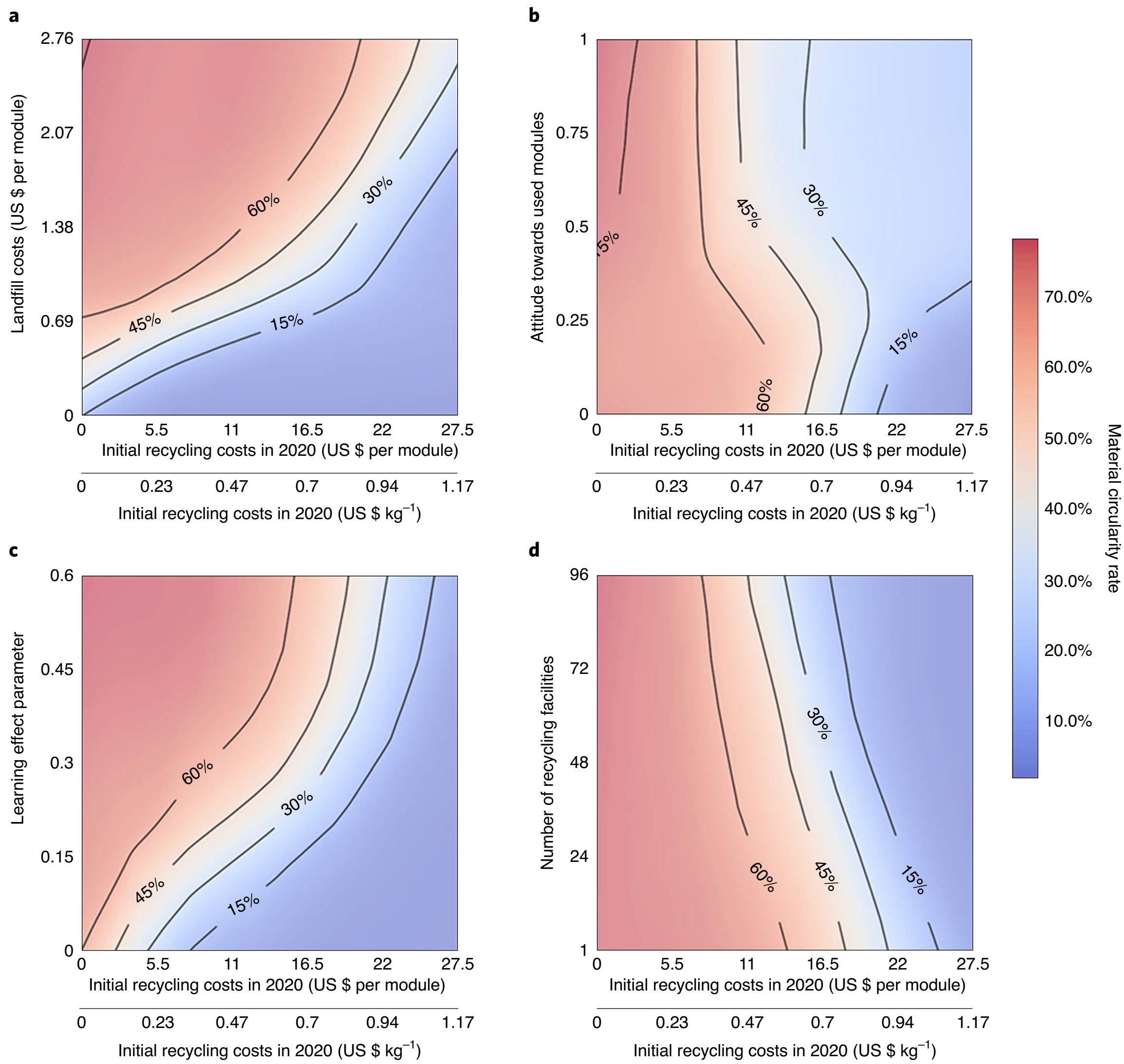

Fig. 6 | Fractions of PV module materials in circular pathways in 2050 as a function of the initial recycling costs. a–d, Landfill costs (**a**), attitude towards used modules (**b**), learning effect parameter (**c**) and number of recycling facilities (**d**).

installers, recyclers and manufacturers); in the real world, the decisions of intermediary actors (for example, brokers and insurers) may also affect PV circularity.

We limited the number of PV owner agents to one thousand, whereas more than one million real-world PV systems are in the United States[36]. Moreover, PV owners are not geographically characterized, albeit related through a social network. Although we use distributions to represent some geographical disparity, we distribute total installed PV capacity evenly between agents. Combining this ABM with a distributed PV model with a better spatial resolution, such as the National Renewable Energy Laboratory's Distributed Generation Market Demand model, could yield useful insights (for example, regarding geopolitical and demographic regional differences)[37].

Our study yields several implications for PV circularity. First, our results suggest that CE strategies compete, in line with the literature[38]. Thus, CE programmes should be based on the adoption rates for all circular pathways rather than focus on one CE strategy. Second, for reuse to be effective, the used product supply must match demand, and therefore secondary markets must be mature[39]. For example, only when PV owner attitudes towards used modules improve (for example, through warranties) does demand grow and start to substantially absorb used module supplies. Improving reuse is critical from an energy perspective, because recycling destroys most of the embedded energy of products[40,41]. However, owing to the growing PV demand as well as the lower efficiency and lifetime of used modules, even a 100% reuse rate could not satisfy PV demand, so recycling must be developed in concert with reuse initiatives.

Our results also highlight the critical roles of the total recovery fraction of materials and the learning effect to achieve profitable recycling (Fig. 1b,f, respectively), in line with existing literature[30]. Interestingly, the storage pathway acts as a buffer, which provides time for recycling processes to become more economical and ultimately diverts some modules from landfills (Fig. 3a, purple wedge). This result suggests that encouraging recycling may be particularly critical where storage space is more limited (for example, Japan).

Exploiting the ABM approach, we extended the traditional techno-economic analysis to include social factors, such as conformity to peers and general attitude towards a specific behaviour. Accounting for attitude is especially relevant for PV, because households and businesses may be inclined to environmental protection and thus recycling[42,43]. Our ABM can also be used to study interconnections and dynamics among different factors, as suggested by Lapko et al.[38].

Our results confirm the importance of factors such as the learning effect, research and development to reduce recycling costs, and public engagement[38]. Interestingly, the importance of the factors changes with the focus on different output metrics. The attitude towards used PV modules, for instance, seems less important considering the overall material circularity rate because the number of reused modules is low compared with the number of overall modules. However, this factor is the most influential regarding the overall societal cost because reuse retains more value within the economy than material recovery through recycling. Thus, ignoring social factors (such as attitude) may misrepresent the efficacy of CE interventions.

Although there are currently no manufacturers of silicon wafers in the United States[44], recycling modules in a facility near the manufacturing line is a competitive advantage, because it makes manufacturing more resilient to supply restrictions and potentially facilitates the recycling of manufacturing waste, such as silicon kerf. Recycling manufacturing waste is critical to improve the circularity, because scrap materials are less contaminated and have compositions that are better known, compared with those of postconsumer materials[45]. Such a strategy is already used by First Solar, a cadmium–telluride PV module manufacturer (Supplementary Fig. 6). The results also show that a landfill ban, such as the one in Washington State[31], could increase PV circularity substantially (Fig. 1a). However, legislation alone may be insufficient. Current European legislation, for instance, encourages mass recycling, but not necessarily high-quality multimaterials recycling[26].

Finally, our results show that high subsidies for a few years could be among the most efficient solutions to encourage recycling. In contrast with Deng et al., who found that landfill costs have the most potent effect, followed by recycling costs, we found that the initial recycling costs have the most substantial effect, followed by landfill costs[30]. This difference may occur for different reasons, for instance, because of different data used in the analysis or because the proposed model includes social factors, which impact recycling and purchasing behaviours and, thus, the results. Moreover, when looking at output metrics other than the material circularity rate, the ranking of the most influential factors changes (Fig. 5 and Supplementary Figs. 12 and 13).

In summary, this work highlights the importance of considering social factors in future CE studies. When such factors are ignored, the results may be overestimated or underestimated as they may not represent what happens in the real world. Moreover, the key to improve PV material circularity and retain maximum value in the economy may be in social interventions that aim to improve customer attitudes towards used PV modules (for example, with better certifications and warranties). Could it be possible to have a secondary market for used PV as strong as the market for used cars[34]? In future work, the ABM could be used to study other scenarios, such as the effect of public information campaigns on recycling rates. Moreover, although a design-related intervention is briefly presented (Fig. 1e), more scenarios related to the design stage, such as modules with different backsheet materials[46], could be explored. This approach, combining ABM and ML, could also be developed further to study the circularity of other technologies, such as consumer electronics, or to include environmental considerations.

Methods

Overview. Our ABM represents the main actors of the US PV sector that are involved in the transition to a more circular PV industry. Its objective is to find the techno-economic and social conditions that improve materials circularity for EOL PV modules. The ABM's primary outputs are the mass volumes of modules that reach each EOL pathway (that is, amounts that are reused, repaired, recycled, landfilled or stored), the net revenue and cost for each CE actor, the value from recovered materials and the number of years it takes to reach a specific objective. The overview, design concepts and details protocol is used to describe the ABM in this section[47], followed by details on the ML approach used to build a metamodel of the ABM and the sensitivity analysis method.

The purpose of the ABM is to study the implementation of CE strategies within the PV industry and identify the conditions that improve circularity. Four types of agents are defined: PV owners, installers, recyclers and manufacturers. Agents of a specific type behave similarly, but have heterogeneous characteristics represented by probability distributions (for example, recyclers may have different recycling costs). Agents are related to each other according to a social network that represents the real-world relationships among the CE actors. In the simulation, a time step represents a year. The start of the simulation is 2020, with 30 time steps chosen because many installations will reach their EOL around 2050[5].

The ABM builds on several existing models (referred as submodels in Supplementary Table 1). At each time step, the submodels are used in coordination to generate the output metrics. The ABM starts by modelling the cumulative amount of PV modules in use (that is, the stocks), following an approach from the literature[5]. Then, the amount of EOL PV modules is computed from a model and data from the same source[5]. We apply another submodel to represent how agents make decisions regarding a particular CE strategy. The modelled CE strategies include repair, reuse (of a repaired and/or refurbished product) and recycle, and the two other options landfill and storage. Agent decisions are based on techno-economic factors—which include technical feasibility, such as whether the modules can be repaired, and costs, such as landfill costs—and market factors (such as attitudes and social norms). The parameters used in this submodel were taken from meta-analyses on recycling and purchasing behaviours, in which it was reported that consumers influence each other's behaviours in addition to being influenced by behaviours' costs[48,49].

To compute the material circularity and the societal costs (that is, net costs of manufacturers, recyclers and installers), the ABM uses a submodel of PV module efficiency growth[5], the mass fraction of material in the modules[5], the different recycling processes' material recovery fractions[26,50] and prices of virgin and scrap materials. The recycler learning effect also uses a model and data from the literature[28]. Another submodel estimates the transportation costs related to the different EOL pathways (Supplementary Table 1 and Supplementary Fig. 14). The resulting volumes of repaired, reused, recycled, landfilled and stored change with each time step of the simulation. Supplementary Fig. 1 presents an overview of the model, Supplementary Table 1 and the sections below provide more methodological details.

Design concept. The ABM is designed in a modular fashion to ensure it can be used for different case studies; different types of agents may be defined and easily added to the model. Each agent type is defined as a Python module. In these modules, agent types are defined as Python classes, and it follows that each agent is an instance of the class of its type. A Python model module contains all the user-defined inputs, activates the agents and collects the outputs of the simulation. This modular structure is per the Mesa Python package[51]. This package is used to facilitate the activation of the agents and set up batch runs of simulations. The NetworkX Python package is also used to build the social networks relating the agents[52].

Interactions between actors of the CE are captured at several levels in the ABM (that is, within agents of the same type and between agent types). First, because interactions between PV owners may influence their decisions regarding EOL management[22,48,53], they are accounted for in the model. Second, information flows between agents of different types. For instance, PV owners have access to recyclers' recycling costs, and installers access the amount of PV modules being sold by PV owners. As another example, manufacturers know the amounts of materials being recovered by recyclers and compute the economic benefits of using those materials rather than virgin materials.

The model also contains several stochastic elements. First, the Watts–Strogatz algorithm, which is widely used to build small-world networks, requires us to rewire each edge of a regular graph with a certain probability[52,54,55]. Small-world networks are recognized as representing many real-world networks, which include social networks[54–57]. Second, some of the agents' characteristics are drawn from probability distributions to model their variability or uncertainty (for example, recycling or landfill costs may be different across the United States). Finally, the system's overall behaviour emerges from the agents' interactions and decisions during the simulation.

Details. At the beginning of the simulation, the network of agents is created. The stocks of PV modules from 2000 to 2020 are reported in the ABM and divided among PV owner agents. We chose stocks from 2000 to 2020 to account for the existing installed capacity, assuming that, before 2000, the cumulative installed capacity was negligible. From there, several submodels are used to represent various dynamics of the hypothetical circular PV sector.

The environment of the ABM is the United States. Various interventions may be enacted in the environment to see their effects. For instance, scenarios that study the implementation of a tax or a ban may be modelled as part of the environment agents that evolve within.

Moreover, agents' interactions are dependent on a social network that represents the real-world relationships between the PV industry actors (Supplementary Table 1 and Supplementary Fig. 15). In contrast with aggregated models, the ABM enables the modelling of different social network structures and provides insights into the social network role in the overall behaviour of the system[54]. Different network structures are adapted to different real-world situations. For instance, a fully connected network is more adapted to describing small groups and tight communities. For sociotechnical systems, such as the power grid or cities, the small-world or scale-free networks are more realistic[54,56]. In the ABM, a small-world network is drawn using a rewiring probability and the average number of neighbours of 0.1 and 10, respectively. These parameters are close to those of other works and real-world networks such as email communications[54,58].

Owing to computational limitations, the number of PV owners was restricted to 1,000 agents. Although it limits the representativeness of the ABM, this number of agents enables the capture of network effects and the existing variability of PV owners (for example, regarding landfill costs across the United States or attitudes towards CE pathways). The PV owners make two decisions: to purchase a new or a used product, and to manage the EOL of their products (Supplementary Table 1 and Supplementary Fig. 16).

Several processes also occur in the PV owners' module. First, the amount of product purchased each year is determined according to a piecewise function, following previous work[5], and thus similar results for the projected installed capacity are obtained, although we only consider US c-Si PV modules. Values for the model's parameters can be found in Supplementary Information, Supplementary Tables 1, 7 and 8. Still following the literature, the efficiency growth of PV modules is accounted for with an exponential function[5]. Next, a Weibull function (from which the parameters are based on empirical data[5]) is used to generate the amount of PV modules of agent i that reaches EOL at time t, ELPV_i^t (equation (1)):

$$\mathrm{ELPV}_i^t = \sum_t \mathrm{RPA}_i^t \times \left(1 - \mathrm{e}^{-(t/T)^{\alpha}}\right) \tag{1}$$

In the equation, T is the average lifetime of the PV modules, α the shape factor (which controls the typical S shape of the Weibull curve) and RPA_i^t is the remaining amount of PV modules installed by agent i at time step t. The Weibull function is appropriate to model the PV waste generation[5].

The TPB[59] is used to model the PV owners' decisions to purchase used or new modules and the EOL management of these modules. The TPB stipulates that human behaviours are influenced by the attitude A individuals hold towards the behaviour (that is, how the behaviour is perceived as favourable or unfavourable), the subjective norm SN, which refers to the perceived social pressure to perform or not perform the behaviour and the perceived behavioural control (PBC), which relates to the perceived ease or difficulty of performing the behaviour (equation (2)):

$$\mathrm{BI} = w_A A + w_{\mathrm{SN}}\mathrm{SN} + w_{\mathrm{PBC}}\mathrm{PBC} \tag{2}$$

In the equation, BI is the intention to perform the behaviour, and w_A, w_{SN} and w_{PBC} are the weights of each factor in the overall decision. The TPB is often used in ABMs of sociotechnical systems because it explains the process of individual decision making straightforwardly[21,24,60] and has been applied in many waste-management ABMs[21,22,24]. The theory explains consumers' decisions[49,61] as well as decisions within companies[13,62–64]. In our ABM, a score is attributed to each EOL pathway according to the TPB. The attitude level of each agent regarding the CE pathways (repairing, reusing and recycling) is normally distributed between 0 (negative attitude) and 1 (positive attitude). The attitude level towards linear pathways (landfilling and storing) is simply assumed to be one minus the attitude held for CE pathways. Although this distribution of agents is rather simple when compared with that in the literature[21], it is deemed sufficient for this exploratory analysis. As the parameters of the truncated normal distribution were unknown, they were calibrated. Thus, an iterative process was undertaken to find the values that reproduce low recycling[3,8] and reuse[65] rates, as they represent today's situation. The second element of the TPB, the subjective norm SN_{ip}^t of agent i and pathway p at t, is defined as per equation (3):

$$\mathrm{SN}_{ip}^t = \sum_n \frac{\mathrm{Path}_{np}^t}{N} \tag{3}$$

with Path_{np}^t being 1 if agent i's neighbour n has selected path p and zero otherwise, and N being the total number of neighbours of agent i. Thus, the subjective norm takes values between zero (no peer pressure) and one (maximum peer pressure). In the ABM, although neighbours designate nodes that share an edge in the small-world network, they may represent various relationships among PV owners in the real world (for example, friends, family, co-workers and actual neighbours). The third element of the TPB, the perceived behavioural control (that is, the perceived economic or cognitive ability to perform the behaviour), PBC_{ip}^t of agent i and pathway p at t is given by equation (4):

$$\mathrm{PBC}_{ip}^t = -\max\left(0; \frac{\mathrm{Cost}_{ip}^t}{\left|\max\left\{\mathrm{Cost}_{ip}^t \forall p\right\}\right|}\right) \tag{4}$$

where Cost_{ip}^t is the cost of choosing the pathway p at t for agent i. Finally, the behavioural intention BI_{ip}^t of agent i for pathway p at t is defined by equation (5):

$$\mathrm{BI}_{ip}^t = w_A A_{ip}^t + w_{\mathrm{SN}}\mathrm{SN}_{ip}^t + w_{\mathrm{PBC}}\mathrm{PBC}_{ip}^t \tag{5}$$

In equation (5), the values for the attitude, subjective norms and perceived behavioural control factor coefficients (w_A, w_{SN} and w_{PBC}, respectively) are taken from an existing meta-analysis on factors that affect EOL management decisions[48]. Given the high uncertainty of the coefficients' values (Supplementary Table 9), the agents could behave differently than described in this work. Supplementary Table 6 shows the results of a sensitivity analysis on the TPB's coefficients. Alternatively, the coefficients' values could be calibrated (however, the lack of empirical data on current and projected PV EOL management prevents us from conducting such extensive calibration). The agent then selects the EOL pathway with the highest score (and the amount of EOL modules ELPV_i^t is recorded as following the selected pathway for further use by other agents and the output metrics).

The TPB is also used to model the purchase decision, similar to how the EOL decision is modelled. Two options are represented in this ABM, the purchase of a new or of a used module. Another meta-analysis is used to determine the TPB coefficient values for the purchase decision[49]. The TPB may be interpreted in terms of material efficiency potentials. If one defines w_A and w_{SN} to be 0, the techno-economic potentials of the recycling, repairing and reusing CE strategies may be studied on their own. Otherwise, the social factors of the model (the subjective norm and attitude) may be added, which enables study of the achievable (or market) potential of material efficiency[15].

Installers are the second type of agent (Supplementary Table 1 and Supplementary Fig. 17). In the PV sector, installers may be in charge of collecting the EOL PV modules and eventually sorting them before selling them on the secondary market[66] (Supplementary Information, Supplementary Table 1 and Supplementary Fig. 18). They may also repair failed modules if PV owners opt for that EOL pathway. If there is insufficient demand for used modules or if they are too damaged or cost too much to be repaired (equations (6) and (7)), installers send them to a recycler or landfill, or they store them (for a limited period defined in Supplementary Table 1) until another decision is made depending on the cheapest decision at the time of the simulation (using equation (4)). Although installers' repairing costs may decrease due to the learning effect, it is assumed that handling used PV modules bears the same repair costs (whether the modules are repaired directly for PV owners or sold as used products), regardless of the possible damage to the EOL modules:

$$V_j^t = \frac{\mathrm{RR} \times \left(\sum_i V_i^t + \sum_k V_k^t\right)}{\sum^j} \text{ for } i \text{ and } k \text{ such that } \mathrm{RC}_i^t \leq \mathrm{RP}_j^t \text{ and } \mathrm{RC}_k^t \leq \mathrm{RP}_j^t \tag{6}$$

$$\mathrm{RA}_j^t = \begin{cases} V_j^t \text{ if } \sum\limits_j V_j^t \leq \sum\limits_i \mathrm{DU}_i^t \text{ for } i \text{ such that } \mathrm{PU}_i^t = 1 \\ 0 \text{ otherwise} \end{cases} \tag{7}$$

In the equations, V_j^t is the volume of modules available for sale on the secondary market by installer j. Next, RR is the module repair rate, V_i^t and V_k^t are the volume of modules that flow from the PV owner i and recycler k at time t, respectively, RC_i^t and RC_k^t are the repair costs of modules from PV owner i and recycler k at time t, respectively, and RP_j^t is the price at which agent j is selling the used modules on the secondary market at time t. Finally, RA_j^t is the amount of used modules handled by installer j that is sold on the secondary market at time t; it depends on the demand for used modules from PV owners ($\sum \mathrm{DU}_i^t$). In equation (7), PU_i^t is a Boolean that is one when the PV owner i has decided to purchase a used module at time t and zero otherwise. Installers also improve their repair processes owing to the learning effect, and thus decrease repair costs. The learning effect can be characterized by several mechanisms, such as technology advancement, increased labour productivity, economies of scale and improved material and energy efficiency[28]. As the volume of EOL PV modules dealt with by an installer increases, at least three of these mechanisms may apply: increased labour productivity, economies of scale and energy efficiency. In the ABM, the learning effect is modelled as a function of the repaired volume, following the literature[28].

Recycler agents are similar to installers in two ways. First, they may take on the responsibility of sorting EOL PV modules that can be sold on secondary markets (with those modules then flowing to installers); this behaviour was assessed via interviews with a US recycler (RecyclePV, personal communication). Second, recyclers improve their recycling processes in the model, which simulates the learning effect (Supplementary Table 1 and Supplementary Fig. 19). Another recycler role is to recover materials from EOL PV modules. In the ABM, this is simply modelled from the material recovery rates of a given recycling process (for example, simple mechanical processes or the FRELP process[26]), the fractions of materials that constitute PV modules and the volume of modules being recycled. In the ABM, PV owners pay a fee to recycle EOL PV modules, whereas manufacturers buy recycled materials at market prices. With the current US recycling processes, revenue from the recovered materials is insufficient to cover recycling costs[26].

Manufacturer agents purchase recovered materials from recyclers (Supplementary Table 1 and Fig. 20). The avoided costs from using recovered rather than virgin materials can be computed within the model based on their respective values. For instance, the price of aluminium scrap is often about 60% of the price of virgin aluminium[67], which brings profits for manufacturers that use aluminium. The model does not consider price fluctuation, given the price volatility of materials such as silicon and silver.

We applied four validation techniques to ensure the quality of the results produced by the model: theory validation, data validation, model output validation and face validation[68]. First, regarding theory validation, only empirically validated models were used (for example, TPB). Next, for the baseline scenario, empirical data were mostly used; when parameters were unknown, they were calibrated[3,5,8,65]. Given that several parameter combinations could lead to the same results (that is, equifinality), we further analysed the impact of different values for the two calibrated parameters (that is, the attitude values for the purchase of second-hand PV modules and EOL management) on the results (Supplementary Fig. 21). Then, the cumulative installed capacity and the mass of EOL PV modules generated during the 2020 to 2050 period were validated with the literature[5] (Supplementary Fig. 5). Finally, the results of the ABM went through an internal revision process with ABM and PV experts to ensure the model was behaving in a meaningful way, and extreme scenarios were also studied (Supplementary Table 10).

Multilayer perceptron regressor metamodel and sensitivity analysis. The combination of ABM and ML has recently gained attention owing to the complementarity of the two approaches[69]. These methods can be combined in two ways: ML can generate agent behavioural rules from data[35], and an ABM can be explored in depth (that is, varying the ABM inputs to examine a wide range of possible outputs) by building a ML metamodel that avoids computationally intensive simulations and saves time[70]. The exploratory nature of this work meant we used the second approach in this study. Following Vahdati et al., we built a ML metamodel of the ABM described above[70]. Using the Scikit-learn Python library[71], we constructed different ML models using different combinations of hyperparameters. In our study, all the features (input data) and output data are known in the dataset generated by the ABM; thus, a supervised ML is used.

In this study, the training dataset is generated with the ABM. To produce the dataset that best represents the behaviour space of our model while limiting the required number of simulations, we used a quasi-Monte Carlo approach. First, we defined the range of each parameter to vary in the quasi-Monte Carlo simulations. For some parameters, it is merely their minimum and maximum possible values (for example, for ratios). For parameters without theoretical bounds, realistic ranges were defined according to the literature. For landfill costs, for instance, the minimum value was set to zero and the maximum value was set to twice the average value of the baseline scenario; it seems unrealistic that landfill costs could be higher than that based on current trends[27]. A similar logic was applied to other parameters (Supplementary Table 5). Next, the method from Saltelli was used to generate the Sobol sequences of parameter value combinations[72]. Sobol sequences aim to approximate the model's behaviour within the parameter space by attempting to cover as much of the parameter space as possible as quickly (with the fewest samples) as possible. This is one of the highest-performing methods (for example, compared with the Latin hypercube design) regarding the quality of results obtained as a function of computational time, and it is often used to build metamodels[73,74]. Thus, using the SALib Python library[75], 2,800 parameter value combinations were generated, to which we added the baseline parameter value combination as well as variants of the baseline, varying each parameter to its lower and upper bound (to include extreme cases in our dataset). In total, 2,810 parameter value combinations were run 6 times (this number of replicates was found sufficient to account for the model's stochasticity, based on a stability analysis reported in Supplementary Fig. 22), which amounted to 16,860 simulations.

Next, we iterated a tenfold cross-validation, varying the ML algorithm, its hyperparameters and the output metric considered in the dataset. We kept the multilayer perceptron regressor algorithm, which yields a good compromise between computation time and a high coefficient of determination in all the output metrics (Supplementary Table 11). Once trained, the metamodel was used to predict the outputs of parameter value combinations not run with the ABM. The SALib library was finally used to conduct a variance-based (Sobol) sensitivity analysis and thus measure the variability of model outputs that can be accounted for by changes in the model inputs. We used the Sobol method because of its ability to evaluate interaction effects and the low risk that dependencies exist between the parameters of our ABM. Moreover, we compared the results from the variance-based sensitivity analysis with results from a moment-independent sensitivity analysis to confirm the rankings of the parameters (Supplementary Table 3). The use of the ML metamodel means results from Figs. 3b, 5 and 6, Supplementary Tables 3–5 and Supplementary Figs. 9–13 are approximations of the ABM's results.

Data availability

The authors declare that the data supporting the findings of this study are available within the paper and its Supplementary Information.

Code availability

The source code for the model developed in this study can be accessed at https://github.com/NREL/ABSiCE.

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Author contributions

J.W., A.C. and G.A.H. developed the study concept. J.W. designed the methodology. J.W. built the model. J.W. performed the analysis. J.W., A.C. and G.A.H. wrote the paper.

Competing interests

The authors declare no competing interests.

Additional information

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