DATA DRIVEN DECISION SUPPORT FRAMEWORK FOR PRODUCT LEVEL REUSE PRIORITISATION AND BARRIER DIAGNOSIS

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Abstract

This paper proposes a three-stage workflow to prioritise reusable building product groups in Dutch demolition outflows, addressing the gap between impact potential and implementation feasibility. Stage 1 screens 139 groups using an impact proxy combining mass outflow and the environmental cost indicator, shortlisting ten candidates. Stage 2 applies a five-criteria multi-criteria analysis with weights from eight experts using the Best–Worst Method, where supply–demand balance dominates (0.296) and sustainability ranks lowest (0.137). Stage 3 links ranking to barrier diagnosis through a masonry case, identifying contamination, certification, and coordination challenges. The workflow supports identifying high priority product groups for early-stage reuse planning.

Introduction

Problem context

The construction sector remains a major contributor to material demand and embodied environmental impacts, which makes improving circular performance a priority in the transition toward a circular economy (Kirchherr et al., 2017). Yet, reuse implementation in practice remains limited, particularly at the demolition stage where large volumes of potentially reusable products leave the building stock and are often downcycled or disposed of (Arora et al., 2020).

This study focuses on demolition outflows from Dutch residential and utility buildings (B&U). In this context, environmental relevance is quantified computationally as mass outflow × MKI, where MKI (Milieu Kosten Indicator) is a Dutch aggregated environmental cost indicator and impact values are operationalised using the A1 indicator set as implemented in the national database (Nationale Milieudatabase (NMD), 2025). This framing enables a consistent comparison of heterogeneous product groups by combining (i) how much material becomes available at the end-of-life and (ii) to what extent environmentally relevant that material is under the same indicator system.

However, identifying environmentally relevant product groups does not automatically translate into reuse uptake. Practical decision-making is often constrained by fragmented information about what leaves the building stock, under what conditions, and whether reuse is feasible, timely, and economically viable within real project constraints (Bellini et al., 2024). This results in a persistent gap between circular ambition and operational reuse uptake in the built environment (Planbureau voor de Leefomgeving (PBL), 2025).

Related work and research gap

This section focuses on decision-support approaches for product-level reuse prioritisation in the built environment, rather than reviewing circular economy literature more broadly.

Research has extensively documented barriers to circular construction and product reuse, including technical constraints, market uncertainty, and institutional and behavioural factors (Kanters, 2020; Wuni, 2022). Two limitations are particularly relevant for this study.

First, high environmental relevance does not imply high reuse feasibility. Product groups with high mass outflow × MKI can still face major implementation barriers such as contamination, certification requirements, liability concerns, and misaligned supply and demand (Giorgi et al., 2022). This implies that computational decision support must separate "impact potential" from "implementability" rather than assuming they overlap (De Wolf et al., 2024).

Second, existing approaches often lack an explicit, reproducible computational pipeline that turns heterogeneous demolition outflow data and expert knowledge into transparent prioritisation outputs. In particular, reuse prioritisation requires combining impact-based signals with feasibility-related dimensions, such as cost barriers, risk barriers, supply–demand balance, and technical feasibility, rather than relying on impact alone (Yu et al., 2023). To address this, the study applies an MCA structure with five criteria—cost, risk, supply–demand balance, technical feasibility, and sustainability impact—and derives criterion weights from eight expert interviews using the Best–Worst Method (BWM) (Rezaei, 2015).

This means that environmental relevance alone is not enough to identify reuse potential. Instead, prioritisation requires explicitly accounting for implementation-oriented criteria such as cost, risk, technical feasibility, and supply–demand balance alongside impact-based indicators.

Computing-oriented circularity research in the built environment increasingly treats the existing building stock as a quantifiable “secondary resource” that can be measured, forecast, and prioritised through data pipelines rather than narrative assessments (Arora et al., 2021). At the city/building-stock scale, computational approaches typically combine stock modelling with environmental accounting to estimate future availability of recoverable components and associated impact reduction opportunities (Röck et al., 2021). Such pipelines support “where-to-focus” decisions by identifying high-leverage materials/components before stakeholders invest in detailed feasibility studies (Wuyts et al., 2022).

However, much of the stock/potential modelling literature remains oriented toward estimating quantity and theoretical circularity potential, while practical implementation still depends on socio-technical constraints (e.g., dismantling feasibility, market absorption, regulatory permission) (Röck et al., 2021). This calls for a workflow that links data-driven screening to decision criteria such as cost, risk, technical feasibility, and market balance, instead of assuming that high potential also means easy implementation (Van Den Berg et al., 2023).

Multi-Criteria Analysis (MCA) is widely used in construction and demolition contexts because circular decisions are inherently multi-dimensional: environmental benefits must be assessed alongside cost, risk, feasibility, supply chains, and stakeholder acceptance (Banias et al., 2010; Bajwa et al., 2025). Methodologically, MCA offers a transparent aggregation structure—criteria, weights, and scores—that can be audited and updated as assumptions or stakeholder inputs change (Bajwa et al., 2025). Within circular construction research, barrier- and driver-oriented studies often operationalise implementation constraints into evaluative criteria, creating a bridge between qualitative insights and decision models (Kanters, 2020).

In C&D waste and circular practice assessments, MCA has been applied to compare strategies, prioritise interventions, and structure complex trade-offs across stakeholders (Swarnakar and Khalfan, 2024). Yet, a recurring limitation is that MCA is frequently applied after a case or material is selected, rather than being computationally coupled with an upstream, data-driven filtering step that justifies why a given product group deserves priority attention from a system-wide list (Wuyts et al., 2022).

A central methodological challenge in MCA is how to elicit reliable criterion weights, especially when expert time is limited and decision contexts are complex (Peykani et al., 2026). The Best–Worst Method (BWM) has been proposed as a robust multi-criteria weighting approach that reduces the number of pairwise comparisons while improving consistency (Rezaei, 2015). Compared to more comparison-heavy weighting methods, BWM structures expert judgement around two anchors (best and worst criteria), which is easier to communicate and reproduce in a computational workflow (Rezaei, 2016).

For computing-in-construction venues, the relevance of BWM is not only that it yields weights, but that it supports an auditable pipeline: expert inputs can be stored, checked for consistency, and re-run when either the criteria set or the stakeholder group changes, enabling iterative refinement and sensitivity testing (Peykani et al., 2026).

Combine a quantity factor (e.g., mass outflow or material availability) with an impact factor (e.g., environmental burden per unit) to identify candidate materials/components with both sufficient scale and meaningful sustainability leverage (Arora et al., 2020). This logic aligns with urban mining perspectives that frame cities and building stocks as measurable repositories whose recovery potential can be quantified and prioritised (Ghisellini et al., 2022). Building-stock studies further show that “future supply” assessments become more actionable when they are resolved into component/product categories that map onto real recovery processes and market channels (Orenga Panizza and Nik-Bakht, 2024).

In the Dutch context, impact-based filtering can leverage the national environmental cost indicator (MKI) and associated databases/tools to operationalise environmental relevance in a standardised way (Nationale Milieudatabase (NMD), 2025). Sectoral material-flow datasets provide product-group resolution for construction-related inflows/outflows, enabling computational shortlisting across many product groups before deeper feasibility analysis begins (EIB; Metabolic, 2022). The key methodological opportunity is to connect stock flow quantification with decision support prioritisation in one framework, rather than treating them as separate analytical exercises (Wuyts et al., 2022).

Two research gaps are especially relevant here. First, urban mining and stock-flow studies provide useful system-level signals on material availability and environmental impact, but they rarely translate these signals into prioritisation approaches that reflect practical feasibility, such as cost, risk, technical constraints, and supply–demand balance (Röck et al., 2021). Second, barrier and driver studies explain why reuse remains difficult, but they are less often incorporated into an explicit decision workflow. In practice, this means that few studies combine quantitative screening, weighted multi-criteria ranking, and structured barrier diagnosis in a single approach that can support intervention design (Wuni, 2022).

To address these gaps, the study treats reuse prioritisation as a decision-support task that combines impact screening, MCA-based ranking, and barrier diagnosis: product groups are first filtered using impact-based signals, then prioritised using MCA with explicit weighting, and finally connected to a demonstrative barrier diagnosis to show how quantitative ranking can guide targeted implementation strategies (Van Den Berg et al., 2023).

Existing reuse metrics and stock-based assessments are useful for identifying material availability, environmental relevance, or theoretical recovery potential, but they often stop before implementation conditions are examined. By contrast, this study does not propose another single reuse score. It combines impact-based screening with implementation-oriented multi-criteria ranking and a case-based barrier diagnosis. The key distinction is therefore methodological rather than purely metric-based: the workflow is designed to move from environmental relevance to ranked action candidates and then to an explanation of why high-potential product groups may still face barriers in practice.

Research question

The study addresses the following main research question:

RQ: How can high-potential product groups for reuse be computationally identified from Dutch B&U demolition outflows using mass outflow × MKI, and how can key implementation barriers be diagnosed to inform targeted circular interventions?

Contributions

This study makes three contributions. First, it develops a three-stage workflow for product-level reuse prioritisation that combines impact-based filtering, weighted multi-criteria analysis, and case-based barrier diagnosis. Second, it operationalises public Dutch demolition-flow and environmental-impact data together with structured expert elicitation, making the ranking logic explicit and updateable when new data become available. Third, it shows how ranking outputs can support intervention-oriented diagnosis rather than stopping at score comparison alone, using masonry brickwork as an illustrative case.

Methodology

Research design

This study uses a mixed-method design to identify, rank, and further examine reusable product groups in Dutch demolition outflows. The design combines public product-group flow data, environmental impact data, and two rounds of semi-structured interviews. The first interview round supports Stage 2 by eliciting implementation-oriented judgement for MCA weighting and selected product-level scoring. The second round supports Stage 3 by examining how the highest-ranked product group performs in practice through stakeholder interviews along the brick value chain. This design was chosen because product-level reuse cannot be assessed from environmental relevance alone; it also requires evidence on implementation conditions, actor perspectives, and sector-specific bottlenecks.

Workflow overview

The study develops a three-stage workflow to identify, rank, and further examine reusable product groups in Dutch demolition outflows. The workflow combines impact-based screening, multi-criteria ranking, and barrier diagnosis to support product-level comparison under real implementation constraints (Swarnakar and Khalfan, 2024).

In this paper, 'computational' means that product groups are assessed through explicit indicators, weighted aggregation, and reproducible ranking rules (Papamichael et al., 2023).

As illustrated in Figure 1, the framework consists of three sequential stages. First, an impact-based filtering stage is applied to identify product groups with high environmental relevance based on demolition-related material outflows and environmental impact indicators (Atta and Bakhoum, 2024; Nationale Milieudatabase (NMD), 2025). Second, a multi-criteria prioritisation stage evaluates the shortlisted product groups by explicitly accounting for economic, technical, and supply–demand considerations using a structured decision-analysis method (Rezaei, 2015). Third, a case-based barrier diagnosis is conducted for the highest-ranked product group to demonstrate how the framework supports the identification of dominant implementation barriers (Giorgi et al., 2022; Wuni, 2022).

Each stage uses explicit indicators and scoring rules. This makes the workflow easier to reproduce and adapt to other datasets (Yang et al., 2023). The framework is not intended to optimise a single material or project case, but to support early-stage circular construction planning under data constraints (Papamichael et al., 2023).

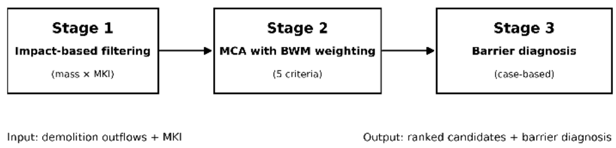

Figure 1: Overview of the computational prioritisation workflow

Stage 1 – impact-based candidate filtering (data-driven)

The first stage aims to reduce the initial set of demolition-derived product groups to a manageable number of candidates that are environmentally relevant for reuse considerations (Wuyts et al., 2022). The analysis is based on a dataset comprising 139 distinct product groups identified within the Dutch residential and utility building stock (EIB; Metabolic, 2022; Nationale Milieudatabase (NMD), 2025).

Each product group is characterised by two quantitative indicators:

(i) the annual mass outflow generated during demolition activities, and

(ii) an aggregated environmental impact indicator, expressed as the Environmental Cost Indicator (Milieu Kosten Indicator, MKI), which reflects life-cycle environmental burdens (Nationale Milieudatabase (NMD), 2025).

An impact score is derived by combining these two indicators, enabling the identification of product groups that exhibit both substantial material quantities and high environmental relevance (EIB; Metabolic, 2022). To avoid bias towards a single material category, the selection procedure includes both overall high-impact product groups and the highest-ranking representatives within major material classes (EIB; Metabolic, 2022).

As a result, the initial set of 139 product groups is reduced to a shortlist of ten high-impact candidates, which are subsequently evaluated in greater detail in the following stage. The shortlist combines the highest-impact product groups with category representatives to avoid a shortlist dominated by a single material family.

Stage 2 – multi-criteria prioritisation

While the first stage identifies product groups with high environmental relevance, it does not capture constraints related to practical implementation (Byers et al., 2024). Therefore, the second stage applies a multi-criteria decision analysis (MCA) to assess the feasibility of reuse across the shortlisted product groups (EIB; Metabolic, 2022).

Five evaluation criteria are defined to capture key dimensions influencing reuse implementation:

(1) economic barriers,

(2) technical feasibility,

(3) sustainability/impact,

(4) risks related to uncertainty and liability, and

(5) supply–demand balance.

Each product group is scored on a five-point ordinal scale for each criterion using evidence from the literature and expert judgement (Peykani et al., 2026). Criterion weighting and product-level scoring served different purposes. Weighting was used to capture broader implementation priorities across the five reuse criteria, whereas product-level scoring of cost and risk required more specific familiarity with particular product groups. To reflect the relative importance of the criteria, weights were derived using the Best–Worst Method (BWM), which provides a structured form of preference elicitation (Rezaei, 2016).

Criterion weights were obtained from eight semi-structured interviews with relatively independent experts in circular construction and reuse. The interviewees were selected to provide cross-sector perspectives rather than product-specific advocacy. In the BWM step, each expert identified the most important and least important criterion and then compared the remaining criteria to these two anchors on a 1–9 scale. Individual weights were calculated and averaged to obtain the final weight set. Product-level scoring of cost and risk was restricted to interviewees who indicated sufficient familiarity with specific product groups, to avoid speculative ratings at that level. To test robustness, the weighting step was recalculated by excluding one expert at a time. This allowed the ranking to be checked for sensitivity to individual expert input.

The overall prioritisation score for each product group is calculated using a weighted additive model:

$$S_i = \sum_{j=1}^{n} w_j \cdot x_{ij}$$

where S_i denotes the aggregated score of product group i, w_j represents the weight of criterion j, and x_{ij} is the normalised score of product group i under criterion j (Jato-Espino et al., 2014).

This procedure allows different product groups to be compared using the same logic, while keeping environmental relevance separate from implementation feasibility (Byers et al., 2024). Criterion weighting used all eight expert interviews, whereas product-level scoring of cost and risk was restricted to interviewees who indicated sufficient familiarity with specific product groups.

Stage 3 – barrier diagnosis

Stage 3 examines why the product group ranked highest in Stage 2 may still face implementation bottlenecks in practice. Brick masonry is used as the demonstration case. A qualitative analysis is conducted to examine its value-chain structure and identify dominant barriers affecting reuse implementation. The diagnosis draws on five stakeholder interviews across the brick value chain and uses literature-derived barrier categories as a coding frame to identify constraints related to coordination, certification, contamination control, and process organization (Wuni, 2022). The purpose of Stage 3 is analytical explanation rather than statistical validation: it links the ranking output to observed implementation barriers and shows how prioritisation results can support intervention-oriented diagnosis (Rakhshan et al., 2020; Wuyts et al., 2022).

Data sources and reproducibility

The workflow combines public quantitative datasets with interview-based expert judgement. Product-group outflow data were taken from the EIB/SGS-Search mass-flow dataset for Dutch residential and utility buildings, while environmental impact values were retrieved from the Dutch National Environmental Database (NMD) using MKI-based product matches. Data cleaning, product-group merging, thresholding, and impact calculations were implemented in Microsoft Excel using explicit rules and formula-based operations. Public input datasets, decision rules, and scoring procedures are described in the methodology. Interview responses are not reported in full because of ethics and anonymity requirements, but the interview protocol, weighting procedure, and sensitivity checks are summarised in the paper.

Evaluation logic

The framework is evaluated as a demonstration rather than as a full external validation exercise. Its usefulness is assessed in three ways: first, whether Stage 2 meaningfully reorders the Stage 1 shortlist once implementation-oriented criteria are introduced; second, whether the weighting results remain stable under leave-one-out recalculation; and third, whether the masonry case reveals barriers that are not visible in impact screening alone. Together, these checks show whether the workflow produces distinct, interpretable, and implementation-relevant outputs.

Results

Impact screening results

This section presents the results from the three stages of the workflow. Stage 1 yields a shortlist of high-impact product groups, Stage 2 produces a reuse-oriented prioritisation ranking, and Stage 3 uses masonry brickwork for demonstration only to illustrate the quantitative–qualitative linkage between computational prioritisation and barrier diagnosis (Hopkinson et al., 2019).

After applying the predefined merging rules, the initial product-group list was reduced from 139 to 115 groups. Candidate filtering first applied a mass-flow threshold, retaining groups with relative mass outflow ≥ 0.5%; groups in the 0.5–0.1% band were re-examined for possible merging effects, but no additional merges qualified. The average relative mass outflow of the Top-5 groups was more than 29× that of the 24th group, supporting the assumption that contributions below the threshold can be neglected. For shortlisted groups, environmental impact was computed as mass outflow × MKI, where MKI values were retrieved from the Dutch National Environmental Database (NMD) and multiplied by the corresponding outflow mass to obtain an impact proxy in euros (€). To avoid dominance by stone-like products in the Top-5, the shortlist also includes the highest-impact representatives from steel, wood, glass, mixed and plastics; see Figure 2.

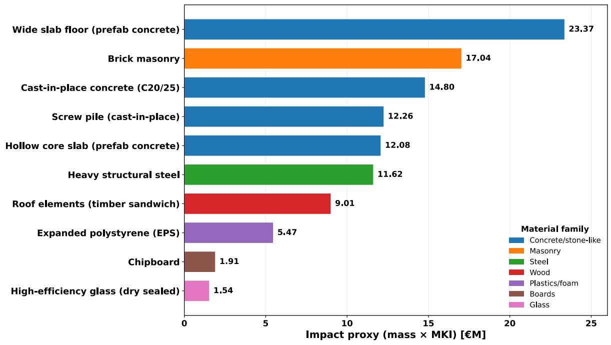

Figure 2: High-impact candidate groups based on impact proxy (mass × MKI)

MCA ranking results

Stage 2 applied MCA to the ten shortlisted product groups. Expert elicitation indicated that supply–demand balance was the most influential criterion (average weight 0.296), more than twice the weight assigned to sustainability/impact (average weight 0.137), underscoring the role of market viability in enabling reuse. This weighting structure provides quantitative evidence that implementation readiness can dominate environmental relevance in computational reuse prioritisation. While all experts contributed to criteria weighting, only a subset provided sufficiently confident and consistent product-level scores for cost and risk; therefore, product scoring draws on those inputs, while the final aggregation uses the combined weights across experts. The resulting MCA ranking shows a clear top tier: brick masonry achieved the highest total score (4.04/5), followed by heavy structural steel (3.29/5), while the third-ranked option (hollow core slabs) scored notably lower (2.78/5). A saturation test indicated that the Top-2 positions remain stable under different expert combinations; see Figure 3.

All eight experts were included in the criterion-weighting step, as they indicated sufficient confidence in judging the relative importance of the five MCA criteria. However, only four experts were retained for product-level scoring of cost and risk. The remaining interviewees reported insufficient familiarity with specific product groups to provide reliable comparative ratings at that level. This separation was intentional: criterion weighting captured broader implementation priorities, whereas product-level cost and risk scoring required more detailed knowledge of particular materials and products.

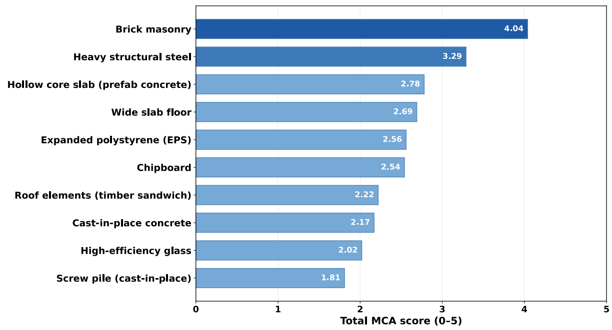

Figure 3: MCA-based reuse prioritisation ranking

Barrier diagnosis results

Although heavy structural steel ranks highly, its end-of-life value retention and established recycling/reuse practices suggest a smaller incremental knowledge gap. By contrast, masonry brickwork is typically downcycled (e.g., crushed for road base), indicating a larger opportunity for value retention if direct reuse can be enabled. Together with its top MCA score and supporting qualitative insights, masonry was selected as the demonstration product group.

To reduce over-interpretation of absolute values, Table 1 is presented as an illustrative comparison. Using estimates reported for an industry tool, direct reuse of brickwork yields an MKI reduction of approximately €24/t, whereas steel reuse yields about €60/t (general reuse) or €80/t (reuse as structural material). However, given masonry's much larger mass flow, the system-level impact of increasing brick reuse is estimated to be 2–3× higher than that of heavy structural steel when scaled by national outflow volumes.

Table 1: Illustrative MKI savings and potential impact reduction (brick vs. steel)

Product	MKI (€/t)	MKI saving (€/t)	Current impact (M€)	Potential impact saving (M€)	Relative savings (%)
Heavy structural steel	120	60	11.62	5.81	50.0
Heavy structural steel (structural reuse)	120	80	11.62	7.74	66.7
Brick masonry	26.3	24	17.04	15.55	91.3

The demonstration barrier diagnosis indicates that the most constraining bottlenecks for brick reuse relate to cleaning and contamination control (including mortar separation), quality consistency and certification, and the time/coordination costs associated with selective deconstruction and matching supply to demand. Corresponding leverage points include selective deconstruction to increase recoverable quality, standardised quality control and certification schemes, and reorganising testing/grading processes across supply-chain nodes to reduce schedule conflicts (Knoth et al., 2022). Based on these constraints, the paper outlines possible intervention directions, such as standardised quality assessment and improved demolition–demand coordination, to show how the ranking results can support practical action.

Discussion

The results indicate that product-group prioritisation for reuse cannot be inferred from environmental relevance alone. While the Stage 1 shortlist is dominated by high-mass, stone-like products, Stage 2 shows that implementation-oriented criteria—especially supply–demand balance—can substantially reorder priorities. This is reflected by masonry brickwork ranking first despite comparatively weaker scores on cost and technical feasibility, suggesting that market fit can outweigh near-term process constraints in determining reuse readiness (Wuni, 2022). This aligns with broader observations that circular implementation is shaped by interacting economic, technical and institutional drivers and barriers rather than single-factor optimisation (Tura et al., 2019). Importantly, the dominance of supply–demand balance over environmental impact in the weighting structure illustrates that reuse prioritisation should not be treated as a single-criterion screening exercise. This suggests that reuse potential should be assessed through both environmental relevance and implementation conditions, rather than environmental relevance alone.

The value of the workflow lies not only in identifying high-impact candidates, but in showing how rankings change once implementation conditions are introduced. In this study, the shift from Stage 1 to Stage 2 demonstrates that environmental relevance alone is not sufficient for prioritisation, while Stage 3 shows why even highly ranked options may still face coordination, certification, or contamination-related barriers. In this sense, the paper offers a proof-of-concept that ranking and diagnosis provide more decision-relevant insight than impact screening alone.

Implications for practice

The barrier configuration observed for brick reuse suggests that scaling requires interventions that simultaneously address (i) quality assurance and certification, (ii) time alignment between demolition and new-build demand, and (iii) process innovations for cleaning and contamination control. Existing reuse toolkits and sector protocols can support standardisation efforts, but their effectiveness depends on embedding them in procurement and early planning routines (SGS Search; Cirkelstad, 2021). In parallel, digital marketplaces and matchmaking platforms may reduce supply–demand uncertainty by enabling earlier visibility of upcoming demolition streams and reusable stock (DigiC, 2024). These implications also matter for computing in construction: reuse is not only a material challenge, but also a coordination challenge involving data availability, timing, and cross-organisational alignment (Knoth et al., 2022).

Limitations and robustness considerations

Several limitations should be noted. First, Stage 1 relies on the availability and consistency of product-group MKI values; while this supports comparability, it also makes results sensitive to database assumptions and boundary definitions (Nationale Milieudatabase (NMD), 2025). Second, the MCA scoring uses ordinal scales and expert judgement, which introduces subjectivity and may vary with expert composition and sector familiarity. Third, the current implementation does not propagate uncertainty from mass-flow estimates, impact factors and scoring into the final ranking; future work could incorporate uncertainty analysis to quantify ranking stability under data and judgement variance. Finally, Stage 3 is deliberately illustrative; it demonstrates linkage to barrier diagnosis but does not validate the effectiveness of specific interventions or business arrangements.

Research and implementation directions

Future development can proceed along three directions. (1) Data enrichment and automation: linking product-group datasets to spatially resolved building-stock models and material-passport data streams to improve timeliness and granularity (Wuyts et al., 2022). (2) Decision-support extensibility: integrating additional objectives (e.g., logistics distance, storage constraints, and risk-adjusted costs) while maintaining the same computational backbone. (3) Governance and standardisation alignment: connecting prioritisation outputs to emerging sector standards and assessment protocols to reduce liability concerns and enable procurement uptake (NEN, 2023).

Together, these directions position the framework as an extensible computational layer that can support circular decision-making across multiple products and contexts.

Conclusions

This paper develops a three-stage workflow for product-level reuse prioritisation in Dutch demolition outflows and shows that reuse potential cannot be inferred from environmental relevance alone. After screening 139 product groups, masonry brickwork emerges as the highest-ranked option, as implementation-oriented factors—especially supply–demand balance—outweigh environmental impact in expert weighting. The masonry case further demonstrates that scaling reuse depends on contamination control, certification, and coordination between demolition and processing.

The main implication is that reuse planning should combine environmental relevance with implementation conditions and use ranking outputs to guide targeted interventions. Although demonstrated on Dutch data and a single case, the contribution lies in the workflow rather than the specific product group, making it transferable to contexts with comparable mass-flow and environmental-impact data. While environmental relevance is operationalised using MKI from the NMD in the Dutch case, alternative indicators—such as monetised LCA metrics or EPD-based impact values—can be adopted in other jurisdictions. The MCA structure is likewise adaptable, provided that criteria and weights are aligned with local market and regulatory conditions (Honic et al., 2021; Giorgi et al., 2022).

References

Arora, M., Raspall, F., Fearnley, L., Silva, A., 2021. Urban mining in buildings for a circular economy: Planning, process and feasibility prospects. Resour. Conserv. Recycl. https://doi.org/10.1016/j.resconrec.2021.105754

Arora, M., West, J., Patterson, M., Daly, M., 2020. Buildings and the circular economy: Estimating urban mining, recovery and reuse potential of building components. Resour. Conserv. Recycl. https://doi.org/10.1016/j.resconrec.2019.104581

Atta, I., Bakhoum, E.S., 2024. Environmental feasibility of recycling construction and demolition waste. Int. J. Environ. Sci. Technol. 21, 2675–2694. https://doi.org/10.1007/s13762-023-05036-y

Bajwa, A.U.R., Siriwardana, C., Shahzad, W., Naeem, M.A., 2025. Material selection in the construction industry: a systematic literature review on multi-criteria decision making. Environ. Syst. Decis. 45, 8. https://doi.org/10.1007/s10669-025-10001-w

Banias, G., Achillas, C., Vlachokostas, C., Moussiopoulos, N., Tarsenis, S., 2010. Assessing multiple criteria for the optimal location of a construction and demolition waste management facility. Build. Environ. 45, 2317–2326. https://doi.org/10.1016/j.buildenv.2010.04.016

Bellini, A., Tadayon, A., Andersen, B., Klungseth, N.J., 2024. The role of data when implementing circular strategies in the built environment: A literature review. Clean. Environ. Syst. 13, 100183. https://doi.org/10.1016/j.cesys.2024.100183

Byers, B.S., Raghu, D., Olumo, A., De Wolf, C., Haas, C., 2024. From research to practice: A review on technologies for addressing the information gap for building material reuse in circular construction. Sustain. Prod. Consum. 45, 177–191. https://doi.org/10.1016/j.spc.2023.12.017

De Wolf, C., Byers, B.S., Raghu, D., Gordon, M., Schwarzkopf, V., Triantafyllidis, E., 2024. D5 digital circular workflow: five digital steps towards matchmaking for material reuse in construction. Npj Mater. Sustain. 2, 36. https://doi.org/10.1038/s44296-024-00034-8

EIB; Metabolic, 2022. Materiaalstromen in de bouw en infra: 2019, 2030, 2050. URL https://www.eib.nl/publicaties/materiaalstromen-in-de-bouw-en-infra/ (accessed 1.21.26).

Ghisellini, P., Ncube, A., Casazza, M., Passaro, R., 2022. Toward circular and socially just urban mining in global societies and cities: Present state and future perspectives. Front. Sustain. Cities 4. https://doi.org/10.3389/frsc.2022.930061

Giorgi, S., Lavagna, M., Wang, K., Osmani, M., Liu, G., Campioli, A., 2022. Drivers and barriers towards circular economy in the building sector: Stakeholder interviews and analysis of five European countries policies and practices. J. Clean. Prod. 336, 130395. https://doi.org/10.1016/j.jclepro.2022.130395

Honic, M., Kovacic, I., Aschenbrenner, P., Ragossnig, A., 2021. Material Passports for the end-of-life stage of buildings: Challenges and potentials. J. Clean. Prod. 319, 128702. https://doi.org/10.1016/j.jclepro.2021.128702

Hopkinson, P., Chen, H.-M., Zhou, K., Wang, Y., Lam, D., 2019. Recovery and reuse of structural products from end-of-life buildings. Proc. Inst. Civ. Eng. - Eng. Sustain. 172, 119–128. https://doi.org/10.1680/jensu.18.00007

Jato-Espino, D., Castillo-Lopez, E., Rodriguez-Hernandez, J., Canteras-Jordana, J.C., 2014. A review of application of multi-criteria decision making methods in construction. Autom. Constr. 45, 151–162. https://doi.org/10.1016/j.autcon.2014.05.013

Kanters, J., 2020. Circular Building Design: An Analysis of Barriers and Drivers for a Circular Building Sector. Buildings 10, 77. https://doi.org/10.3390/buildings10040077

Kirchherr, J., Reike, D., Hekkert, M., 2017. Conceptualizing the circular economy: An analysis of 114 definitions. Resour. Conserv. Recycl. 127, 221–232. https://doi.org/10.1016/j.resconrec.2017.09.005

Knoth, K., Fufa, S.M., Seilskjær, E., 2022. Barriers, success factors, and perspectives for the reuse of construction products in Norway. J. Clean. Prod. 337, 130494. https://doi.org/10.1016/j.jclepro.2022.130494

Nationale Milieudatabase (NMD), 2025. MKI Viewer Tool [WWW Document]. NMD. URL https://milieudatabase.nl/en/latest/news/en-mki-van-de-bouw-blijft-stijgen-bij-business-as-usual/ (accessed 1.21.26).

NEN, 2023. NTA 8713:2023 — Hergebruik van constructiestaal. https://www.nen.nl/nta-8713-2023-nl-307691

Orenga Panizza, R., Nik-Bakht, M., 2024. Building stock as a future supply of second-use material – A review of urban mining methods. Waste Manag. Bull. 2, 19–31. https://doi.org/10.1016/j.wmb.2024.03.001

Papamichael, I., Voukkali, I., Loizia, P., Zorpas, A.A., 2023. Construction and demolition waste framework of circular economy: A mini review. Waste Manag. Res. 41, 1728–1740. https://doi.org/10.1177/0734242X231190804

Peykani, P., Emrouznejad, A., Nouri, M., 2026. Best-worst multi-criteria decision-making method: A review of the literature. Socioecon. Plann. Sci. 104, 102345. https://doi.org/10.1016/j.seps.2025.102345

Planbureau voor de Leefomgeving (PBL), 2025. Integrale Circulaire Economie Rapportage (ICER) 2025. https://www.pbl.nl/publicaties/integrale-circulaire-economie-rapportage-2025

Rakhshan, K., Morel, J.-C., Alaka, H., Charef, R., 2020. Components reuse in the building sector – A systematic review. Waste Manag. Res. 38, 347–370. https://doi.org/10.1177/0734242X20910463

Rezaei, J., 2016. Best-worst multi-criteria decision-making method: Some properties and a linear model. Omega 64, 126–130. https://doi.org/10.1016/j.omega.2015.12.001

Rezaei, J., 2015. Best-worst multi-criteria decision-making method. Omega 53, 49–57. https://doi.org/10.1016/j.omega.2014.11.009

Röck, M., Baldereschi, E., Verellen, E., Passer, A., Sala, S., Allacker, K., 2021. Environmental modelling of building stocks – An integrated review of life cycle-based assessment models to support EU policy making. Renew. Sustain. Energy Rev. 151, 111550. https://doi.org/10.1016/j.rser.2021.111550

SGS Search; Cirkelstad, 2021. Beslisboom hoogwaardig hergebruik bouwproducten [WWW Document]. SGS Search. URL https://www.sgssearch.nl/over-search/search-in-de-media/beslisboom-hoogwaardig-hergebruik-bouwproducten.html (accessed 1.21.26).

Swarnakar, V., Khalfan, M., 2024. Circular economy in construction and demolition waste management: an in-depth review and future perspectives in the construction sector. Smart Sustain. Built Environ. https://doi.org/10.1108/SASBE-02-2024-0056

Tura, N., Hanski, J., Ahola, T., Ståhle, M., Piiparinen, S., Valkokari, P., 2019. Unlocking circular business: A framework of barriers and drivers. J. Clean. Prod. 212, 90–98. https://doi.org/10.1016/j.jclepro.2018.11.202

Van Den Berg, M., Hulsbeek, L., Voordijk, H., 2023. Decision-support for selecting demolition waste management strategies. Build. Cities 4, 883–901. https://doi.org/10.5334/bc.318

Wuni, I.Y., 2022. Mapping the barriers to circular economy adoption in the construction industry: A systematic review, Pareto analysis, and mitigation strategy map. Build. Environ. 223, 109453. https://doi.org/10.1016/j.buildenv.2022.109453

Wuyts, W., Miatto, A., Khumvongsa, K., Guo, J., Aalto, P., Huang, L., 2022. How Can Material Stock Studies Assist the Implementation of the Circular Economy in Cities? Environ. Sci. Technol. 56, 17523–17530. https://doi.org/10.1021/acs.est.2c05275

Yang, X., Hu, M., Shan, W., Zhang, C., Li, T., Pan, Y., 2023. Integrating bottom-up building stock model with logistics networks to support the site selection of circular construction hub. J. Clean. Prod. 430, 139677. https://doi.org/10.1016/j.jclepro.2023.139677

Yu, Y., Yazan, D.M., van den Berg, M., Firdausy, D.R., Junjan, V., Iacob, M.-E., 2023. Circularity information platform for the built environment. Autom. Constr. 152, 104933. https://doi.org/10.1016/j.autcon.2023.104933