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Multi-criteria decision analysis (MCDA) as a context-adaptable weighting method for life cycle assessment impact categories in sustainable nutrition science

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HIGHLIGHTS

- MCDA was applied for weighting LCA impact categories at the food group level.
- A case study prioritized six environmental criteria for five Dutch food groups.
- Food group weighting is informative for distinct (local) environmental challenges.
- MCDA considers spatio-temporal and socio-cultural variability in sustainable diets.
- Health, economic, and social criteria can be added to assess realistic trade-offs.

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ABSTRACT

Current dietary practices are not sustainable to support the growing global population. Environmental sustainability of diets can be indicated by multiple environmental impact categories (EICs). Generic EIC weights may help identify sustainable diets overall but overlook the environmental impact specific to relevant food groups in different contexts. This paper aims to explore if food group specific EIC weighting schemes improve interpretation of overall impact of foods and to assess the suitability of multi-criteria decision analysis (MCDA) for developing such schemes.

First, six EICs and five food groups from the Dutch context were selected for proof of principle (problem structuring). Second, data was normalized using appropriate functional units (scoring alternatives against criteria). Third, a panel of eight Dutch LCA experts answered choice-based questions, facing trade-offs between EICs for each food group (preference modelling).

Greenhouse gas emissions (GHGE) were ranked important across all food groups. Importance of blue water consumption (BWC) and freshwater eutrophication varied depending on the food group. MCDA-based food group weighting schemes have benefits over one generic weighting scheme for food groups with specific (local) environmental challenges (e.g., nuts and seeds with considerable BWC) and for foods with distinct EIC trade-offs (e.g., GHGE and BWC).

EIC weighting for sustainable diets may thus be improved by considering food group specific environmental challenges. MCDA holds valuable potential to learn more about weighting various EICs, considering spatio-

Abbreviations: BWC, Blue Water Consumption; EF, Environmental Footprint; EIC, Environmental Impact Category; EU, European Union; FWE, Freshwater Eutrophication; GHGE, Greenhouse Gas Emissions; JRC, Joint Research Centre; LCA, Life Cycle Assessment; LU, Land Use; MWE, Marine Water Eutrophication; RIVM, Dutch National Institute for Public Health and the Environment; TA, Terrestrial Acidification.

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temporal and socio-cultural variability in sustainable diets. Future application of MCDA in the sustainable nutrition transition may navigate evolving priorities by incorporating economic or health-related criteria.

1. Background

The environmental sustainability of our food systems is an increasingly prominent topic, considering it is required to support a growing global population. Life Cycle Assessment (LCA) is a method for quantifying environmental impact of food from production to consumption. Environmental impact data throughout the lifecycle is summarized into different environmental impact categories (EICs), such as greenhouse gas emissions (GHGE), land or water use, and acidification or eutrophication of soil and water. In interdisciplinary research, comprehensive interpretation of overall environmental impact of food consumption is challenging due to the need to prioritize or integrate multiple criteria (Harrison et al., 2022; Ran et al., 2024; van Dooren et al., 2018). Specifically, weighing methods to combine EICs as relevant to production systems of different food groups and specific to particular contexts is lacking.

Currently, dietary GHGE are often evaluated as a single criterium for environmental impact or selected EICs are reported separately in relation to health, failing to assess how important each criterion is in relation to the others (Hallström et al., 2021; Heerschop et al., 2021; Kesse-Guyot et al., 2021; Laine et al., 2021; Stubbendorff et al., 2024; Tepper et al., 2022; van Dooren et al., 2018; Vellinga et al., 2019). Synergies and trade-offs among various EICs add complexity to assessing the overall environmental impact of foods and/or diets (Aleksandrowicz et al., 2016; Jarmul et al., 2020). The difficulty of optimizing for multiple EICs potentially hinders accountability of scientific, industrial, or policy efforts towards sustainable diets. To evaluate the environmental footprint of our diet in a meaningful and comprehensive way, it is crucial to develop methods capable of incorporating multiple criteria.

No objective standard exists to determine the relevance of different EICs, so weighting methods are prone to subjectivity. Essentially, scoring diets by multiple EICs requires input of decision makers who gather and synthesize relevant information from different environmental and societal perspectives. Weighting schemes thus inherently involve value choices depending on policy, culture, ideology, and ethics. As a result, a gold weighting standard cannot be established for all contexts (Goedkoop et al., 2013). Using an existing weighting scheme should always acknowledge the underlying value choices. An overview of normalization and weighting approaches and methods in LCA is available (Cerutti et al., 2018; Roesch et al., 2021). For instance, the Joint Research Centre (JRC) of the European Commission suggested weighting factors for aggregating EICs into a single index for environmental footprint (EF) (Cerutti et al., 2018). For their EF approach, different options for weighting EICs were discussed and available weighting sets were reviewed. Finally, a weighting set according to the preferred option was developed: a hybrid evidence- and judgement-based weighting set. Simultaneously, it was recognized that a “one size-fits-all” approach was “bound to fail” because of uncertainties and pluralism. While the JRC has demonstrated that reaching a consensus on weighting EICs is feasible, context-specific values and considerations will improve accuracy of total environmental impact estimation.

As alternative to generic weighting schemes such as by the JRC, EIC weighing schemes that consider diverse production systems at the food group level and specific to different dietary contexts do not exist. However, food items in a food group share production and/or consumption characteristics. Due to such differences in production systems, various food groups differ in how they impact the environment (Heller et al., 2013). Figure A.1 in appendix A illustrates the heterogeneity in GHGE and blue water consumption (BWC) across food groups. For instance, while meat is associated with high GHGE, nuts and seeds – another protein source – have a high impact on BWC. If we consider only GHGE and eat nuts instead of meat to reduce environmental impact, we overlook the substantial effect on BWC, which could have serious consequences in drought-prone regions (Hollander et al., 2021; Vanham et al., 2020). Essentially, different food groups involve diverse (inter) national production systems with context-specific environmental concerns. Since existing weighting schemes such as the JRC EF serve diverse products and rely on generic assumptions, meaning that the underlying value choices are uniform across all supply chains rather than tailored to the specific product being assessed, these can be improved by accounting for the distinct environmental contexts of different food groups.

Multi Criteria Decision Analysis (MCDA) provides opportunities for EIC weighting schemes tailored to food groups in a particular research context. MCDA involves a range of methods aiding decision making in problems with potentially conflicting criteria, such as evaluating different food options for multiple EICs. Similarly, MCDA is being applied to assess trade-offs between LCA impact categories in diverse fields such as energy, waste management, building materials, and fuel selection (Zanghelini et al., 2018). The major benefit of MCDA over other estimation methods is that the different stages allow tailoring decision problems and corresponding data-driven value choices to specific production systems, cultures and/or research questions. Accordingly, this method offers potential for balancing LCA impact categories in a justifiable and replicable manner. Therefore, MCDA can overcome limitations of generic weighting approaches by weighting EICs at the food group level within the research context, resulting in more detailed and realistic interpretation of overall environmental impact.

This paper answers the following research question: to what extent are food group specific EIC weighting schemes relevant for interpreting overall environmental impact of foods, and is MCDA suitable as an adaptable method for developing such schemes? In doing so, we present a model based on MCDA to assign environmental value to food items within a food group, incorporating potential synergies and trade-offs across LCA impact categories. The model considers context-specific LCA data and value systems, tailoring outcomes to spatio-temporal and socio-cultural nutritional settings. To illustrate the application of this model, we conduct a proof of principle study for selected food groups relevant to the Dutch context.

2. Methods

The following sections work through a proof of principle study regarding the weighting of context-specific LCA data on GHGE, land use, terrestrial acidification, freshwater and marine water eutrophication, and blue water consumption for foods eaten in the Netherlands (RIVM, 2021). Distinct weighting schemes were established for five selected food groups. This was achieved by completing the following three MCDA stages: problem structuring, scoring alternatives against criteria, and preference modelling. The stages and (intermediate) results are visualized in Fig. 1.

2.1. Problem structuring: food groups taking into account the consumer perspective

In MCDA, the decision problems are structured according to the available data. The Dutch LCA dataset (version 2019) entails a total of 242 food items covering 71 % of foods consumed in the Netherlands. Blonk Consultants (Gouda, the Netherlands) provided life cycle inventories from cradle-to-plate. The RIVM performed the life cycle impact assessment using ReCiPe-2016 and SimaPro software (version 8.52). Thereupon, extrapolations were established by the RIVM based on similarities in types of food, production systems and ingredient composition. A more detailed description of the development of the primary dataset and extrapolations thereof has been published (Vellinga et al., 2019). The final dataset contained 2131 food items in total (RIVM, 2021).

The problem structuring stage involves selection of food groups (decision problems) and the food items (decision alternatives) to evaluate for the EICs (decision criteria). Food items were classified into food groups that are regularly consumed in a Dutch meal pattern, aligned with (inter)national standards for food classification combining EFSA FoodEx2, the Dutch food-based dietary guidelines, and the EAT-Lancet reference diet (European Food Safety Authority (EFSA), 2015; Kromhout et al., 2016; Willett et al., 2019). The rationale, definition, and composition of the food groups in this proof-of-principle study are presented in appendix B. To start, categories from the EFSA FoodEx2 hierarchy aligning with EAT-Lancet categories were selected. To allow evaluation and improvement of environmental impact of a meal, food groups were further refined to be composed of food items that have a similar function in the same meal using Dutch food-based dietary guidelines and expert judgement (Kromhout et al., 2016). Thus, from the consumer perspective, one food item from a food group could be replaced for another item within the same food group in a culturally

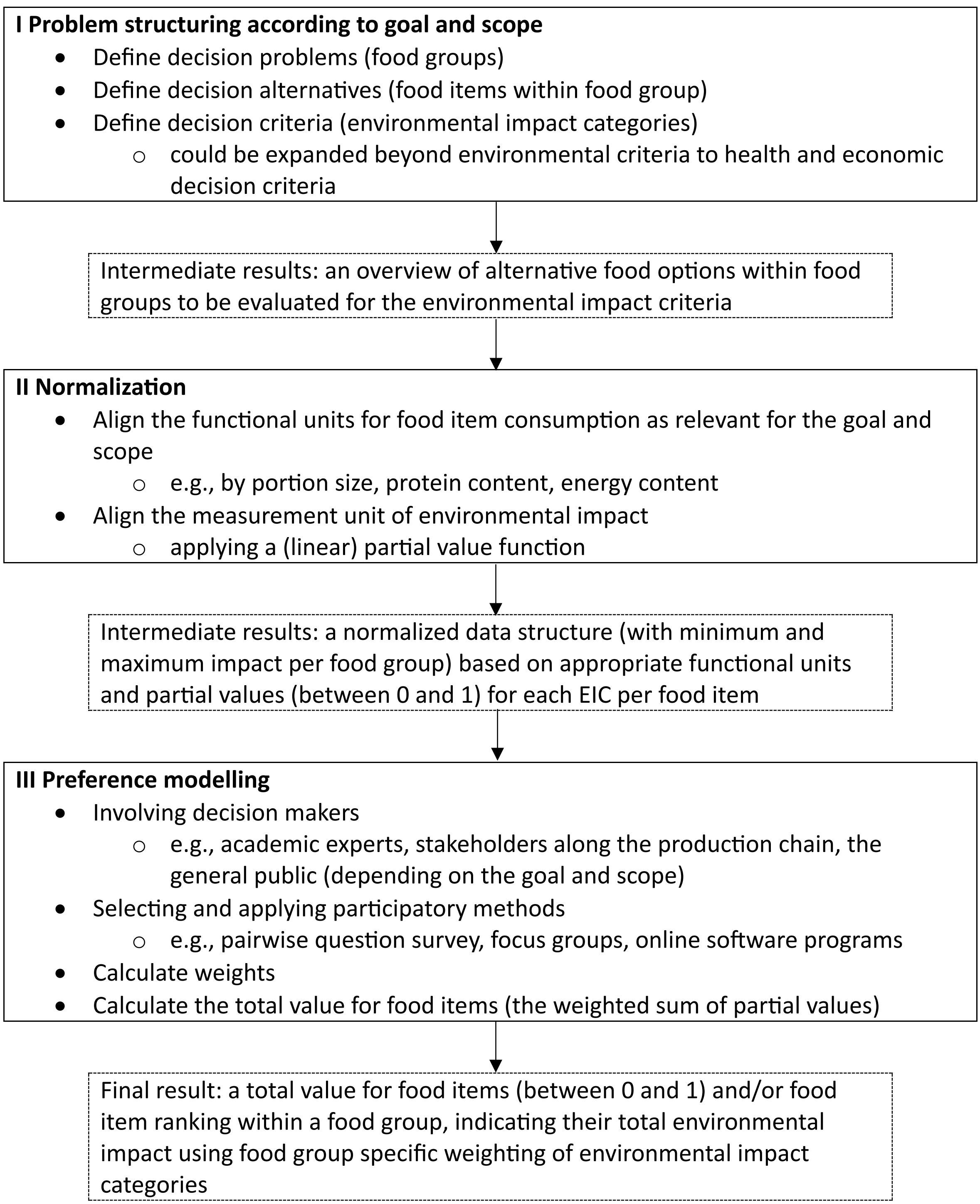

Fig. 1. Flow chart for applying MCDA for weighting EICs in sustainable nutrition science.

acceptable way, for example, choosing boiled potatoes instead of French fries.

Food groups in this proof-of-principle study were selected based on their contribution to Dutch dietary patterns (cultural relevance), their inclusion in the Dutch food-based dietary guidelines (health relevance), and/or acknowledged challenges due to trade-offs between EICs (environmental relevance). The selected food groups were potatoes, meats, vegetables, milk and dairy, and nuts and seeds (appendix B). Since food items had to be realistic alternatives within the same meal, lunch meat was excluded from the food group 'meat'. Using similar reasoning, cheese and butter were not considered alternatives for milk and dairy, and oil fruits (e.g., olives) were no alternatives for nuts and seeds. We further excluded dried seaweed, concentrated tomato puree and sun-dried tomatoes from vegetables, and cooking cream from dairy products. Each food group naturally contained a different number of alternatives: 35 food items in 'potatoes', 127 food items in 'meat, 176 food items in 'vegetables', 152 food items in 'milk and dairy', and 33 food items in 'nuts and seeds'.

This study utilizes the available quantitative data on environmental impact in the Netherlands. All EICs that were available in the Dutch LCA dataset were included as decision criteria for sustainability of food items. The six included EICs are GHGE (kg CO_2-eq), land use (m^2 per year), terrestrial acidification (kg SO_2-eq), freshwater eutrophication (kg P-eq), marine water eutrophication (kg N-eq), and blue water consumption (m^3). If more EICs (e.g., biodiversity loss, toxicity) become available for a particular country or context, pre-selection of EICs can be considered to decrease the burden of decision making. This requires careful consideration of EIC interpretation, perhaps by initially holding a focus group with experts.

2.2. Scoring: impact criteria and scale ranges

The scoring stage facilitates comparison of food items across EICs by normalizing values for different criteria to appropriate functional units of food consumption.

Firstly, functional units were considered for comparing food items within food groups. In this case study, it was assumed that functional portions of food items within a food group are comparable based on weight (e.g., one 250 g of broccoli compares to 250 g of carrots). The LCA data on food items is given per 1 kg of consumed product, thus functional portion required no adaptation and the weight-based functional units remained mostly unchanged. For concentrated unprepared products, however, the functional portion is not comparable to the prepared product. Therefore, LCA data were adapted to reflect 1 kg of the prepared and consumed product. Based on the RIVM portion sizes database, LCA data was recalculated for mashed potato powder (170 g for 1 kg) and milk powder (130 g for 1 kg) (RIVM, 2024). Alignment of the functional units of foods resulted in the final data structure for the five decision problems (Table 1).

Thereupon, the different measurement units for EICs were normalized. The EIC values of items were calculated into partial values from 0 to 1, retaining the proportional distances, where 0 equals the highest impact and 1 equals the lowest impact. The linear partial value function $v_{jk}(x_{ijk})$ scales the environmental impact x_{ijk} by food item i for EIC j between worst and best food option in food group k (equation (1)). The worst ($x_{jk}(max)$) to best ($x_{jk}(min)$) food option within a food group define the $swing_{jk}$ per EIC (i.e., the environmental improvement potential).

$$v_{jk}(x_{ijk}) = \frac{x_{ijk} - max\ (x_{jk})}{-(max\ (x_{jk}) - min\ (x_{jk}))} \qquad \text{(eq. 1)}$$

For example, broccoli is a vegetable option with GHGE of 1.84 kg CO_2-eq per kilogram. The maximum GHGE among vegetable options is 5.21 kg CO_2-eq per kilogram, and the swing (distance between minimum and maximum) for vegetables is 4.81 kg CO_2-eq (Table 1). With these data, we calculate that broccoli receives a partial value for GHGE of (1.84–5.21)/-4.81 = 0.70. To demonstrate, partial value functions for nuts and seeds are visualized in appendix C.

Ultimately, the scoring phase provided normalized data per food group (partial values between 0 and 1) for each EIC, based on appropriate functional units.

Table 1
Data structure per decision problem with a functional unit of 1 kg prepared product.

	GHGE kg CO_2-eq	LU m^2 per year	TA kg SO_2-eq	FWE kg P-eq	MWE kg N-eq	BWC m^3
1. Potatoes and potato products						
Minimum	0.83	0.32	0.004	0.00007	0.0011	0.01
Maximum	6.15	2.65	0.019	0.00056	0.0053	0.09
Swing	5.32	2.33	0.015	0.00048	0.0043	0.08
2. Meat						
Minimum	5.73	3.75	0.050	0.00044	0.0061	0.06
Maximum	31.34	16.29	0.545	0.00132	0.0902	0.36
Swing	25.61	12.54	0.495	0.00088	0.0841	0.30
3. Vegetables and vegetable products						
Minimum	0.40	0.02	0.001	0.00003	0.0000	0.01
Maximum	5.21	2.66	0.020	0.00065	0.0060	0.24
Swing	4.81	2.64	0.019	0.00062	0.0060	0.23
4. Milk and dairy products (excluding cheese)						
Minimum	0.20	0.15	0.002	0.00001	0.0005	0.00
Maximum	4.99	3.45	0.063	0.00054	0.0089	0.08
Swing	4.78	3.30	0.061	0.00053	0.0084	0.08
5. Nuts and seeds						
Minimum	1.67	0.39	0.006	0.00018	0.0015	0.10
Maximum	7.35	13.94	0.069	0.00332	0.0201	4.48
Swing	5.69	13.56	0.063	0.00313	0.0186	4.38

Minimum and maximum indicate the lowest and highest values for the food items in the food group. Swing indicates the difference between the highest and lowest values for food items within a food group (i.e., the improvement potential).
GHGE, greenhouse gas emissions; LU, land use; TA, terrestrial acidification; FWE, freshwater eutrophication; MWE, marine water eutrophication; BWC, blue water consumption.

2.3. Modelling: preference elicitation and weight calculation

In the third stage, the relative importance of EICs per food group is determined using expert input through choice-based ranking of the EIC swings (Heidenreich et al., 2024). A group of Dutch LCA experts, the decision makers, completed a questionnaire. Sustainable nutrition experts were recruited through a national academic network and, once involved, invited to refer additional experts from their own networks. Non-academic institutions were approached to participate, but lacked experts qualified across diverse food groups. Data were collected and managed using REDCap electronic data capture tools hosted at the University Medical Center Groningen (Harris et al., 2009, 2019).

Pairwise questions involved data-driven EIC tradeoffs by comparing two hypothetical food items within a food group. These hypothetical food items were defined using the minimum and maximum values per food group (presented in Table 1). Thus, item A has maximum impact for one EIC (e.g., GHGE) and minimum impact for another (e.g., land use), while item B shows the opposite pattern (Fig. 2). Experts choose the more sustainable hypothetical food item, indicating which EIC they prioritize minimizing when faced with trade-offs. All six EICs were evaluated in pairs, resulting in 15 comparisons per food group and therefore 75 pairwise questions per expert (15 trade-offs * 5 food groups). Since our survey software did not allow randomization of questions and answer options, the same trade-off structure was applied to each decision problem. Instead of evaluating all EIC trade-off pairs, for instance when more than six EICs are evaluated causing an

Considering the food group "nuts and seeds", which of the following two food items would you argue is more sustainable?

A. Greenhouse gas emissions are 1.67 kg CO_2-equivalent[a] and land use is 13.94 m^2 per year[b]

B. Greenhouse gas emissions are 7.35 kg CO_2-equivalent[c] and land use is 0.39 m^2 per year[d]

Fig. 2. An example pairwise comparison question for fifth decision problem on nuts and seeds. Option A is a hypothetical nut or seed product with the lowest possible GHGEs[a], but the highest possible land use[b] among nuts and seeds. Option B is a hypothetical nut or seed product with the highest possible GHGEs[c], but the lowest possible land use[d] among nuts and seeds. Numbers are based on the normalized LCA data for 1 kg consumed product (Table 1).

exponential increase in questions, logic can be applied to decrease the number of trade-offs required (i.e., if A > B and B > C then A > C). Existing software methods are specifically designed for such more complex decision making problems (1000minds.com). Appendix D demonstrates the choice-based questions for potatoes and potato products. For questions on the other food groups the numbers on environmental impact were adjusted conform Table 1.

Experts were instructed to consider the production systems specific to each food group when interpreting the numbers. All experts were provided with a science-based framework. This included definitions of and risks associated with the considered EICs, histograms of absolute EIC impact of diets in the Dutch Lifelines cohort, and boxplots of the EIC impact of food items (per 1 kg consumed) within each food group (Baart et al., 2021; Richardson et al., 2023). The choice-based analysis method thereby emphasized both data structure (i.e., food group impact (variation) for each EIC) and context (i.e., the Dutch (inter)national food system and environmental challenges). The questionnaire was piloted amongst colleagues to ensure understandability of the questions and completeness of the science-based framework.

EIC weights per food group were calculated as the total "wins" of one EIC over all other EICs (8 experts * 5 trade-offs per EIC = 40 wins maximum), divided by the total trade-offs considered (8 experts * 15 trade-offs = 120). Since the weights are developed irrespective of existing synergies and trade-offs of EICs within food items, but follow value judgements on hypothetical tradeoffs, synergies between EICs within a food group do not affect the weighting factors.

In the end, partial values for each EIC are combined into one total value for each food item using the established weights. This is done by a linear additive value function for each food group $v_k(x_{i1k}, x_{i2k}, \ldots, x_{ijk})$ (equation (2)), in which $v_{jk}(x_{ijk})$ refers to the partial value calculated in equation (1) for each EIC per food item. Here w_{jk} refers to the weight calculated for EIC j for food group k. When using generic weighting schemes, w_{jk} refers to the weights for EIC j, for example adapted from the EU report for product footprint, which are the same across food groups k.

$$v_k(x_{i1k}, x_{i2k}, \ldots, x_{ijk}) = \sum_{j=1}^{j} w_{jk} v_{jk}(x_{ijk}) \qquad \text{(eq. 2)}$$

2.4. Illustrative example for nuts and seeds

To illustrate the application of the MCDA-based food group specific weights, a total environmental value for nut and seed items was calculated and compared to the total values calculated using generic weights according to the EF methodology (Cerutti et al., 2018). Importantly, the LCA data for this illustrative example did not undergo a critical review as specified in the International Organization of Standardization (ISO)-14040 norm and may therefore not be used for public communication on comparing food items (RIVM, 2021). This example serves to demonstrate the possibilities of the method.

3. Results

3.1. Relative importance of EICs per food group

The panel included 8 academic Dutch sustainable nutrition experts, with mean working experience with sustainable nutrition of 10.5 (SD 5.7) years. The experts were representatives of the Dutch National Institute for Public Health and the Environment (RIVM), Wageningen University and Research (WUR), Merieux Nutriscience (Blonk Sustainability), the World Wildlife Fund (WWF-NL), and the applied university of Agro Food and Sustainability (HAS Green Academy). Experts spent on average 33 min on the questionnaire, equally distributed across the five food groups.

Table 2 displays the calculated weights for each EIC per food group, along with literature-based alternative options. For most food groups, the greatest importance is given to GHGE, which is also ranked first according to the EF methodology for normalization and weighting. Nuts and seeds show a different pattern, where BWC is ranked most important and GHGE second. Freshwater eutrophication is indicated as the second most important for vegetables, milk and dairy, and nuts and seeds, but ranked (shared) last in de rescaled EF weighting scheme. For meat, land use is second most important. More weight variation between food groups appeared for GHGE (0.19–0.31) and blue water consumption (0.10–0.29), compared to, for example, land use (0.16–0.21). Marine water eutrophication is across all food groups not weighed higher than 0.14, which is lower than equal weighting (0.17). Fig. 3 provides a visual representation for the weights per food group, compared against generic EF weights and equal weights.

When plotting the weights calculated for each expert separately, we observe the heterogeneity between experts underlying the panel averages (appendix E, figure E.1). Certain experts show a strong preference for one EIC in all food groups, for example blue water consumption or marine water eutrophication, and therefore consistently score this criterion the highest. Other experts show more variation in prioritizing EICs depending on the food group considered. Although an interesting research finding, such heterogeneity may affect robustness of the results of this proof-of-principle study.

3.2. Illustrative example

A total score for nuts and seeds in the RIVM LCA dataset was calculated using the linear partial value function (eq. (1)) and the linear additive value function (eq. (2)). In the second equation, both MCDA-based food group specific weights and the generic EF weights were

Table 2
Different weighting factors for EICs based on food group specific MCDA and generic literature.

	Food-group specific weights calculated based on MCDA pilot-study results (weight (rank))					Literature-based generic weights		
	Potatoes	Meat	Vege-tables	Milk and dairy	Nuts and seeds	Common practice[a]	Equal weights	JRC EF report[b]
GHGE	0.31 (1)	0.28 (1)	0.23 (1)	0.25 (1)	0.19 (2)	1	0.17	0.42 (1)
BWC	0.10 (5)	0.11 (5.5[c])	0.18 (3)	0.12 (5.5[c])	0.29 (1)	0	0.17	0.17 (2)
LU	0.18 (3)	0.21 (2)	0.16 (4)	0.16 (4)	0.18 (3)	0	0.17	0.16 (3)
TA	0.09 (6)	0.15 (3)	0.13 (5)	0.18 (3)	0.09 (5)	0	0.17	0.13 (4)
FWE	0.18 (2)	0.14 (4)	0.20 (2)	0.18 (2)	0.17 (4)	0	0.17	0.06 (5.5[c])
MWE	0.14 (4)	0.11 (5.5[c])	0.11 (6)	0.12 (5.5[c])	0.08 (6)	0	0.17	0.06 (5.5[c])

GHGE, greenhouse gas emissions; LU, land use; TA, terrestrial acidification; FWE, freshwater eutrophication; MWE, marine water eutrophication; BWC, blue water consumption; JRC EF, Joint Research Centre Environmental Footprint.
[a] In current literature researchers often select one (or few) impact categories and disregard others.
[b] Rescaled for the six EICs considered in this case-study.
[c] Shared rank.

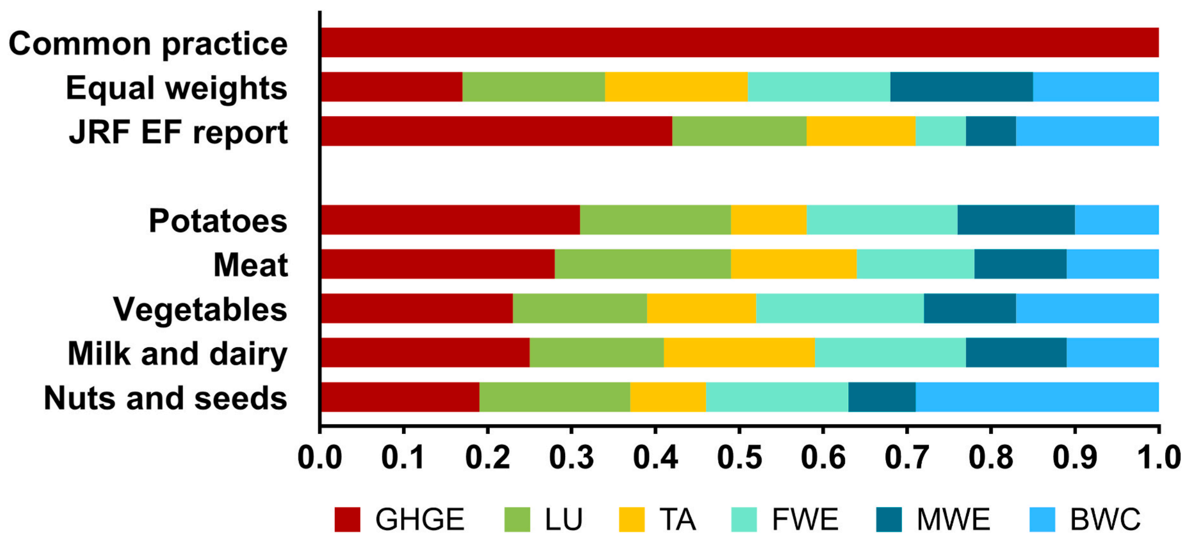

Fig. 3. Stacked bars for relative importance of EICs based on single criterium selection (common practice), equal weighting, the JRC EF report, or MCDA-based food group specific weights.
GHGE, greenhouse gas emissions; LU, land use; TA, terrestrial acidification; FWE, freshwater eutrophication; MWE, marine water eutrophication; BWC, blue water consumption; JRC EF, Joint Research Centre Environmental Footprint. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

used for comparison (Table 2). Since the data on food items did not undergo a critical review for consistency with the International Standards on LCA, these results only serve as proof-of-principle and may not be interpreted or communicated as scientifically based knowledge.

Using the MCDA-based weights, the mean score for nuts and seeds is 0.58. Based on the generic EU weights, the mean score is 0.56. For both weighting schemes, pumpkin seeds score highest (0.97 for MCDA-based weights and 0.93 for generic EF weights), whereas cashews score lowest (0.28 for MCDA-based weights and 0.33 for generic EF weights). The different approaches lead to distinct distributions, with MCDA-based weights resulting in higher maximum scores, lower minimum scores, and therefore greater variability.

Fig. 4 displays the contribution of weighted EICs to the single environmental value of the selection of nuts and seeds in the primary LCA dataset, excluding the extrapolations to enhance clarity. In fact, extrapolated food items with the same LCA data obtain the same total value following eq. (1) and eq. (2). The contribution of EICs to the total value of a food item equals its partial value multiplied by the EIC weight (eq. (2)). Since a higher partial value equals lower environmental impact compared to other nuts and seeds, a higher total value (i.e., score) equals lower overall environmental impact.

Considering the MCDA-based weights (top figure), flax seeds are scored highest (0.80), followed by peanuts (0.71). A significant proportion of these high scores is due to low blue water consumption compared to other nuts, resulting in high partial values contributing for 29 % (Table 2). Cashews also have relatively low blue water consumption compared to other nuts and seeds, but have highest environmental impact for land use, terrestrial acidification, and marine water eutrophication, equivalent to a partial value of zero. Consequently, despite less blue water consumption with the highest weight, the total value of cashews is the lowest (0.27). Unsalted pistachios have the highest blue water consumption and therefore receive zero partial value counting for 29 % of the total value. However, in their total value (0.44) this is compensated by relatively low impact for the other EICs. Almonds score low (0.37) due to relatively high blue water consumption, terrestrial acidification, and marine water eutrophication.

Comparing the value profiles calculated using food group specific MCDA-based weights to those calculated based on generic EF weights (bottom figure) indicates differences in the ranking of nuts and seeds. The total values for most individual food items marginally differ, while the contribution of EICs to the single environmental value does visibly change. With the exception of peanuts, differences in total values by the different weighting schemes range from −0.07 to 0.02 (from the MCDA- to the EF-approach), representing the correlation between EIC values. With these synergies in mind, flax seeds can thus be considered a win-win product, whereas cashews score overall lower with regards to

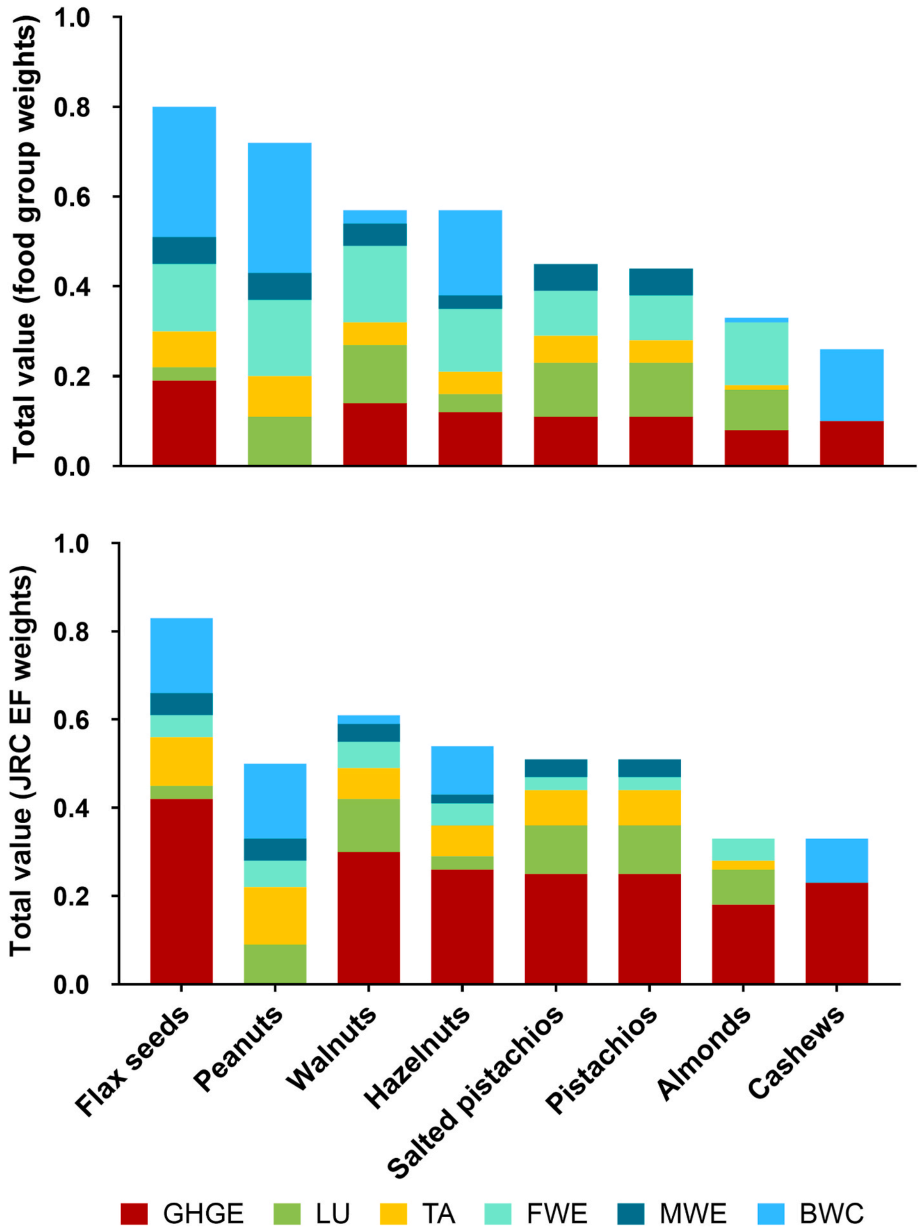

Fig. 4. Calculated total value profiles for a selection of nuts and seeds using MCDA-based weights for nuts and seeds (top) or generic weights by the JRC EF methodology (bottom). The total value (weighted sum of partial values) is inversely related to environmental impact. The colored bars show how the EICs per food item contribute to the total value of that food item (a longer bar equals *lower* impact with respect to that EIC after weighting).
GHGE, greenhouse gas emissions; LU, land use; TA, terrestrial acidification; FWE, freshwater eutrophication; MWE, marine water eutrophication; BWC, blue water consumption. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

environmental impact amongst nut and seed options. Otherwise, a difference of 0.22 between weighting schemes is observed for peanuts, which rank second for the MCDA-based weighting scheme, but sixth for the EF weighting scheme. This difference follows the trade-off of relatively low BWC, most important in the MCDA weighting scheme, but relatively high GHGE, most important in the EF weighting scheme. Thus, the two weighting schemes lead to different total values to varying extents, and, consequently, a different ranking of food items based on the total environmental value.

4. Discussion

This study demonstrated how MCDA is useful for developing weighting schemes for multiple environmental impact categories (EICs) at the food group level. With this method, EIC weights are tailored to the spatio-temporal (i.e., (local) environmental) and socio-cultural context. The adaptable MCDA model can be used to calculate a total environmental value of foods within a range of food items, for example based on culturally acceptable or nutritional alternatives, and thereby rank interchangeable dietary options for their sustainability. Potential applications for MCDA results include integration into dietary guidelines, sustainability labels, or LCA-based policy tools.

This proof-of-principle study confirmed that a food group approach in estimating dietary environmental impact can have benefits over an overall approach for the entire diet. It showed that environmental impact categories that are generally assumed relevant for evaluating diets (such as GHGE or BWC) are not equally important for different food groups. Vice versa, EICs that are relevant for specific food groups (such as eutrophication) are less relevant considering the total diet. Total environmental impact on a food group level offers a more realistic picture of the environmental burden for, for instance, nuts and seeds or dairy, by considering specific local (non-)challenges of the food groups. Furthermore, MCDA holds valuable potential to learn more about weighting various EICs at the food group level. The methodology is adaptable to diverse environmental (research) contexts. It allows the integration of socio-cultural dimensions across diverse dietary patterns through selection of relevant food groups. This structured approach can incorporate diverse value perspectives in decision making and also provides transparency on the robustness of results. This enhances functionality of realistic weighting patterns in evolving contexts.

Certain food groups show a more distinct EIC weighting pattern compared to generic weighting than others. GHGE is ranked first for four out of five food groups, and second for the fifth. Otherwise, BWC ranks second in the generic EF weighting scheme but ranges from first to last important EIC depending on the food group. FWE gains considerably more value for each food group compared to generic weighting for product footprint (Cerutti et al., 2018). It has been stated that the environmental burden depends on (inter)national production systems and regional conditions, which may involve different trade-offs (Heller et al., 2013). Expert comments with the questionnaire confirmed that such local challenges of food production were considered when prioritizing EIC trade-offs. To illustrate, meat as well as dairy weighting schemes value FWE notably higher than BWC, representing local eutrophication issues associated with these product groups in a country with no threat of water scarcity (Hollander et al., 2021; Stokstad, 2019). Conversely, by giving higher weight to BWC, weighting schemes for vegetables as well as nuts and seeds represent how these food groups are often imported from regions under blue water stress (Hollander et al., 2021; Vanham et al., 2020). The calculated total environmental value of peanuts therefore depends heavily on the weighting scheme used, because peanuts, compared to other nuts and seeds, score lowest for GHGE but highest for BWC. Because the environmental impact across EICs for other nut and seed products are closely related (i.e., EICs correlate), the calculated total environmental value is comparable regardless of the weighting scheme used. This allows identification of win-win products with overall low impact across EICs (i.e., the total value is close to 1). The MCDA approach is thus valuable for food groups with distinct environmental challenges (such as nuts and seeds) and when trade-offs exist between EICs (like for peanuts), or for identifying food items with overall low impact compared to its alternatives (like flax seeds).

This study demonstrated how MCDA deals with limitations of existing methods for weighing EICs, including scenario assumptions, spatial and temporal variations, variable LCA data, and (pre)selection of parameters. As various production systems differ and change, such methodological limitations lead to uncertainty in generic LCA interpretation. Not interpreting the relative importance of multiple EICs often leaves the reader to decide over complex trade-offs and may unfoundedly assign the same value to each category (Roesch et al., 2021; Zanghelini et al., 2018). Besides the generic JRC EF normalization and weighting approach, ReCiPe2016 converts LCA midpoints (EICs) into three endpoints corresponding to three areas of protection (Huijbregts et al., 2016). However, both methods are not specific to foods and representative for the European and global scale respectively, increasing uncertainty in interpretation (Cerutti et al., 2018; Goedkoop et al., 2013). Likewise, the planetary boundaries framework can be referred to for interpreting impact, but those metrics do not directly compare to LCA results due to a (spatial) difference in environmental processes and corresponding measurements (Richardson et al., 2023; Sala et al., 2020). One major advantage of MCDA is that it judges environmental impact relevant to spatio-temporal research contexts with ecological differences. This study evaluated the impact by specific food chains for Dutch consumption, so the EIC weights are accurate for current environmental challenges of these production systems. Furthermore, whereas general EIC weighting approaches disregard the actual impact by different products, weighting in MCDA is based on trade-offs between alternative foods using real numbers. MCDA thus anticipates (context-specific) LCA data for realistic weighting schemes. Quality and granularity of LCA data increase over time and production systems evolve (van Paassen et al., 2023). Updated LCA datasets, perhaps with extra EICs added, involve different trade-offs requiring updated weighting schemes. Moreover, it is important to (re-)establish EIC prioritization according to spatio-temporal variations in LCA data. In this way, more realistic environmental impact estimations are directly related to the context, e.g. for interpreting sustainability of diets in individuals, regions or populations (Springmann et al., 2018).

Sustainable diets encompass not only spatio-temporal variation but also socio-cultural diversity. Defining sustainable diets is considered a “wicked problem” as emphasized by Heller et al. (2013), because it involves complex interactions between environmental, health, and social factors. This requires breaking down the problem, involving stakeholders, aiming for adaptive solutions, and avoiding the one-size-fits-all mentality. In addition to spatio-temporal considerations, MCDA facilitates this process by allowing to structure dietary alternatives following health-related reasoning and/or population habits. This proof-of-principle study considered five food groups relevant to Dutch dietary culture and could expand to all relevant food groups with applications in Dutch nutrition science or policy making. This can for example be the basis for a product group-based front-of-package label for supporting sustainable choices. Future study objectives could consider alternative decision problems with socio-cultural relevance, such as comparing alternative protein sources standardized for protein content based on production system details (i.e., domestic cheese or imported soy). Another promising future application of MCDA for sustainable diets is integrating other sustainability criteria than EICs, such as health, economic feasibility, or public preferences (Biesbroek et al., 2023; Harrison et al., 2022). This helps to assess different sustainability trade-offs and clarify priorities for sustainable diets over time. Thus, while it is still possible to take a generic approach, making it comparable to existing methods, MCDA allows for tailoring sustainable diet solutions to population specific dietary habits and behaviors.

In MCDA, the estimated overall sustainability of foods is determined by the panel of decision makers who make value judgements depending on the scenario. MCDA ensures transparency and provides insight in the degree of agreement as well as diversity of expert opinion when prioritizing sustainability criteria. The expert panel in this study, comprising scientists specializing in Dutch food chain environmental impacts, encountered challenges in assessing less-studied EICs, representing the complexity of decision making. GHGE is the most prominent EIC in literature, potentially shaping experts' judgements. GHGE, as a global concern, also contrasts with other EICs that primarily affect local contexts (Heller et al., 2013; Springmann et al., 2018). Differences in prioritization underscore the importance of incorporating diverse expertise. Different stakeholders may emphasize the evolving criteria differently. Food group specific experts or stakeholders along the production chain may provide insights or perspectives that could be overlooked by generic expertise. Moreover, bottom-up input for the public debate can be generated by using general public judgements of simplified sustainability trade-offs in an MCDA model. The MCDA model thus not only provides solutions to sustainable food decisions but also identifies underlying priority conflicts, facilitating informed public debate and guiding the adaptive implementation of sustainable diets across national, local, and personal contexts.

Although the model in this case study successfully proves the principles it applies, its limitations should be acknowledged for future improvements. As MCDA is a toolbox with various assets, it can be improved and tailored to study purposes. In this study, a linear relationship for severeness of impact across the swing of the food group was assumed. Moreover, the weights calculation method, chosen for understandable demonstration of the principle, limits the weight space per EIC to a maximum of 0.33 (5 preferred trade-offs per EIC out of 15 trade-offs total). More advanced methods for normalizing and weights calculation can increase modelling accuracy (Marsh et al., 2017). Since the data-driven preference elicitation method depends on the data structure (minimum and maximum values per food group), data quality and completeness should also be carefully considered. Different preference elicitation methods can further strengthen the use of MCDA. Focus groups can help preselect relevant criteria. Focus groups can also stimulate interaction among the panel for comprehensive decision-making. Regarding the data presented in this study, it should be considered that this is a proof-of-principle project. An expert panel of eight demonstrated the principle of MCDA but may not be sufficient to generate robust and representative results. Consequently, the numerical values presented in this report are subject to data uncertainty, small sample size, and limited generalizability. In future applications of the method, a larger pool of experts allows for sensitivity analyses like internal consistency of agreement tests on expert value judgements, bootstrapping or weight perturbation. Moreover, when applied in a real-world setting, quantitative validation such as sensitivity analyses, correlation tests (e.g., comparing different scoring systems), or robustness checks (e.g., inter-rater reliability measures) can be conducted to assess the stability of the model under different assumptions or using different data sources. Thus, MCDA is an adaptable methodology providing opportunities for diverse (research) objectives towards adopting more sustainable diets.

For future application and transferability to different cultural and/or geographical settings, the MCDA methodology can be adapted at each stage of the model. For instance, decision problems (food groups) and alternatives (food items) may be adapted to specific dietary cultures and decision alternatives (EICs) may be adjusted based on relevance or data availability. Using LCA data specific to the geographical region for input data naturally increases accuracy of results. Functional units may be adjusted to the research question, for instance when aiming to compare food items based on protein or energy content. As mentioned before, the background of the panel of experts should also be specific to the setting of the study and the participatory methods can be chosen as appropriate. Existing (online) MCDA software programs, such as 1000Minds, can help upscaling MCDA efforts for more robust results (1000minds.com). For example, an MCDA project could investigate the total environmental impacts of different protein sources that are culturally acceptable in a particular context, drawing on expertise from academia and industry familiar with their supply chains. The results can be integrated into LCA-based policy tools or algorithms for product labeling. Moreover, incorporating economic decision criteria into the model could enhance its applicability, supporting more informed choices in industry settings. Overall, interpretation of MCDA results depends on the decisions in the development of the model, tailoring it to the goal and scope of the project. This flexibility can transfer the model to diverse contexts, including policy development, consumer preferences, industry practices, and nutrition guidelines.

5. Conclusion

This paper explored to what extent food group specific EIC weighting schemes are relevant for interpreting overall environmental impact of foods, and to assess the suitability of MCDA as a method for developing such schemes. Food group specific weighting schemes can differ considerably from generic weighting schemes, in particular for other EICs than GHGE and for food groups in which GHGE is relatively low compared to the (local) environmental impact of other EICs. MCDA is a useful method for LCA interpretation that can be tailored to different spatio-temporal and socio-cultural contexts and (research) objectives. It formalizes decision making where subjectivity plays an inherent role and can generalize perspectives from experts in the field or from other stakeholders. Additionally, it can assess the level of (dis)agreement in the estimate of interest. The method is adaptable to other tradeoffs related to dietary sustainability, including health and economic decision criteria. Navigating diverse priorities and avoiding the one-size-fits-all mentality, using MCDA, may support the transition to sustainable food consumption.

CRediT authorship contribution statement

Elise W. de Boer: Writing – review & editing, Writing – original draft, Visualization, Project administration, Methodology, Investigation, Formal analysis, Conceptualization. **Douwe Postmus:** Writing – review & editing, Methodology, Formal analysis. **Reina E. Vellinga:** Writing – review & editing. **Erik Buskens:** Writing – review & editing, Supervision, Conceptualization. **Pieter van 't Veer:** Writing – review & editing, Supervision, Conceptualization. **Eva Corpeleijn:** Writing – review & editing, Supervision, Project administration, Conceptualization.

Data statement

The data supporting this study are not openly available due to privacy restrictions, but requests can be submitted to the corresponding author upon reasonable request.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jclepro.2025.147362.

Data availability

The data that has been used is confidential.

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