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The life cycle climate impacts of industry-specific machinery technologies: A meta-analysis

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A B S T R A C T

Machinery technologies enable industrial production and societal development but can contribute substantially to greenhouse gas emissions and are often underrepresented in environmental assessments. This meta-analysis identified 86 life cycle assessment (LCA) studies of industry-specific machinery and synthesized the life cycle climate impacts of 39 machinery technologies from 10 categories ($n = 150$ datapoints). Median cradle-to-grave emissions ranged from 89.2 t CO_2e/unit for additive manufacturing machinery to 1790 t CO_2e/unit for lifting and handling equipment. Median cradle-to-gate emissions ranged from 4.7 to 336 t CO_2e/unit. Across most technologies, the use-phase dominated total impacts; however, manufacturing impacts were not negligible for multiple technologies and can become relatively more important under low utilization and decarbonization pathways such as electrification. To address drivers beyond normalization, we applied rank-based correlation analyses to quantify how key parameters (mass, lifetime, and use intensity) relate to phase-specific climate impacts. Mass showed the strongest associations with both cradle-to-gate and operation impacts, while operating-time proxies were most informative for explaining burden allocation rather than consistently predicting absolute operational impacts across heterogeneous technologies. Finally, we developed an evidence-based, exploratory archetype map that positions technologies in a stage-resolved space defined by cradle-to-gate share, annual operating hours, and mass (embodied scale), and translates technology placement into prioritized circular economy strategies (R0–R9; narrowing, slowing, and closing resource loops). This can provide technology-linked guidance for bottom-up modeling and for prioritizing resource-efficiency and decarbonization interventions across machinery technologies. We also identified major evidence gaps, particularly limited manufacturing inventory transparency and underrepresentation of several machinery categories.

1. Introduction

Machinery technologies are essential for our society, enabling the production of goods and services that drive human development. At the same time, however, they are responsible for enormous environmental impacts (Södersten et al., 2018; Wang et al., 2023), and alongside buildings, vehicles, and infrastructure represent one of the largest consumers of resources and materials globally (Krausmann et al., 2017; Krausmann et al., 2020; United Nations Environment Programme, 2024). Furthermore, it is estimated that in 2015 around 8% of total greenhouse gas (GHG) emissions stemmed from machinery material production (Hertwich, 2021), and in 2020 5% of the global GHG emissions were caused by the metal footprint embodied in these technologies (Jiang et al., 2023).

The machinery sector has been central for the development of Global North regions (De Long and Summers, 1993; Lian et al., 2019; Zeira, 1998). However, as shown by the stock development in the last years (Jiang et al., 2023), in Global North regions like the European Union (EU) the stock has begun to saturate. Nevertheless, in many Global South regions continues to grow (Jiang et al., 2023). Consequently, Global South regions may increase their machinery stock, a trend that is further fueled by the outsourcing of manufacturing operations to these regions. Furthermore, innovations and labor-shortage issues in the Global North have led to the prevalent replacement of machinery. So, machinery will continue contributing to resource use and climate-related impacts.

Numerous public policies address the sector's environmental footprint. For example, Chinas "Industrial Equipment Upgrading Action Plan" (ChinaBriefing 2025), supports replacing outdated equipment (e.

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g., machine tools), upgrading equipment in key sectors (e.g., aerospace), the integration of industrial robots and digitalization, as well as adopting more sustainable technologies. Similarly, the EU's Clean Industrial Deal[12] aims to make decarbonization achievable and profitable, staying in course with the European Green Deal objectives of achieving carbon neutrality by 2050 (The European Green Deal - European Commission 2025). These policies aim to enhance energy efficiency and reduce carbon emissions to address the climate crisis, prioritizing the circular economy (CE) model, where materials and products are used as long as possible (European Commission, 2025). Due to machinery's high capital costs and long lifetimes, CE strategies have been intrinsically present in the sector, especially through lifetime extension measures (CECIMO, 2025; Nasr et al., 2018), while long-lived, capital-intensive machinery can also reinforce carbon lock-in (Unruh, 2000; Seto et al., 2016), increasing its relevance for decarbonization. These policy agendas, however, imply potential trade-offs of replacing old machines with new more efficient ones, which may be crucial in terms of environmental impacts. From a material cycle perspective, the machinery sector is poised to become one of the most valuable material (e.g., metal) flows, considering the mentioned ongoing and anticipated developments.

Although macro-level sustainability studies have included machinery in economy-wide models e.g., (Krausmann et al., 2020; Jiang et al., 2023; Aguilar-Hernandez et al., 2021), these approaches (e.g., material flow analysis (MFA), environmentally extended input-output (EEIO)) often lack the technology-level detail needed to comprehensively assess environmental consequences and mitigation strategies (Aguilar-Hernandez et al; Tukker and Rueda Cantuche, 2024; Pauliuk et al., 2017). Product-level data (i.e., micro-level) may improve the estimation of carbon footprint and mitigation strategies in the sector (Jiang et al., 2023), by providing crucial insight and granularity (e.g., detailed material composition, specific technologies). It can also support bottom-up macro-level modeling approaches like stock-flow-nexus models (Haberl et al., 2017; Pauliuk et al., 2021) and integrated assessment models (IAM) (Arvesen et al., 2018), thereby enabling a more accurate quantification and understanding of the consequences of policy implementations (Pauliuk et al., 2021; Gibon et al., 2015; Hertwich et al., 2020; Hertwich et al., 2015; Luderer et al., 2019). Moreover, to comprehensively understand the overall environmental impact of future developments (e.g., robotics, automation) in the industry (Commission et al., 2021), maintaining a life cycle perspective is crucial to avoid burden shifting. These interactions can be better understood through technology-level environmental assessments, for which Life Cycle Assessment (LCA) is the most established and developed methodology.

To address the need for more granular data in this sector, this study focuses on industry-specific machinery technologies. While the machinery and equipment sector is broad and complex, machinery categories directly linked or manufactured for specific industries (i.e., the Statistical Classification of Economic Activities in the European Community (NACE) codes 28.3 Manufacture of Agricultural and Forestry Machinery, 28.4 Manufacture of Metal Forming Machinery and Machine Tools, and 28.9 Manufacture of Other Special-Purpose Machinery), are particularly relevant. They are integral to the industrial value chain, playing prominent roles in material efficiency and cost, and can be directly linked to material losses or savings during manufacturing. For instance, in the EU, they represent over 50% of the total production value of the entire machinery and equipment sector (European Commission, 2024), as indicated by the PRODCOM (a French acronym for 'Production Communautaire') statistics on the manufacturing goods production. This focus may contribute to economy-wide top-down modeling approaches (e.g., EEIO, Computational General Equilibrium (CGE)) which often disaggregate the economy by these larger industrial sectors and could use a better bottom-up understanding of such technologies (Aguilar-Hernandez et al; Donati et al., 2020; Wood et al., 2015).

Despite machinery's known environmental impacts (Frischknecht et al., 2007), especially in terms of GHG, in most environmental assessments, their impact is usually neglected or simplified to plain use-phase impacts (Kellens et al., 2012; Kellens et al., 2012). In comparison to the buildings and vehicle sectors, machinery seems to have been largely under-represented in the literature, especially in terms of quantitative environmental LCA studies (Hertwich and Jiang, 2025). While micro-level studies do exist, they tend to focus on specific machinery types (Daniyan et al., 2021), often not quantitatively. Most of the review studies found on environmental impacts of machinery, focus predominantly on the use-phase, assessing energy-related impacts (Gutowski et al., 2006; Sihag and Sangwan, 2020; Zhou et al., 2016), as well as air pollution impacts (Qi et al., 2019; Shen et al., 2023) during operations, rather than assessing the full life cycle. Other studies compare technologies from the same category, for instance, assessing the impact between types of mining machinery like a mining truck and a conveyor belt (Erkayaoğlu and Demirel, 2016); however, not always sufficiently detailed. Or comparisons between diesel fueled and electric powered construction machinery (Khan and Huang, 2023; Wiik et al., 2023), and agricultural machinery technologies (Bortolini et al., 2014; Bortolini et al., 2014; Martelli et al., 2023), with many assessing the innovative or electrified technologies (Martelli et al., 2023; Lagnelöv et al., 2021; Liu et al., 2024). Moreover, comprehensive life cycle inventory (LCI) data for agricultural machinery exists (Mantoam et al., 2020; Pradel, 2023), but does not provide full life cycle impact assessment (LCIA) results. A comprehensive study by Schischke et al. (Schischke et al., 2012) primarily analyzed representative machine tools and similar machinery technologies from a market, techno-economic, and environmental perspective in the EU. It estimated environmental impacts using LCA and costs with Life Cycle Costing (LCC) methods, focusing primarily on energy, considering best cost options and energy savings. However, this study is now more than 12 years old. A comprehensive study directly analyzing the life cycle climate impacts across different types of the industry-specific machinery technologies could not be found. This gap highlights a need for a broader and current analysis, particularly from a life cycle perspective, to inform policy and circular economy strategies effectively.

The primary goal of this study was thus to systematically review and analyze existing micro-level life cycle GHG assessments of industry-specific machinery technologies. Specifically, to identify and compare the life cycle climate impacts of such technologies based on available bottom-up environmental assessments. The central research questions guiding this study is as follows: i) what are the climate impacts of industry-specific machinery, considering the existing environmental LCA (Life Cycle Assessment) assessments? ii) how do parameters such as mass, lifetime, and use intensity influence those impacts?

The remaining sections of this work are as follows: firstly, Section 2 describes the methodology employed for the literature review and the meta-analysis, including the statistical and correlation analyses. In Section 3, the results of the meta-analysis, a non-parametric statistical analysis, as well as a rank-based correlation analysis are presented. The subsequent Section 4 involves the discussion of the results, an exploratory archetype map to interpret mitigation strategies, and the limitations of the work. Finally, in Section 5 the conclusion and outlook are described.

2. Materials and methods

In this work we focused on industry-specific machinery technologies. These types play a central role core stages in the value chain of products, and represent the main capital assets of the largest economic sectors. The scope was defined using the NACE classification (European Commission, 2025) from the EU as reference. The NACE categories included in this work were 28.22 Lifting and Handling Equipment (LHE), 28.30 Agricultural and Forestry Machinery (AFM), 28.41 Metal Forming Machinery, 28.42 Other Machine Tools (OMT), 28.91 Machinery for Metallurgy (MM), 28.92 Machinery for Mining, Quarrying and Construction (MMC), 28.93 Machinery for Food, Beverage and Tobacco Processing (MFP), 28.94 Machinery for Textile, Apparel and Leather Production (MTP), 28.95 Machinery for Paper and Paperboard Production (MPP), 28.96 Plastics and Rubber Machinery (PRM), 28.97 Additive Manufacturing Machinery (AMM), and 28.99 Other Special-Purpose Machinery n.e.c. i.e., not elsewhere classified (OSPM). Additionally, technologies from 28.22 (Lifting and Handling Equipment) and 28.29 (i.e., packing machinery) were included due to their frequent overlap with categories like 28.92 and 28.93, respectively. These categories collectively define what we refer to as 'industry-specific machinery technologies' throughout this study.

This meta-analysis consisted of a systematic literature review, the data extraction and processing, a non-parametric statistical analysis, and a rank-based correlation analysis which are described next.

2.1. Literature review

We focused first on finding the existing studies assessing the environmental impacts of machinery technologies using LCA under the defined scope. The systematic literature review followed the LCA (STARR-LCA) checklist (Zumsteg et al., 2012), which is a standardized technique for assessing and reporting LCA studies. Zumsteg et al. (2012) proposed a nine-step checklist for conducting consistent systematic reviews of environmental assessments. The checklist includes the rationale and objectives for the review, which we described in the introduction. Furthermore, the description of the review protocols employed, which are presented in this section. The synthesis of the features and findings of individual studies, the assessment bias, the limitations of the review, as well as the summary of findings and conclusions are presented in the Results and Discussion sections. In the case of this review, quantitative and qualitative synthesis methods were used. The review was carried out on July 2025. The search took place in the Web of Science (WoS) and Scopus databases and the searched studies were in English language. Moreover, snowballing was also used to complement the list of studies.

The search revolved around two main keywords, namely “machinery” and “environmental assessment”. The strategy used based on searching the title of the different machinery technology per the defined categories. For example, for Agricultural and Forestry Machinery (AFM) keywords such as “tractor”, “harvester”, and “forestry machine” were used. Moreover, a broad search for machinery was also included with keywords such as "machinery and equipment" OR "machine" OR "equipment". On top of that, searching over title, abstract, and keywords was carried out for the “environmental assessment” keywords. In this case, keywords such as "life cycle assessment" OR "environmental assessment" OR "LCA" OR "environmental analysis*" OR "life cycle analysis" OR "environmental footprint" were entered. This strategy was followed in both Scopus and WoS databases. The full detail of the searched keywords is found in Supplementary Table S5.

Additionally, the list was complemented with existing assessments from environmental declarations such as Environmental Product Declarations (EPD) (EPD Library, 2025), PEP Product Environmental Profile (P.E.P. Association, 2025) and Eco Platform (ECO Platform AISBL, 2025) databases were also screened. We also searched the grey literature using Google, with the search terms ‘product carbon footprint’ and ‘machinery’. We screened the first 100 results for potentially relevant documents. Case studies from a government-commissioned technical study focused on machine tools and related machinery (Schischke et al., 2012) were also considered. The list was finally completed with existing process inventory data from ecoinvent (Wernet et al., 2016), which is the most used background database in the context of environmental assessments.

The inclusion and exclusion criteria based on the defined scope and the data required to estimate the life cycle climate impacts. We only included publications in English and from peer-reviewed journals. We excluded machinery technologies outside our scope, as well as non-quantitative environmental assessments. Studies with undefined system boundaries or product systems, and life cycle inventory (LCI) studies without impact assessment results, were also excluded. Studies without functional unit results that could be scaled up to quantify life cycle impacts, or that focused only on a single phase (e.g., the use-phase), were also excluded. Similarly, studies without impact results for the climate change (i.e., global warming) impact category were not included (see Table S2).

2.2. Life cycle GHG assessments of industry-specific machinery

In total, we identified 86 studies quantifying the life cycle impacts of industry-specific machinery technologies. 38 of which were Product Carbon Footprints (PCFs), 25 from journal articles, 19 from EPDs, two from the ecoinvent database, and two from the grey literature. The life cycle GHG assessments were clustered in the mentioned NACE categories and per technology based on the PRODCOM list (European Commission. Statistical Office of the European Union, 2024). The filtering process carried out in the review is depicted in Fig. 1a). More than 800 studies were found in total, after the initial filter, other studies added via snowballing and complementing the list with environmental declarations (e.g., EPDs, PCFs), the final list for the comparison of studies resulted of 86 life cycle GHG assessments of a total 150 impact results. Considering the NACE classification, 46 assessments focused in MMC, followed by OSPM with 16 and then MFM with eight. AFM was next with seven. From the rest of the categories three or less assessments were found. This is shown in Fig. 1b).

The specific technologies from the various studies were classified using the PRODCOM classification from the EU (European Commission, 2024). The full detail of the classifications and technologies included can be found in Supplementary Information (SI) 1 (Table S1).

2.3. Data extraction and processing

To compare the climate impacts of the different machinery technologies, data from the studies were extracted and processed. Since we aimed to compare different technologies i.e., products, different functional units (FU) were found in many studies. For instance, hours of operation (Wiik et al., 2023; Kwak et al., 2012; Vujičić et al., 2013), hectares of work (Lagnelöv et al., 2021; Liu et al., 2024), or product outputs (Bortolini et al., 2014; Balboa-Espinoza et al., 2023; Diaz-Elsayed et al., 2010; Extrusion, 2023; Guglielmi et al., 2021; Stefanini et al., 2022) were some of the FUs found. Thus, we referred to (Schischke et al., 2012) which also assessed different types machinery technologies, and we followed their approach of considering the environmental impacts during the service life of the machinery, i.e., their entire life cycle. So, instead of using one hectare of work or one produced part for the comparison, we considered the impacts of the machinery over their entire life cycle, i.e., from cradle-to-grave. These impacts were also categorized per life cycle phase, considering cradle-to-gate (i.e., manufacturing), use-phase (i.e., operation), and end-of-life (EOL) phases. We defined cradle-to-grave as the sum of these three phases (see Figure S1).

The environmental impacts of the different machinery technologies were measured in CO_2e., given that global warming potential (GWP) is one of the most used indicators to assess the environmental impacts of products and technologies. Moreover, it is one the best understood, as well as with a high correlation to other environmental indicators (Pascual-González et al., 2016; Steinmann et al., 2016).

From the identified list of studies, we also focused on relevant information from a life cycle assessment perspective such as system boundary, regional and temporal scope, as well as important parameters such as mass, lifetime, and use intensity. The list of qualitative and quantitative aspects considered are described in Table 1.

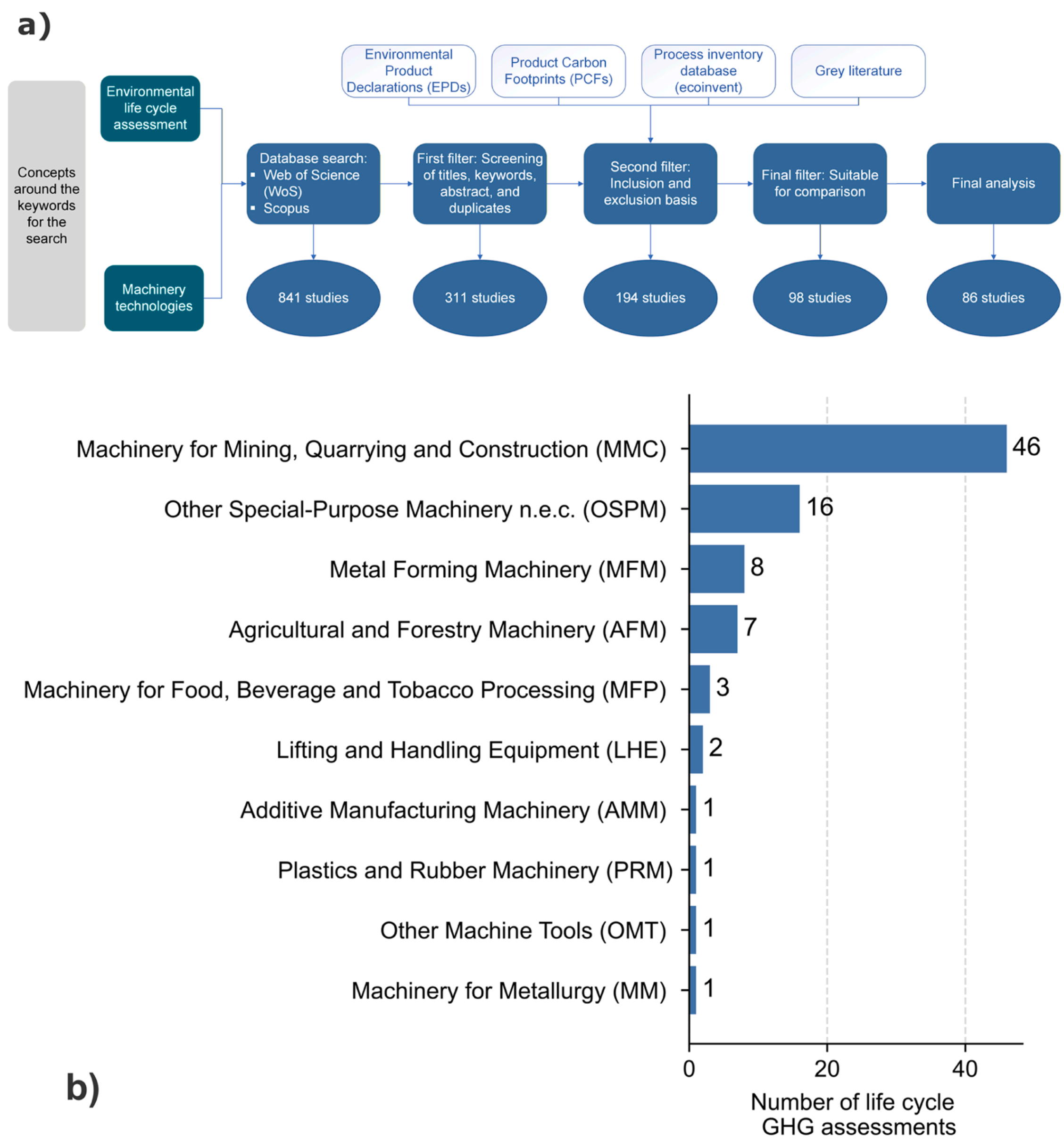

Fig. 1. a) Literature review filtering process. b) Life cycle GHG assessments of machinery categories following the NACE classification. ($N = 86$).

2.4. Quantification of the life cycle climate impacts

To derive the various impacts, we calculated the cradle-to-gate, use-phase, EOL, and life cycle climate impacts using the impact results from the assessments. The included processes and system definition of this work is presented in Supplementary Figure S1. In many cases, the process was straightforward, with the results of the LCA directly informing the comparison. As shown in Eqs. (1), (2), and (3).

$$LC = \mathrm{CTG} + \mathrm{UP} + \mathrm{EOL} \tag{1}$$

$$CTU = CTG + UP \tag{2}$$

$$UP\_EOL = UP + EOL \tag{3}$$

where LC is the life cycle impact of the machinery technology during its entire lifetime (i.e., cradle-to-grave), CTG is the cradle-to-gate impact, UP is the use-phase impact, and EOL is the end-of-life impact of the machinery technology. CTU is cradle-to-use and UP_EOL is use to end-of-life as described in the system definition (see Figure S1).

However, in certain instances, it was necessary to upscale the results reported per FU to the life cycle impact of the machinery technology. For instance, a functional unit $LC_{\mathrm{machine,\ FU}}$ of "one-hour operation given 1800 h of operation per year and a reference study period and lifetime of 10 years" (Wiik et al., 2023) was scaled to the total hours the machinery operates over its lifetime FU_{total}(e.g., total hours of operation), considering the total hours, 1800 h, and the total years of operation. Thus, we employed Eq. (4) to derive the life cycle impacts of the different machinery technologies:

$$LC_{\mathrm{machinery,\ total}} = LC_{\mathrm{machine,\ FU}} * FU_{\mathrm{total}} \tag{4}$$

This conversion applied proportional scaling using the study-reported functional unit (including embedded operating assumptions); thus, it assumed a constant average operating regime over the scaled service amount. Accordingly, uncertainty in operating hours or lifetime affected lifetime totals (and stage shares) proportionally, but did not change per-FU intensities; this is discussed further as a limitation especially relevant for intermittent/duty-cycle-dependent equipment in Section 4.5.2. For output-/service-based FUs, FU_{total} was derived from study-reported lifetime output/service or throughput where available; where not reported, throughput or lifetime output assumptions were

Table 1
Qualitative and quantitative data extracted of the industry-specific machinery environmental studies.

Aspect	Description
Machinery category	Machinery type according to the NACE classification
Machinery technology	Machinery technology aligned to the PRODCOM list
Material aspects	Material composition, material yields, and efficiency included
System boundary	Life cycle phases included and system boundary defined
Assembly and manufacturing	Energy and material inputs included during assembly and manufacturing described
Product system	Product system defined
Mitigation potential	Mitigation or improvement potential calculated
Impact assessment method	Impact assessment method defined
System model	System model used in the assessment
Temporal scope	Year of data
Regional scope	Regional scope of the data, with a focus on electricity mix
Functional unit (FU)	Functional unit defined
Mass	Mass of the machinery in kg
Lifetime	Useful lifetime of the machinery in years
Use intensity	Useful hours of operation throughout its lifetime
Installed/nominal power	Installed or nominal power in kW
Life cycle impact results	Greenhouse gas emission results, normally in carbon dioxide equivalent (CO_2e)

Data processing was carried out using Microsoft Excel and Python with NumPy and Pandas libraries.

applied and are documented in Table S7.

We normalized per unit results considering important parameters related to the climate impact of machinery, namely mass and operating time. Mass was measured in kg, whereas operating time was measured in years and hours of operation. We directly normalized the results of each technology using Eqs. (5) and (6):

$$LC_{\text{machinery,ot}} = \frac{LCI_{\text{machinery, total}}}{lifetime_{\text{machinery}}} \tag{5}$$

$$LC_{\text{machinery, mass}} = \frac{LCI_{machine,\ total}}{mass_{\text{machinery}}} \tag{6}$$

where $LC_{\text{machinery,ot}}$ is the impact during the operating time of the machinery technology depending on the useful lifetime of the machinery $lifetime_{\text{machinery}}$ in years or hours, and $LC_{\text{machinery, mass}}$ the impact per $mass_{\text{machinery}}$ in kg.

Machinery lifetime is a relevant aspect influencing impacts, since the use-phase (e.g., operating time) causes a large part of climate impacts. However, estimating the use-phase impacts of machinery (or any product), usually can be challenging, because it strongly depends on how the users operate the equipment (e.g., longevity, frequency of use, and intensity of operation). Regarding operational lifetime, most included studies did describe it, some of them directly in the functional unit (FU) or as an assumption/technical parameter, generally reported in years and/or hours of operation (Wiik et al., 2023; Kwak et al., 2012; Bacenetti, 2022). Thus, these two parameters were also used as a basis to compare the technologies considering their useful life. Where lifetime operation hours were not explicitly reported, they were harmonized based on the study's stated assumptions and available operational information; therefore, use intensity is interpreted as a proxy indicator and may contribute to heterogeneity in pooled results.

2.5. Non-parametric statistical analyses

2.5.1. Group comparisons across machinery categories (Kruskal–Wallis and Dunn's tests)

To assess the differences between machinery categories, we carried out non-parametric statistical analyses because the compiled impact data were not normally distributed and sample sizes were unequal across categories. We applied the Kruskal–Wallis H-test (Kruskal and Wallis, 1952), which ranks all observations and evaluates whether rank distributions differ between categories. Because the normality and homoscedasticity assumptions required for parametric ANOVA were not met, Kruskal–Wallis was selected as the appropriate omnibus test. The null hypothesis H_0 was that machinery categories have equal rank distributions, implying no statistically significant difference in their central tendencies. To complement the significance testing, we calculated the Epsilon-squared (ε^2) effect size to quantify the magnitude of the observed differences. Following the classification by Rea and Parker (Rea and Parker, 2014), the strength of association was interpreted as: weak/negligible $(\varepsilon^2 < 0.10)$, moderate $(0.10 \leq \varepsilon^2 < 0.20)$, or strong $(\varepsilon^2 \geq 0.20)$. Where the omnibus test indicated significance, we performed Dunn's post-hoc test (Dunn, 1964) for pairwise comparisons, which is a recommended choice for unequal sample sizes, such as the ones from this data. To control the family-wise error rate, we applied the Holm–Bonferroni adjustment for multiple comparisons (Holm, 1979). A significance level of $\alpha = 0.05$ was considered for all statistical tests. Categories with fewer than two data points were excluded from the analyses and only reported descriptively, namely MM and PRM.

2.5.2. Rank-based Spearman correlation analyses

To examine associations between machinery characteristics and life cycle climate impacts, we computed Spearman rank correlations (ρ) across the extracted datapoints ($n = 150$). Variables included machinery mass (kg), lifetime (years), annual operating hours ($h\cdot yr^{-1}$; calculated as lifetime operating hours divided by lifetime years), and installed/rated power (kW) as a scale proxy for machinery capacity. Climate impact indicators comprised cradle-to-gate emissions per unit, use-phase and EOL emissions per unit, as well as cradle-to-gate share (reported as %). Because mass and installed power showed a strong correlation, partial Spearman correlations were additionally calculated to assess the independent associations of mass and power with stage-specific impacts. Correlations were computed using pairwise complete observations.

All statistical analyses were conducted in Python using SciPy and scikit-posthocs.

3. Results

The results of this work are presented in this section. First, the results of the literature review focused on the life cycle GHG assessments found are presented. Then, the comparison of the climate impacts of the various industry-specific machinery technologies are displayed, followed by the statistical analysis of the various comparisons. Finally, the rank-based correlation analysis results are presented.

3.1. Results of literature review

The assessments obtained after the inclusion criteria were further analyzed following the mentioned relevant aspects (see Table 1). These aspects included functional units, system boundaries, impact assessment methods and mitigation strategies, among others. Moreover, mass, lifetime, and use intensity which allowed the extended comparison of the different impacts were extracted. Many different functional units were found, as well as dissimilar system boundaries. Furthermore, not all the studies presented mitigation strategies for the environmental impacts quantified. Also, a notable simplification or exclusion of manufacturing (i.e., assembly) and material yields were found in several studies e.g., (Khan and Huang, 2023; Wiik et al., 2023; Balboa-Espinoza et al., 2023; Diaz-Elsayed et al., 2010; Guglielmi et al., 2021; Stefanini et al., 2022; Li et al., 2021). However, in many studies, in addition to operational fuel and energy consumption, ancillary material and energy inputs (e.g., maintenance, operation fluids, consumables and spare parts) during the use-phase were included. In numerous instances, the use-phase was found to be more comprehensively modelled than the manufacturing phase. A summary of relevant qualitative aspects of the studies included are presented in Table 2.

3.2. Climate impacts of industry-specific machinery technologies

The climate impacts of various industry-specific machinery technologies are presented next, with results normalized by unit, mass (kg), lifetime (years), and use intensity (hours). Because machinery technologies differ substantially in lifetime operating hours and utilization patterns, per unit cradle-to-grave values reflect impacts per machine and are not necessarily comparable in terms of functional service delivered.

3.2.1. Per unit impacts of industry-specific machinery technologies

We compared the cradle-to-gate, use-phase and end-of-life (EOL), as well as cradle-to-grave climate impacts of 39 different technologies from 10 NACE categories, comprising 150 datapoints in total. The overall cradle-to-grave impacts varied significantly, with a range from a minimum of 2.42 t CO_2e from a machine tool for working wood (OMT) to a maximum of 31.4 kt CO_2e per unit from a tower crane (LHE). The mean climate impact was 1.97 kt CO_2e per unit, with a median of 542 t CO_2e per unit. A standard deviation of 4.37 kt CO_2e per unit, larger than both the mean and median, which indicates significant data skewness. Fig. 2 illustrates these impacts across the machinery categories, while Table 3 summarizes the corresponding median values by category. To support interpretation given uneven sample sizes, the Interquartile Range (IQR) widths (Q75−Q25; 25th–75th percentile) for all reported category results are provided in Table S13.

LHE exhibited the largest median climate impact 1.79 kt CO_2e per unit, while MMC followed with around 680 t CO2e per unit. AFM technologies OMT and AMM were the ones with the smallest per unit impact with median values of less than 180 t CO_2e, as presented in Table 3. AFM and OMT demonstrated to be the most homogenous categories with a coefficient of variation (CV) of less than 1.05, while MFM, MFP, and OSPM had the most disperse values (CV > 1.50).

When examining individual technologies from a cradle-to-grave perspective, the highest median impacts were observed for presses for working metal (26.1 kt CO_2e per unit, 1 datapoint) and tower and jib cranes (18.9 kt CO_2e per unit, 2 datapoints), as shown in Fig. 3. Other highly impactful technologies included flexographic printing machinery (9.03 kt CO_2e) and motor graders (4.35 kt CO_2e). It is notable that among the top 10 most impactful technologies, only hybrid and conventional SP-mechanical shovels, excavators, and loaders, along with vacuum evaporators, contained more than two datapoints. Most technologies exhibited mean and median values between 100 t CO_2e and 2.66 kt CO_2e per unit. Conversely, technologies with the lowest impacts (mean and median values <100 t CO_2e per unit) included harvesting machines, vertical machining centers for working metal, and industrial robots. These lower impacts were three orders of magnitude lower than those of presses for working metal. Furthermore, electric and hybrid variants consistently demonstrated lower climate impacts than their conventional counterparts; for instance, electric work trucks had approximately 40% less impact, and electric tower and jib cranes showed a 90% reduction compared to conventional ones. A comprehensive list of per unit impacts for all 39 technologies is provided in SI 2 Table S7.

LHE was also at the top in both mean and median values in the cradle-to-gate related impacts. MMC, MM, and MFP resulted with similar median values. AMM, OMT, and PRM were the categories with the lowest median cradle-to-gate values.

Among individual technologies, conventional tower cranes (4.88 kt CO_2e), presses for working metal (1.27 kt CO_2e), and motor graders (7.21 kt CO_2e) led cradle-to-gate impacts. Notably, industrial robots and automated feeding machines had the lowest cradle-to-gate impacts with less than 1.40 t CO_2e per unit.

For the use-phase and EOL impacts per unit, the category results showed a similar tendency to the cradle-to-grave results, with LHE and MMC demonstrating the largest median impacts. While AFM and OMT had the lowest mean and median impact. The median values per life cycle phase of each category are presented in Table 3, as well as the median parameter values for mass, lifetime, and hours of operation.

For individual technologies, the use-phase and EOL results remained consistent to the cradle-to-grave results regarding the top and bottom impactful technologies. Notably, many of the most impactful technologies were represented by a limited number of datapoints (e.g., only three of the top 15 median impacts came from technologies with more than two datapoints), suggesting potential outlier influence in the category results. Detailed per unit impacts for all technologies across all life cycle phases are presented in SI 2 Table S7.

3.2.2. Per mass climate impacts of machinery

To account for the mass differences between technologies, we normalized results to t CO_2e per kg of machinery. This significantly shifted the ranking compared to the per unit analysis, as illustrated in Fig. 4.

The median cradle-to-grave impacts per kg were led by OSPM (1.23 t CO_2e/kg), followed by AMM and MM. Notably, LHE and MMC, which were the most impactful categories on a per unit basis, exhibited the lowest median impacts per kg (see Table 3). Considering the top 10 most impactful technologies, ranging from 1.43 t CO_2e to 0.16 t CO_2e, three of them were from MFM, including non-NC metal working machine tools and machine tools for finishing metal. And, three from OSPM, including industrial robots and vacuum evaporators. The largest single value from the per unit results (i.e., presses for working metal) yielded an intermediate value of 89.3 kg CO_2e. E-SP-work trucks, NC press brakes, and E-dumpers for off-highway use yielded the lowest cradle-to-grave per kg median impacts.

Regarding cradle-to-gate impacts per kg, OSPM had the largest median value of 13.7 kg CO_2e/kg, followed by PRM. LHE and MFM had the lowest median cradle-to-gate per kg values. Considering the specific technologies, vacuum evaporators and hybrid low powered tractors had the largest median impact from the category during the manufacturing phase. E-Dumpers for off-highway use and E-SP-work trucks had the lowest cradle-to-gate impacts per kg of machinery.

The results of the use-phase and EOL impacts per kg were consistent with those of the cradle-to-grave per kg comparison, at both category and technology levels. The category and technology level detailed results are found in Table S7.

3.2.3. Per lifetime and operation time climate impacts of machinery

Normalizing the climate impacts per year showed the results align with the cradle-to-grave per unit results for the top categories (See SI 1 Figure S2). AMM, which had the lowest per unit impact, resulted with the third lowest cradle-to-grave per year impact. OMT was the category with the lowest median environmental burden per year.

When taking the specific technologies into consideration, the most impactful remained. However, conventional tower and jib cranes had the largest median cradle-to-grave impact per year, at 997 t CO_2e. Of the ten largest impacts, four came from MMC technologies, such as motor graders, as well as hybrid and conventional SP-mechanical shovels, excavators, and loaders. NC press brakes and automated feeding machines, had the smallest.

Manufacturing impacts per year showed LHE with the largest median impact of around 22.4 t CO_2e, followed by MMC. The rest of the categories hat a median impact ranging between 6.13 t CO_2e and 1.21 t CO_2e. PRM and OMT had the lowest cradle-to-gate median impact per year. The technology per year results considering the manufacturing phase remained mostly aligned to the per unit results.

The use-phase and EOL impacts remained consistent with the cradle-to-grave per year metric, indicating that the rank of categories remained unaltered. At the technology level the results followed a similar trend as the cradle-to-grave per year ranking, however, presses for working metal had the largest median use-phase and EOL impact. The

Table 2
Summary of studies included.

Machinery category	No. of impact results	Temporal scope	Regional scope	Functional units	End use sector	Summary of system boundaries	Common methodological approaches	Impact assessment methods	References
Additive Manufacturing Machinery (AMM)	2	2013	United Kingdom	1) Product output (i.e., parts produced)	Manufacturing of metal products	Cradle-to-gate: raw materials and manufacturing of the AM system hardware. Use-phase: energy consumption during operation of machinery and consumables, also feedstock (aluminum powder) is included, as well as EOL: Impacts from EOL for all materials, including parts printed, support structures and other waste from printing, and the AM system hardware were modelled as disposal to landfill.	Cut-off system model was used. Primary data and ecoinvent database for background data were employed. No allocation rules mentioned but ecoinvnent, allocation method was inherently used.	ReCiPe Midpoint H und ReCiPe Europe Endpoint H/A method v1.12	(Faludi et al., 2017)
Agricultural and Forestry Machinery (AFM)	11	2012, 2014, 2018, 2023, 2024	Global, Europe, China, Italy, Sweden	1) Hours of operation 2) Hectares worked 3) Mass of machinery per year 4) Product output (e.g., wrapped hay bales produced)	Cultivation	Most of the studies included: Raw material extraction and production, manufacturing and assembly of components, in the cradle-to-gate phase; maintenance (spare parts, lubricant), consumables, and operation of machinery (fuel and electricity consumption) in the use-phase. And, disassembly, waste treatment, and disposal at EOL.	Most of the studies considered a cut-off system model, however, not all explicitly described it, and some considered avoided burden. Most of the studies relied on ecoinvent data and its allocation rules, but also the GREET Model was considered.	IPCC 2021 ReCiPe 2016 Midpoint and Endpoint PCCAR6/2021, CML2002, IMPACT2002+, and ReCipe2008	(Bortolini et al., 2014, Martelli et al., 2023, Lagnelöv et al., 2021, Liu et al., 2024, Wernet et al., 2016)
Lifting and Handling Equipment (LHE)	5	2013, 2017	Europe, China	1) Hours of operation 2) Machinery impact along entire life cycle	Transportation and storage	Most of the studies included: Raw material extraction and production, manufacturing of components, and assembly of machinery, in the cradle-to-gate phase; consumables, and operation of machinery (fuel and electricity consumption) in the use-phase. And, disassembly, waste treatment, recycling and disposal at EOL. Generally, inclusion of maintenance and material input during operation phase was not detailed.	Cut-off system model was mentioned, however, avoided burden for EOL was also used. Generally, primary data and data from the Gabi database were considered. No allocation procedures explicitly described.	ReCipe 2008 CML 2001	(Vujičić et al., 2013, Wen et al., 2017)
Machinery for Food, Beverage and Tobacco Processing (MFP)	21	2020, 2022	Europe, China, Pakistan, Russia	1) Product output (e.g., 1000 filled approved packages)	Manufacturing of food	Cradle-to-gate: Extraction and production of materials for spare parts. Extraction and production of main materials. Components manufacturing and assembly. Transport of components and spare parts.	Most of the studies are EPDs based on PCR Machines for filling and packaging of liquid food 2012:18 version 2.02 (EPD International AB 2025). Background data provided via ecoinvent.	CML method PEF framework (EF 3.0)	(Stefanini et al., 2022, Ecolean 2017, Ecolean 2017)

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Table 2 (*continued*)

Machinery category	No. of impact results	Temporal scope	Regional scope	Functional units	End use sector	Summary of system boundaries	Common methodological approaches	Impact assessment methods	References
						Final machine assembly and transport Use-phase: Production of consumables. Operation and maintenance. EOL: Disposal of machinery after use. Important: not all studies included assembly of the machine, packaging, and EOL impacts and most of the studies included the production of consumables in the use-phase and the transport to customer in the manufacturing phase.			
Machinery for Metallurgy (MM)	1	2020-2022	Europe	1) Machinery impact along entire life cycle	Manufacturing of non-ferrous metals	Cradle-to-gate: Raw material extraction and production. Production of auxiliary materials for maintenance. Manufacturing and assembly for main parts and components. Packaging. Use-phase: Installation. Production of consumables. Operation and maintenance. EOL: Disassembly. Waste treatment of machine and packaging.	Mass allocation was used for the manufacturing generated impacts. Cut-off by classification system model used. Primary data was used and background data was provided via ecoinvent.	Environmental Footprint 3.0 method	(Presezzi Extrusion 2024)
Machinery for Mining, Quarrying and Construction (MMC)	69	2000, 2012, 2016, 2020-2024	Europe, Chile, Norway, USA	1) Product output (e.g., tons of material transported or crushed) 2) Hours of operation 3) Machinery impact along entire life cycle	Mining, quarrying and construction	Most of the studies considered the following system boundary: Cradle-to-gate: raw material acquisition, manufacturing. Use-phase: Operation of machinery and planned maintenance/service. EOL: waste treatment only of ferrous metals at EOL. However, not all studies included EOL.	Most of the studies (Volvo Construction Equipment 2025) assumed a cut-off system model for EOL. As well as mass allocation (by weight) and volume allocation (by hours or number of units). Primary data and ecoinvent data was used by some studies, however, no full details regarding data used by the volvo PCFs was available.	Eco-Indicator 99 ReCiPe Midpoint Hierarchist v1.13 method CML2001 – Jan 2016 IPCC 2021 Environmental Footprint 3.0	(Wiik et al., 2023, Kwak et al., 2012, Balboa-Espinoza et al., 2023, Volvo Construction Equipment 2025, Ebrahimi et al., 2020, Landfield and Karra, 2000)
Metal Forming Machinery (MFM)	18	2010, 2011, 2012, 2016, 2021, 2023	Global, Europe, China, Japan, USA	1) Product output (e.g., parts produced, cutting metals) 2) Hours of operation 3) Years of operation	Manufacturing of metal products	Most of the studies included: Raw material extraction and production, manufacturing and assembly, packaging in the cradle-to-gate phase; spare parts, consumables, and operation of machinery in the use-phase. But not all the studies explicitly included EOL impacts.	Various system models were employed, however cut-off was the mostly used, as well as allocation rules from ecoinvent database, although this was not always explicitly described. Most of the studies included primary data from manufacturers or industry associations and secondary data, as well as from the ecoinvent database as background.	Traci 2.1 Eco-indicator 99 Environmental Footprint 3.0 CML-IA baseline v4.2	(Schischke et al., 2012, Diaz-Elsayed et al., 2010, Guglielmi et al., 2021, Cao et al., 2012, Grupo Nicolás Correa 2017, Ma et al., 2023, Song et al., 2010)

(*continued on next page*)

Table 2 (*continued*)

Machinery category	No. of impact results	Temporal scope	Regional scope	Functional units	End use sector	Summary of system boundaries	Common methodological approaches	Impact assessment methods	References
Other Machine Tools (OMT)	4	2011	Europe	1) Machinery impact along entire life cycle	Manufacturing of wood products	Cradle-to-gate: Raw material production, assembly of machinery. Use-phase and EOL: (electricity and consumables e.g., oil, lubricants), and end-of-life considered as waste treatment (e.g., recycling) without disposal considered.	Cut-off system model used. And primary data as well as expert input data was used, including ecoinvent data for the background. No allocation procedures explicitly described, but ecoinvent allocation rules are included.	Eco-indicator 99	(Schischke et al., 2012)
Other Special-Purpose Machinery n.e.c. (OSPM)	18	2016, 2017, 2020, 2021, 2023, 2024	Global, Europe, Asia, United States of America (USA)	1) Machinery impact along entire life cycle 2) Years of operation 3) Hours of operation 4) Product output (e.g., packages delivered)	Manufacturing, Transportation and Storage, Water and wastewater treatment	Most of the studies considered Cradle-to-gate: Raw material extraction, parts production, transport to manufacturing site, manufacturing and assembly of machinery (e.g., soldering and assembly, testing), packaging. Use-phase and EOL: Transport to customer, operation of machinery (e.g., energy consumption), maintenance, and waste disposal. However, various studies, especially those focused on industrial robots, did not include EOL impacts.	Cut-off system model for EOL was assumed by most studies. Primary data and background data from ecoinvent was mostly used. Mass allocation was used by most studies as well as ecoinvent allocation rules.	Global Warming Potential 100 years according to the impact method IPCC 2013	(Li et al., 2021, CandG Depurazione Industriale Srl 2024, CandG Depurazione Industriale Srl 2025, CandG Depurazione Industriale Srl 2025, CandG Depurazione Industriale Srl 2025, CandG Depurazione Industriale Srl 2025, CandG Depurazione Industriale Srl 2025, CandG Depurazione Industriale Srl 2025, Lemardelé et al., 2023, Manuguerra et al., 2024, Stuhlenmiller et al., 2021, Wyatt et al., 2017)
Plastics and Rubber Machinery (PRM)	1	2024-2025	Italy	1) Machinery impact along entire life cycle	Manufacturing of plastics and rubber products	Cradle-to-gate: raw materials extraction, material production, components manufacturing, machinery assembly, packaging. Use-phase: transport to use-site, operation of machinery (energy consumption, water consumption), consumables (e.g., lubricants, degreaser, ethanol) and spare parts (abrasion teeth of aluminum and rubber). EOL: Disassembly, transport to waste treatment facility, waste management.	Cut-off system model was used. Primary data, data from OKOBAUDAT, and ecoinvent 3.11 database were used. No explicit allocation rules were described, but ecoinvent allocation rules are included.	Core environmental impact indicators of EN 15804:2012+A2:2019/ AC:2021 based on Environmental Footprint 3.1	(C.S.I 2025)

For the detailed analysis from each study, including system boundary, mass, lifetime and installed/nominal power of each technology see SI 2 Table S7.

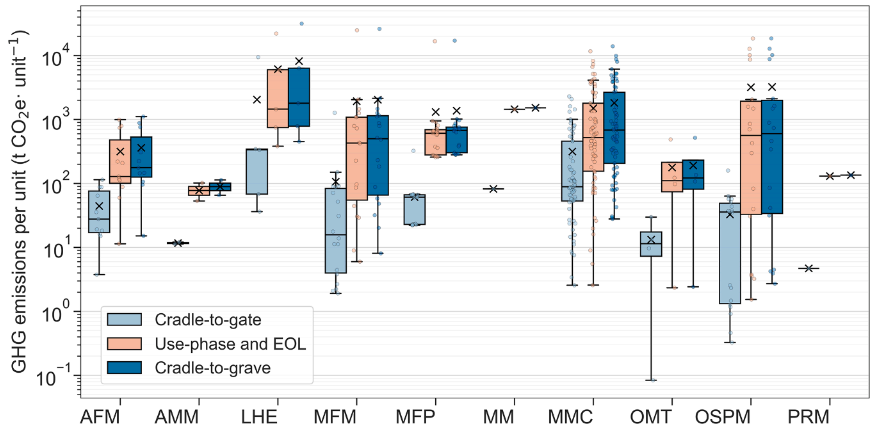

Fig. 2. Climate impacts of machinery technologies during the manufacturing phase (i.e., cradle-to-gate) in light blue, use-phase and EOL in orange, and cradle-to-grave (dark blue) in t CO2e per unit of machinery ($n = 150$) (log scale). The horizontal lines indicate the median, crosses (×) denote mean values, and bubbles (o) represent the individual datapoints. Abbreviations used for machinery categories: AFM = Agricultural and Forestry Machinery, AMM = Additive Manufacturing Machinery, LHE = Lifting and Handling Equipment, MFM = Metal Forming Machinery, MFP = Machinery for Food, Beverage and Tobacco Processing, MM = Machinery for Metallurgy, MMC = Machinery for Mining, Quarrying and Construction, OMT = Other Machine Tools, OSPM = Other Special-Purpose Machinery n.e.c., PRM = Plastics and Rubber Machinery.

technologies exhibiting the lowest impact remained constant.

Additionally, we considered the use intensity in terms of useful hours as a normalization parameter (see SI 1 Figure S3). In this analysis, MMC, LHE, and AFM yielded the largest median impacts from a cradle-to-grave perspective per hour of operation (see Table 3). PRM and OMT had the smallest median values with less than 5.00 kg CO_2e per hour of operation considering cradle-to-grave results.

MMC (e.g., motor graders, H-SP-mechanical shovels, excavators, and loaders) and AFM (e.g., hay-making machinery and harvesting machines) contributed with four and three of the ten most impactful technologies, respectively. Presses for working metal and conventional tower cranes demonstrated large median impacts, as well. The technologies with the least cradle-to-grave impact per unit remained.

Cradle-to-gate median impacts per hour of operation were also led by MMC, LHE, and AFM. OMT and PRM had the smallest median cradle-to-gate per hour values. At the technology level the cradle-to-gate per hour median results coincided with the cradle-to-grave per hour ones, with most of the top impact technologies belonging to MMC and AFM.

Use-phase and EOL impacts remained similarly consistent with the cradle-to-grave per hour of operation results at the category level.

3.3. Statistical group comparisons (Kruskal–Wallis and Dunn's test results)

To statistically compare the various industry-specific machinery technologies, a Kruskal–Wallis H-test was carried out. We found that across most normalization types and life cycle stages considered, at least one category to be statistically significantly different from the others (p-values$\leq$0.05). Especially, in the cradle-to-gate comparisons were the results the most statistically significant (p-values $\leq$0.001). Nevertheless, the effect sizes (ε^2) were identified as moderate to strong in only eight of the twelve comparisons. The associations for cradle-to-grave and in the use-phase and EOL were found to be weak when impacts were normalized per unit or per year. The complete results of the Kruskal–Wallis test are presented in SI 1 Table S3.

To better understand which specific categories differed from each other, we subsequently carried out a Dunn's test with Holm-Bonferroni adjustment, which showed many pairwise categories to have statistically significant differences. The results are presented in Fig. 5.

From a cradle-to-gate per unit perspective, MMC (Mdn= 88.7 t CO_2e) showed to have statistically significantly larger CO_2e emissions than OSPM (Mdn= 25.5 t CO_2e; p-adjusted $\leq$0.001) and MFM (Mdn= 15.8 t CO_2e; p-adjusted $\leq$0.05). Furthermore, LHE (Mdn = 336 t CO_2e) also demonstrated a statistically significantly larger impact compared to OSPM (Mdn = 35.8 t CO_2e; p-adjusted $\leq$0.05). No statistically significant differences were found in the use and EOL phases, nor in the cradle-to-grave comparison per unit between categories (see SI 2 Table S4).

For GHG emissions normalized per kilogram, OSPM consistently demonstrated statistically significantly higher impacts across all three life cycle stage analyses (cradle-to-gate, use-phase and EOL, and cradle-to-grave) compared to most other categories (see Table 3). For instance, in the cradle-to-gate phase, OSPM (Mdn = 13.7 kg CO_2e/kg) had statistically significantly higher emissions than MFM (Mdn = 2.81 kg t CO_2e/kg; p-adjusted $\leq$ 0.001), MMC (Mdn = 4.49 kg CO_2e/kg; p-adjusted $\leq$0.001), and OMT (Mdn = 3.42 kg CO_2e/kg; p-adjusted $\leq$ 0.01). Moreover, AFM showed to have statistically significantly larger impacts than MFM considering the manufacturing phase.

Similar patterns were observed in the use and EOL phase and cradle-to-grave stages, where OSPM continued to show the highest emissions, being statistically significantly higher than MMC, MFM, and LHE in most pairwise comparisons within these stages. In contrast, categories like MMC and MFM generally showed lower impacts across all three stages when normalized per kilogram. Specific comparisons, such as MFP showing significantly higher impacts than MMC, also emerged in both stages (e.g., use-phase and cradle-to-grave).

In the per year comparison, statistically significant differences were observed only during the manufacturing phase. Namely, MMC (Mdn= 8.87 t CO_2e/yr) demonstrated to have statistically significantly larger CO_2e emissions than OSPM (Mdn= 3.18 t CO_2e /yr; p-adjusted$\leq$0.001), MFM (Mdn= 1.21 t CO_2e/yr; p-adjusted $\leq$0.01), and OMT (Mdn=57.3 t CO_2e/yr; p-adjusted $\leq$ 0.05). Moreover, LHE (Mdn=22.4 t CO_2e/yr) also exhibited statistically significant larger impacts than OSPM (p-adjusted $\leq$0.05) and OMT (p-adjusted $\leq$ 0.05).

Finally, for GHG emissions normalized per hour, MMC consistently demonstrated the largest impacts across all three life cycle stages. In the cradle-to-gate phase, MMC (Mdn = 5.40 kg CO_2e/h) had statistically significantly larger impacts than OSPM (Mdn = 0.86 kg CO_2e/h; p-adjusted $\leq$0.001), MFP (Mdn = 0.99 kg CO_2e/h; p-adjusted $\leq$0.001), MFM (Mdn = 0.62 kg CO_2e/h; p-adjusted $\leq$0.001), and OMT (Mdn = 0.35 kg CO_2e/h; p-adjusted $\leq$0.01). Furthermore, AFM (Mdn = 3.68 kg CO_2e/h) exhibited to have statistically larger impacts in comparison to OSPM (p-adjusted $\leq$ 0.01), MFP, and MFM (p-adjusted $\leq$ 0.05).

Likewise, MMC demonstrated statistically significantly larger impacts across its comparisons in the use-phase and EOL, as well as in the cradle-to-grave analyses. For example, in the former, MMC (Mdn = 41.0 kg CO_2e/h) had statistically significantly larger impacts compared to

Table 3
Median parameter values and climate impacts (t CO_2e) of machinery categories per life cycle phases and per unit, kg, year, and hour of use.

Machinery categories	No. of impact results	Median mass (kg)	Median lifetime (yr)	Median hours of operation (h)	Life cycle phase	Median value (t CO_2e per unit)	Median value (t CO_2e per kg)	Median value (t CO_2e per year)	Median value (t CO_2e per hour)
Agricultural and Forestry Machinery (AFM)	11	2500	12	10000	Cradle-to-gate	2.78×10^{1}	8.16×10^{-3}	2.78×10^{0}	3.68×10^{-3}
					Use-phase and EOL	1.28×10^{2}	7.10×10^{-2}	1.28×10^{1}	1.47×10^{-2}
					Cradle-to-grave	1.77×10^{2}	8.15×10^{-2}	1.77×10^{1}	1.77×10^{-2}
Additive Manufacturing Machinery (AMM)	2	1449	8	34339	Cradle-to-gate	1.17×10^{1}	8.07×10^{-3}	1.46×10^{0}	1.17×10^{-3}
					Use-phase and EOL	7.75×10^{1}	5.35×10^{-2}	9.69×10^{0}	5.56×10^{-3}
					Cradle-to-grave	8.92×10^{1}	6.16×10^{-2}	1.12×10^{1}	6.72×10^{-3}
Lifting and Handling Equipment (LHE)	5	115000	15	75000	Cradle-to-gate	3.36×10^{2}	3.00×10^{-3}	2.24×10^{1}	4.48×10^{-3}
					Use-phase and EOL	1.45×10^{3}	1.26×10^{-2}	9.66×10^{1}	2.13×10^{-2}
					Cradle-to-grave	1.79×10^{3}	1.76×10^{-2}	1.20×10^{2}	2.39×10^{-2}
Metal Forming Machinery (MFM)	18	5800	16	43600	Cradle-to-gate	1.58×10^{1}	2.81×10^{-3}	1.21×10^{0}	6.21×10^{-4}
					Use-phase and EOL	4.28×10^{2}	7.33×10^{-2}	3.56×10^{1}	8.85×10^{-3}
					Cradle-to-grave	5.00×10^{2}	7.60×10^{-2}	4.09×10^{1}	9.28×10^{-3}
Machinery for Food, Beverage and Tobacco Processing (MFP)	21	7100	10	57437	Cradle-to-gate	6.13×10^{1}	8.82×10^{-3}	6.13×10^{0}	9.95×10^{-4}
					Use-phase and EOL	6.09×10^{2}	1.02×10^{-1}	6.09×10^{1}	9.52×10^{-3}
					Cradle-to-grave	6.74×10^{2}	1.11×10^{-1}	6.74×10^{1}	1.05×10^{-2}
Machinery for Metallurgy (MM)	1	12674	20	102300	Cradle-to-gate	8.21×10^{1}	6.48×10^{-3}	4.11×10^{0}	8.03×10^{-4}
					Use-phase and EOL	1.44×10^{3}	1.14×10^{-1}	7.20×10^{1}	1.41×10^{-2}
					Cradle-to-grave	1.52×10^{3}	1.20×10^{-1}	7.61×10^{1}	1.49×10^{-2}
Machinery for Mining, Quarrying and Construction (MMC)	69	21528	10	10000	Cradle-to-gate	8.87×10^{1}	4.49×10^{-3}	8.87×10^{0}	5.40×10^{-3}
					Use-phase and EOL	5.20×10^{2}	2.28×10^{-2}	4.61×10^{1}	4.10×10^{-2}
					Cradle-to-grave	6.80×10^{2}	2.67×10^{-2}	6.09×10^{1}	4.91×10^{-2}
Other Machine Tools (OMT)	4	3750	20	32500	Cradle-to-gate	1.15×10^{1}	3.42×10^{-3}	5.73×10^{-1}	3.53×10^{-4}
					Use-phase and EOL	1.10×10^{2}	5.00×10^{-2}	5.50×10^{0}	3.39×10^{-3}
					Cradle-to-grave	1.22×10^{2}	5.38×10^{-2}	6.08×10^{0}	3.74×10^{-3}
Other Special-Purpose Machinery n.e.c. (OSPM)	18	302	10	41600	Cradle-to-gate	3.58×10^{1}	1.37×10^{-2}	3.18×10^{0}	8.60×10^{-4}
					Use-phase and EOL	5.62×10^{2}	1.18×10^{0}	5.63×10^{1}	1.35×10^{-2}
					Cradle-to-grave	5.98×10^{2}	1.23×10^{0}	5.98×10^{1}	1.44×10^{-2}
Plastics and Rubber Machinery (PRM)	1	470	15	30000	Cradle-to-gate	4.71×10^{0}	1.00×10^{-2}	3.14×10^{-1}	1.57×10^{-4}
					Use-phase and EOL	1.30×10^{2}	2.77×10^{-1}	8.67×10^{0}	4.33×10^{-3}
					Cradle-to-grave	1.35×10^{2}	2.87×10^{-1}	8.98×10^{0}	4.49×10^{-3}

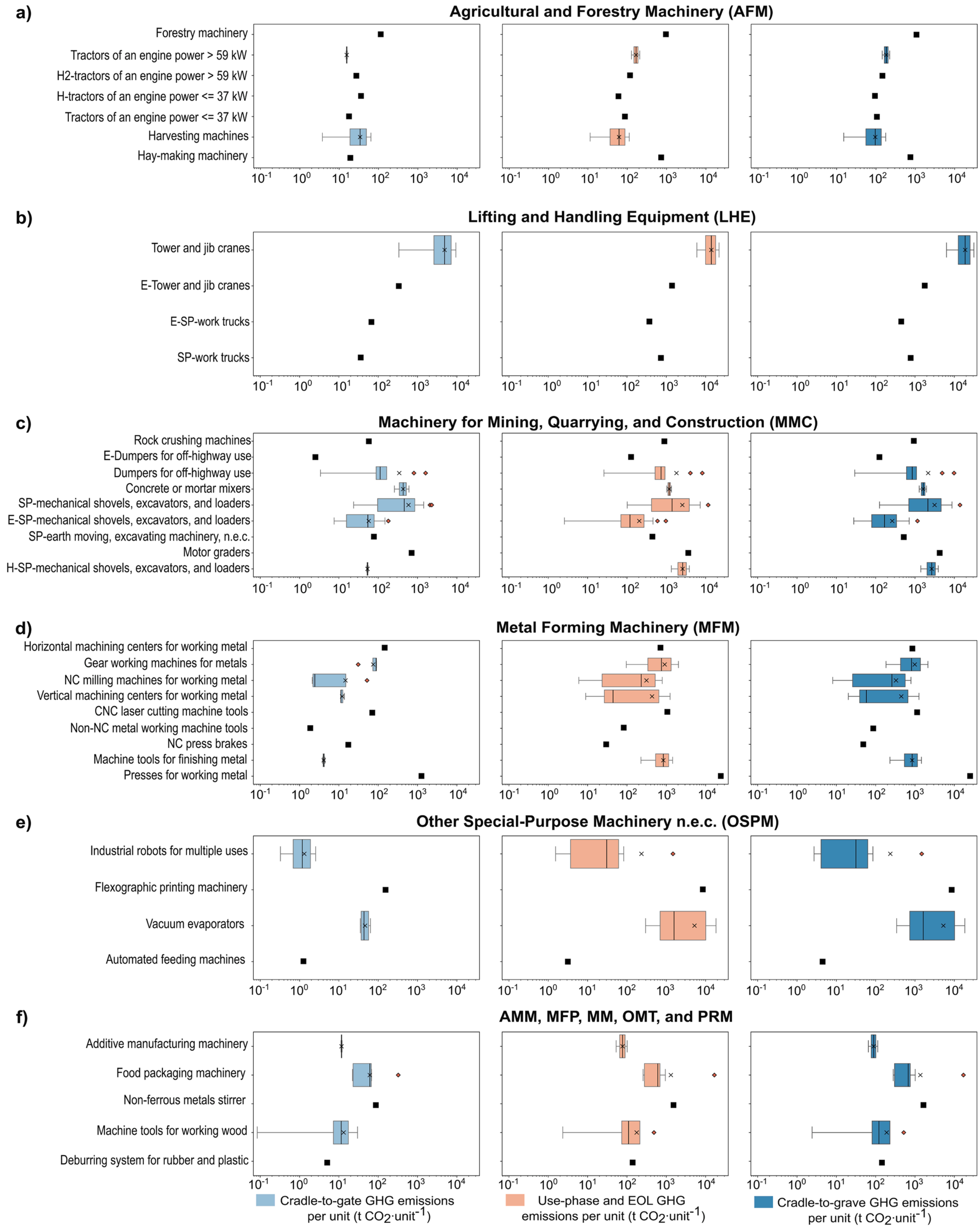

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Fig. 3. Wide-ranging cradle-to-grave climate impact results between 39 different machinery technologies from 10 NACE categories. Left: manufacturing phase (i.e., cradle-to-gate) in light blue. Center: use-phase and end-of-life in orange. Right: cradle-to-grave impacts in dark blue. All in t CO_2e per unit (log scale). ($n = 150$). The horizontal lines indicate the median, crosses (×) denote mean values, and diamonds mark outliers. The black squares represent single data values. Abbreviations used for machinery categories: a) AFM = Agricultural and Forestry Machinery, b) LHE = Lifting and Handling Equipment, c) MMC = Machinery for Mining, Quarrying and Construction, d) MFM = Metal Forming Machinery, , e) OSPM = Other Special-Purpose Machinery n.e.c., f) AMM = Additive Manufacturing Machinery, MFP = Machinery for Food, Beverage and Tobacco Processing, MM = Machinery for Metallurgy, OMT = Other Machine Tools, PRM = Plastics and Rubber Machinery. Note: E-= electric, H-= Hybrid SP= self-propelled CNC=computer numerical control NC=numerical control H2= Hydrogen fuel cell powered. Across all machinery categories, the use-phase consistently dominated overall impacts, with shares ranging from 75% (LHE) to 99% (OSPM). With technologies such as low-powered hybrid-tractors, concrete and mortar mixers, and conventional tower and jib cranes exhibiting a cradle-to-gate impact of over 25%. Conversely, End-of-Life (EOL) impacts were found to be negligible, never exceeding 0.5% on average for any category, indicating that the remaining impacts originated from the manufacturing (cradle-to-gate) phase.

MFM (Mdn = 8.85 kg CO_2e/h; p-adjusted ≤ 0.01) and MFP (Mdn = 9.52 kg CO_2e/h; p-adjusted ≤ 0.01). A comparable pattern was observed in the cradle-to-grave stage, where MMC also exhibited statistically significant larger impact in comparison to other categories, namely, MFP, MFM, OMT, and OSPM (see Table 3).

Most machinery categories showed statistically significant differences in CO_2e emissions across various life cycle stages and normalization methods. However, the ranking of categories by climate impact varied substantially depending on the normalization metric applied. For example, OSPM consistently demonstrated the highest emissions when normalized per kilogram. In contrast, MMC generally exhibited the largest impacts when emissions were normalized per unit or per hour across the assessed life cycle stages. Differences in impacts normalized per year were predominantly observed within the manufacturing phase. Additionally, the results showed that considering the data and analysis carried out in this study, no statistically significant differences with respect to their CO_2e impacts were observed in the following comparison categories: LHE vs. MMC, and MFM vs. OMT. Furthermore, AMM did not exhibit to have any statistically significant differences across all normalization types and life cycle stages considered.

Comprehensive results for all pairwise comparisons are provided in SI 2 Table S4.

3.4. *Spearman correlation analysis of influencing factors*

We conducted a Spearman rank correlation analysis (ρ) across the extracted datapoints ($n = 150$) to explore how key parameters relate to life-cycle climate impacts of machinery. Variables included machinery mass (kg), installed/rated power (kW), lifetime (years), and annual operating hours ($h \cdot yr^{-1}$), alongside manufacturing and operation impact indicators (i.e., cradle-to-gate emissions per unit, use-phase and EOL emissions per unit), and cradle-to-gate share (%). Given multiple pairwise correlations, we interpret p-values cautiously and emphasize effect sizes; confidence intervals are reported for partial correlations. Results are shown in Fig. 6 (full results in Table S8).

Mass showed the strongest positive correlation with both cradle-to-gate ($\rho = 0.79$, $p < 0.001$) and use-phase and EOL emissions ($\rho = 0.52$, $p < 0.001$), whereas lifetime exhibited only weak relationships with them, including a small positive correlation with the use-phase emissions ($\rho = 0.20$, $p = 0.016$) and no significant association with cradle-to-gate emissions ($\rho = 0.15$, $p = 0.062$). Annual operating hours showed a strong negative association with cradle-to-gate share ($\rho = -0.45$, $p < 0.001$), but did not exhibit significant correlation with use-phase per unit ($\rho = 0.08$, $p = 0.325$).

Given strong correlation between mass and installed power ($\rho = 0.79$), we applied partial Spearman correlations. Cradle-to-gate emissions per unit remained strongly associated with mass after controlling for power (partial $\rho = 0.62$, 95% CI $[0.51, 0.71]$, $p < 0.001$), while power was not associated with cradle-to-gate once mass was controlled (partial $\rho = 0.03$, 95% CI $[-0.13, 0.19]$, $p = 0.746$). In contrast, use-phase and EOL, as well as total cradle-to-grave emissions retained small independent associations with both mass and power (See Table S9).

We also computed category-specific (within-category) Spearman correlations for categories meeting minimum evidence-structure criteria ($n \geq 5$ datapoints and ≥ 5 unique sources: AFM, MFM, MMC, and OSPM; see Table S10). The results indicated that AFM and MFM exhibited a clearer association between annual operating hours and use-phase and EOL emissions, together with a negative association between annual operating hours and cradle-to-gate share, consistent with utilization-related burden shifting within these categories. In contrast, MMC and OSPM are more strongly structured by machinery scale and technology characteristics, with annual operating hours showing weak or no association with absolute impacts. This likely reflects confounding by duty intensity and size mix (high-duty machines used fewer hours but with higher energy per hour), compounded by differences in study assumptions and system boundaries. Across all four categories, mass remained positively associated with cradle-to-gate impacts.

To complement the rank-based correlations with direct comparison illustrations (same technology group and consistent boundary assumptions), we include a small set of within-source comparisons (see Table S11). For example, two wheel loaders (Volvo Construction Equipment 2025) assessed under the same framework show that the higher-mass (and higher-capacity) model has higher cradle-to-gate and higher use-phase emissions, while two tractors within the same study (Liu et al., 2024) illustrate configuration-driven burden shifting under comparable use intensity assumptions.

4. Discussion and limitations

4.1. *Literature gaps*

We identified various studies quantifying the life cycle impacts of industry-specific machinery, however, environmental assessments remain notably scarce for many categories. While some categories like MFM, MMC, and AFM are relatively well-assessed, others such as AMM, MM, PRM, and MTP have notably few available studies. This impacted representativeness and the analysis. For AMM, only one study met the inclusion criteria due to a prevalent lack of material and manufacturing impact data in other identified assessments. This lack of data also prevented a robust statistical analysis at the technology level, limiting detailed insights into inter-technology differences. This uneven representation likely stems from the varying economic relevance of macro sectors, with less heterogeneous and widely researched categories (e.g., MFM) being better documented. In contrast, OSPM, being more diverse and specialized across sectors, has historically seen less investigation, though recent publications, particularly for industrial robots and in EPDs (CandG Depurazione Industriale Srl 2024; Lemardelé et al., 2023; Wyatt et al., 2017; Ars Automation S.r.l 2025), indicate a growing trend. Notably, many of the studies omitted the machinery within the system boundaries e.g., (Diaz-Elsayed et al., 2010; Extrusion, 2023; Presezzi Extrusion 2024; CandG Depurazione Industriale Srl 2024; CandG Depurazione Industriale Srl 2025).

Overall, findings highlight the need for more cradle-to-grave LCA studies in the machinery sector. Future studies should prioritize transparent manufacturing inventories, including material composition and fabrication yields. More consistent reporting of lifetime, annual operating hours, and duty-cycle assumptions is also needed, as these strongly

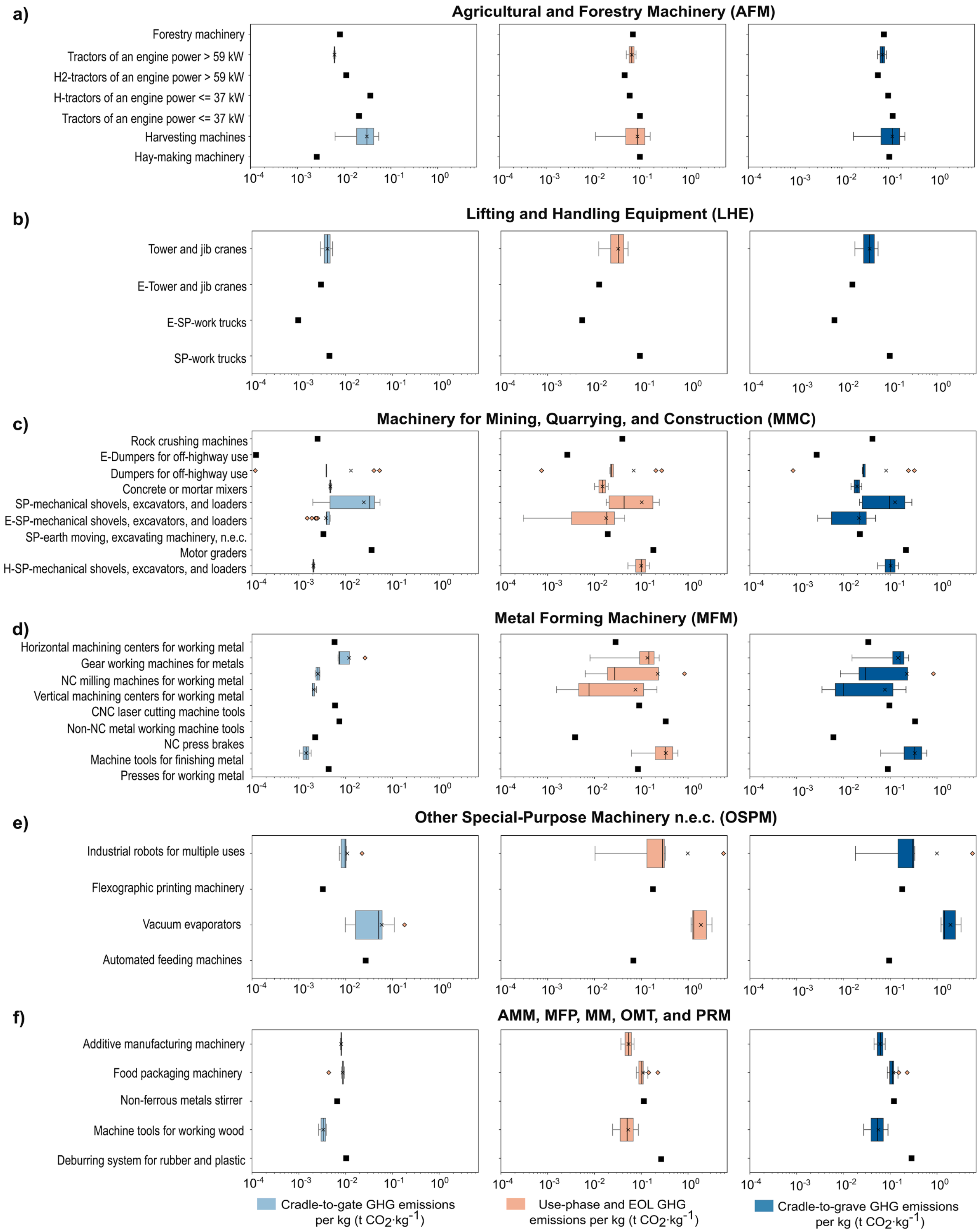

Fig. 4. Differing median cradle-to-grave climate impacts per kg of machinery (t CO_2e per kg of machinery). Largest impacts were demonstrated by OSPM, while the lowest impacts were shown by LHE and MMC, contrasting to the per unit results. Left: manufacturing phase (i.e., cradle-to-gate) in light blue. Center: use-phase and end-of-life in orange. Right: cradle-to-grave impacts in dark blue (log scale) ($n = 150$). The horizontal lines indicate the median, crosses (×) denote mean values, and diamonds mark outliers. The black squares represent single data values. Abbreviations used for machinery categories: a) AFM = Agricultural and Forestry Machinery, b) LHE = Lifting and Handling Equipment, c) MMC = Machinery for Mining, Quarrying and Construction d) MFM = Metal Forming Machinery, f) AMM = Additive Manufacturing Machinery, e) OSPM = Other Special-Purpose Machinery n.e.c., f) AMM = Additive Manufacturing Machinery, MFP = Machinery for Food, Beverage and Tobacco Processing, MM = Machinery for Metallurgy, OMT = Other Machine Tools, PRM = Plastics and Rubber Machinery. Note: E-= electric, H-= Hybrid SP= self-propelled CNC=computer numerical control NC=numerical control H2= Hydrogen fuel cell powered.

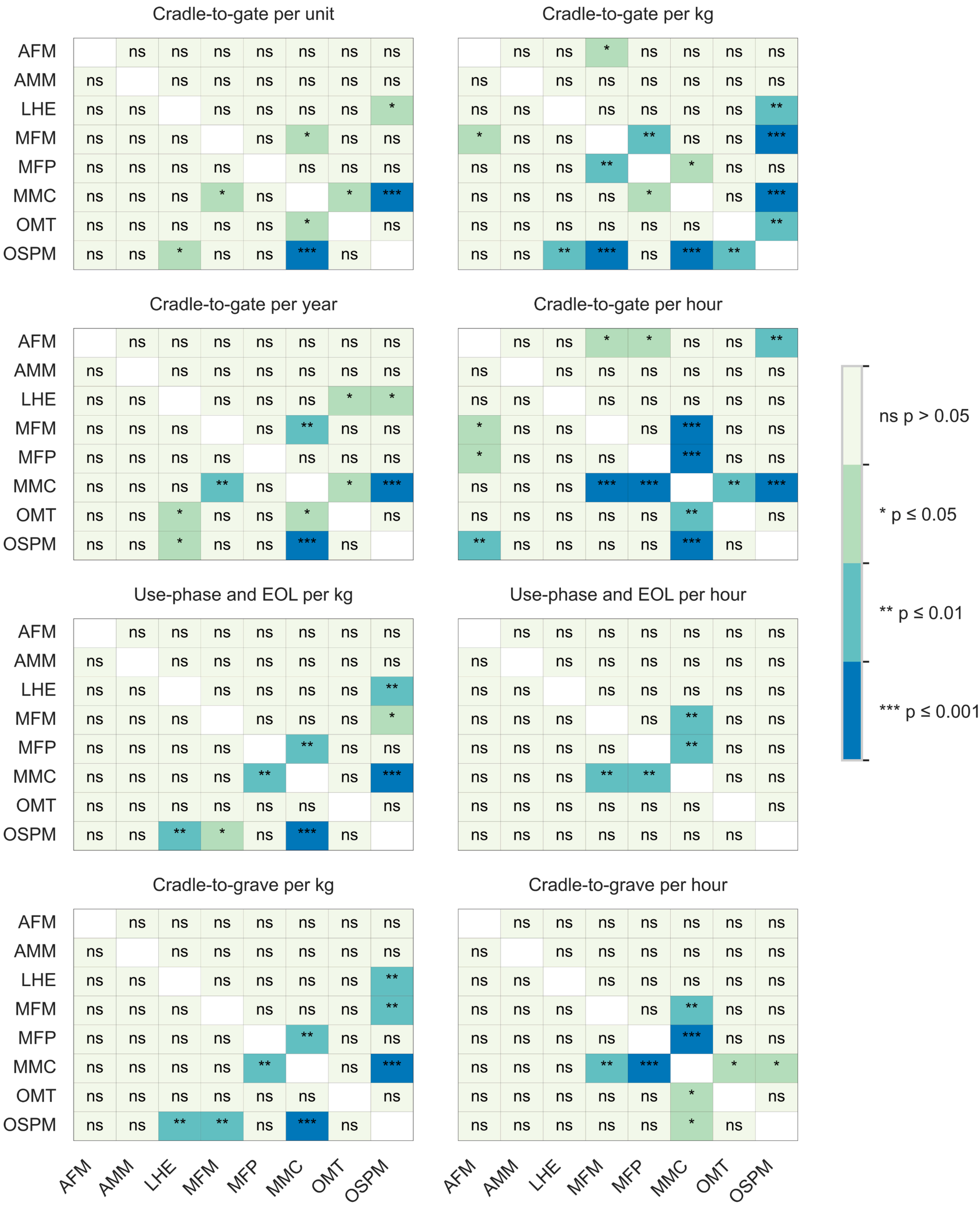

Fig. 5. Dunn's post hoc test results. Note: only the phases and normalization methods with statistically significant results are displayed. *$p \leq 0.05$; **$p \leq 0.01$; ***$p \leq 0.001$, not significant (ns) $p > 0.05$. Abbreviations used for machinery categories: AFM = Agricultural and Forestry Machinery, AMM = Additive Manufacturing Machinery, LHE = Lifting and Handling Equipment, MFM = Metal Forming Machinery, MFP = Machinery for Food, Beverage and Tobacco Processing, MMC = Machinery for Mining, Quarrying and Construction, OMT = Other Machine Tools, OSPM = Other Special-Purpose Machinery n.e.c.

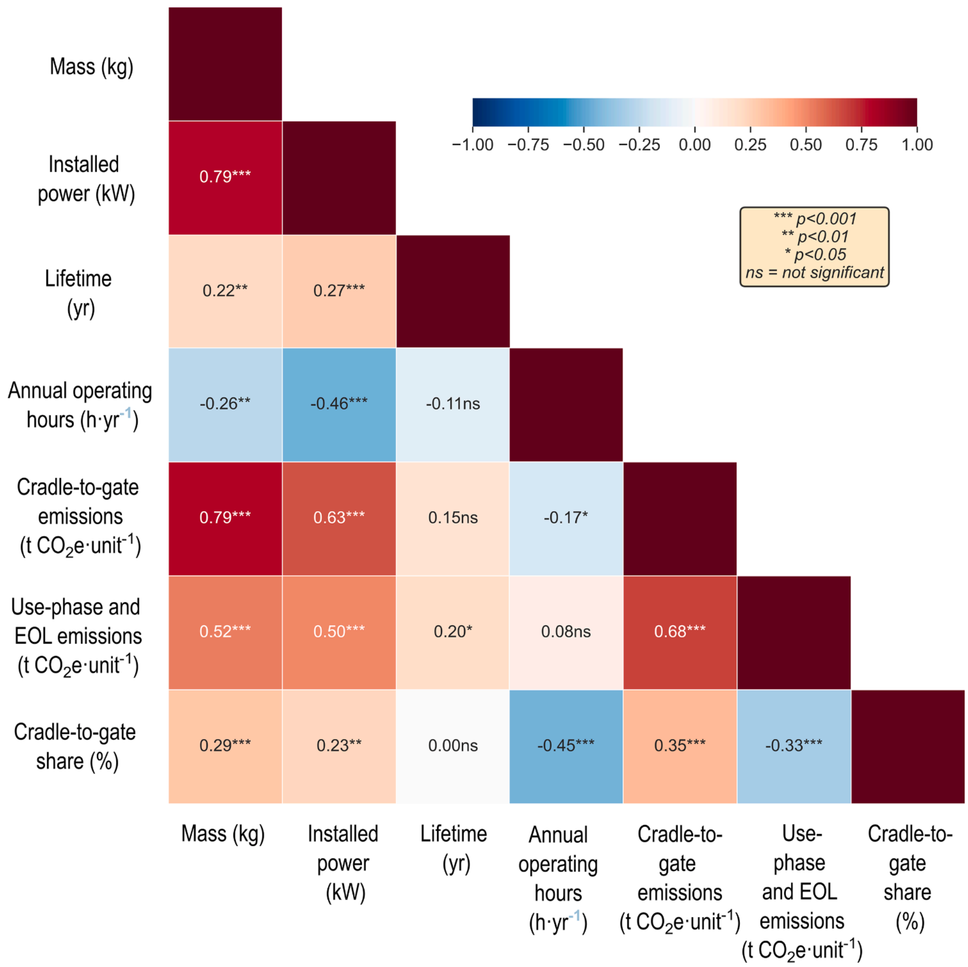

Fig. 6. Heatmap of Spearman rank correlations between machinery parameters and climate impact indicators ($n = 150$). Blue = negative correlation. Red = positive correlation. Near-zero correlations are neutral. Darker gradients denote stronger correlations. Statistical significance is indicated as *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; ns $p \geq 0.05$. Note: Cradle-to-gate share (%) refers to the percentage of cradle-to-grave impacts corresponding to the cradle-to-gate phase; annual operation hours represent the lifetime operation hours divided by the total lifetime in years ($h \cdot yr^{-1}$).

influence the interpretation of use-phase impacts and burden allocation across life cycle phases. In addition, more transparent and harmonized EOL modelling assumptions would improve the robustness and comparability of results, particularly in the context of circular economy strategies. Finally, clearer and more consistent system boundary definitions are essential, although this will remain challenging in a heterogeneous sector such as machinery; greater use of PCRs may help improve consistency in methodological choices and reporting across studies.

4.2. Normalization and inter-category comparisons

Our findings rejected the null hypothesis that there were no statistically significant differences between the central tendency of their climate impacts. Instead, statistically significant differences were identified among various machinery categories, particularly evident when considering different normalization approaches, and should therefore be interpreted as contextual rather than determinative. Still, some tendencies were identified, first, MMC consistently exhibited statistically the largest climate impacts across most life cycle phases and per unit, per hour, and per year normalization types. While OSPM exhibited statistically significant GHG emissions in the per kg comparison. Notably, there were no statistically significant differences between MMC and LHE, which may be relevant given their frequent overlap. Similarly, OMT did not exhibit statistically significant differences with MFM. However, given they belong to the same 28.4 NACE code, this finding is expected.

LHE and MMC were the most impactful categories on a per unit basis but had the lowest median impacts per kg, demonstrating the mass implications of their overall footprint. Thus, suggesting they fulfill their function with a significantly lower per kg impact than other technologies. In contrast, the majority of impact results derived from OSPM (e.g., vacuum evaporators and industrial robots) are likely to include climate-intensive materials, as well as customer-specific and energy-intensive processes, a characteristic that is well-documented (Wilke et al., 2025) and that was also suggested by the correlation analysis of that category. AMM had an intermediate median impact in the cradle-to-gate per kg analysis, suggesting the manufacturing phase of this technology may be relevant (Faludi et al., 2017). A consideration that is frequently disregarded in many AMM studies (Bekker and Verlinden, 2018; Jiang et al., 2019; Kellens et al., 2014; Schmidt et al., 2024; Serres et al., 2011).

There were no statistically significant differences during the use-phase in the per unit and per year comparisons indicating that the significance of the operation stage is clear in all categories. OMT consistently exhibited one of the lowest GHG impacts, suggesting that use intensity may contribute to these lower impacts (Schischke et al., 2012). A similar tendency is observed in AFM, where the operating characteristics of the agricultural sector (Bacenetti, 2022) imply more irregular operating patterns compared to continuously operated industrial machinery (e.g., MFM) (Schischke et al., 2012). Short operation hours make cradle-to-gate impacts more relevant, especially, considering the number of hours during AFM is in operation (<20%). This was consistent with Section 3.4, since operating-time proxies explain burden allocation more robustly than absolute operational impacts across heterogeneous technologies, and within-category correlations indicate stronger operating hours and use-phase alignment in AFM/MFM than in MMC/OSPM. For longer operating technologies (e.g., LHE operate around 50% of their useful lifetime), the inverse is true. This study demonstrated the relevance that longer useful lifespans may have in per kg impacts (e.g., in presses for working metal, concrete mixers, and tower cranes). Despite their substantial mass and use-phase impacts per unit, they exhibited bottom-half use-phase impacts per kg This may partly reflect extended operational lifetimes and higher delivered service per unit mass, but may also be influenced by duty intensity, scale/capacity differences, and assumption differences across sources. Some of these tendencies can be also observed in other studies (Kasah, 2014).

For OSPM and machinery with large cradle-to-gate impacts, increasing manufacturing material yields, substituting climate intensive materials, and reducing use of primary resources may be relevant strategies (Allwood and Cullen, 2012; Allwood and Music, 2024). For MMC and large per year or per hour impact machinery, reducing impacts could be achieved through energy efficiency and accelerating implementation of trends such as electrification, as shown by some of the studies (Wiik et al., 2023; Lagnelöv et al., 2021; Liu et al., 2024; Balboa-Espinoza et al., 2023; Volvo Construction Equipment 2025). Moreover, supporting lifetime extension measures to decrease the resource demand, may be a critical strategy for most of the technologies. However, to what extent this may decrease the environmental impact needs to be better understood, as trade-offs may be expected (Bacenetti, 2022; Barkhausen et al., 2024; Blum et al., 2020). These patterns are synthesized in the archetype map (Section 4.4), which translates technology characteristics into prioritized mitigation strategies.

It was notable that AFM, despite its inclusion of various sources and technologies, was one of the most homogeneous categories, suggesting that this category might be less challenging to assess. This is particularly relevant when one considers the existing comprehensive LCIs of the sector (Mantoam et al., 2020; Pradel, 2023). In contrast, the impact results of MFP, MFM, and OSPM demonstrated a significant dispersion, even when considering the limited number of technologies included in MFP and OSPM. This suggests that their impacts may exhibit considerable variation. It was observed that other categories, including AMM and OMT, exhibited reduced heterogeneity. The findings may be inconclusive due to the limited sources and technologies included.

4.3. Life cycle phases contributions and influencing factors

The cradle-to-grave per unit impacts were driven by the use-phase, which is in line with the common understanding of the relevance of this phase in the machinery sector (Frischknecht et al., 2007; Schischke et al., 2012). However, as mentioned above, cases such as low-powered tractors from AFM, and technologies from MMC and LHE, the manufacturing impacts were not insignificant (27%–38%). Moreover, specific MMC studies (Wiik et al., 2023) showed the shifting of the impacts to the manufacturing phase, in some cases over 90%, under electrified configurations. This suggests that manufacturing-phase emissions may become increasingly important as operational emissions decline through electrification (e.g., AFM, LHE, MMC) and other decarbonization pathways (Wiik et al., 2023; Lagnelöv et al., 2021; Liu et al., 2024; Liu et al., 2024; Balboa-Espinoza et al., 2023; Volvo Construction Equipment 2025). Policy agendas that promote industrial decarbonization and equipment renewal (ChinaBriefing 2025; European Commission 2025) may accelerate upgrade/replacement cycles, shifting the balance between embodied and operational emissions and material demand. This reinforces the need to evaluate trade-offs between replacement and lifetime extension measures (e.g., retrofit/remanufacturing), which can influence carbon lock-in dynamics (Unruh, 2000; Seto et al., 2016).

To directly address the second research question and move beyond normalization, we quantified associations between key machinery parameters and stage-specific climate impacts using Spearman and partial Spearman correlations (Section 3.4). These results clarify which parameters are most informative for which life-cycle phases. First, manufacturing impacts were strongly related to machinery mass: partial correlations show that cradle-to-gate emissions remained strongly associated with mass after controlling for installed power, while installed power shows no association with cradle-to-gate once mass is controlled. This stage-specific result supports a material-scale interpretation of embodied impacts, and it implies that simplified representations of machinery based only on operational proxies (e.g., installed power) may underrepresent embodied emissions and material-focused mitigation levers. Second, operational impacts retained small independent associations with both mass and installed power, suggesting that use-phase variability reflects “scale/capacity” effects that were not captured by a single proxy.

Utilization-related parameters primarily affected the burden split rather than consistently predicting absolute operational impacts across heterogeneous technologies. In the pooled dataset, annual operating hours were strongly negatively associated with cradle-to-gate share, consistent with burden shifting toward the use-phase as more service is delivered per machine, yet annual operating hours did not show a consistent association with use-phase and EOL emissions per unit. This is plausible in a cross-technology meta-analysis because absolute operational burdens depend on duty cycle, load factors, energy carriers, technology design, and system boundary choices (e.g., inclusion of consumables and maintenance). Category-specific correlations (Table S10) further suggest that annual operating hours align more clearly with operational impacts within AFM and MFM than within MMC and OSPM, where variability is more strongly structured by machinery scale and technology characteristics. Annual operating hours alone is therefore insufficient to predict absolute operational impacts across machinery types, and bottom-up models should combine operating time with a duty/intensity proxy (e.g., load factor or energy-use intensity) alongside a scale proxy.

Finally, limited detail on manufacturing inventories and material yields in many studies may lead to underestimation of cradle-to-gate impacts, because manufacturing and material implications were often simplified (see Table S7 for full detail). The fabrication yield improvement may therefore represent a crucial mitigation strategy with large potential (Allwood and Music, 2024). Similarly, EOL was also frequently simplified across the reviewed studies. As material-related policy developments (ChinaBriefing 2025; European Commission 2025; European Commission 2015; NPC 2008) increasingly emphasize reducing primary material demand and promoting high-quality recycling, improving transparency and consistency in EOL modeling for machinery —and using simulation-based approaches to quantify realistic circularity and recycling potentials at the product and material level (Reuter et al., 2019) —will become increasingly important for robust impact estimates and mitigation assessments.

These phase-specific associations are synthesized in the archetype framework presented next.

4.4. Strategy prioritization using CE archetypes (R0–R9 framework)

Fig. 7 presents an exploratory archetype map that translates the empirical patterns into strategy priorities. The map positions the 39 machinery technologies by cradle-to-gate share (%) (burden structure) and annual operating hours ($h \cdot yr^{-1}$) (use intensity proxy), with mass (kg) represented as bubble size to indicate material/embodied scale. Technologies are plotted using median values and the number of underlying datapoints (n) is shown next to each technology label to indicate evidence strength. Quadrant assignment is determined by whether a

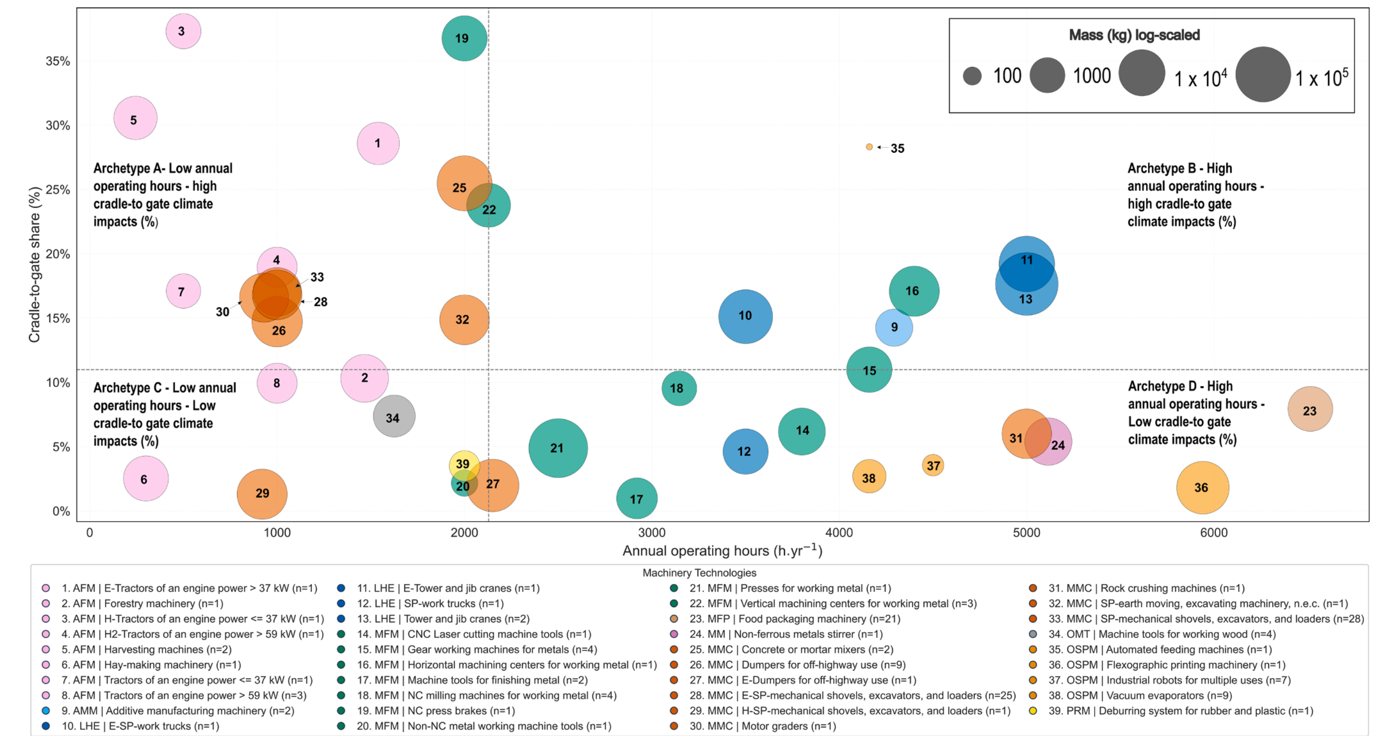

Fig. 7. Machinery archetype map based on technology cradle-to-gate share (%), annual operating hours (h·yr^{-1}) and mass (kg) median values (n = 150 datapoints). Each bubble represents the median cradle-to-gate share (x-axis) and median annual operating hours (y-axis) of a machinery technology; bubble size indicates median mass (kg, log-scaled for visualization). The number of underlying datapoints (n) supporting each technology is shown next to its label. Quadrant boundaries are defined by the median of technology medians (horizontal and vertical dashed lines), yielding four exploratory archetype regions used to discuss decarbonization and circular economy strategy prioritization. Median values of all datapoints: cradle-to-gate share (%) = 10.9% (horizontal line); annual operating hours (h·yr^{-1}) = 2128 h·yr^{-1} (vertical line).; mass (kg) = 8000 kg.

technology's median cradle-to-gate share and median annual operating hours lie above or below the median-of-medians thresholds shown as dashed lines in Fig. 7 (10.9% and 2128 h·yr^{-1}). Technologies from the same NACE category can occupy different regions, indicating that burden structure and use patterns are more informative than category labels for prioritizing interventions. Notably, MFM spans all four archetype regions, while AFM and nearly all MMC technologies lie on the low-annual operating hours side.

To prioritize mitigation options, we interpret the archetype map using a CE strategy framework that distinguishes "narrowing", "slowing", and "closing" resource loops, operationalized through the R0-R9 ("10R") strategy set (Potting et al., 2017; Bocken et al., 2016). "Narrowing" corresponds to R0–R2 (Refuse–Rethink–Reduce; including intensified use via sharing and product-service models under Rethink), "slowing" corresponds to R3–R7 (reuse, repair, refurbishment, remanufacturing and related value-retention strategies), and "closing" corresponds to R8–R9 (recycling/recovery). This framing is consistent with established CE strategy literature and provides a systematic basis for strategy prioritization across machinery technologies.

Across the dataset, median cradle-to-gate share is generally modest (11%); however, multiple technologies exhibit higher manufacturing shares (e.g., ≥15%), often combined with lower annual operating hours. This implies that embodied emissions can become strategically important where machines are under-utilized, where operational emissions decline (e.g., electrification), or where lifetime service delivered per machine is low. Bubble size additionally highlights where embodied magnitude and material stock are largest; in these cases, slow (R3–R7) and close (R8–R9) strategies could yield particularly high absolute climate benefits by avoiding or delaying new material production and enabling high-quality recovery.

The archetype (A-D) descriptions below should be read as technology-linked guidance: technologies located in each region inherit the corresponding priority mix of narrowing (R0–R2), slowing (R3–R7), and closing (R8–R9) strategies, with technology-level assignment reported in Table S12.

Archetype A — Low annual operating hours & high cradle-to-gate share. Primary: Slow (R3–R7). Prioritize lifetime extension strategies that avoid new production (repair, refurbishment, remanufacturing, reuse/second-life). Secondary: Narrow (R1–R2), including intensified use where feasible; support with Close (R8-R9) for high-quality recovery where replacement cannot be avoided.

Archetype B — High annual operating hours & high cradle-to-gate share. Primary: Narrow + Slow. Combine manufacturing-side resource efficiency (yield improvement, material efficiency, recycled/low-carbon inputs where feasible) with operational efficiency and mid-life remanufacturing/modular upgrades. Secondary: Close (R8–R9) due to larger material stocks and recovery value.

Archetype C — Low annual operating hours & low cradle-to-gate share. Primary: Narrow (R1 Rethink). Prioritize utilization-oriented strategies (pooling/sharing, scheduling, service-based operation) to increase service delivered per machine and reduce redundant stock. Secondary: Slow (repair/maintenance/upgrades) where replacement could occur despite low utilization.

Archetype D — High annual operating hours & low cradle-to-gate share. Primary: Narrow (R2 Reduce). Prioritize operational resource/energy efficiency and low-carbon energy supply (efficiency upgrades, electrification where applicable). Secondary: Slow (R3-R7) e.g., via retrofit/refurbish and predictive maintenance to sustain efficiency and extend useful life.

For example, tractors of an engine power > 59 kW fall into the quadrant corresponding to Archetype C because their median annual operating hours are below 2128 h·yr^{-1} while their median cradle-to-gate share lies below 10.9%; thus, Narrow/Rethink strategies to increase intensity of use should be prioritized (see Table S12).

Although archetype placement is determined at the technology level, the map reveals a notable tendency: in our dataset, mobile technologies (e.g., AFM, and most MMC) are predominantly located in the low-annual operating hours region (left side), whereas stationary technologies (e.g., MFM, MFP) more often occupy the higher-annual operating hours regions (right side) (see mobile/stationary classification in Table S12). This tendency supports interpreting R1 ('Rethink') strategies (e.g., sharing/pooling/service models) as often more feasible for mobile, intermittently used machinery, while R2 ('Reduce') strategies (operational efficiency upgrades) may be more central for high-intensity stationary equipment. However, electrification should remain considered as a critical lever towards decarbonization of mobile machinery.

Policy instruments consistent with these CE priorities could include eco-design and repairability requirements (supporting slow/close loops), procurement criteria recognizing remanufacture/retrofit options (slow), and incentives for operational upgrades and high-quality material recovery systems (narrow/close), targeted according to the archetype region rather than category labels alone. Because datapoint coverage varies across technologies and some operating assumptions are harmonized across studies, archetype placement should be interpreted as indicative where n is small.

The added value of this synthesis lies not in the CE framework itself, but in the evidence-based positioning of specific machinery technologies within the archetype space and the resulting technology-linked prioritization of CE strategies to support decarbonization of the machinery sector. Accordingly, the archetype map should be interpreted as a screening and prioritization framework. It provides an empirical basis for identifying which CE strategies may be most relevant for a given machinery technology and for directing subsequent technology-specific analyses of feasibility, trade-offs, and climate mitigation potential.

4.5. Limitations

4.5.1. Heterogeneity of included studies and implications for cross-category comparisons

This study's findings are subject to some limitations primarily due to the heterogeneity of the underlying literature. Although LCA methods are standardized, cross-study comparisons of machinery technologies remain challenging because system boundaries, background assumptions, and reporting conventions vary. Differences included boundary definitions (e.g., including lubricants and consumables or just energy during operation) (Schischke et al., 2012), manufacturing setup (i.e., experimental/low-scale vs commercial/large-scale), impact assessment methods, inconsistent inclusion or omission of processes (often unclearly described), and the level of disaggregation of LCIA results. For example, the transport to the customer was included in cradle-to-gate in (Ecolean 2017; Ecolean 2017), while in some EPDs the EOL impacts were not differentiated and embedded in the use-phase (Presezzi Extrusion 2024; CandG Depurazione Industriale Srl 2024; C.S.I 2025; Ars Automation S.r.l 2025). EOL impacts were often inconsistently reported, sometimes as credits or included in other life cycle phases. Moreover, the level of process detail also varied, with some studies comprehensively modeling manufacturing and assembly (Bortolini et al., 2014; Martelli et al., 2023; Faludi et al., 2017; Lemardelé et al., 2023), while in others manufacturing was simplified (Khan and Huang, 2023; Wiik et al., 2023; Diaz-Elsayed et al., 2010; Stefanini et al., 2022; Volvo Construction Equipment 2025). Likewise, the electricity mixes between the various assessments differed across regional contexts, affecting both manufacturing and use-phase emissions. Consequently, across-study pooled medians should be interpreted as indicative central tendencies rather than universally representative values; thus, cross-category differences may partly reflect structural differences in the underlying studies.

4.5.2. Other limitations

Beyond heterogeneity, an important limitation was not having the same number of studies for each category. In addition, restricting the dataset to studies that disclose both cradle-to-gate and use-phase results, may have affected the results. Moreover, a few individual studies or EPDs represented a substantial portion of the analyzed sample e.g., (Schischke et al., 2012; Volvo Construction Equipment 2025; CandG Depurazione Industriale Srl 2024; CandG Depurazione Industriale Srl 2025), potentially influencing the results for certain technologies and categories. These features also affected the correlation analyses: Spearman and partial-Spearman results are descriptive associations rather than causal estimates, and datapoints are clustered within studies (i.e., not fully independent observations), which may inflate or bias correlation magnitudes. Given the number of pairwise correlations tested, p-values should be interpreted cautiously, with emphasis on effect sizes and consistency of patterns. Differences in parameter definitions across sources (e.g., rated vs installed power, lifetime and operating-hour assumptions) could still affect estimated associations.

The focus on GHG may divert attention from other relevant impact indicators (e.g., water use, toxicity, land use, resource criticality), which improve the decision-making process to identify trade-offs regarding mitigation strategies. Similarly, basing the analysis not only on machinery life cycle impacts but normalizing by product output (Schischke et al., 2012) may provide a more nuanced perspective on efficiency.

The archetype mapping was an exploratory, rule-based segmentation intended for prioritization rather than prediction. Archetype placement depended on technology medians and on the chosen quadrant thresholds, thus, technologies near thresholds may shift under alternative cut-offs. Moreover, archetype placement was more uncertain for technologies supported by few datapoints, and annual operating hours may be partly derived or harmonized from study assumptions, so utilization-related interpretations should be read more qualitatively.

Finally, the operational patterns and lifetime estimates and assumptions, particularly for per hour comparisons, must be interpreted with caution. While lifetime in years may be more predictable, precise hourly operation patterns often involve high variability. Extrapolating impacts to a full lifetime by assuming constant operational hours may overlook fluctuations in load factors, utilization rates, and shifting grid carbon intensities over time. While stationary industrial technologies often exhibit relatively stable operation, intermittent machinery such as AFM, LHE, and MMC are characterized by highly variable duty cycles. Consequently, the assumption of a constant load factor and utilization represents a limitation that may result in the under- or over-estimation of use-phase impacts.

5. Conclusion and outlook

In this study, the life cycle climate impacts of 39 distinct industry-specific machinery technologies across 10 NACE categories were analyzed. A substantial range of impacts was identified, differing by several orders of magnitude. Overall, we found a notable under-representation of environmental studies of machinery in existing literature. It was also found that many studies lacked detailed material yield and manufacturing data, thus representing a significant gap in environmental assessments of the sector.

The analysis showed that the use-phase is generally the dominant contributor to cradle-to-grave impacts per unit, indicating that improving material and energy efficiency during operation is often the greatest lever for GHG reductions. At the same time, the cradle-to-gate impacts were not negligible for multiple machinery types and can become relatively more important under low utilization and under decarbonization pathways such as electrification, which can shift the burdens toward embodied materials and manufacturing.

By quantifying parameter-impact relationships using Spearman correlations, the results indicated stage-specific drivers: cradle-to-gate impacts were strongly associated with machinery mass independent of installed power, while operational impacts retained smaller independent associations with both mass and installed power as complementary scale proxies. Operating-time proxies were most informative for explaining burden allocation rather than consistently predicting absolute operational impacts across heterogeneous technologies. This supports phase-specific bottom-up parameterization: mass-informed modeling for cradle-to-gate impacts and a use-phase representation that combines operating time with an intensity proxy (e.g., duty/load factors or energy-use intensity), rather than operating hours alone.

A key contribution of this work is the evidence-based positioning of various machinery technologies in a stage-resolved archetype space using cradle-to-gate share, annual operating hours, and mass (as embodied scale indicator), and the translation of these positions into prioritized CE strategies. This showed that mitigation priorities may depend more on burden structure and use patterns than on NACE category labels alone, enabling technology-linked prioritization of circular economy interventions and supporting bottom-up representations and scenario exploration of machinery climate impacts.

Future research could build upon these foundational insights by expanding the analysis to other significant NACE categories, such as general-purpose machinery (28.1 and 28.2) and electrical equipment (27.9). Furthermore, subsequent studies may couple these findings with top-down approaches (e.g., EEIO analyses) to gain valuable insights into the sector's broader environmental footprint. Integrating the environmental impacts of capital assets with future demand scenarios would also allow for more dynamic and comprehensive assessments.

Glossary

Abbreviations	Description
AMM	Additive Manufacturing Machinery
AFM	Agricultural and Forestry Machinery
CO_2e	Carbon dioxide equivalent
CE	Circular Economy
CGE	Computational General Equilibrium
EEIO	Environmentally-extended Input-Output
EOL	End-of-life
EPD	Environmental Product Declaration
EU	European Union
GWP	Global warming potential
GHG	Greenhouse gas emissions
IAM	Integrated assessment model
LCA	Life cycle assessment
LCIA	Life cycle impact assessment
LCI	Life Cycle Inventory
LHE	Lifting and Handling Equipment
MFP	Machinery for Food, Beverage and Tobacco Processing
MM	Machinery for Metallurgy
MMC	Machinery for Mining, Quarrying and Construction
MTP	Machinery for Textile, Apparel and Leather Production
MFA	Material Flow Analysis
MFM	Metal Forming Machinery
NACE	Statistical Classification of Economic Activities in the European Community
OMT	Other Machine Tools
n.e.c.	Not elsewhere classified
OSPM	Other Special-Purpose Machinery n.e.c.
PRM	Plastics and Rubber Machinery
PCF	Product Carbon Footprint
PCR	Product Category Rules
WoS	Web of science

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, we used ChatGPT (GPT-5) and DeepL Write to check for grammatical errors and improve readability and language. Having used these tools, we reviewed and edited the content as necessary, taking full responsibility for the published article.

CRediT authorship contribution statement

Alejandro Arias-Castillo: Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Data curation, Conceptualization. **Tobias Viere:** Writing – review & editing, Supervision, Methodology, Funding acquisition, Conceptualization.

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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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.rcradv.2026.200354.

Data availability

All data generated or analyzed during this study are included in the Supporting Information.

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