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A multi-agent system to dynamically devise an LCA framework weighting system taking into account socio-technical and environmental consideration

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This research article explores the need to adapt the weighting system of a life cycle assessment (LCA) framework to a wide range of socio-technical and environmental considerations, which are complex and sensitive to external stressors. The study demonstrates the potential of agent-based systems to adapt a weighting system to dynamic conditions, and suggests integrating an agent-based model to handle uncertainties of weighting in environmental impact assessment. Generative adversarial networks (GANs) and multi-agent systems (MAS) are utilized to address data limitations and simulate diverse scenarios. We confirm the potential of agent-based systems to analyse the effective management of uncertainties and customization of weighting systems in environmental impact assessments to improve decision making. Furthermore, the study emphasizes the importance of continuous adaptation and recalibration to ensure the system remains relevant in dynamic environments. The results confirm that MAS is a powerful tool for managing uncertainty, customizing weighting systems and improving decision making in environmental assessments. Moreover, the study acknowledges challenges and sets the groundwork for future research.

1. Introduction

In modern decision-making processes, assessing the environmental impact is crucial [1,2]. It promotes sustainable practices and minimizes negative effects. However, as ecosystems become more complex and change rapidly, traditional methods struggle to handle uncertainties [3,4]. Building upon the imperative to place people at the centre of sustainable transitions, one of the co-authors of this paper emphasizes the importance of integrating socio-technical and environmental considerations into decision-making processes [5]. Rezgui argues that climate policies should move beyond mere carbon counting to ensure just and prosperous transitions, focusing on life cycle assessment (LCA) that incorporates occupant feedback and circular resource management. This perspective aligns with the proposed multi-agent systems (MAS) approach in this paper, which addresses the dynamic interactions between social, environmental and technical factors within LCA frameworks. By advocating participative and adaptive approaches to sustainability, the study aims to enhance the effectiveness and inclusivity of environmental impact assessments. To tackle uncertainties, we propose a novel technique that utilizes MAS to analyse the weighting process in environmental impact assessments [6]. This approach addresses key research questions and lays the groundwork for future investigations. LCA involves complex interactions among consumers, producers, suppliers and regulatory bodies. To model these interactions, MAS represents each entity as an autonomous agent with its own decision-making rules and objectives. Given the dynamic nature of environmental and social systems, MAS can adapt to changing conditions by enabling agents to learn and evolve their behaviour based on feedback and new information. Researchers can use MAS to simulate various scenarios, such as shifts in consumer behaviour, changes in production practices or policy interventions and study their effects on environmental and social indicators [5].

Therefore, this study introduces a new approach to handling uncertainties in assessing complex and ever-changing ecosystems. This allows for a more personalized approach to weighting systems and a better ability to handle complexities. Although there are still challenges to overcome, this study establishes a foundation for future improvements that will enhance the effectiveness of agent-based systems in dealing with uncertainty weights in LCAs. The study confirms that agent-based systems can potentially analyse uncertainties of weighting in environmental impact assessment. The proposed model also identifies difficulties when integrating MAS, such as ensuring the model is accurate, dealing with computational complexity and calibrating parameters. These challenges can inspire future research efforts to improve the use of agent-based systems in assessing environmental impact. The contributions answer the following research questions:

(i) *Can agent-based systems provide an acceptable solution for delivering the weighting system of an environmental impact assessment framework to address the uncertainty linked to the complex and dynamic ecosystem of buildings?*

(ii) *How can we ensure continuous fitness for such a weighting system, and what factors should trigger its recalibration?*

Experts can assess the solution and determine its acceptability. We utilize a psychological research-based theoretical framework of social influence and implement it in an agent-based behaviour model. For the case study, we use survey data on experts' weighting of environmental impact assessments. We chose generative adversarial networks (GANs) to address our data limitations because they can generate high-quality synthetic data that closely mimic complex, multidimensional distributions [7]. Unlike traditional methods like SMOTE, which risk overfitting and struggle with high-dimensional relationships [8], GANs effectively capture and reproduce the nuanced variability of expert assessments, enhancing the robustness of our agent-based model without introducing bias. Advanced GAN architectures, such as conditional GANs [9], offer additional flexibility by allowing data generation conditioned on specific parameters, aligning well with our modelling needs. In summary, GANs provide a sophisticated and flexible solution to our data limitations, making them more suitable than other methodologies for this study. We then fit model parameters to the empirical data and compare the simulation output with empirical data for validation. Once all variants of the behaviour model are validated with the empirical data, we can test the model variants against each other to determine the best-performing model.

This article is structured as follows: §2 prepares the literature reviews; §3 covers the methodologies of MAS and GANs; §4 focuses on a case study; §5 contains the results and discussion; and in §6 we present the conclusions drawn from the findings.

2. Related work

People are fascinated by natural events like volcanoes, floods, tsunamis, earthquakes and pandemics, even though the timing and severity of these events are unpredictable. These seemingly localized events can affect people's values and personalities globally. The number of natural disasters for which clear-up costs over a billion dollars has increased significantly over the past four decades, rising from an average of 3 per year in the 1980s to 13 per year during the 2010s, according to usafact.org [10,11]. Survey sampling methodologies are essential for investigating people's interest in natural events and disasters. Understanding how individuals respond to and are captivated by these phenomena is crucial for comprehending societal perceptions, assessing risks and developing coping mechanisms [12]. Survey sampling involves selecting individuals from a population based on various attributes for surveying purposes. Skinner & Wakefield provided an overview of the mathematical complexity analysis in surveys [13]. Beliefs about desirable outcomes or actions that transcend specific circumstances are known as values. They inform the evaluation and choice of behaviour and events and are ranked according to personal importance. Values can affect behaviour directly or indirectly and may be influenced by attitudes, norms or beliefs specific to certain behaviours [14,15]. Human societies are complex and ever-changing systems, and their behaviour cannot be determined by analysing each part separately. This makes them unpredictable, and their history often influences their characteristics. The complexity of societies is due to the many nonlinear interactions between individuals, which involve transmitting knowledge that affects the behaviour of recipients. Therefore, analysing society as a whole by studying individuals one at a time is impossible [16]. Weighting is a complex and contentious issue in environmental impact assessments, mainly because it involves social, political and ethical values stemming from voter actions. Environment or the composition of a panel or questionnaire can influence weighting factors. Assigning weights in a survey is intricately linked with an individual's values, encompassing fundamental beliefs and priorities. These values influence the judgement of the relative importance of survey parameters, showcasing the subjective nature of responses and underscoring the role of personal values in interpreting data and making decisions. Influence is an interesting concept in psychology, as it often occurs unconsciously. People can be influenced without even realizing it. This is because individuals often seek a sense of belonging while also wanting to stand out. As a result, people tend to make choices that they believe are popular or will help them fit in. Hoi-Wing Chan *et al.* have shown that valuing the group's wellbeing over personal interests encourages actions that benefit the environment [17]. However, it is important to note that individuals may not always follow their values, as the connection between values and actions may vary based on cultural and societal factors [18].

Agent-based modelling places a greater emphasis on human behaviour, as demonstrated by its application in social networks. This is due to the complex, nonlinear, discontinuous or discrete nature of the interactions between agents in these networks and the heterogeneous population and complex topology of the interactions. However, agent-based models often lack theoretical foundations and must be validated against real-life data [19,20]. Figure 1 shows a general semantics MAS in human values simulation.

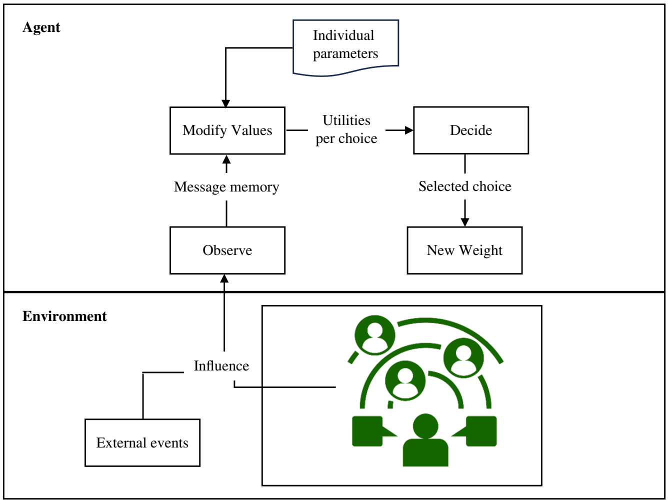

Figure 1. A general semantics MAS in human values simulation.

Compared to human societies and other complex systems, MAS are small-scale models of genuine systems that adhere to the same dynamics and principles. It is relatively simple to modify individual behaviour by implementing rules that affect the behaviour of individual agents [21,22].

This study simplifies the model by focusing on five key factors influencing individuals' environmental values: education, age, close friends, supervisors and media. Education provides vital knowledge for understanding environmental challenges, while close friends significantly influence beliefs and behaviours. Media shapes perceptions through diverse information sources, and supervisors in the workplace can foster sustainability practices. Age reflects evolving environmental values over a lifetime, with younger generations increasingly embracing eco-conscious perspectives. These factors highlight the complex interplay of social, educational and generational influences on environmental attitudes.

— *Education*: a person's level of education has a significant effect on their attitudes towards the environment. According to a study conducted by Sun *et al.* in China [23], individuals with higher education levels are more likely to show concern for climate change and take measures to protect the environment. Education plays a key role in shaping environmental values, often involving discussions on environmental issues, sustainable practices and climate change. People with higher education levels are generally better informed about these matters and tend to prioritize environmentally friendly behaviours [24–26]. Kollmuss & Agyeman showed that people with higher education levels generally possess greater environmental awareness and are more likely to adopt pro-environmental behaviours [27]. A survey by Muttarak & Chankrajang [28] found that gender and education are the key personal characteristics influencing the adoption of behaviours that help reduce greenhouse gas emissions. It has been discovered that individuals with higher levels of education tend to have a greater level of concern about climate change. This is probably owing to their better understanding of science and familiarity with a broader range of issues compared to those with less education. The evidence in the literature regarding the relationship between age and climate-change related attitudes and behaviours remains inconclusive, as reported by Frederiks *et al.* [29].

— *Close friends*: the individuals that a person spends time with can greatly influence their values. The effect of close friends is significant, as people tend to adopt behaviours and values that align with their social circles. For instance, if a close friend is environmentally conscious, it is more likely that others will be inspired to adopt similar values [18,30,31]. The influence of close friends on a person's environmental values is significant.

Discussions and social interactions with friends regarding environmental issues can shape attitudes and behaviours. Studies have indicated that interpersonal communication about environmental issues can moderate the effect of media on pro-environmental conduct. Friends can offer support, share information and motivate others to participate in eco-friendly practices [32]. Videras *et al*. demonstrated that close friendships and neighbourhood associations are linked to pro-environmental actions [30].

— *Media*: the media has the power to shape our environmental values. According to Huang [33], individuals exposed to more environmental news in the media are more likely to express concern about climate change. However, it is important to exercise critical thinking when consuming information from the media as it can convey mixed messages about the environment. Countries with high media diversity offer various viewpoints for individuals to consider [34–36]. Research has indicated that being informed about global warming and environmental concerns through media sources can increase the likelihood of engaging in pro-environmental actions [32]. Increased media exposure can help raise awareness, shape attitudes and inspire individuals to safeguard the environment. Nonetheless, it is of note that the effect of media coverage can differ depending on how each person interprets and perceives the information.

— *Supervisor*: the values towards the environment can be affected by a supervisor. If a supervisor is mindful of the environment, they are more likely to create a work environment that supports environmental values. Studies conducted by Raineri & Paillé [37] showed that employees working for companies that prioritize environmental friendliness are more likely to have environmental awareness themselves. While a supervisor's effect on environmental values in the workplace is significant, it may be less noticeable when compared to other factors [38,39].

— *Age*: many millennials and members of Generation Z are passionate about environmental issues and actively participate in environmental activism. This age group often advocates for policies and actions that address climate change and promote sustainability. This may be due to their upbringing, as they have grown up aware of environmental concerns and have witnessed firsthand the effects of climate change [40,41]. According to research [42], younger people are generally more aware of environmental issues and are more likely to take actions that support the environment than older people. This is possible because younger people are exposed to more education and awareness campaigns about the environment during school and university. Additionally, younger people may feel more urgency about the effect of climate change on their future. Although research indicates that many older individuals are passionate about protecting the environment, some studies suggest that age may not significantly affect pro-environmental behaviours or may result in inconsistent effects [43,44].

It is worth noting that these factors are interconnected and can influence each other. For instance, a person's education may influence the media they consume, affecting their social circle. As a result, the combined effect of multiple factors is often more effective than any individual one. The following section will outline the research approach and review closely related works.

3. Methodology

In this section we propose a multidisciplinary approach to studying dynamic weighting in surveys, using MAS to analyse them in environmental impact assessments. MAS are ideal for this study owing to their ability to model the complex dynamics of LCA stakeholders as autonomous agents with distinct objectives [45,46]. This captures adaptive behaviours in evolving environmental and social ecosystems, which is crucial for analysing uncertainties in environmental impact assessments and simulating emergent phenomena. Incorporating learning mechanisms allows agents to adjust behaviours based on new information, enhancing the accuracy and adaptability of the LCA weighting process [47]. Integrating social influence theories enables simulation of how agents decisions are affected by others, which is vital for understanding collective decision making in environmental assessments. By simulating dynamic, nonlinear stakeholder interactions, MAS address key challenges in environmental impact assessment modelling and aid in developing nuanced, personalized weighting systems [48]. They also incorporate heterogeneous data sources and explore various scenarios, providing a robust framework for sensitivity analyses and policy evaluations. By simulating the long-term consequences of different weighting approaches, MAS support the development of more sustainable and socially acceptable environmental assessment methodologies. We use a theoretical framework of social influence from psychological research and implement this framework in an agent-based behaviour model.

For the case study, we use survey data of experts' weighting of environmental impact assessments. To increase the amount of data, we used a GAN method as the data were limited. We then fit model parameters to the empirical data and compare the simulation output with observed data for validation. Once all variants of the behaviour model are validated with the empirical data, we test the model variants against each other to determine the best-performing model. Figure 2 illustrates the concepts involved in dynamically evaluating weights in LCA. In the next section, we will discuss using a class of machine learning models to solve numerical data limited availability.

(a) GANs

In some instances, obtaining numerical data can be challenging owing to its limited availability, high cost or the need for specialized expertise to collect it. Additionally, confidential information may prevent the publication of such data. These limitations can make it difficult to process and analyse data or restrict research related to clustering. Finding alternative methods to supplement or augment the available data is necessary to overcome these obstacles. Synthetic data refers to data that is artificially created to imitate the statistical properties of real-world data. This data type is usually generated using algorithms or models specifically designed to replicate the patterns and relationships found in the original data. Synthetic data can come in various forms, including tabular data, time series, text, images, videos or even simulations of environments. Suppose there is a lack of survey data when conducting a weighting survey. In that case, a GAN can generate synthetic data replicating the original characteristics and is compatible with the model through deep learning techniques.

Initially, generative models were developed to create examples resembling samples drawn from the distribution utilized for training the model. Among the most influential generative models currently available is the GAN, first introduced in 2014 by Goodfellow *et al*. [7]. GANs are a class of machine learning models that leverage a unique architecture comprising two neural networks—a generator and a discriminator—to generate synthetic data that closely resembles real-world data. The GAN architecture comprises an input layer with parallel input neurons, multiple hidden layers and an output layer arranged as a directed graph. The model is trained on a variation of the gradient-descent backpropagation algorithm. The flow chart for the general semantics of GAN is illustrated in the figure 3.

The image shown in figure 3 displays the objective function that is being optimized. The function for the discriminator is labelled as D, while the function for the generator is labelled as G; P_z refers to the probability distribution of the latent space, typically a random Gaussian distribution, P_{data} refers to the probability distribution of the training dataset. When a sample is taken from P_{data}, the discriminator aims to classify it as an actual sample. On the other hand, when $G(z)$ (a generated sample) is input, the discriminator aims to classify it as a fake sample. The discriminator aims to reduce the $D(G(z))$ probability to zero. Therefore, it seeks to maximize $(1 - D(G(z)))$. On the other hand, the goal of the generator is to increase the probability of $D(G(z))$ to 1, so the discriminator mistakenly identifies a generated sample as accurate. Thus, the generator aims to minimize $(1 - D(G(z)))$. Equation (3.1) describes an optimization problem

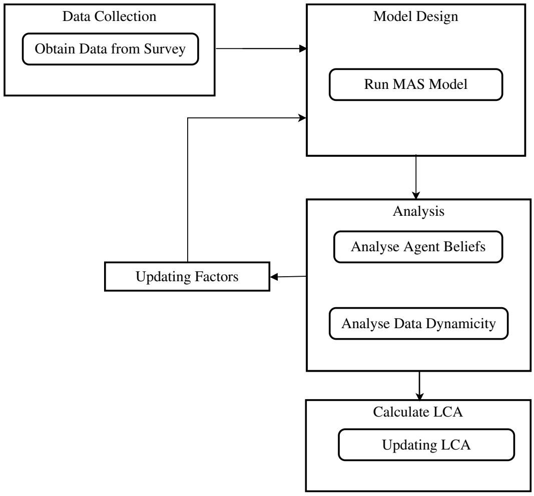

Figure 2. Dynamically evaluating weights in LCA.

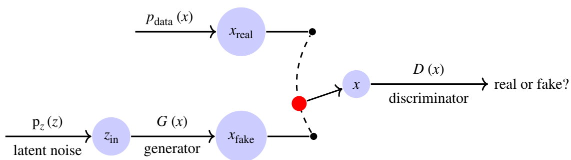

Figure 3. The general semantics flow chart of GAN.

where the generator seeks to minimize the objective function while the discriminator attempts to maximize it:

$$\underset{G}{min}\,\underset{D}{max}V(D,G) = \mathbb{E}_{x \sim p_{data}(x)}[logD(x)] + \mathbb{E}_{z \sim p_z(z)}[log(1 - D(G(z)))], \tag{3.1}$$

where $p_{data}x$ is the real data distribution and $p_{\theta}(z)$ is the latent distribution; $\mathbb{E}_{x \sim p_{data}(x)}$ means taking the expectation concerning x drawn from $p_{data}(x)$ and $\mathbb{E}_{z \sim p_z(z)}$ means taking the expectation concerning z drawn from $p_z(z)$. Initially trained on real-world data, the discriminator network learns to distinguish between genuine and fake data. Meanwhile, the generator network produces random noise, fine-tuned based on feedback from the discriminator network, to create a transformation function capable of generating a random variable that matches the desired distribution. The success of GANs lie in the discriminator's ability to accurately differentiate between real and synthetic data, making it a powerful tool for data generation and simulation in various domains.

Creating a reliable general-purpose GAN for tabular datasets is a complex task, as different types of data, such as numerical, categorical, time, text and cross-table references, can be present in the table. Moreover, the distributions of these variables can take on various shapes, including multimodal, long tail and others [49]. A table $\mathbb{T}$ consists of n_c continuous random variables $\{C_1, \ldots, C_{n_c}\}$ and n_d discrete (multinomial) random variables $\{D_1, \ldots, D_{n_d}\}$. These variables follow an unknown joint distribution $\mathbb{P}(C_{1:n_c}, D_{1:n_d})$. Each row represents one sample from the joint distribution and is denoted using a lowercase $\{C_{1,j}, \ldots, C_{n_c,j}, d_{1,j}, \ldots. d_{n_d,j}\}$. The rows are sampled independently; sequential data are not considered. The objective is to learn a generative model $\mathbb{M}(C_{1:n_c}, D_{1:n_d})$ that can create a synthetic table $\mathbb{T}_{synth}$ satisfying the following criteria. First, a machine learning model trained on $\mathbb{T}_{synth}$ should achieve a similar accuracy on a real test table $\mathbb{T}_{test}$ as a model trained on data from $\mathbb{T}$. Second, the mutual information between any two variables i and j in $\mathbb{T}$ and $\mathbb{T}_{synth}$ should be similar [50].

Table 1. Parameters and features used in the survey.

Weights (LCA impact categories)	GWP, ODP, AP, EUT, POCP, ADPmm, ADPfos, PM, IRP, ETP-fw, water, HTP, SQP, hazard, non-hazard
Demographic factors	Age, gender, education, marriage, race, religion, occupation, organization
Personality factors HEXACO personality inventory	H, E, X, A, C, O

Various GAN models have been developed to handle tabular data. Phillips *et al.* [51] created the Multi-Output Regression GANs (MOR-GANs) for multi-output regression. TGAN focuses on generating tabular data with mixed variable types [50], while CTGAN implements mode-specific normalization to overcome non-Gaussian and multimodal distributions [52]. MedGAN proposes a method to circumvent categorical values in GANs by using autoencoders [53,54]. Conditional Wasserstein GAN offers an oversampling approach based on a conditional Wasserstein GAN and pays special attention to the downstream classification task through an auxiliary classifier loss [55]. TableGAN introduces information loss and a classifier into the GAN framework and specifically adopts a convolutional neural network for the generator, discriminator and classifier [56]. G-PATE aims to train a scalable differentially private data generator that preserves generated data utility [57]. All the GANs mentioned above aim to meet two requirements: achieving comparable accuracy on the test set and similarity in mutual information between any two variables.

4. Case study

In this section we discuss the key components that form the foundation of the case study methodology and analysis. These components comprise the weights, features and parameters utilized in the research framework.

(a) Weights, features and parameters

The weights, features and parameters used in the research framework are listed in table 1. This set of agent parameters is presented in three distinctions: a weighting set (of LCA impact categories), demographic factors and personality factors. The following paragraphs describe each set of parameters in turn.

LCA impact categories form the weighted values in this investigation. The impact categories in these works align with those described in the British Standard BS EN 15804 Sustainability of Construction Products. While other works focus only on a subset of the impact categories set out in the standard [58], this study utilizes a complete set of environmental impact categories described by BS EN 15804. It operates on the belief that the importance of each category should be decided by building stakeholders and not pre-filtered by the authors. Table 1 lists the complete set of environmental impact categories, though a short description of each category is presented here:

(i) *Global warming potential (GWP)*: an indicator of potential global warming owing to emissions of greenhouse gases.
(ii) *Depletion potential of the stratospheric ozone layer (ODP)*: an emission indicator that destroys the ozone layer.
(iii) *Acidification potential—accumulated exceedance (AP)*: an indicator of the potential acidification of soils and water owing to the release of gases.
(iv) *Eutrophication potential (EP)*: an indicator of the enrichment of ecosystems with nutritional elements owing to emissions.

(v) *Formation potential of tropospheric ozone (POCP)*: an indicator of emissions that affect the creation of photochemical ozone in the lower atmosphere.
(vi) *Abiotic depletion potential of minerals and metals (ADP-mm)*: an indicator of the depletion of non-fossil resources.
(vii) *Abiotic depletion potential of fossil resources (ADP-fossil)*: an indicator of the depletion of fossil resources.
(viii) *Water deprivation potential (WDP)*: an indicator of the relative amount of water used.
(ix) *Particulate matter emissions (PM)*: an indicator of the potential incidence of disease owing to particulate matter emissions.
(x) *Ionizing radiation (IRP)*: an indicator of damage to human health and ecosystems owing to radionuclide emissions.
(xi) *Eco-toxicity—freshwater (ETP-fw)*: an indicator of the effect on freshwater organisms from toxic substances.
(xii) *Human toxicity (HTP)*: an indicator of the effect on humans from toxic substances.
(xiii) *Potential soil quality index (SQP)*: an indicator of changes in soil quality.
(xiv) *Hazardous + radioactive waste disposed (HRD)*: a measure of the hazardous and radioactive waste disposed.
(xv) *Non-hazardous waste disposed (NHD)*: a measure of the non-hazardous and non-radioactive waste disposed.

A weighting set for the impact categories described above is derived for each respondent (participant or agent). Responses are captured through a survey that implements an analytical hierarchy process to derive the relative importance of each environmental impact category.

This study utilizes the HEXACO Personality Inventory as a third set of agent parameters to incorporate personality structure into the MAS. HEXACO is a six-dimensional personality structure framework developed in 2006 as a viable alternative to the Big Five model [59]. It has been used in studies to predict the ideological orientation of participants within political ideology and voting and has been found to outperform the Big Five Model [60]. The HEXACO model contains six dimensions that structure personality [61].

— Honestly—Humility (H)
— Emotionality (E)
— Extraversion (X)
— Agreeableness (A)
— Conscientiousness (C)
— Openness to experience (O)

A lexical strategy is used in the HEXACO Personality Inventory to explore personality through self-rating. This study utilizes the 100-question survey called the HEXACO Personality Inventory-Revised edition [61].

Multiple rounds of training data were created and tested to develop the MAS. Initially, testing was performed on a synthetic dataset with $n = 50$, where responses related to the environmental impact category were given more importance and demographic information was generated randomly. However, this approach resulted in inconsistent data, and the importance of factors was not always consistent. For example, A was sometimes considered more important than C, even though A was originally rated lower than C. A large language model was used to test training data with high internal consistency; it was interrogated to create profile agents for possible building stakeholders. Poe, which is a proprietary artificial intelligence bot similar to ChatGPT, was employed by the authors to rate the significance of each environmental impact category from the point of view of potential building occupants/stakeholders, i.e. Architect, Engineer, Student, Policy Maker, General Public, Researcher, Health and Safety Professional, Academic and LCA practitioner.

After analysing the responses and rankings received from the Poe survey, rule-based profiles were created for each building stakeholder. These profiles were then used to limit the generation of random responses to produce another $n = 50$ synthetic dataset with no internal logical inconsistencies. The profiles above were then requested to generate responses to the demographic and personality aspects of the survey. A selection was made randomly from an extensive list of options for the demographic elements, which was informed through X standards. While generating responses to the personality-based elements, rule-based constraints were again applied, but only to the extent necessary to produce realistic results.

The survey was conducted in July 2023. Each respondent was asked to complete three elements related to the parameters listed in table 1:

— A digital questionnaire which asked participants to provide pairwise comparisons of each environmental impact category.
— A digital questionnaire eliciting high-level demographic information.
— A HEXACO-PI-R questionnaire to determine the participants' personality structure.

(b) Data preparation and applying a GAN

Generating data can either aim to augment existing data or create more representative training datasets for machine learning models. These models require a large amount of accurately labelled data to perform well. Synthetic data generators offer a viable alternative to reduce the time and costs associated with data collection. The study utilized CTGAN architectures and concentrated on continuous numerical data to supply alternative or supplementary data for the weighting. A table containing discrete and continuous variables with approximately 50 rows was obtained from a survey. The dataset had 28 columns, with 13 serving as features and the remaining 15 columns as weights. The total of all weight columns added up to 1. This study uses SDV, a Python package that generates synthetic data based on the provided dataset [62]. Efforts are made to minimize risks when using synthetic samples. Overusing such samples may create patterns and features not found in real data, causing the model to learn to recognize these patterns instead of the true underlying ones. Furthermore, if the synthetic data are not generated with care, bias and distortions may be introduced into the dataset that could affect the performance of the classification algorithm. The synthetic data produced consisted of 500 rows representing agents, and the overall per percentage was 93.71%. The synthetic data accurately mimic the mathematical properties of the columns in the dataset. Also, column pair trends were 98.23% and column shapes were 89.18% (see table 2). The synthetic data comprised 91.8% of the total data and included more than 90% of the numerical ranges found in the real data. Moreover, over 90% of the synthetic rows were unique and not duplicates of the real data. The synthetic data adhered to more than 90% of the minimum and maximum boundaries specified by the user. Figure 4 shows real data versus synthetic data for GWP, AP, EUT and ODP as the samples.

(c) Interaction design

When designing agent-based applications, interactions between agents are crucial. Each agent has unique values that influence how they negotiate and interact with others. When agents interact with each other, there are certain protocols and rules in place to determine when the interaction is complete. In this model, each agent (represented by the variable i) holds a 15-dimensional opinion. In this case study, these dimensions j, which are weights (w_{ij}), are represented by real values that fall from zero to 1 and can change at specific trigger times, denoted t. For time t and agent i, the summation of weights equals 1. Based on the reviews, five key factors that affect an individual's stance towards environmental issues are education, close friends, media, supervisors and age. The result of these factors will affect each agent's top four weights.

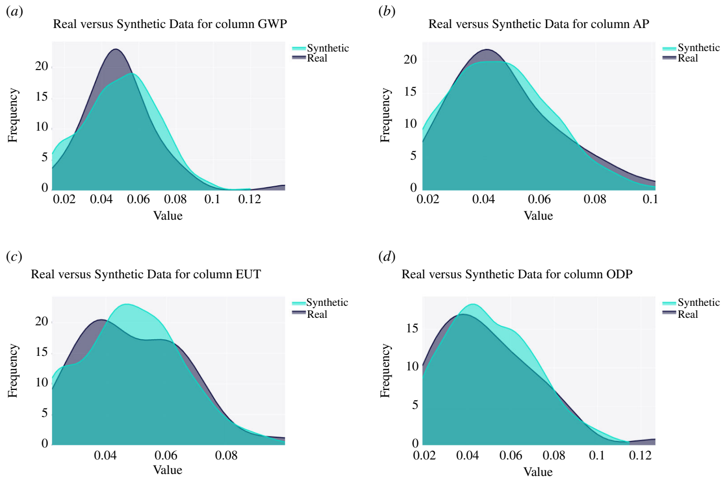

Figure 4. Illustrating the real data versus synthetic data for (*a*) GWP, (*b*) AP, (*c*) EUT and (*d*) ODP as the samples.

Table 2. Evaluation of the synthetic data replication of the mathematical properties.

	Evaluation results
Overall quality score	93.71%
Column shapes	89.18%
Column pair trends	98.23%

Whenever an agent is prepared to modify their beliefs about the weights, it is represented by a motivation variable Q. This variable has a binary choice, where zero signifies that the agent is unwilling to change the weights, while 1 indicates that the agent is ready to change the weights. When the influencing parameter I surpasses a given threshold for an agent i at time t, the motivation variable is set to 1 and the weights will increase or decrease by an assumed percentage:

$$Q_i(t) = IF(I_i(t) > \xi, 1, 0)\,. \tag{4.1}$$

Six algorithms have been defined to outline the steps for implementing influence and interaction rules that modify agents' beliefs regarding the weights in an environmental impact assessment framework: main algorithm, supervisor algorithm, friend algorithm, media algorithm, age algorithm and education algorithm.

The electronic supplementary material includes the class diagram and flowchart related to the MAS algorithms.

Algorithm 1: Running Agent-based simulation

input : Data base

α ▷ The percentage of the supervisor's influence on weight
β ▷ The percentage of the friends' influence on weight
μ ▷ The percentage of Media's influence on weight
θ ▷ The percentage of the agent's age influence on weight
λ ▷ The percentage of education's influence on weight
ϕ_1 ▷ The maximum probability of media's influence on decreasing weight
ϕ_2 ▷ The maximum probability of media's influence on increasing weight
η ▷ The probability of moving to the next age group
γ_1 ▷ The probability of attaining an education level of level 3
γ_2 ▷ The probability of attaining an education level of 4
γ_3 ▷ The probability of attaining an education level of 5
m ▷ Number of agents
Supervisor ▷ Agent selected as supervisor
Friend ▷ Agent selected as friend
Weight-Agent ▷ An array to keep the position and values of the agent's top four weights
Weight-Sup ▷ An array of the nominated supervisor's weights corresponding to the agent's top four weights
Weight-Friend ▷ An array of the nominated friend's weights corresponding to the agent's top four weights
V-SupInc ▷ Variable to show the increasing impact of supervisor on weight (0 or 1)
V-SupDec ▷ Variable to show the decreasing impact of supervisor on weight (0 or 1)
HigherNum-Fr ▷ Number of friends that have higher weights than the agent's top four weights (0-6)
LowerNum-Fr ▷ Number of friends that have lower weights than the agent's top four weights (0-6)
Average-Weight(z) ▷ An array to keep the average weight z for all agents
Age_{Friend} ▷ Friend's age
$Education_{Friend}$ ▷ Friend's education
R ▷ Random variable
ω ▷ Half of the number of found friends plus one

output: Modified weights

```
t ← 1                                   ▷ Counter for time of trigger
i ← 1                                   ▷ Counter for agent
k ← 1                                   ▷ Counter for top four weights
f ← 1                                   ▷ Counter for the number of friends
z ← 1                                   ▷ Counter for the number of weights for each agent
V-SupInc ← 0
V-SupDec ← 0
for t ← 1 to 4 do
    for i ← 1 to m do
        - Supervisor Algorithm
        - Friends Algorithm
        - Media Algorithm
        - Age Algorithm (only at t=2 or 4)
        - Education Algorithm (only at t=4)
        i ← i+1
    end
    t ← t+1
end
```

(d) Effectiveness of MAS in managing uncertainties

The MAS weighting system effectively addresses specific uncertainties in environmental impact assessment. First, it manages the dynamic nature of stakeholder preferences and behaviours by representing stakeholders as adaptive agents, reducing uncertainties related to outdated weighting factors. Second, MAS handles complex interdependencies within environmental and social systems that are often identified in LCA environments by simulating emergent phenomena from agent interactions, effectively capturing ecosystem complexities that conventional models struggle with. Additionally, integrating GANs for data augmentation mitigates uncertainties owing to limited or biased data, enhancing model robustness and improving calibration.

(e) Model verification, validation and sensitivity analysis

We conducted thorough verification and validation processes to ensure that the MAS was implemented correctly and functioned as intended [9].

Algorithm 2: Supervisor Algorithm

```
Supervisor ← Rand (1,m)
for k ← 1 to 4 do
    Update Weight-Agent for agent i
end
for k← 1 to 4 do
    if Weight-Sup>Weight-Agent then
        Weight-Agent←(1+α)*Weight-Agent
        V-SupInc← 1
    else if Weight-Sup<Weight-Agent then
        Weight-Agent←(1-α)*Weight-Agent
        V-SupDec← 1
    else
        Do nothing
    end
    k ← k+1
end
```

(i) Verification and validation

For verification:

— We systematically examined the model's code to identify and correct errors. This process involved reviewing the implementation of agent behaviours, interaction protocols and data processing routines. Peer reviews were instrumental, with colleagues providing independent assessments that enhanced code quality and consistency.

— Individual components and agent behaviours were tested in isolation to confirm they operated according to specifications. Test cases covered typical scenarios and edge cases to ensure robustness.

— During initial simulation runs, we observed agent interactions and output metrics to verify expected behaviours.

Algorithm 3: Friends Algorithm

```
for f← 1 to 6 do
    Friend ← Rand (1,m)
    if Age_Friend ==Age_i & Education_Friend ==Education_i then
        for k← 1 to 4 do
            if Weight-Friend>Weight-Agent then
                HigherNum-Fr←HigherNum-Fr+1
            else if Weight-Friend<Weight-Agent then
                LowerNum-Fr←LowerNum-Fr+1
            else
                Do nothing
            end
            k ← k+1
        end
    end
    f ← f+1
end
for k← 1 to 4 do
    if HigherNum-Fr>=ω & V-SupInc==1 then
        Weight-Agent←(1+β)*Weight-Agent
    else if LowerNum-Fr>=ω & V-SupDec==1 then
        Weight-Agent←(1-β)*Weight-Agent
    else
        Do nothing
    end
    k ← k+1
end
```

For validation:

— We aligned model outputs with data from expert surveys, including the GAN-augmented synthetic data. The MAS outputs closely corresponded with observed expert opinions, indicating accurate representation.

— We used statistical measures such as correlation coefficients to quantify the alignment between model outputs and empirical data.

— We consulted domain experts who reviewed the model's assumptions, agent behaviours and outputs. Their feedback affirmed the model's plausibility and relevance to real-world dynamics.

(ii) Sensitivity analysis and robustness testing

— We varied input parameters and explored plausible scenarios to assess the model's responsiveness to changes in agent behaviours and environmental factors.

— Different plausible scenarios were simulated to evaluate the model's responsiveness to changes in environmental factors and agent behaviours.

Algorithm 4: Media Algorithm

```
R ← Rand (0,1)
for k← 1 to 4 do
    if R ≤ φ1 then
        Weight-Agent←(1-μ)*Weight-Agent
    else if φ1 <R≤ φ2 then
        Weight-Agent←(1+μ)*Weight-Agent
    else
        Do nothing
    end
    k ← k+1
end
```

Algorithm 5: Age Algorithm

```
if t==2 or t==4 then
    R ← Rand (0,1)
    if R < η then
        if Age==1 or Age==2 then
            Age← Age+1
            for k← 1 to 4 do
                Weight-Agent←(θ)*Weight-Agent
                k ← k+1
            end
        else
            Do nothing
        end
    end
end
```

Algorithm 6: Education Algorithm

```
if t==4 then
    R ← Rand (0,1)
    if (Education==2 and R < γ1) Or (Education==3 and R < γ2) Or (Education==4 and R <
      γ3) then
        Education← Education+1
        for k← 1 to 4 do
            Weight-Agent←(λ)*Weight-Agent
            k ← k+1
        end
    else
        Do nothing
    end
end
```

5. Results and discussion

The study's hypotheses were formulated based on a disparity in the literature regarding the effect of close friends and supervisors on individuals' environmental values. The investigation focused on two essential scenarios. The hypotheses played a crucial role in organizing the investigation and examining different viewpoints from the literature.

The *first scenario* suggests that close friends significantly affect an individual's attitudes and behaviours, thereby taking precedence over the role of supervisors. This scenario hypothesizes that close friends are the primary drivers of shaping environmental values. On the other hand, the *second scenario* presents an alternate perspective, wherein the literature emphasizes the significant role of supervisors in influencing individuals' environmental values. In this case, supervisors are considered the dominant influencers, with close friends playing a complementary role. The model runs in cycles of four periods, during which the supervisor, friends and media influence on agents are evaluated during each period in Algorithms (1–4). The minimum trigger time is six months (one period). Additionally, age effects are introduced in the second and fourth periods in Algorithm (5), and education effects come into play in the fourth period in Algorithm (6). The assumption about trigger time for education and age was based on the assigned education categories and the age of the survey participants.

Initially, the weights of each agent are sorted in descending order. The effect of media on an agent is then determined by generating a random number between zero and 1. If this number is below ϕ_1, media decreases the top four weighted attributes by a factor of (1 - μ). If the number is between ϕ_1 and ϕ_2, the media increases these attributes by a factor of (1 + μ). The media has no effect if the number exceeds ϕ_2. The new weights are retained for subsequent calculations involving the effect of friends and the supervisor. Six friends are randomly selected, ensuring they are the same age and education as the agent. The effect of the friends is determined by comparing their attributes with the agent's top four attributes.

In the first scenario, where friends have priority over the supervisor, if the number of friends is at least equal to ω, the agent's top four attributes are compared to the friends' corresponding attributes. For each attribute, if the friends' attribute value is higher or lower than the agent's, the agent's attribute value is raised or lowered accordingly by β. If the count of friends with greater weights matches those with lesser weights, the friends have no effect on the agent. Moreover, if the number of friends possessing weights identical to the agent's weight equals the number of friends with an effect of increase or decrease on the agent's weight, then the agent's weight will be influenced by the effect of those friends with an increased or decreased effect. This process is repeated for the agent's top four attributes out of a possible 15.

For the effect of the supervisor, a random supervisor is chosen. A comparison is be made between the top four values of the agent's weights and the corresponding supervisor's. In cases where the supervisor's influence on the agent's weight is on the rise while the effect of friends is diminishing, or vice versa, the agent's weight remains unaffected by the supervisor's influence. Conversely, when both friends and the supervisor exert an effect of increasing (or decreasing) influence in the same direction on the agent's weight, the weights of the agent will experience a compounded effect, resulting from the multiplication (division) of both the supervisor's factor (α) and the friends' factor (β). In the absence of any friends for the agent, the agents' weights are solely subject to the influence of the supervisor. This procedure is be reversed for the second scenario, where the supervisor is prioritized over friends. The sum of 15 weights should equal 1. This process is repeated for the second, third and fourth periods. For the second period, dedicated to increasing the agent's age, an additional step is introduced alongside the existing procedure for the media, friends and the supervisor's effect. A random number is generated within the range of zero to 1. If this number is less than η and the agent belongs to age groups one or two (among three available age groups), the agent's age will be incremented by one, signifying a shift to a higher age group. Meanwhile, if the generated number does not meet these conditions, the age group of the agent remains unchanged. To quantify the effect of this age increment, the top four values of the agent's weights are multiplied by the age factor, set at (θ). In the fourth period, the educational effect is considered in addition to the influences of media, friends, the supervisor and age. Consequently, a random number between zero and 1 is be generated, and the agent's education group is increased under the following conditions:

— If the generated random number is less than γ_1 and the agent's education group is two.
— If the generated random number is less than γ_2 and the agent's education group is three.
— If the generated random number is less than γ_3 and the agent's education group is four.

Subsequently, the top four values of the agent's weights is multiplied by the education factor set at (λ). The entire cycle is iterated for the desired number of repetitions to evaluate the long-term effect of these factors. Finally, the average weight values for all agents in the fourth period at the end of each iteration are calculated for further analysis.

Analysis of what-if (sensitivity analysis)—Two distinct experiments have been formulated for investigation.

Experiment 1—Influence of close friends on attitudes and behaviours supersedes supervisors. Figure 5 shows the variation of the weighting when close friends have priority versus supervisors.

Experiment 2—Supervisors are seen as the primary influencers, with close friends playing a supporting role. Figure 6 shows the variation of the weighting when supervisors have priority versus close friends.

As depicted in the graphs, the results provide valuable insights into the dynamic nature of weights assigned by survey participants over time in the context of MAS analysis. Although assumptions based on the expert ideas and literature reviews were used, it should be noted that the main objective of these graphs is not to establish the relative importance of specific weights or to determine whether they increased or decreased during the study period. Instead, they aim to provide an overall understanding of the data and demonstrate the capacity of MAS to adapt and respond to changing rules and assumptions within the survey framework. These results underscore the dynamicity of the MAS approach in analysing complex surveys and its potential as a valuable tool for dynamic life cycle assessment (DLCA). By showcasing how MAS can capture and model the evolving weights assigned by survey participants, this study highlights the versatility and robustness of MAS in addressing the intricate dynamics inherent in survey data, ultimately contributing to more informed decision-making processes in complex contexts. The significant contribution of this paper was applying a MAS in the weighting system of an environmental impact assessment framework and answering the following research questions:

Can agent-based systems provide an acceptable solution for delivering the weighting system of an environmental impact assessment framework to address the uncertainty linked to the complex and dynamic ecosystem of buildings?

The study showed that agent-based systems can indeed offer a suitable solution for addressing the uncertainty linked to the complex and dynamic ecosystem of buildings in the context of the weighting system of an environmental impact assessment framework. Here is how agent-based systems can provide a solution for delivering a weighting system in an environmental impact assessment framework:

∗ *Modelling complexity and dynamics*: MAS excelled in modelling weighting systems for environmental impact assessments of buildings.
∗ *Uncertainty management*: MAS could handle uncertainty by incorporating stochastic elements into agent behaviours.
∗ *Behaviour simulation*: the designed system allowed decision makers to simulate how small-scale interactions aggregate to produce larger-scale outcomes.
∗ *Scenario analysis and sensitivity testing*: with the proposed model, decision makers can run simulations under different scenarios and test the sensitivity of the results to changes in various parameters.

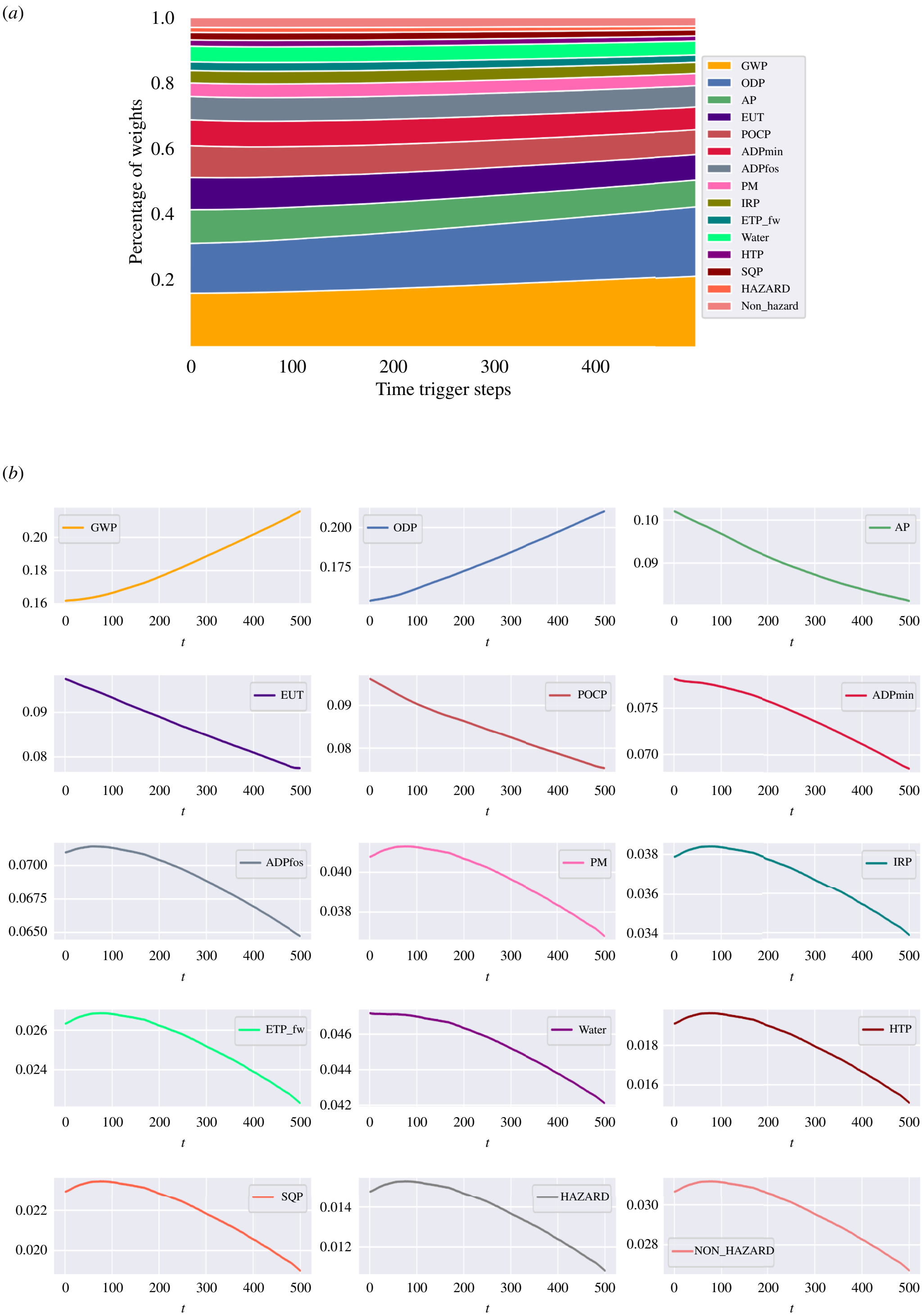

Figure 5. The variation of the weighting when close friends have priority versus supervisors with $\alpha = 0.0007$, $\beta = 0.0007$, $\mu = 0.0018$, $\theta = 1.0008$, $\lambda = 1.0009$, $\phi_1 = 0.01$, $\phi_2 = 0.09$, $\eta = 0.06667$, $\gamma_1 = 0.22$, $\gamma_2 = 0.26$ and $\gamma_3 = 0.02$. (*a*) Stacked area plot illustrating the relative composition and dynamic changes of weighting parameters as percentages over time. (*b*) Individual plots showing the different weighting parameters over 500 time steps.

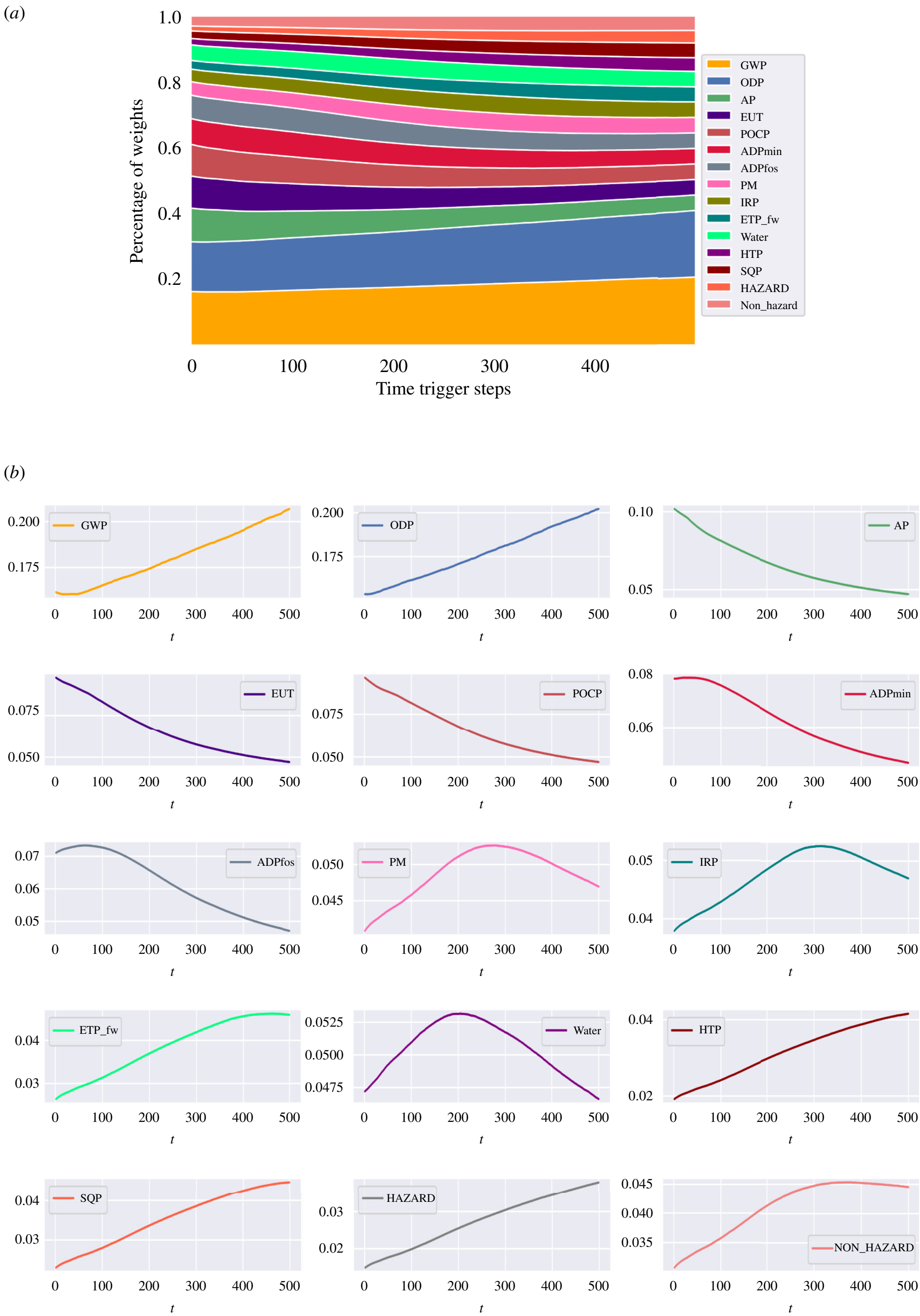

Figure 6. The variation of the weighting when supervisors have priority versus close friends with $\alpha = 0.0007$, $\beta = 0.0018$, $\mu = 0.0018$, $\theta = 1.0008$, $\lambda = 1.0009$, $\phi_1 = 0.01$, $\phi_2 = 0.09$, $\eta = 0.06667$, $\gamma_1 = 0.22$, $\gamma_2 = 0.26$, $\gamma_3 = 0.02$. (*a*) Stacked area plot illustrating the relative composition and dynamic changes of weighting parameters as percentages over time. (*b*) Individual plots showing the different weighting parameters over 500 time steps.

∗ *Adaptability and learning*: the results showed that the model can be designed to allow agents to adapt their behaviours over time based on changing conditions or new information.

How can we ensure continuous fitness for such a weighting system, and what factors should trigger its recalibration?

To maintain the effectiveness of the above agent-based weighting system, it is important to constantly monitor, evaluate and adjust the system as needed. Recalibration should be initiated when there are indications of changes in the environment or the agents' values. Here is a detailed process to follow and factors to consider:

∗ *Monitoring and evaluation*: keeping a close eye on the agent-based weighting system performance and outcomes is important to catch any discrepancies, shifts or emerging issues. This may include analysing system outputs and seeking feedback from experts.
∗ Factors that may trigger recalibration:

- *Environmental changes*: the weighting system may need recalibration to reflect the new context if significant changes in the national or global environment, such as natural disasters.
- *Performance drift*: consistent deviation of the system outcomes from actual outcomes indicates that the system parameters or assumptions may need adjustment.
- *Expert feedback*: if experts report issues with the system outputs or express changing needs, it is a clear signal that recalibration might be necessary.
- *Recalibration process*: recalibration involves running MAS with expert consultations, parameter adjustment and model validation.

Limitations: based on the study and the results of MAS experiments, the limitations of MAS in the weighting system of an environmental impact assessment framework are:

(i) To comprehend intricate and ever-changing societies, we require suitable data for analysis. Traditional sociological analysis techniques involved collecting qualitative data through interviews, observations or documents and conducting surveys of individuals. Although qualitative data can effectively demonstrate the formation of institutions from individual actions, such analyses tend to remain somewhat impressionistic owing to the nature of the data.

(ii) When it comes to studying societies, relying solely on typical survey data may not provide the necessary level of accuracy. Survey data treat individuals as isolated entities, with little attention paid to the effect of their interactions with others. However, data intended for studies of social networks, where respondents are asked about their communication and friendships, are more representative. Still, such sociometric surveys can be challenging to make representative. Quantitative sociology is not the only good approach to understanding social interactions.

The combination of scenario formulations, MAS analysis and agent-based systems have provided valuable insights into the dynamics of environmental values within the surveyed population. The experiments showed how close friends and supervisors can affect attitudes and behaviours, confirming the scenarios' significance. The adaptability and responsiveness of the MAS, as discussed, are evident in the observed dynamicity of survey participant weights over time, highlighting its robustness in handling complex survey data. Furthermore, the agent-based system multifaceted contributions, including modelling complexity and scenario analysis, underscore its efficacy in environmental impact assessments. The process for ensuring continuous fitness and recalibration aligns seamlessly with the dynamic nature of weights, providing a comprehensive framework for interpreting, refining, and applying the study findings to make informed decisions in complex contexts.

6. Conclusion

This study's key contribution is implementing a MAS weighting system within the environmental impact assessment framework. The agent-based system effectively manages uncertainties inherent in complex and dynamic LCA by modelling complexities, simulating emergent behaviours and accommodating adaptive responses, demonstrating the significant potential for real-world application.

The MAS weighting system offers practical benefits for stakeholders like building owners and managers. By capturing complex interactions among agents—such as occupants, maintenance personnel, energy suppliers and regulators—it enables more informed decisions regarding environmental performance. For instance, simulating changes in building usage patterns or adopting energy-efficient technologies helps identify optimal strategies for reducing energy consumption and improving sustainability practices. The system's adaptability allows it to adjust to new information, ensuring ongoing compliance with evolving regulations and proactively enhancing environmental performance. This supports decision making that balances economic objectives with sustainability goals, contributing to more socially responsible building management.

Integrating agent-based systems into environmental impact assessments enhances decision making by capturing dynamic interactions among diverse stakeholders. Simulating individual behaviours and interactions allows observation of emergent phenomena that traditional models may overlook. Understanding these behaviours helps anticipate unintended policy consequences and adjusts strategies accordingly, leading to more effective environmental management. The adaptability and learning capabilities of agent-based systems improve responsiveness to changing conditions, allowing exploration of various scenarios and assessment of potential LCA impacts under uncertainty, thus enhancing the resilience and sustainability of environmental strategies.

The study emphasizes the importance of monitoring, evaluation and recalibration to ensure the continuous fitness of the MAS weighting system. Environmental changes, performance drift and expert feedback trigger recalibration. Challenges in MAS implementation—including model validation, computational complexity, and parameter calibration—highlight areas for further attention.

Future research should focus on enhancing the validation and credibility of agent-based models by investigating alternative data collection methods, such as sociometric surveys or panel studies, to enrich model input. Beyond environmental impact assessment, applying MAS to address uncertainties could extend to fields like urban planning, healthcare and social policy design, revealing new opportunities and challenges. In that respect, the authors are currently applying the proposed MAS methodology to promote a more inclusive, just and participative approach to LCA by focusing on its social dimension and factoring in citizen's needs and aspirations [5], thus placing people at the centre of sustainable transitions.

Ethics. This work did not require ethical approval from a human subject or animal welfare committee.

Data accessibility. Python code can be accessed from [63].

Supplementary material is available online [64].

Declaration of AI use. We have not used AI-assisted technologies in creating this article.

Authors' contributions. A.G.: data curation, formal analysis, methodology, software, validation, visualization, writing—original draft, writing—review and editing; Y.R.: conceptualization, funding acquisition, investigation, project administration, supervision, writing—review and editing; I.P.: investigation, writing—review and editing; T.B.: investigation, writing—review and editing; J.Y.: methodology, software, writing—original draft; A.G.: data curation, methodology, software, validation, writing—original draft, writing—review and editing.

All authors gave final approval for publication and agreed to be held accountable for the work performed therein.

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