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The environmental footprint of point-of-care diagnostics: quantitative review and a practical eco-design metric

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Single-use biosensors such as lateral flow assays (LFAs) have transformed point-of-care (PoC) diagnostics, yet their environmental footprint is rarely considered during design. As deployment scales globally, this oversight raises pressing sustainability concerns. Although early integration of eco-design principles could reduce environmental burdens, biosensor developers lack practical tools to operationalize sustainability during early-stage development. This practical review proposes a quantitative, multi-scale design methodology that bridges materials selection and system-level performance. We compile environmental indicators for materials commonly used in biosensors and conduct a PRISMA-based review of life-cycle assessments, revealing distinct orders of magnitude in carbon footprint across LFAs, instrumented devices, and PCR-based systems. Building on these findings, we introduce the Environmental Cost of Performance (ECoP), a simplified eco-design metric that links analytical sensitivity to environmental impact and reframes conventional performance-driven technology roadmaps into performance-impact trade-off approaches. This practical review is intended to serve as a quantitative toolbox, enabling scientists to integrate eco-design principles into their development practices and to arbitrate between design options using operational environmental metrics. In doing so, it represents a first step beyond generic sustainability claims, paving the way for broader impact assessments that integrate environmental, economic, and societal dimensions into PoC diagnostic innovation.

KEYWORDS
biosensors, diagnostics, eco-design, environmental footprint, lateral flow assay (LFA), life cycle assessement (LCA), point-of-care (POC), sustainability

1 Introduction

The detection and identification of pathogens in clinical, food, and environmental samples is a global priority for safeguarding both public health and ecosystem integrity (Ikuta et al., 2022). Conventional pathogen detection methods (such as culture, ELISA, PCR, and MALDI-TOF-MS) provide high sensitivity and specificity, but remain limited by cost, operational complexity, infrastructure requirements, and long turnaround time. These limitations have accelerated the development of point-of-care (PoC) diagnostics, i.e., rapid, affordable, and field-deployable systems that operate without specialized laboratory infrastructure (Land et al., 2018). PoC platforms, often referred to as Lab-on-a-Chip (LoC), typically integrate microfluidics, selective biorecognition elements, and optical or electrochemical transduction, enabling diagnostic results within minutes. Among them, lateral flow assays (LFAs) have emerged as the most widely adopted technology, especially during the COVID-19 pandemic, where their simplicity and accessibility have driven massive global adoption. The United Nation alone distributed more than 140 million LFA kits worldwide during the pandemics (WHO, 2022), while statistical data reports that 4.21 billion COVID-19 diagnostic tests have been done in a set of 122 countries around the globe (Ji et al., 2022). Their simplicity, low cost, and regulatory demand for more frequent testing continue to drive global deployment across healthcare, food safety, and environmental monitoring sectors. Today, LFAs are estimated to exceed 2 billion units produced annually, generating approximately 20,000 tons of plastic waste each year worldwide (Street and Kersaudy-Kerhoas, 2025). Although individually lightweight, single-use devices generate substantial cumulative waste when deployed at global scale. While this widespread adoption brought immense public-health benefits, it also exposed a critical blind spot: the environmental burden of disposable diagnostics.

By design, PoC diagnostics prioritize rapid use. However, their functional lifetime, often only minutes, contrasts sharply with the material and energy resources required for their production (Boisson, 2024). LFAs typically consist of multiple plastic components (cassettes, membranes, pads), silica desiccants, printed instructions, sealed reaction containers, and multilayer packaging. In high-throughput settings, PoC devices can account for 5%–20% of daily medical waste, amounting to several tons per institution annually (Ongaro et al., 2022). Moreover, most PoC devices are not designed with end-of-life considerations. In healthcare settings, contamination with biological materials classifies them as biohazardous waste, leading primarily to incineration or landfilling, both associated with greenhouse gas emissions and irreversible material losses. In low-resource contexts, inadequate waste management systems further exacerbate environmental risks through inefficient incineration or open dumping, increasing pollutant release and ecosystem contamination (Cook et al., 2023; Janik-Karpinska et al., 2023). The presence of reactive reagents, including nanomaterials or cyanide-based compounds, may further amplify environmental and health hazards if improperly disposed of (Ongaro et al., 2022).

Growing public concern intensified during the COVID-19 pandemic (Adyel, 2020) and underscored the unsustainability of the current diagnostic model. This growing concern prompts a broader question: are PoC devices invariably part of the solution, or can they also contribute to emerging environmental burdens (Morris and Haworth, 2022; Deman et al., 2024)? These observations call for a systemic perspective on the PoC diagnostic landscape. Rather than focusing mainly on analytical performance, such an approach integrates upstream (materials, processes, design), downstream (end-of-life), and stakeholder-related dimensions that are often neglected in conventional PoC sensor design frameworks (Figure 1).

In response to this systemic challenge, eco-design has emerged as a key approach to reduce environmental impacts across the lifecycle of PoC devices. Defined by ISO 14062, eco-design involves incorporating environmental considerations into the product development process (ISO, 2020), from material selection and fabrication to use, disposal and recyclability. Several eco-design tools can be used, differing mainly in the recommendation and assessment levels they provide (Pirson et al., 2024). Quantifying the environmental impacts across a product life cycle is conventionally performed using Life Cycle Assessment (**LCA**), the internationally standardized methodology (ISO 14040/44) (ISO, 2006b). Eco-design strategies sometimes follow the "10Rs" hierarchy which includes strategies like Refuse, Reduce, Reuse, Repair, and Recycle (Morseletto, 2020). These principles are increasingly aligned with legislative and economic drivers (e.g. Scope 3 emissions reporting, HSE impact audits, sustainability criteria in public procurement approaches), especially in the context of large-scale healthcare procurement (Ongaro et al., 2022). The decarbonization of medical devices is increasingly becoming a policy priority in Europe, with national initiatives identifying PoC diagnostics as a target category for environmental impacts reduction (Boisson, 2024). However, eco-design remains difficult to implement in practice, especially in early-stage research and prototyping (technology readiness level, TRL 1–4), when design flexibility is maximal and environmental improvements can still be most effectively realized. This reflects the well-known *design paradox*: most environmental impacts are locked in during early design, yet the data needed for a comprehensive LCA are rarely available at that stage (Buyle et al., 2019). When conducted later in the product development, LCAs offer limited influence over core design decisions.

Conducting full LCAs on early PoC concepts is often impractical due to (i) limited technical maturity and parameter uncertainty (Buyle et al., 2019; Moni et al., 2020), (ii) lack of sustainability expertise integrated in the training of PoC device scientists or in their collaborative networks (Core, 2023), (iii) the resource- and time-intensive nature of conventional LCA (Hetherington et al., 2014). Simplified LCA (sLCA) methods offer a partial solution. By reducing the number of impact categories and input data requirements, these approaches make life-cycle thinking more accessible, albeit at the cost of some loss of granularity (Ecoinfo, 2012). However, sLCA remains underutilized in the diagnostic device community. As a result, most eco-design efforts in diagnostics are still qualitative, guided by generic sustainability recommendations rather than quantifiable trade-offs. This limits the ability of researchers and developers to rationalize material or process choices based using explicit sustainability metrics. Recent reviews (Ongaro et al., 2022; Deman et al., 2024) and industry analyses (Unitaid, 2023) call for the development of quantitative yet accessible tools to support decision-making when facing sustainability trade-offs in the design of single-use diagnostic devices.

This paper contributes to bridging this methodological gap by providing a quantified and design-oriented review of the environmental impacts of PoC diagnostic devices and their constituent material, with a particular focus on biosensors. It is structured as follows. First, a material-level sustainability analysis is conducted. Breakdowns of material types used in both research and commercial settings are presented. We compile and compare quantitative life-cycle indicators (carbon footprint, water use, and embodied energy) for the materials most frequently used in PoC diagnostic devices, aiming to support preliminary material selection through sLCA screening at early TRLs. These indicators are complemented by macro-economic parameters to extend the

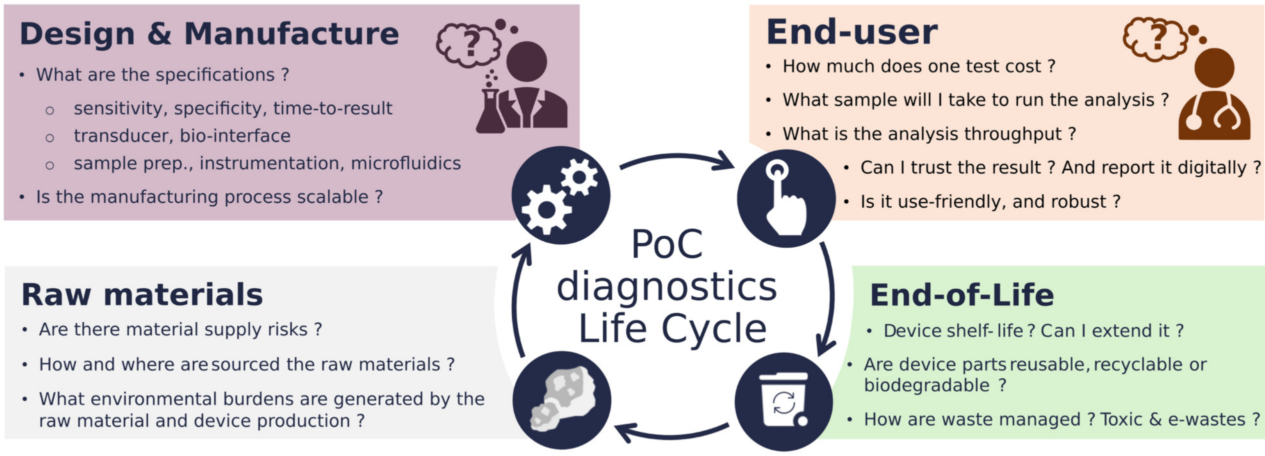


FIGURE 1
System view of the point-of-care (PoC) diagnostics landscape. Design efforts, particularly in academic research, tend to concentrate primarily on the scientific and technical aspects of biosensor development, often overlooking critical considerations arising from stakeholders (e.g., end-users) as well as from other life-cycle stages, including raw material sourcing and end-of-life management. Integrating these dimensions is essential to develop technologies that are suitable for long-term deployment, large-scale dissemination, and meaningful societal impact.

sustainability analysis beyond the environmental dimension. Second, a system-level assessment is performed through a PRISMA-guided review of existing full LCAs on PoC diagnostic systems. To the best of our knowledge, no dedicated quantitative review of LCAs on biosensors currently exists. As a result, consistent information on how researchers evaluate the environmental performance of their devices remains fragmented. The system-level therefore pursues three objectives: (1) to identify research studies that address sustainability through LCA of biosensor devices and consolidate their environmental impact results, (2) to analyze the motivations driving these assessments and (3) to examine methodological trends and gaps in current research to highlight priorities for improvement. Finally, we propose a practical eco-design indicator that builds on the preceding analyses to support informed decision-making during early development phases. By making explicit the trade-offs between analytical performance and environmental impact, this simplified metric provides a quantitative entry point for eco-design in biosensor development, without aiming to prescribe universal solutions. Overall, this work supports the broader transformation of next-generation diagnostics by operationalizing environmental sustainability as a design criterion, thereby contributing to a diagnostics industry that is not only effective and accessible, but also environmentally responsible.

2 Methodology

2.1 Classification of point-of-care diagnostic devices and their conventional figures of merit

To enable structured assessment and comparison of environmental performance among PoC diagnostic devices, we first establish a classification that reflects the main existing technological platforms currently commercialized or published in literature (Figure 2). This classification is aligned with typical biosensor use-cases (e.g. rapid screening, quantitative diagnostics, or decentralized molecular detection).

Paper-based devices - LFAs use paper or nitrocellulose strips embedded in plastic cassettes, enabling unidirectional spontaneous capillary-driven flow and colorimetric or fluorescent readouts. They are low-cost, instrument-free, and ideal for rapid screening (e.g., COVID-19, pregnancy), though they suffer from lower sensitivity and limited multiplexing (Budd et al., 2023). To overcome LFA structural limitations, microfluidic paper-based analytical devices (μPADs) are highly attractive in research since they exploit the ability to wick fluids in multiple dimensions in the cellulose-based substrate through patterning of hydrophobic channels (e.g. wax) (Martinez et al., 2007; Singh et al., 2018; Noviana et al., 2021).

Instrumented PoC devices - Instrumented PoC devices often integrate microfluidics (microchannels), reaction chambers, and onboard reagents into disposable plastic, glass, ceramic or silicon encapsulated cartridges, typically requiring a portable reader for detection. These devices integrate sample processing and detection, often with electrochemical or optical readouts. These are suited to more complex cases (e.g., glucose monitoring (Gokhale et al., 2025), or cartridges for coliform detection in water (Sudheshwar et al., 2023)), offering better analytical performance but with higher costs and potential e-waste from electronics. The microfluidic paper-based electrochemical devices (μPEDs) trend is an added value to the μPADs since it combines the merits of paper-based capillarity, to the high sensitivity and selectivity of bioelectrochemical detection (Silveira et al., 2016).

PCR devices - Portable PCR-based platforms miniaturize nucleic acid amplification and detection into single-use cartridges paired with compact thermocyclers (Ji et al., 2022). Used mainly in clinical and veterinary diagnostics, they offer high sensitivity and specificity.

Overall, each class typically combines disposable foil pouches, extraction tubes, cartridges or cassettes, containing materials like non-degradable polymers or ceramics, metals, membranes, reagents, and sometimes electronics.

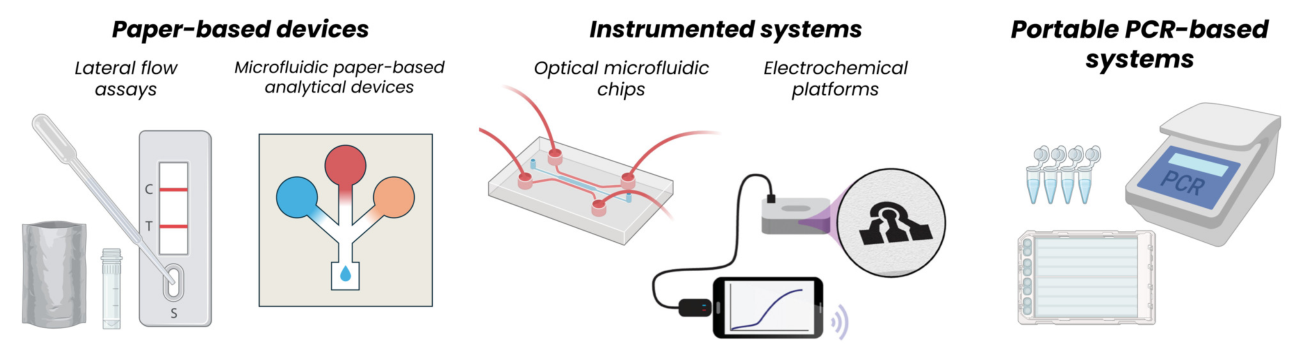


FIGURE 2
Main classes of PoC diagnostic devices. Schematic overview of the dominant technological platforms used in point-of-care diagnostics. Figure created with BioRender. Electrochemical platform reproduced from (Bezinge et al., 2024).

TABLE 1 Share of main substrate material types in commercial PoC diagnostic devices (Ongaro et al., 2022).

Material type	Share in commercial devices	Examples
Thermoplastics	59%	PMMA, PP, ABS
Glass/silicon	12%	Soda-lime glass, borosilicate
Paper/Nitrocellulose	12%	Cellulose, nitrocellulose membranes
Elastomers	6%	PDMS
Epoxy	6%	Epoxy resins, hybrid composites
Others	5%	Natural fibrous materials, biopolymers

At the core of every PoC device lies the *substrate* material, which serves as both the mechanical support and the interface for microfluidics, detection, and reagent deposition. Substrate materials play a central role in the technical performance of a PoC device and its manufacturability, but also on its environmental footprint. Based on industry and academic surveys (Table 1) (Ongaro et al., 2022), thermoplastics dominate commercial use due to low cost and compatibility with injection molding, typically used for sample preparation tools used in biochemistry and mixing channels (Whitesides, 2013). Silicon or glass substrates, mainly used in micro-electromechanical system (MEMS)-based or lab-on-a-chip integrated platforms, offer high sensitivity and chemical resistance but remain at higher cost and their production process is resource-intensive (Jenkins et al., 2015). Cellulose papers and nitrocellulose are favored for LFAs and µPADs due to their spontaneous microfluidics, ease of integration in large-scale manufacturing process (e.g. roll-to-roll) and compatibility with biomolecules, therefore offering low-cost, biodegradable substrates suitable for rapid screening (Martinez et al., 2007; Fridley et al., 2013). Elastomers such as polydimethylsiloxane (PDMS) are widely used in academic prototyping but rarely in commercialized devices.

To determine how sensors would perform as PoC devices, they are generally assessed through the ASSURED framework proposed by the WHO (Affordable, Sensitive, Specific, User-friendly, Rapid and Robust, Equipment-free, Deliverable to end-users). Quantitative Figures of Merit (FoMs) associated with these criteria, such as cost per test, detection limit, time to result, reproducibility, and usability, are compiled in Table 2.

2.2 Environmental and systemic indicators for material-level sustainability assessment

Conventional biosensor performance reviews rarely report environmental indicators (Mazur et al., 2023). Similarly, considerations for lowering environmental impacts or anticipating end-of-life treatment are typically excluded from design requirements so far. For example, to the best of our knowledge, the conventional structure of Target Product Profiles (TPPs), which guide manufacturers on market needs and technical specifications, typically excludes considerations related to waste management or end-of-life disposal.

In the last decade, developments in global health diagnostics frameworks have introduced the REASSURED criteria (Land et al., 2018), which extend the original ASSURED principles to include two new priorities: Real-time connectivity and **E**nvironmental sustainability. The latter explicitly acknowledges the need to reduce the environmental footprint of diagnostic devices throughout their life cycle. In recent topical reviews (Ongaro et al., 2022; Belfakir et al., 2024) and industry analyses (Unitaid, 2023), the environmental sustainability dimension remains largely qualitative and insufficiently operationalized. Recommendations for diagnostic devices typically focus on material substitution (e.g., single-use fossil-based plastics with bio-sourced polymers or cellulose), waste minimization *via* design-for-disassembly and the use of recyclable materials (Morseletto, 2020), sustainable alternatives or avoidance of toxic or high-impact reagents, energy-efficient manufacturing and process optimization, or ensuring safe disposal of electronic components (Ongaro et al., 2022). While valuable, these guidelines provide limited actionable support for

TABLE 2 Conventional specifications and Figures of Merit (FoMs) according to the ASSURED criteria. Compiled from (Land et al., 2018; Budd et al., 2023; Le Brun, 2023).

ASSURED criterion	Description	Quantitative figure of merit	Typical target values
Affordable	Cost-effective and scalable in low-resource settings	Unit cost (€/test)	0.5–10 € per test depending on application field
Sensitive	Detects low analyte concentrations	Limit of Detection (LoD)	10^2–10^3 CFU/mL for bacteria; <10 ppb for metals
Specific	Avoids false positives and cross-reactivity	Specificity rate (%)	>90% specificity under realistic conditions
User-friendly	Easy to operate by non-trained users	Number of operational steps	<3 simple steps (e.g., collect, apply, read)
Rapid	Provides fast results	Time to result (min)	15–60 min
Robust	Maintains performance under storage and use constraints (e.g. real samples)	Reproducibility (CV %), shelf-life, temperature resistance	CV < 10%, 4 °C–40 °C operation
Equipment-free	Minimal or no instrumentation required	Instrument dependency/Mass of equipment	None or portable (<1 kg)
Deliverable	Logistics-compatible for remote or resource-limited regions	Storage constraints, shelf-life, mass per unit	>12 months shelf-life, ambient storage, <100 g and <0.5 L per test

TABLE 3 Environmental and systemic FoMs for PoC device materials. These metrics form the core of the material-level sustainability screening discussed in this paper. They allow early differentiation of material candidates beyond their technical performance alone.

Category	Systemic FoM	Typical units	Purpose
Embodied footprint	Embodied Energy (EE)	MJ/kg	Total energy used in material extraction, processing, and fabrication
	Carbon Footprint (CFP)	kg CO_2-eq/kg	Greenhouse gas emissions from cradle to gate
	Water Footprint	L/kg	Freshwater use during production
	Manufacturing Process Energy/Emissions	MJ/kg; kg CO_2-eq/kg	Energy and emissions associated with shaping or assembly (e.g. injection)
Material sourcing	Material abundance in Earth's Crust	ppm (by weight)	Scarcity of the raw material
	Annual Global Production	Tons/year	Market availability
	Critical Raw Material Risk	Yes/No	Dependency on economically sensitive resources (risk of supply shortage)
	Market Price	€/kg	Economic constraint for substitution

early-stage design decisions, where quantitative trade-offs between materials, architectures, and sourcing strategies must be evaluated. As a result, eco-design in PoC diagnostics is still predominantly guided by general sustainability principles rather than by structured, evidence-based decision tools.

To address this gap, we compiled a set of quantitative sustainability indicators from the LCA and environmental engineering literature, focusing on materials commonly used in PoC devices (Table 3). These indicators include both material-level and system-level FoMs, such as embodied environmental footprints and resource sourcing. They are selected based on their relevance to early-stage quantitative design decisions and their availability in publicly accessible material and environmental databases that do not require full LCA expertise to interpret (Ashby, 2016).

While aspects related to material durability and end-of-life performance (e.g. recyclability, biodegradability, and compatibility with recycling or downcycling streams) are essential components of a comprehensive environmental assessment, they are not expressed here through standardized quantitative metrics. This limitation reflects the current lack of harmonized, accessible, and comparable datasets across materials and recycling contexts. Nevertheless, these dimensions are considered in the eco-design recommendations discussed in this review. Their rigorous quantification will require dedicated studies integrating the full recycling value chain and its associated stakeholders, representing an important direction for future research.

2.3 Literature review of life cycle assessment studies of point-of-care diagnostic devices

The PRISMA review was conducted using the Scopus database, which was last queried in October 2025. Since the focus is on LCAs, only the keywords "life-cycle assessment" and "life cycle assessment" were used for the sustainable aspects. These two keywords were systematically combined with various other to select studies on biosensors. The resulting search strings were.

- (TITLE-ABS-KEY ("biosensor") AND TITLE-ABS-KEY ("Life-cycle assessment" OR "Life cycle assessment"))

TABLE 4 Inclusion and exclusion criteria for the PRISMA review.

Inclusion criteria	Exclusion criteria
Language	
English language	Other languages
Article Type	
Journal articles	Conference Papers, Reviews, Book Chapters, Books, Editorials, Letters, Notes, Erratum
Year of publication	
Any year	
Demographic origin	
Any region in the world	
Life Cycle Assessment	
Performed and described	Results only, Mention or No mention
Sensor	
Biological or biochemical target	No biological or biochemical target

- (TITLE-ABS-KEY ("sensor") AND TITLE-ABS-KEY ("Life-cycle assessment" OR "Life cycle assessment"))
- (TITLE-ABS-KEY ("point of care" OR "point-of-care")) AND (TITLE-ABS-KEY ("Life-cycle assessment" OR "Life cycle assessment"))
- (TITLE-ABS-KEY ("rapid test" OR "rapid testing")) AND (TITLE-ABS-KEY ("Life-cycle assessment" OR "Life cycle assessment"))
- (TITLE-ABS-KEY ("diagnostic")) AND (TITLE-ABS-KEY ("Life-cycle assessment" OR "Life cycle assessment"))
- (TITLE-ABS-KEY ("detection") AND TITLE-ABS-KEY ("Life-cycle assessment" OR "Life cycle assessment"))

One author screened the papers based on their titles, abstracts, keywords, and full texts. A second author reviewed the screening results. Table 4 presents the eligibility criteria. All articles that have been submitted to the screening process are compiled in an *ad hoc* Excel table available in the Supplementary Material. One author extracted relevant data and collected it in a summary table. The variables of interest included information about the biosensor studied, information about the motivations of the environmental study, and information about the LCA methodology. Note that potential bias can originate from the limited number of authors and the use of only one database.

3 Results

3.1 Exploring material-level sustainability metrics for more informed material choices

Figures 3, 4 present the key environmental performance metrics of materials commonly used in PoC diagnostic platforms, including bio-based materials, thermoplastics, elastomers, and inorganic materials (e.g., metals, semiconductor-grade silicon, ceramics). Each point corresponds to a distinct material or element (e.g., PMMA, PDMS, aluminum), while colors and markers denote material classes. The large number of points reflects the number of different materials included in the analysis rather than multiple datasets for the same material. Only selected representative materials are labeled in the figures and discussed in the text for clarity. The complete numerical dataset is provided in the Supplementary Material.

The embodied energy (EE) [MJ/kg], carbon footprint (CFP)[kg CO_2-eq/kg], and water [L/kg] intensity values correspond to cradle-to-gate averages compiled from harmonized industrial datasets, primarily following (Ashby, 2016). EE refers to the primary energy required to produce a material from its raw form per unit mass, including extraction and refining steps (Gutowski et al., 2013). These intensities are not intrinsic material constants but system-dependent indicators, varying with energy mix, resource quality, processing routes, recycling content, and plant efficiency. As discussed in (Gutowski et al., 2013), such variability may reach ±20% or more around representative values. In principle, each material could therefore be represented by a range rather than a single point. However, for early-stage eco-design screening and cross-material comparison, consistent global-average values are used. The figures also present systemic metrics (abundance, critical material risk, world production and world market price). These indicators and macro-economic conditions reflect both upstream impacts and supply-chain constraints, offering a complementary perspective to the technical FoMs introduced earlier. These intensity and macro-economic values are derived from harmonized literature-based datasets and specialized organization reports (Allwood et al., 2011; Graedel et al., 2015; Ashby, 2016; Wall et al., 2017; International Energy Agency, 2023; World Gold Council, 2023; U.S. Geological Survey, 2023), and may have evolved over time due to technological improvements, geopolitics and changes in industrial energy systems.

A strong correlation is observed between EE and CFP ($R^2 \approx 0.92$), confirming that CFP is primarily driven by primary energy requirements, i.e. the carbon dioxide intensity of material production is dominated by the energy intensity of production and the implied fuel usage, rather than material-specific emission factors (Gutowski et al., 2013).

Metals, precious metals (e.g. gold), rare earth and semiconductors exhibit high to very high EE (100–600,000 MJ/kg) and CFP (10–30,000 kg CO_2-eq/kg). The disparities between these classes primarily stem from energy-intensive extraction, refining, and purification steps (Weng et al., 2016). This is particularly apparent for semiconductors (6–9N electronics-grade purity silicon), which reflect its purification and wafer fabrication processes, including energy-demanding steps like Czochralski crystal growth (Boyd, 2012). Water usage varies significantly across material classes, particularly for certain metals requiring large volumes during pulping or hydrometallurgical processing (Peña and Huijbregts, 2014). Noble and strategic metals such as gold, palladium, indium, and gallium are widely employed and essential to certain microelectronic biosensors components for signal transduction and electronic interfaces (e.g., in surface-enhanced raman spectroscopy (SERS), field-effect transistors (FETs), or electrochemical sensing modalities) (Leïchlé et al., 2020). While technically enabling high-performance

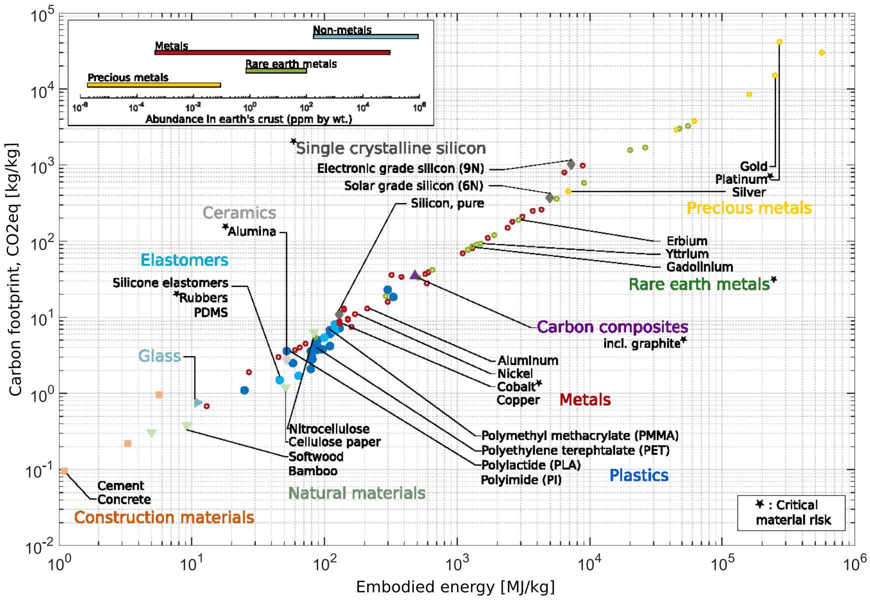


FIGURE 3
Embodied Energy and Carbon Footprints of classes of materials used in PoC diagnostic device. Each point represents a distinct material using a representative cradle-to-gate value. Colors/markers denote material classes. The complete dataset is provided in the Supplementary Material.

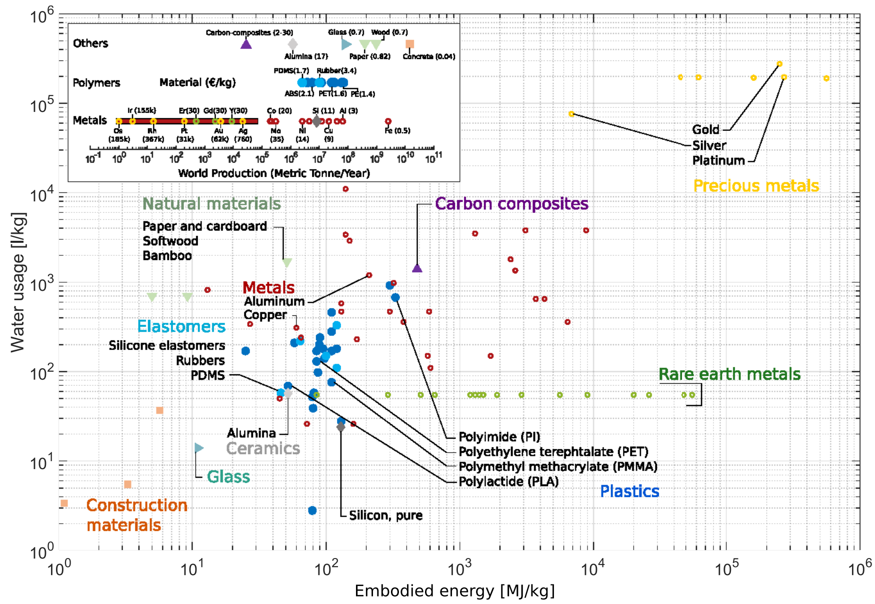


FIGURE 4
Water consumption per unit material produced [L/kg]. Inset: World production with material price. Each point represents a distinct material using a representative cradle-to-gate value. Colors/markers denote material classes. The complete dataset is provided in the Supplementary Material.

diagnostics, these elements combine high embodied carbon and water intensities.

Plastics and elastomers occupy an intermediate position in terms of environmental intensity. Their EE and CFP span wide ranges (typically 80–150 MJ/kg and 4–9 kg CO_2-eq/kg), which depend on polymer type and processing route (e.g., extrusion, injection molding). They are generally less water-intensive than paper-based materials and significantly less than semiconductor-grade silicon. For example, PMMA displays an EE of approximately 110 MJ/kg and a CFP of about 7 kg CO_2-eq/kg. PDMS, widely used in academic microfluidics and rapid prototyping, exhibits moderate embodied energy (~130 MJ/kg) but suffers from limited scalability and concerns related to the toxicity of solvents used in the manufacturing process (Shakeri et al., 2021). Although recent studies have shown that PDMS-based microfluidic devices can be scaled up through injection molding (Filion et al., 2025), its overall environmental performance remains questionable, making it a less favorable option for large-scale or single-use PoC applications despite its strong technical versatility.

Natural materials exhibit comparatively low EE and CFP, typically within 10–100 MJ/kg and below 8 kg CO_2-eq/kg). For instance, cellulose paper has been reported with an EE of approximately 51 MJ/kg EE and a CFP of 1.2 CO_2-eq/kg, whereas nitrocellulose reaches about 90 MJ/kg and 7.5 CO_2-eq/kg, respectively (Vandeputte, 2021). This apparent advantage, however, is offset by very high water consumption (which can exceed 3000 L/kg), driven by pulp processing and washing steps. Such water intensity is often underreported in diagnostic eco-design literature but could become critical in low-resource settings. Beyond cellulose and nitrocellulose, bio-based and biodegradable polymers such as PLA, bamboo-derived substrates, chitosan, gelatin, and silk are increasingly investigated as attractive alternative to conventional petroleum-based polymers for the manufacture of sustainable PoC systems. Although their mass-scale cost-competitive production with reproducible properties must still be demonstrated, the diversity of the proposed bio-sourced materials could be a major advantage because each material could address different applications depending on its properties (Zimmer et al., 2026). However, as emphasized in (Street and Kersaudy-Kerhoas, 2025; Core, 2023), biodegradable plastics does not inherently ensure lower environmental impacts since they may entail trade-offs related to agricultural land availability, the mix of fossil fuels with biomass in their manufacture, and end-of-life scenarios (e.g. release of potentially harmful micro-bioplastics). In addition, harmonized cradle-to-gate EE and CFP datasets for several emerging biopolymers remain limited or highly process-dependent (Zimmer et al., 2026). Therefore, for methodological consistency, only materials supported by comparable environmental intensity data are quantitatively represented in Figures 1, 2. Emerging bio-based alternatives are discussed qualitatively in recent reviews as promising yet context-dependent options. However, their full environmental performance remains insufficiently assessed and requires dedicated life-cycle assessment studies (Ongaro et al., 2022; Batet and Gabriel, 2025; Zimmer et al., 2026).

Beyond intrinsic material intensities, the environmental burden of PoC devices is strongly influenced by processing routes. As quantitatively highlighted in (Irimia-Vladu, 2014), electronic-grade inorganic materials often require high-temperature purification, vacuum deposition, and nanostructuring steps, leading to very high manufacturing energy demands. By contrast, thermoplastic polymers are compatible with extrusion or injection molding, which operate at lower temperatures and are generally less energy-intensive. At an even lower processing-energy level, paper-based and natural substrates enable ambient or low-temperature fabrication methods such as printing, wax patterning, and reel-to-reel manufacturing, without cleanroom or vacuum infrastructure (Jenkins et al., 2015). Therefore, material selection alone is insufficient, and the sustainability of PoC platforms also depends critically on the compatibility of materials with low-energy, scalable processing technologies.

In addition to environmental metrics, resource availability, sourcing constraints and price offer further insights for early-stage screening. Commodity materials such as paper or common thermoplastics benefit from high global availability, relatively low criticality, and low market price (typically below 3 €/kg). With low natural abundance, geopolitical concentration of mining, limited suppliers and price volatility, specialty substrates like PDMS and metals, including rare earths and semiconductors may face supply disruption risks, especially under geopolitical or market tension (Graedel et al., 2015). Therefore, several of these metals rank high in criticality indices, raising both environmental and strategic concerns. These combined environmental, economic, and strategic trade-offs are therefore central to material selection, particularly when designing scalable and affordable single-use PoC diagnostics.

Environmental Impacts of Bioreceptors - Among biorecognition elements, antibodies, both monoclonal (mAbs) and polyclonal (pAbs), remain dominant in commercial PoC and immunoassay systems. Although used in milligram (or lower) quantities per test, the energy and carbon intensity of mAb production is several orders of magnitude higher than that of natural or polymeric substrate materials due to biological production routes and reliance on energy- and resource-intensive processes (tightly controlled cell culture in bioreactors). According to (Renteria Gamiz et al., 2019; Amasawa et al., 2021; Budzinski et al., 2022; Béchu et al., 2024), the carbon footprint of mAb production ranges from 5 to about 100 kg CO_2-eq per Gram of purified antibody, depending on process yield and configuration. Two main production modes are typically distinguished: continuous (perfusion bioreactors), in which culture medium is continuously renewed while cells are retained within the reactor, and fed-batch, in which the culture is maintained until the end of the run. Reported water consumption for upstream and downstream processing is 35–50 L per Gram, while cumulative energy demand can exceed 50 MJ per mg of final product (Bunnak et al., 2016). The dominant contributors to the environmental footprint include cell culture media, single-use plastic consumables (bags, filters, tubing), and electricity consumption associated cleanroom infrastructure and cold-chain utilities. Finally, it should be noted that pAb production, although less well quantified environmentally due to its animal-based process (immunization and serum collection), raises other sustainability concerns such as animal welfare and batch-to-batch variability. From an eco-design perspective, these findings emphasize the relevance of exploring recombinant or cell-free expression systems and synthetic recognition elements (e.g., aptamers, molecularly imprinted polymers, MIPs) as potential strategies to reduce the overall environmental burden of bioreceptors in PoC diagnostics.

These results, spanning biological, organic, and inorganic materials used in PoC diagnostics, collectively demonstrate that no single material is environmentally optimal across all FoMs. Instead, the analysis highlights situations where design choices inevitably lead to arbitrages: reducing environmental burdens may come at the expense of resource accessibility or technical utility, as these variables do not necessarily improve in the same direction. For example, while paper-based substrates are attractive

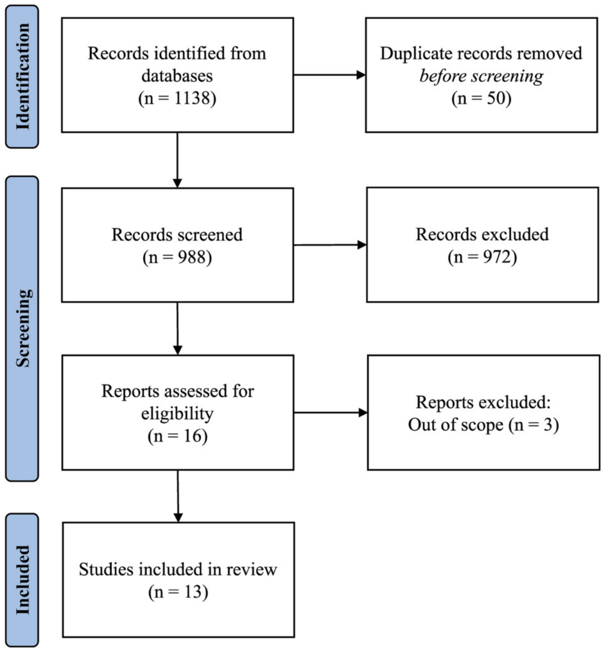


FIGURE 5
Study selection process (PRISMA flow diagram) divided into 3 phases: identification, screening, and inclusion (Page et al., 2021).

for low carbon intensity and low cost, their high-water usage and limited functionality may constrain use in high-performance diagnostics. On the contrary, silicon substrates can offer highly performant devices but are linked with significant environmental costs. These material-level insights should ultimately be validated through device-level assessments that account for the actual mass and proportion of each component in the final product.

3.2 Review of LCA of PoC diagnostic devices highlights a significant gap in the literature

3.2.1 Study selection and dataset overview

The initial search yielded 988 potential sources. Of those, 629 were scientific journal articles reporting original results. Of those articles, 427 conducted an LCA; 78 were sensor studies; and only 25 considered biosensors. Ultimately, only 16 articles performed an LCA on biosensors (Figure 5). After screening, 16 papers that met the criteria proceeded to a full-text review. Thirteen articles satisfied the imposed requirements and were included in the analysis. Table 5 summarizes the systematic review of studies that performed an LCA on biosensors. For a detailed table of source selection, readers can consult the Supplementary Material.

Years and authors - The articles included in the review were all published within the last 4 years (2022–2025), except for one (Torres et al., 2018) that was published in 2018. Despite the existence of LCA framework for many years, with the ISO 14040 and ISO 14044 standards both published in 2006 (ISO, 2006a; ISO, 2006b), the systematic review suggests that the consideration of the environmental burden of biosensors is a recent development. The review also reveals that only one paper was authored by scholars from multiple countries (Sudheshwar et al., 2023), and two papers by scholars from different disciplines. The integration of environmental assessments into articles is rarely the result of international or transversal collaboration. Instead, these assessments are typically performed by the research groups developing the sensor. Because environmental assessments are rarely embedded into early design frameworks (e.g. TPP) or mandated by research funders, they tend to remain opportunistic, typically conducted by sensor designers enthusiastic about environmental concerns, rather than through structured interdisciplinary collaboration.

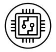
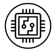
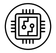
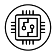
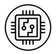
Biosensors - This review identified 13 studies that assess the environmental burden of biosensors. Using the classification system outlined in Section 2.1, two articles examined paper-based devices, eight examined instrumented PoC devices, and three examined PCR devices. Concerning the transduction system, a substantial number of electrochemical biosensors are represented, in addition to two types of colorimetric biosensors (antigen-based rapid diagnostic test and color reagent test strip) and four different PCR-based tests. Nonetheless, the absence of other types of transducers, such as fluorescent sensing, results in a lack of environmental data on entire branches of biosensing. Despite the ubiquity of biosensors in academic research, the dearth of environmental data combined with the lack of device diversity in such studies underscores the imperative for conducting LCAs for each biosensor class.

Although some studies fall outside the scope of this review, their findings could prove beneficial to practitioners. Readers are invited to consult Supplementary Material for more details and other studies, such as LCA of gold nanoparticles.

3.2.2 Motivations for conducting LCA studies

The motivation of each LCA study is described with keywords representing two distinct features of the research conducted. The terms "reporting" and "comparative" refer to the type of LCA conducted and how the results are presented. *"Reporting"* signifies that the paper reports the result of the environmental impacts attributed to their processes, while "*comparative*" means that the results are compared with a reference. The terms *"Demonstrative"* and *"Prospective"* refer to the objectives of the study. *Demonstrative* papers are studies that aim to demonstrate the environmental advantages of their biosensors compared to a reference, while *prospective* papers intend to either identify sustainability hotspots or to provide insight on process improvement. According to these definitions, almost all papers reported on the environmental impact, thereby shedding light on the environmental burden and filling the data gap on biosensor impact. We could only encourage this practice to gain a better global view of the impact of biosensors. Similarly, almost all papers compared their results with a reference. The identification of sustainability hotspots is one of the strengths of LCA, and only half of the article conducted their studies for this purpose. To optimize the sustainability impact of the device, it is imperative to consider it at the earliest possible stage. The remaining half of the studies demonstrate that their process had environmental benefits over standards. This practice indicates that environmental

TABLE 5 *Studies that performed Life Cycle Assessment (LCA) on biosensor. Acronyms for life-cycle phases: Raw Material Extraction (ERM), Manufacturing & Processing (M&P), Transportation (T), Usage & Retail (U&R), Waste Disposal (WD). Acronyms for midpoint impact categories: Global warming potential (GWP), Acidification (A), Ozone depletion (OD), Eutrophication (Eu), Energy consumption (EC), Resource (metal) (R), Smog (S), Water depletion (WD), Human toxicity (HT) (include cancer and - non-cancer toxicity), Particulate matter (PM), Ecotoxicity (Et) (freshwater), Land use (LU) and Ionizing radiation (IR). Acronyms for database: European Life Cycle Database (ELCD) and Chinese Life Cycle Database of Foundations (CLCD) database* (Torres et al., 2018; Ji et al., 2022; Martins et al., 2022; Sudheshwar et al., 2023; Surra et al., 2023; Gomes et al., 2024; 2024; Rebelo et al., 2024; Qi et al., 2024; Tjokro et al., 2025; Courdier et al., 2025; Qi et al., 2025).

Citation	Biosensor	Classification*	Environmental impact study	Motivation	Functional Unit	SCOPE	Included life-cycle phases					Impact method (LCIA method)	Impact categories	Database	Software
							ERM	M&P	T	U&R	WD				
(Torres et al., 2018)	Two quantitative polymerase chain reaction (qPCR) kits and on -line monitoring device for waterborne pathogens detection		Compare qPCR kits with both on -line monitoring device using fluorescence and conventional (cultivation-based) methods	Demonstrative, Reporting & Comparative	one analysis	Cradle-to-gate	●	●	●	●	○	ISO 14067:201 & PAS 2050	GWP	ecoinvent (v3.3)	N/A
(Ji et al., 2022)	Reverse transcription-polymerase chain reaction (RT-PCR)-aided test for COVID-19 detection		Evaluate the COVID-19 nucleic acid diagnostics	Prospective, Reporting & Comparative	one analysis	Cradle-to-grave	●	●	●	●	●	TRACI	GWP, A, E, Et & HT	ecoinvent (v3.5), ELCD, surveys from companies & litterature	SimaPro v9.0.0.27
(Martins et al., 2022)	Electrochemical carbon paper -based sensor for 17 α-Ethinylestradiol detection		Compare electrochemical carbon paper -based sensor with liquid chromatography with fluorescence detection	Demonstrative & Comparative	One analysis	Cradle-to-grave	●	●	●	●	●	IMPACT 2002+	GWP, HT, R & Et	ecoinvent (v3.8) & litterature	N/A
(Sudheshwar et al., 2023)	Electrochemical paper -based sensor with printed electronics for drug detection		Identify material and process hotspots in paper - based printed electronic sensor production	Reporting & Prospective	1 unit of devices produced	Cradle-to-gate	●	●	●	○	○	ILCD's 2018	GWP	ecoinvent (v3.7.1)	Activity Browser
(Surra et al., 2023)	Electrochemical carbon paper -based sensor for ketoprofen detection		Comapre electrochemical carbon paper -based sensor with traditional liquid high -performance chromatography using fluorescent detection	Demonstrative, Reporting & Comparative	one analysis	Cradle-to-gate	●	●	●	●	○	ReCiPe	All midpoints	ecoinvent (v3.7)	SimaPro v9.1.1.7
(Gomes et al., 2024)	Electrochemical sensor based on nitrogen - functionalized carbon spherical shells for diclofenac detection		Compare sensing using nitrogen -functionalized carbon spherical shells with sensing using reduced graphene oxide	Demonstrative & Comparative	60 mg of sensing material produced	Cradle-to-grave	●	●	●	●	●	ReCiPe	All midpoints	ecoinvent, BioEnergieDat & EXIOBASE	OpenLCA v2.1.1
(Gokhale et al., 2024)	Electrochemical non -enzymatic sensor for glucose detection		Compare various substrate choices for the electrode chip	Demonstrative, Reporting & Comparative	1 unit of devices produced	Cradle-to-grave	●	●	●	●	●	CML-IA baseline	R, GWP, OD, HT, WD, Et, Eu & A	ecoinvent (v3.8)	OpenLCA v1.11.0
(Rebelo et al., 2024)	Electrochemical molecularly imprinted polymer (MIP-)based sensor for atorvastatin detection		Compare MIP-based electrochemical sensor with classical chromatographic method	Demonstrative, Reporting & Comparative	One analysis	Cradle-to-gate	●	●	●	●	○	ReCiPe	All midpoints	ecoinvent (v3.7)	SimaPro v9.1.1.7
(Qi et al., 2024)	Colorimetric paper -based sensor for Vitamin C sensing		Compare simulated peroxidase production with conventional sensing material synthesis	Demonstrative, Reporting & Comparative	1 kg of sensing material produced	Cradle-to-grave	●	●	●	●	●	N/A	GWP	ecoinvent, ELCD & CLCD	eBalance
(Tjokro et al., 2025)	Colorimetric sensors with various substrates for glucose detection	 	Evaluate three glucose detection devices for both laboratory -scale and commercial-scale production	Prospective & Comparative (reporting in SM)	One analysis	Cradle-to-grave	●	●	●	●	●	Environmental Footprint	All midpoints	ecoinvent (v3.10) & litterature	Activity Browser
(Courdier et al., 2025)	Colorimetric paper -based test and polymerase chain reaction (PCR) test for COVID-19 detection	 	Evaluate self-testing at home, health worker - performed antigen -based rapid diagnostic tests and laboratory -based PCR tests	Prospective, Reporting & Comparative	(a) One analysis & (b) one positive case detected	Cradle-to-grave	●	●	●	●	●	ReCiPe	GWP	ecoinvent (v3.0) & ADEME	Excel tool
(Gokhale et al., 2025)	Electrochemical enzyamatic and non-enzymatic sensors for glucose sensing		Evaluate enzymatic and non -enzymatic sensors combined with various substrate materials and electrode materials	Prospective, Reporting & Comparative	720 analysis	Cradle-to-grave	●	●	●	●	●	ReCiPe	All midpoints	ecoinvent (v3.2)	OpenLCA v2.3
(Qi et al., 2025)	Colorimetric paper -based sensor for neonicotinoid insecticide sensing		Compare simulated peroxidase production with conventional sensing material synthesis	Demonstrative, Reporting & Comparative	1 kg of sensing material produced	Cradle-to-grave	●	●	●	●	●	N/A	GWP	ecoinvent, ELCD & CLCD	N/A

**Classification :*  *Paper-based devices,*  *Instrumented PoC devices, and*  *PCR devices.*

consideration has become a significant argument in favor of new devices. None of the studies included had both a prospective and a demonstrative purpose for their LCA.

3.2.3 Methodological limitations and comparability challenges

Scope and FU - The life-cycle stages considered in the reviewed LCAs are summarized in Table 5. Nine of the thirteen studies included the end-of-life phase within their system boundaries, thereby conducting cradle-to-grave assessments. Incorporating the full life cycle reduces the risk of burden shifting between stages and enables a more comprehensive evaluation of environmental trade-offs. However, although end-of-life was included in scope, the specific modeling assumptions were not consistently reported. Explicit specification of the end-of-life scenario is essential, particularly when recyclability is considered, as certain allocation approaches may result in negative contributions (e.g., avoided carbon emissions).

All selected studies relied on the ecoinvent database, which applies a cut-off allocation model that assigns full responsibility for waste management to the producer, even when materials are recyclable. The producer will not derive any benefit from producing recyclable waste. Alternative allocation models exist in which recycling benefits are partially credited to the producer, potentially leading to different impact distributions. The remaining four studies adopted cradle-to-gate boundaries, three of which additionally considered use and retail phases.

Despite the diversity of biosensor applications assessed, eight of the thirteen studies defined the functional unit as one analysis or one test. While this facilitates internal consistency within each study, it limits cross-comparability, as environmental intensities depend on contextual factors such as regional energy mix, target analyte, detection modality, and device architecture (e.g. transduction system). Nevertheless, the use of a per-analysis functional unit provides valuable order-of-magnitude insight on the environmental burdens, and supports relative comparison and decision-making when evaluating biosensors designed for the same analytical objective.

LCIA and impact category - A variety of LCA methods exists to assess the environmental impacts, transforming the life cycle inventory results into understandable indicators (ISO, 2006b). The most commonly used LCIA methods include the following: Centrum voor Milieukunde Leiden (CML) (Guinee, 2002), Environmental Design of Industrial Products (EDIP) (Hauschild and Potting, 2004), The International Reference Life Cycle Data System (ILCD) (European Commission, 2011; European Commission and Joint Research Centre, Institute for Environment and Sustainability, 2012), IMPACT (Jolliet et al., 2003), Environmental Footprint (EF) (Fazio et al., 2018), ReCiPe (Hauschild et al., 2017) and Tool for the Reduction and Assessment of Chemical and Other Environmental Impacts (TRACI) (Bare, 2011). ReCiPe was the most frequently utilized method among the articles included in the review (Huijbregts et al., 2017). The remaining articles employed a variety of methods, as illustrated in Table 5. A significant challenge in comparing LCA results stems from the heterogeneity of the existing methods (Hauschild et al., 2013). LCIA methods vary by several factors, including, but not limited to, impact categories, inventory classification, characterization models and geographical relevance. Table 6 presents a comparative analysis of the most prevalent LCIA methodologies by geographical relevance, approach used (midpoint or endpoint), and impact categories considered. The primary benefit of midpoint indicators is their substantial scientific robustness, while endpoint indicators are more straightforward to interpret (Bare et al., 2000). For a detailed comparison, readers are encouraged to refer to (Hauschild et al., 2015; Hauschild et al., 2018), which thoroughly examine the differences and similarities between each method by impact category and method. It is imperative to take all these variations into account; otherwise, the findings may be invalid or misleading. In order to help practitioner, Dong *et al.* have proposed a method to attempt to convert the results of eight LCIA (Dong et al., 2021). The 14 midpoint impact categories represented in Table 5 and 6 are also based on the work of Dong et al. for comparison of LCA results. This review focuses on midpoint categories (the intermediate level along the cause-effect chain) instead of endpoint categories (final impact of pollution on human health, ecosystem, and resources) because of their higher transparency and reliability (Buyle et al., 2013). Global Warming Potential (GWP) is systematically reported whereas the other factors vary across the studies. Most of the articles address several midpoint impacts in addition to global warming, or even all the fourteen midpoint impacts. This approach is encouraged since only evaluating one impact category could lead to tremendous damage to other categories. One impact should not be considered alone, especially when comparing several devices.

Background data - All identified LCAs for biosensor technologies rely on the ecoinvent database as a background data source. This prevalence stems from the database interoperability across LCA software platforms, its moderate cost, and transparency regarding modelling assumptions (Weidema et al., 2013). Despite these advantages, ecoinvent data coverage for the healthcare and biotech sectors remains limited, especially for PoC diagnostic products. As a result, LCA practitioners encounter data gaps during model development. Even when specific datasets are available, they may lack the necessary granularity or technological representativeness for PoC technologies, leading to mismatches between foreground models and background datasets. In turn, these limitations often lead LCA practitioners to combine ecoinvent with other background data sources to address data gaps and enhance their models. For instance, seven of the thirteen reviewed studies incorporate background data from multiple sources. However, this approach is generally discouraged in LCA methodology because it can substantially influence LCIA results. As background databases are developed under distinct modelling assumptions and system boundaries, similar products or processes can exhibit significantly different LCI results across background databases (Peereboom et al., 1998; Herrmann and Sieben, 2015; Pauer et al., 2020; Wattiez et al., 2024). To cope with this issue, future releases of ecoinvent could improve data coverage for PoC technologies by developing background activities for diagnostic device-specific materials (e.g., membranes, functional inks, reagents), low-volume or emerging manufacturing processes (e.g., printed electronics, roll-to-roll fabrication, microfluidics), and

TABLE 6 *Comparative analysis of Life Cycle Impact Assessment (LCIA) methodologies* (**Hauschild et al., 2015**; **Hauschild et al., 2018**; **Dong et al., 2021**). *Inspired from* (**Dong et al., 2021**). *Readers are encouraged to consult the original publication to make a comparison of the unit of measure that was utilized for each impact category, in accordance with the LCIA methods. Acronyms for midpoint impact categories: Global warming potential (GWP), Acidification (A), Ozone depletion (OD), Eutrophication (Eu), Energy consumption (EC), Resource (metal) (R), Smog (S), Water depletion (WD), Human toxicity (cancer) (HT C), Human toxicity (non-cancer) (HT NC), Particulate matter (PM), Ecotoxicity (Et) (freshwater), Land use (LU) and Ionizing radiation (IR).*

LCIA method	References	Version (year)	Region validity	Approach	Midpoint impact category													
					GWP	A	OD	Eu	EC	R	S	WD	HTC	HTNC	PM	Et	LU	IR
CML-IA	Guinee (2002)	IA-baseline (2002)	Europe	Midpoint	●	●	●	●	●	●	●	○	●	●	○	●	○	○
EDIP	Hauschild and Potting (2004)	2003 (2005)	Europe	Midpoint	●	●	●	●	●	●	●	○	●	●	●	●	○	○
EF	Fazio et al. (2018)	2.0 (2018)	Europe	Midpoint & endpoint	●	●	●	●	●	●	●	●	●	●	●	●	●	●
ILCD	European Comission - Joint Research Centre (2012)	2011 Midpoint+ (2011)	Europe	Midpoint	●	●	●	●	○	●	●	●	●	●	●	●	●	●
IMPACT	Jolliet et al. (2003)	2002+ (2003)	Europe	Midpoint & endpoint	●	●	●	●	●	○	●	○	●	●	●	●	●	●
IMPACT	Bulle et al., 2019	World+ (2019)	Global	Midpoint & endpoint	●	●	●	●	●	○	●	○	●	●	●	●	●	●
ReCiPe	Huijbregts et al. (2017)	2016 Midpoint(H) (2017)	Global	Midpoint	●	●	●	●	●	●	●	●	●	●	●	●	●	●
TRACI	Bare (2011)	2.2 (2021)	North America	Midpoint	●	●	●	●	●	○	●	○	●	●	●	●	○	○

hybrid systems that combine disposable components with electronic elements. Healthcare-sector-specific databases could also prioritize the development of such datasets.

3.3 Quantitative insights from LCA studies of PoC diagnostics

The quantitative results presented in this section are directly extracted from peer-reviewed LCA studies identified through the PRISMA methodology. Detailed life-cycle inventories, modelling assumptions, and allocation rules are reported in the respective source articles. Although the selected studies adopt varying system boundaries (cradle-to-gate or cradle-to-grave), we have, whenever sufficiently reported and methodologically transparent, extracted and harmonized cradle-to-gate contributions to improve comparability across studies within this review.

3.3.1 Instrumented diagnostic devices

Tjokro et al. focus on microfluidic devices and provide a cradle-to-grave LCA located in UE of PDMS-, paper- and PLA-based glucose sensors, manufactured respectively through soft lithography, wax stamping and 3D-printing (Tjokro et al., 2025). This study is particularly relevant due to its detailed material inventory, clear definition of the functional unit, and inclusion of quantitative results for both laboratory-scale and commercial-scale production. Importantly, it confirms that, for both scales, materials and energy consumption involved in the manufacturing dominate climate change and water use impact categories. Climate change impacts of 0.671 kg CO_2-eq, 0.278 kg CO_2-eq and 2.13 kg CO_2-eq were reported for lab-scale PDMS-, paper-, and PLA-based testing, respectively. At industrial scale, these values remain of similar magnitude, apart from the PLA-based device, whose impact decreases substantially when transitioning from 3D printing to injection molding. It highlights that the substrate material accounts for up to 50% of the GWP in PLA chips, that the paraffin used to coat and functionalize the paper-device contributes most to the environmental burdens, while the energy-intensive plasma bonding process and the material itself dominate in PDMS-based systems (Tjokro et al., 2025). Overall, the study shows that the design of the microfluidic device and its production method are both environmentally important factors when choosing to upscale production and suggests that redesigning was one of the main ways to reduce the environmental impacts of the devices, e.g., by investigating alternative substrate materials.

Several studies have evaluated instrumented PoC devices employing electrical detection methods. The comparative analysis by Ahamed et al. provides life-cycle impacts for production processes of substrate materials (plastic, ceramic, glass, paper, and cotton textile) and electrode materials (gold, silver, platinum, copper, carbon-based) in voltametric screen-printed sensors (Ahamed et al., 2021). They report that cotton textiles and gold electrodes (noble metals in general) lead to the highest environmental burdens. They recommend the ceramic, glass and paper substrate material over plastics, mainly due to the end-of-life consequences (toxicology) of the plastic materials. Similarly, they advise the use of carbon-based electrode materials since they offer the best compromise between sustainability and performance. These two device-level studies align well with our earlier material-level findings where high-performance polymers like PLA appeared as higher-EE and CFP options than materials like paper, glass or ceramics for device substrates, and noble metals are associated with extremely high-EE and CFP. Interestingly, they point out the challenges in integrating actual nanomaterial burdens in LCA, highlighting the difficulty of assessing the potential toxicity risks for the environment and human health due to nanomaterial release, as already pointed out in (Bauer et al., 2008; Le

Brun and Raskin, 2020), which eventually increase the uncertainties of the study. Gokhale et al. build on this by introducing a low-impact alternative sugarcane-based substrate material for electrochemical sensing, which achieved a 67% lower GWP compared to PET while maintaining comparable sensor performance (Gokhale et al., 2024). In a later study, the same authors detailed cradle-to-grave assessments of glucose biosensors fabricated with various substrate, electrode materials, and explored design changes (reusable vs. disposable). Strikingly, they find that electrode material impacts dominate the overall footprint, while reusability scenarios dramatically reduce the device carbon footprint by over 15x (Gokhale et al., 2025). Rebelo et al. reports the cradle-to-gate LCA of ceramic screen-printed carbon electrode electrochemical sensors, comparing their environmental impact with that of conventional analytical technique (liquid chromatography coupled with mass spectrometry, LC-MS). Their findings indicate that a single electrochemical test emits approximately 0.811 kg CO_2-eq for GWP with 47% of this impact related to the sensing device (production of reagents and materials and sensor construction), while the conventional LC-MS approach reaches 2.06 kg CO_2-eq (Rebelo et al., 2024). This substantial impact reduction is in line with other LCA comparing electrochemical sensors and traditional methods. However, the later were excluded from our quantitative comparison due to limited actionable data or relevance (Martins et al., 2022; Surra et al., 2023).

Finally, in a detailed cradle-to-gate LCA aimed at identifying sustainability hotspots in the production of printed electronics, Sudheshwar et al. evaluated a single-use, paper-based biosensor for drug detection. The study highlights critical trade-offs in early-stage development. The device is a single-use and disposable PoC device with short lifespan. Major contributors to the carbon footprint included nanocellulose used for surface functionalization and silver in both conductive inks and adhesives. Nanocellulose accounted for over 56% of the substrate GWP despite representing <1% of its mass, due to its highly energy-intensive production. Silver-based adhesives, especially when manually applied, exceeded the impact of silver inks. Importantly, device miniaturization, and process automation could reduce the footprint by up to 40%. The third-generation design, which included display and battery features, more than doubled the carbon footprint compared to its simpler predecessor (3.3 vs. 1.4 kg CO_2-eq per unit). This study reinforces that selecting "green" materials must be accompanied by a holistic view of manufacturing impacts, especially when scaling PoC devices (Sudheshwar et al., 2023).

Reported cradle-to-gate GWPs for instrumented PoC devices, as extracted from the reviewed LCA studies, range from approximately 0.5–3 kg CO_2-eq per test. Variability reflects differences in system boundaries, device complexity (e.g., microfluidics or transducer technology), integration of electronic components (e.g., batteries, displays, conductive tracks) and manufacturing routes (laboratory prototyping *versus* industrial automation). Device complexity and functional integration emerge as dominant drivers of environmental burden and may exceed the contribution of the substrate material alone. The relatively limited number of comparable LCAs available for instrumented platforms highlights the need for more transparent and harmonized environmental reporting, particularly given the wide diversity of architectures and technological integrations characterizing this segment of PoC diagnostics.

3.3.2 LFA rapid tests

Cradle-to-grave emissions are estimated between 30 and 300 g CO_2-eq per test (Vandeputte, 2021; Morris and Haworth, 2022; Unitaid, 2023), largely driven by materials and packaging. Material audits from (Wöhrle et al., 2025) report total kit weights ranging from 13.7 g to 84 g (mean: 32.2 g), with plastic components representing 36%–52% of the total weight, and paper/cardboard accounting for 35%–52%, depending on kit design. The plastic cassette alone contributes ~30% of the carbon footprint and up to 50% of plastic waste (Morris and Haworth, 2022), despite weighing just ~4.1 g in standard formats and up to 22 g in digital tests with integrated electronics. In particular, packaging materials, including foil pouches, paper leaflets, and desiccants, can account for 34%–89% of the total mass, and are often overlooked despite their significant environmental contribution (Wöhrle et al., 2025). Altogether, test components contribute ~50% of the GHG emissions and up to 66% of plastic waste, while packaging constitutes the remainder (Morris and Haworth, 2022).

Several eco-design strategies have been proposed to mitigate these impacts. Miniaturizing cassettes could cut test mass by ~15–20% and reduce GHG emissions by a similar margin, but would require substantial investment in R&D, retooling, and regulatory requalification (Morris and Haworth, 2022). Material substitution using paperboard or leaflet integration could also lower packaging burdens, though these changes face constraints in user-friendliness and labeling compliance. The unification of buffer and swab components presents another opportunity, potentially streamlining the test kit and simplifying waste. The use of biodegradable plastics is gaining traction. Notably, Okos Diagnostics recently developed bioplastic universal LFA housing, offering mechanical performance comparable to conventional plastics and compatibility with existing molding infrastructure (Okos Diagnostics, 2025; Oladipo et al., 2026). Although efforts to integrate bio-sourced plastics are remarkable and must be pursued, their potential higher costs, limited biodegradation under ambient conditions, and concerns about degradation by-products and micro-bioplastic pollution challenge their environmental credentials, especially in low-resource settings, and must be assessed with specific LCA (Core, 2023; Street and Kersaudy-Kerhoas, 2025). On the other end, reusability, though conceptually appealing, poses serious challenges. A reusable LFA cassette prototype has been proposed (Le Brun et al., 2024a), but cross-contamination risks and cleaning validation represent significant hurdles. The environmental gains of reuse remain speculative until formally assessed.

These insights highlight that even low-complexity diagnostics require integrated consideration of material mass and packaging intensity at the design stage. Given the scale of LFA deployment, modest per-unit improvements could yield significant absolute reductions in environmental burden.

3.3.3 PCR devices and conventional methods

Courdier et al. analyze different types of diagnostic test kits and show that PCR-based systems carry a significantly higher GWP (up to 0.73 kg CO_2-eq per test) compared to antigen-based rapid diagnostic tests (0.12–0.23 kg CO_2-eq). The footprint largely arises due to the consumables and disposable protective equipment required for their implementation (such as gloves and masks), reinforcing the need to optimize test formats and logistics (Courdier et al., 2025). These results are corroborated by Ji et al., who performed a cradle-to-grave LCA of a COVID-19 nucleic acid and emphasize the climate burden of the waste treatment (sterilization and incineration), and from the PCR components production like extraction reagents, plastic tubes and single-use pipes, swabs and protective equipment (Ji et al., 2022). They explore alternative design scenarios as potential environmental impact mitigation strategies. They studied, among others, the substitution of ziplock bags and sealing bags by biodegradable plastic packaging which helps to reduce GHG emissions by 16%.

The study by Torres et al. compares a culture-based ISO method (Colilert-Quantitray™) with a qPCR-based testing kit, both for *Escherichia coli* detection in water, at the laboratory scale (Torres et al., 2018). Their cradle-to-grave LCA results demonstrate the critical importance of transport and single-use consumables in shaping the environmental footprint. When isolating design contributors, i.e. material- and process-related impacts in a cradle-to-gate approach, the qPCR kit exhibited a higher GWP (~5.2 kg CO_2-eq/test) than the culture-based protocol (~4.5 kg CO_2-eq/test). Footprint of the qPCR kits largely arises due to the use of high-performance materials (e.g., filtration membranes, sealed cartridges and high-grade plastics). In contrast, culture methods use more basic materials but require long incubation (≥36 h) and high consumables volume, driving cumulative impact. qPCR kits carry higher per-unit material impacts but allow faster diagnostics and potential for multiplexing (i.e. detection of several strains within the same kit), thereby lowering per-pathogen impact in optimized settings (Torres et al., 2018). These GWP values for PCR kits remain higher than those reported in (Ji et al., 2022; Courdier et al., 2025), which modeled industrial-scale PoC kits. This underlines how scale and device format influence impact interpretation. It also reinforces that single-use consumables in shaping the environmental footprint. Therefore, design decisions around disposables and protocol duration are key levers for minimizing diagnostic footprints.

From a life-cycle perspective, the three main device categories (instrumented devices, LFA rapid tests and PCR) present distinct orders of magnitude in GWP (Figure 6). LFAs typically exhibit the lowest GWP (≈0.03–0.3 kg CO_2-eq per test), driven primarily by material mass and packaging intensity. Instrumented PoC devices span intermediate impacts (≈0.5–3 kg CO_2-eq per test), where electronics integration, manufacturing energy, and additional functionalities significantly influence results. PCR-based systems typically exhibit higher impacts (≈0.7–5 kg CO_2-eq per test), largely due to consumables, protective equipment and thermocycling energy. While absolute comparisons must be interpreted cautiously given differences in diagnostic function, performances and modelling assumptions, these ranges reveal structural differences in environmental intensity across device architectures, reflecting increasing system complexity rather than strict hierarchical rankings.

3.3.4 Limitations

Despite the growing interest in evaluating the environmental performance of PoC diagnostics devices, the analyzed LCA studies remain fragmented and heterogeneous in scope, methodological rigor, and transparency. Several studies focus solely on GWP, often neglecting critical impact categories such as toxicity, resource depletion, and end-of-life scenarios. Inconsistent system boundaries (e.g., cradle-to-gate vs. cradle-to-grave), functional units (per analysis vs. per device), and production scales (proof-of concept or lab-scale levels vs. mass-produced devices) further hinder comparability, with authors themselves acknowledging missing experimental data and high uncertainty (Tjokro et al., 2025).

Across the reviewed literature, key levers for impact mitigation are consistently identified: material substitution (e.g., paperboard vs. plastics), simplification of manufacturing processes, reduction of high-energy steps (e.g., thermal curing), and reuse strategies. Yet, only a few studies quantify the trade-offs between technical performance and environmental burden. Most assessments overlook how design decisions influence user behavior, supply chains, or health system efficiency - externalities that remain crucial yet unmodeled. End-of-life remains particularly underexplored. Recycling is rarely feasible due to contamination risks (Tjokro et al., 2025), and reuse scenarios often assume idealized recovery conditions.

Data uncertainty is a widespread limitation. Many studies lack transparency regarding material flows, emission factors, or geographical assumptions, which are critical given the variation in energy mixes and waste infrastructures worldwide. While some authors (Sudheshwar et al., 2023) explicitly position their work as pedagogical or order-of-magnitude analyses, others fail to clarify if uncertainties in inventory or modeling assumptions dominate the results, potentially leading to misleading interpretations.

A particularly important limitation lies in the lack of comparability between devices of different categories due to fundamental differences in diagnostic function, sensitivity, and operational complexity. While we have seen that component-level or functionally equivalent comparisons (e.g., material selection and substitution, or reuse vs. single-use cases) can yield robust conclusions at this stage, this discrepancy of the device profiles prevents straightforward environmental comparisons between device categories, making it difficult to guide technology selection in the early stages of sensor development. Yet, it is precisely at TRL one to three, during the pre-conceptual phase of design, that researchers and engineers must evaluate competing technological approaches to solve a given diagnostic challenge.

Taken together, these findings illustrate both the strengths and limitations of LCA as a design-support tool for PoC diagnostics. Although current studies offer important directional insights, they rarely translate into operational guidance for early-stage developers navigating technology selection trade-offs at the device-level. This underscores the need for a stronger integration of LCA into biosensor design workflows, with harmonized methodologies across device classes and improved granularity of reported results. Transparent modelling assumptions, clearly defined system boundaries, and class-specific benchmarking would greatly facilitate meaningful cross-comparison and support more robust performance–impact decision-making in future PoC development.

3.4 Beyond sensitivity: A practical metric to balance performance and environmental footprint

Our review of LCA studies motivates the need for integrative, simplified metrics that translate LCA insights into practical

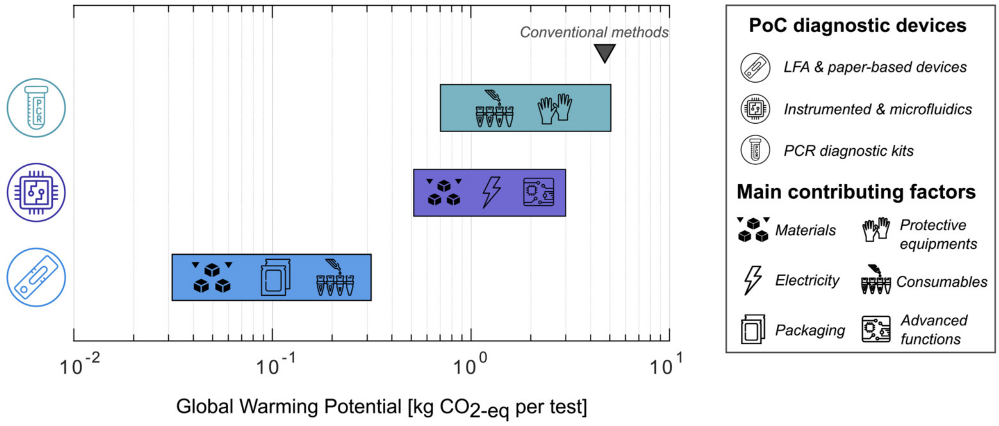


FIGURE 6
Ranges of GWP per test for LFA and paper-based devices, instrumented PoC devices, PCR-based systems, and conventional laboratory diagnostics (culture-based methods). The visual representation is based exclusively on harmonized cradle-to-gate LCA data extracted from the PRISMA reviewed studies. Ranges illustrate variability arising from modelling assumptions, system boundaries, manufacturing scale, device architectures, integration of electronic components, and inclusion of consumables. The figure highlights structural differences in environmental intensity across device classes rather than exact comparative rankings.

decision-making tools at the device level. To address this gap, we propose a new metric: the Environmental Cost of Performance (ECoP). This indicator aims to bridge technical performance and environmental sustainability by normalizing cradle-to-gate environmental impacts by diagnostic performance. We deliberately focus on cradle-to-gate impacts to ensure consistency across the quantitative dataset from the quantitative literature review, given the high variability in system scopes reported in the studies. ECoP uses the LOD as the defining measure of device performance, since it determines whether a device meets its intended use and generally drives TPPs and subsequent development priorities. As the most universal and comparable indicator of analytical sensitivity, LOD provides a consistent basis for cross-technology assessment. On the environmental side, the metric relies on GWP, the most consistently reported, easily quantifiable and robust environmental impact indicator in the reviewed LCA studies. To guide early-stage design choices, ECoP relates GWP to LOD as

$$\mathrm{ECoP} = \mathrm{LOD} \times \mathrm{GWP}.$$

A higher device carbon footprint and/or a higher limit of detection (the latter generally reflecting lower analytical sensitivity) results in an increased ECoP value. In this sense, ECoP integrates both technical and environmental dimensions of diagnostic performance into a single indicator. Rather than replacing conventional figures of merit, ECoP complements them by quantifying the environmental cost required to achieve a given level of analytical performance. It therefore expresses a device absolute carbon burden associated with meeting a targeted diagnostic sensitivity.

To illustrate the practical relevance of this metric, we apply it to two complementary case studies. First, ECoP is used to compare different classes of PoC diagnostic devices that could be considered for a defined application - namely, bacterial pathogen detection at the point of care - in order to inform technology development decisions. Second, we demonstrate how ECoP can guide design choices within a specific device class (LFA), by comparing alternative design formats accessible to the same technological platform.

3.4.1 From performance-driven to carbon footprint-aware development roadmaps

We first examine representative PoC diagnostic device classes commonly used for bacterial pathogen detection, including LFAs, instrumented microfluidics with electrochemical transduction, and PCR-based platforms. To contextualize PoC capabilities, these technologies are benchmarked against conventional laboratory methods, such as culture-based ISO protocols (e.g., Quanti-Tray) (Torres et al., 2018). While the LCA studies analyzed in this review often targeted alternative analytes (e.g., glucose, viral nucleic acids), the core technologies remain transposable to bacterial diagnostics, particularly at low to mid TRLs, where platform design typically precedes assay specificity for the target. The GWP ranges used to compute ECoP for each device class were directly derived from the 13 PRISMA-selected LCA studies depicted on Figure 6. Whenever sufficiently documented, cradle-to-gate contributions were extracted and harmonized in Section 3.3 to reduce methodological heterogeneity between cradle-to-gate and cradle-to-grave assessments. The reported values therefore represent consolidated ranges observed within each device class rather than arithmetic averages of disparate datasets. Because underlying LCAs differ in system boundaries, databases, allocation models, and geographical assumptions, ECoP must be interpreted along with the methodological characteristics of the source studies. ECoP is not a standalone indicator and does not replace LCA, but operationalizes published cradle-to-gate GWP results into a performance-normalized comparative metric suitable for early-stage eco-design reasoning.

In parallel, performance metrics (LOD and detection time) of the PoC device classes were compiled from representative reviews (Váradi et al., 2017; Luo et al., 2020; Wang et al., 2021; Zhao et al., 2024; Liu et al., 2021), and completed by technology-specific studies rather than single-device records. For commercial gold-nanoparticle-based colorimetric LFAs, typical detection thresholds range from 5 × 10^3–10^6 CFU/mL, with results in 5–30 min (Bergua et al., 2021; Mazur et al., 2023; Le Brun et al., 2024b; Wei et al., 2023). Although numerous signal amplification strategies have been reported with improved LODs, they were not included in the quantitative analysis here, as they often involve additional equipment or processing steps that diverge from the original purpose of LFAs, i.e. low-cost pre-screening by non-specialists. Instrumented microfluidic platforms integrated with electrochemical biosensors offer improved sensitivity (~10^2–10^3 CFU/mL) (Kumar et al., 2019). These systems aim to automate complex sample preparation steps (e.g., filtration) allowing to reach lower LODs than LFAs, but the total time to result typically ranges from 30 min to 3 h (Wang et al., 2021), longer than LFAs. PCR systems present high sensitivity (LOD <10 CFU/mL) and intermediate detection times (1–2 h, Váradi et al., 2017). Finally, conventional culture methods, considered the gold standard in sensitivity (<1 CFU/mL), exhibit the longest detection time (minimum 24 h) and highest GWP (Váradi et al., 2017; Torres et al., 2018).

Figure 7a maps the main PoC diagnostic architectures within a conventional performance-driven roadmap structured around LOD and time-to-result. This representation highlights well-known trade-offs between sensitivity and speed and has historically guided technological development priorities (Liu et al., 2021; Augustine et al., 2025), such as attempts to combine the analytical sensitivity of PCR with the simplicity and rapidity of LFAs, overcoming the drawbacks of both techniques (Rubio-Monterde et al., 2023). In contrast, Figure 7b integrates ECoP, repositioning device classes according to the carbon burden associated with a given analytical sensitivity. The ranges are represented as areas to reflect intrinsic variability in LOD, detection time, and cradle-to-gate GWP across literature. This environmentally weighted roadmap shifts the perspective from purely technology-driven optimization toward performance-environmental footprint trade-offs tailored to application-specific constraints. Rather than pursuing maximum sensitivity or shortest detection times at all costs, this roadmap encourages selecting the device class that meets predefined diagnostic thresholds with the lowest environmental burden. Such an approach is particularly relevant at low TRLs, where design flexibility remains high and environmental constraints can still significantly influence platform selection.

For example, for use-cases in which moderate sensitivity is sufficient but rapid response is critical, such as early screening (<1 h), the apparent technical advantage of highly sensitive PCR or advanced instrumented platforms becomes less pronounced when their associated carbon intensity is considered. Therefore, in specific contexts, LFAs may emerge as comparatively favorable options due to their lower absolute carbon burden and operational simplicity, with the trade-off of an increased risk of false negatives due to lower sensitivities. Indeed, as studied in (Courdier et al., 2025), PoC technology selection must be contextualized within full usage scenarios (i.e., including the testing strategy and contamination prevalence) to be generalized: the carbon footprint of LFA self-testing at home by the patient is about half the footprint of a LFA performed by healthcare workers based at testing center, and represents only a fraction of that associated with PCR testing, mainly due the higher consumption of disposable protective equipment by healthcare staff.

Overall, the ECoP indicator allows quantitative prioritization of eco-design strategies in POC device development roadmaps. ECoP-guided roadmap does not prescribe a universal hierarchy among the diagnostic device classes, but enables informed alignment between performance requirements and environmental constraints. Finally, it highlights that device-level metrics should be interpreted alongside operational practices and testing strategies.

3.4.2 ECoP as a design-support metric within the LFA platform

To further demonstrate the operational relevance of ECoP beyond cross-technology roadmap, we apply the metric to a concrete design decision within a single device class: gold nanoparticle-based LFAs for bacterial detection in contaminated liquids (e.g., *Escherichia coli* or *Bacillus cereus* in water), as described in (Bergua et al., 2021; Le Brun et al., 2024b). Importantly, this example does not constitute a full device-level LCA but an illustrative, order-of-magnitude comparison based on literature and harmonized LCA cradle-to-gate datasets. Three LFA configurations were considered: (i) a strip-only LFA without housing cassette, (ii) a conventional LFA enclosed in a 5 g polypropylene (PP) housing cassette, and (iii) a digital LFA integrating a single-use battery-powered electronic reader, similar to that of a digital pregnancy test (22 g module including PCB, small LCD display and button cell battery) (Deus Ex Silicium, 2020). The analytical performance are comparable for the two LFA configurations read with the naked eye (LOD = 10^4 CFU mL^{-1}, time-to-result 15 min), while the digital reader LOD drops at 10^3 CFU mL^{-1} due to a better sensitivity of the optical sensor with similar time-to-result (Wang et al., 2022).

All three LFA formats rely on identical membrane stacks (cellulose sample and absorbent pads, glass fiber conjugate pad, nitrocellulose membrane, polyethylene backing), gold nanoparticles, and antibodies. For simplification, extraction components and packaging were assumed comparable across configurations. Table 7 reports the estimated GWPs and corresponding ECoP using cradle-to-gate carbon intensities derived from harmonized literature datasets.

The electronic module impact was estimated using embodied carbon intensities for small handheld electronic devices, and cross-checked against recent LCAs of portable sensing systems (Wattiez et al., 2025). The primary benefit of the electronic reader lies in achieving a higher optical sensitivity, thereby reduction uncertainty near decision thresholds, and automated result interpretation. However, despite the potential gain in sensitivity, differences in ECoP values span two orders of magnitude between strip-only and digital configurations. While integration of disposable electronics may enhance user confidence through automated signal interpretation, it induces a large increase in environmental cost relative to the incremental sensitivity gain. While such automation may be justified in regulatory or high-risk diagnostic contexts, its carbon intensity becomes explicit when normalized to analytical performance and may be questionable in other settings. Conversely, strip-only formats or cassette-based LFAs without embedded electronics exhibit substantially lower ECoP values, suggesting that reusable external readers or smartphone-based optical interpretation could offer a more balanced trade-off by distributing electronic impacts across multiple tests.

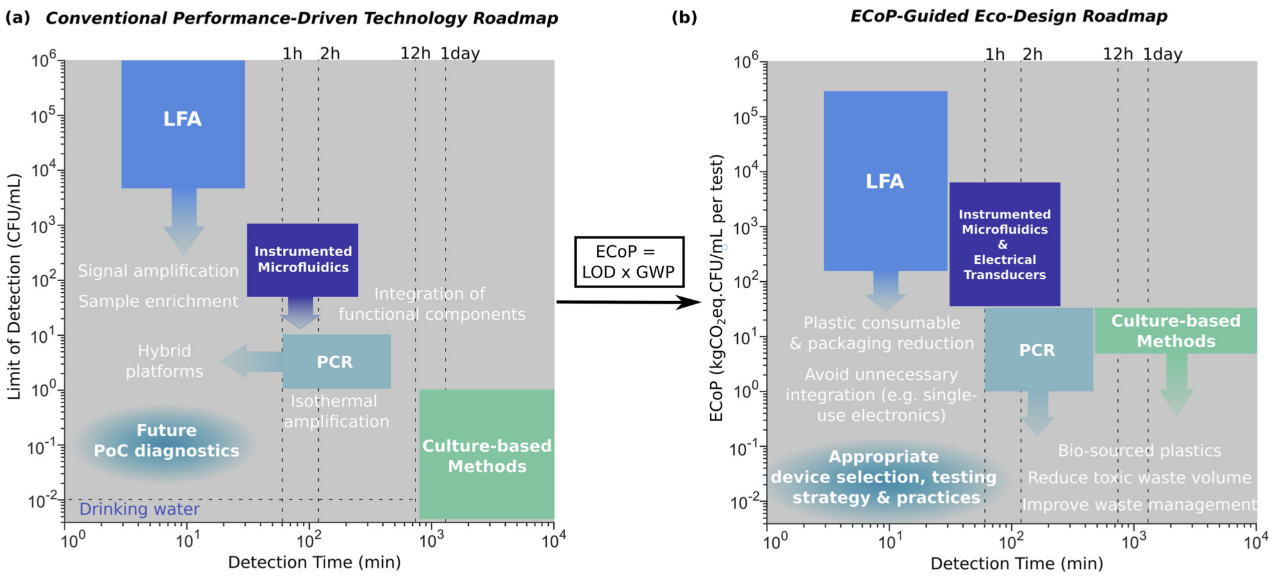


FIGURE 7
(a) Conventional diagnostic roadmap maps device classes based on limit of detection and time-to-result. The roadmap highlights trade-offs between speed and sensitivity, the most popular metrics to guide technical development priorities. **(b)** The integration of environmental footprints into conventional roadmap, *via* the Environmental Cost of Performance (ECoP) metric, repositions device classes according to their absolute carbon burden associated with meeting a targeted diagnostic sensitivity, offering a complementary perspective to support early-stage eco-design decisions.

The strong increase in environmental burden observed when integrating single-use electronic readers into low-impact platforms is consistent with recent early-stage LCAs of wearable and microfluidic sensing systems. For instance, Rabost-Garcia *et al.* demonstrate that, in hybrid wearable sweat sensors, environmental impacts increasingly stem from printed electronics, conductive layers, interconnects, and system integration rather than from housing or polymeric substrates alone (Rabost-Garcia et al., 2025). Their results show that functional electronic layers can dominate the production-phase footprint, even in compact devices, indicating that embedding non-reusable electronics into disposable diagnostic cartridges fundamentally shifts the environmental balance. This underscores the importance of modular design-for-reuse strategies, where electronic components are separated from disposable sensing elements. By enabling reuse, environmental burdens are distributed across multiple tests instead of being embedded in each single-use device. Initial efforts in this direction have already been reported, exploring the decoupling of low-impact single-use components from reusable electronic modules (Le Brun et al., 2021). To further operationalize this principle, dedicated design metrics are required. One promising concept is a *function-to-waste ratio*, linking mechanical and electronic complexity to the number of tests delivered before disposal, emerge in this direction. Such an approach would help identify and prevent over-engineering in single-use diagnostic formats that generate disproportionate electronic waste relative to their functional output.

Comparable performance-normalized environmental metrics have begun to emerge in other areas of sensor engineering. (Delhaye et al., 2021) developed a bottom-up LCA framework for MEMS piezoresistive pressure sensors, quantifying the embodied energy and GWP required to achieve a specified sensitivity across fabrication routes. By expressing impacts per unit of performance, they showed that advanced technologies could reduce the environmental cost per functional output when sensitivity gains compensated for process intensification. However, such approaches remain scarce relative to the pace of technological innovation and would benefit from wider dissemination and integration into routine design practices.

3.4.3 Toward multi-indicator eco-design tools

In the present work, ECoP was formulated using GWP and LOD, primarily because these indicators were the most consistently reported and comparable across the reviewed studies. This choice does not imply that environmental assessment should be restricted to carbon footprint alone. As discussed in Section 3.3.4, focusing on a single impact category is itself a limitation of current LCA practice. In principle, the ECoP framework can be extended to additional environmental indicators (e.g., water use, resource depletion, toxicity), and beyond, to eco-design metrics (e.g., material circularity indicator (Ellen MacArthur Foundation and Granta Design, 2015)), or broader systemic indicators (e.g., critical material intensity). Likewise, LOD is not the only relevant technical figure of merit. Time-to-result, cost per test as discussed in (Jenkins et al., 2015), analytical robustness, operational complexity, or manufacturing process scalability could be incorporated into an expanded performance-impact framework. For example, replacing LOD with cost would enable comparison of environmental and economic trade-offs within the same roadmap. Similarly, time-to-result could be integrated to reflect urgency-driven deployment scenarios. We could define a composite multi-criteria indicator by combining several normalized technical FoMs with one or more environmental indicators. However, for such an aggregated metric to remain meaningful for designers, each contributing dimension must be transparently

TABLE 7 GWP and ECoP comparison for three LFA design architectures for bacterial detection in water. The two LFA read by the naked eye present equivalent analytical performance (LOD = 10^4 CFU/mL), while the digital reader allows to lower the LOD by one order of magnitude.

Configuration	LOD ($CFU \cdot mL^{-1}$)	GWP per test (kg CO_2-eq)	ECoP per test (kg CO_2-eq$\cdot CFU \cdot mL^{-1}$)	Carbon intensity dataset
Strip-only LFA	10^4	0.005	50	Vandeputte (2021)
LFA + PP cassette	10^4	0.03	3×10^2	Morris and Haworth (2022)
Digital LFA	10^3	4.95	4.95×10^3	Ashby (2016)

reported, methodologically harmonized, and visualized to preserve trade-off visibility.

Radar-based multi-indicator representations offer a practical way to expose this complexity without collapsing it into an opaque single score. When applied to the three LFA architectures described in Section 3.4.2., the radar visualization reveals how digital integration substantially improves interpretability and connectivity but at the expense of a dramatic increase in GWP (Figure 8). Conversely, strip-only formats maximize environmental and cost performance while sacrificing automation and digital reporting capacity. The cassette-based format occupies an intermediate position, improving handling without fundamentally altering analytical performance. This exercise therefore represents a conceptual demonstration of how ECoP-derived quantitative results can be extended toward multi-criteria eco-design tools when harmonized and sufficiently granular datasets become available. Radar-based representations are particularly valuable because they preserve the multi-dimensional nature of sustainability assessment rather than collapsing it into a single aggregated score (Kralisch et al., 2018). Such approaches are increasingly recognized as necessary for advancing comprehensive sustainability assessments that integrate environmental, technical, and economic dimensions within product development frameworks. In practice, quantitative prioritization across the multiple indicators displayed in radar charts can rely on established multi-criteria decision analysis (MCDA) methodologies (Cinelli et al., 2014), including outranking approaches such as PROMETHEE (Brans et al., 1986). These methods offer structured and transparent ways to weight, rank, and arbitrate between competing design options while explicitly acknowledging trade-offs.

4 Discussion & future perspectives

The global adoption of PoC diagnostic technologies such as LFAs (e.g., self-tests and pregnancy tests), further accelerated during the COVID-19 pandemic, has brought unprecedented public attention to the environmental burden associated with single-use medical devices. Addressing these challenges requires a systemic perspective that extends beyond the analytical competencies of the sensor scientists and encompasses material sourcing, manufacturing, usage practices, economics, regulations, and end-of-life management (Figure 1). Therefore, eco-design strategies must account for the full life-cycle implications of PoC technologies. Ideally, environmental considerations should be embedded directly within the routine design tools used by scientists and engineers. This would enable environmental impacts to be anticipated and addressed at the earliest stages of the product development process, where design flexibility - and potential environmental gains - remains highest. In other engineering sectors, initiatives are emerging in this direction. For example, the integration of sustainability-oriented material databases (e.g., Granta EduPack) within predictive simulation environments such as Ansys Workbench enables streamlined assessment of material durability and environmental indicators during early-stage product development (Ashby, 2023). However, in the biotechnology sector, and particularly in PoC biosensor development, predictive design tools remain scarce. The intrinsic multidisciplinary of these systems, combining biology, chemistry, materials science, microfluidics, and electronic integration, makes comprehensive modeling significantly more challenging. As a result, it complexifies the integration of environmental metrics into early-stage design workflows. While prior eco-design and green analytical chemistry frameworks, such as the "ten principles of green sample preparation" (López-Lorente et al., 2022) or other metrics (Gałuszka et al., 2012; Pena-Pereira et al., 2020; Agrawal et al., 2021), have promoted process greenness, they remain limited in their ability to quantitatively compare heterogeneous sensor architectures or guide technology selection across distinct diagnostic platforms.

This review demonstrates that integrating eco-design principles with quantitative environmental metrics into PoC diagnostic development is both necessary and operationally feasible. Our quantitative framework aims to addresses this need by spanning multiple scales of PoC design, from material-level screening to device-level integration and system-level performance trade-offs. It provides a structured toolbox for integrating sustainability and LCA considerations into PoC diagnostic development. This framework is grounded in a quantitative bibliographic review of environmental impact studies and reformulated into a pedagogical and operational format, accessible to researchers and designers seeking to implement eco-design principles from the earliest stages. At the material level, screening based on environmental indicators (GWP, embodied energy, water usage) and macro-economic parameters in a simplified framework enables the rapid exclusion of high-impact options when design flexibility is highest (TRL 1–3), before technical constraints lock in material choices. At the device-level, the PRISMA-based review of LCAs reveals clear trade-offs between environmental burden and technical performance (LOD, time-to-result, ease of operation) within the main classes of PoC devices (LFA, instrumented devices, and PCR-based kits). The review highlights the need for systematic and integrated harmonized LCA methodologies into biosensor design processes. Standardized system boundaries, class-specific benchmarking, and improved granularity in reporting would significantly enhance cross-study comparability and strengthen the role of environmental assessment as a design-support tool. Finally, the proposed ECoP metric operationalizes this integration by relating analytical performance to cradle-to-gate environmental

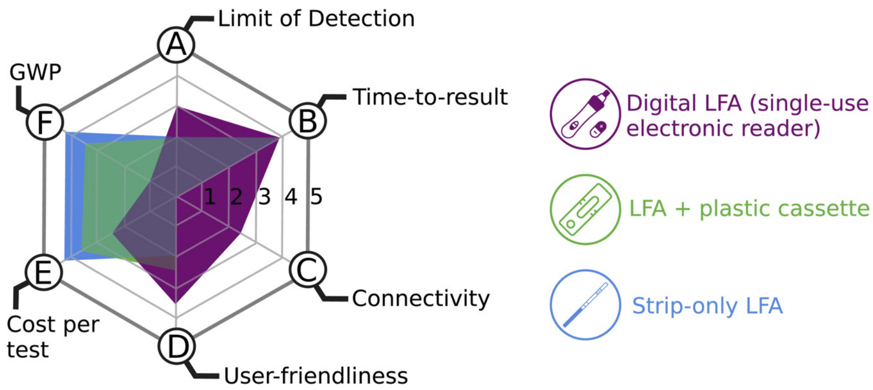


FIGURE 8
The radar visualization illustrates multi-criteria trade-offs without aggregation into a single composite score and serves as an operational demonstration of how ECoP can be extended toward multi-dimensional eco-design assessment. Relative performance scores (0–5 scale) were assigned to economic (cost per test), technical (LOD, time-to-result, user-friendliness, connectivity), and environmental (GWP) dimensions based on three LFA architectures quantitatively analyzed in Section 3.4.2. Values represent comparative positioning between strip-only, cassette-based, and digital configurations rather than absolute measurements.

impact. By aligning carbon footprint with diagnostic sensitivity, ECoP extends beyond the conventional sensitivity-speed trade-off and introduces a quantitative dimension to eco-design prioritization within technology roadmaps. Specifically, ECoP can serve as a decision-support tool that makes performance-environmental impact trade-offs explicit without replacing established technical metrics, as demonstrated through both cross-technology comparisons and intra-platform design scenarios.

Nevertheless, the trade-offs presented in this review require cautious interpretation. The landscape of LCA studies on PoC diagnostics remains fragmented, with heterogeneous system boundaries, inconsistent transparency, and limited consideration of end-of-life scenarios or socio-economic implications. Many assessments are restricted to laboratory-scale prototypes and may not reflect real-world deployment conditions. Consequently, the ECoP metric and extended multi-criteria frameworks should be interpreted as order-of-magnitude, design-support indicators derived from harmonized yet heterogeneous datasets, rather than definitive comparative rankings. Our design metrics are positioned as structured interfaces between environmental assessment and engineering design, making performance-impact trade-offs explicit at early design stages, when design choices remain most flexible. By linking PoC device analytical requirements to their environmental cost, it promotes a transition from generic sustainability claims toward quantitatively grounded, evidence-based decision-making in PoC diagnostic development.

Moving forward, sustainability efforts must go beyond material substitution or footprint minimization. Emphasis should shift toward design-for-circularity, reusability under regulatory constraints, and regionalized production models to reduce both upstream impacts and downstream waste. These shifts will require coordinated advances in business models, policy frameworks, and infrastructure, not just engineering innovation (Deman et al., 2024; Street and Kersaudy-Kerhoas, 2025). Yet, addressing sustainability in PoC diagnostics ultimately requires a broader framework that also accounts for economic, social, and supply-chain dimensions. Integrating such dimensions - sovereignty, resilience, and accessibility - will be key to ensuring that environmentally improved designs also promote equitable deployment (Budd et al., 2023).

To support such transitions, future work should adopt multi-level assessment frameworks. The enabling impact (indirect impact due to organizational or behavioral changes) and structural impact (socio-economic impact due to structural and institutional change) could be regarded as supplementary considerations to the life-cycle impact (Hilty and Aebischer, 2015). In the classical LCA framework, one can also address the social impact of the life cycle of a product. Social and Socio-economic Life Cycle Assessment is a complementary method to LCA that aims to assess the social and socio-economic aspects of products and their potential positive and negative impacts along their life cycle. For instance, social LCA may evaluate the human rights or the working conditions (impact categories) of the workers and local communities (stakeholders) (Benoît and Mazijn, 2009). However, S-LCA fails to integrate the interconnexion between the choice of design and the social aspects. Another complementary tool focusing on the economic aspect is Life Cycle Costing which is a compilation of all costs related to a product, over its entire life cycle. It intends to compute the real cost of product, since that, for many products, the purchase price reflects only a minority of the costs that will be caused by the product (Hunkeler et al., 2008). However, these considerations may not be readily accessible at the early stage of biosensor development, contrary to simplified LCA. Further inquiry may be necessary to incorporate additional factors that ensure the integration of social and socio-economic considerations into design decisions.

The analytical framework developed here provides a robust foundation for evaluating the environmental footprint of PoC diagnostics at the device level. Yet several questions remain open for future research, especially regarding how design changes propagate through technical, economic, and social systems. Beyond quantifying direct environmental burdens, forthcoming work should aim to link material and process choices to broader causal mechanisms, to understand not only which impacts occur, but why and how they spread across scales. A promising research agenda could therefore include.

- Integrating multi-scale analysis, that is extending the environmental focus of simplified LCA toward a representation of impacts that travel from materials and unit operations to entire value chains and territories.
- Characterizing causal relationships, that is identifying not only the magnitude of impacts, but also the structure of the links that connect design decisions, actor behaviors, and institutional responses, distinguishing different mechanisms.
- Combining propagation and feasibility analysis by developing indicators that capture both the intensity of effects (propagation coefficients) and the conditions under which design changes can actually occur (technological, regulatory, behavioral).

Such developments would move eco-design research beyond static footprint comparisons toward a causal understanding of sustainability transitions, one that connects early-stage design decisions with the systemic evolution of diagnostic technologies and their socio-economic environments. They would also provide a bridge between environmental engineering and the economics of innovation, helping to design diagnostic technologies whose sustainability depends as much on their causal propagation as on their material efficiency.

To conclude, we emphasize that the indicators proposed in this framework, like those from LCA more broadly, should be understood as tools to assess environmental burdens, not as fixed targets to achieve. Their purpose is to support balanced decision-making by quantifying trade-offs between diagnostic performance, environmental impact, and societal accessibility. It is essential to interpret these results critically, particularly given the inherent uncertainties of LCA. As Goodhart's law reminds us, when an indicator becomes a target, it ceases to be a good indicator (Goodhart, 1984).

Faced with accelerating ecological and societal pressures, the need for diagnostic systems that are not only effective but also frugal, robust, and low-carbon has never been greater. As Whitesides, pioneer in the field, argued more than a decade ago (Whitesides, 2011; 2013), the future of diagnostics may well lie in doing more with less. This work outlines a pathway to help realize that vision.

Author contributions

GL: Conceptualization, Software, Investigation, Writing – review and editing, Writing – original draft, Data curation, Methodology, Visualization, Validation, Formal Analysis. RM: Methodology, Writing – original draft, Formal Analysis, Visualization, Data curation, Writing – review and editing, Validation, Investigation, Conceptualization, Software. IA: Methodology, Conceptualization, Validation, Supervision, Writing – review and editing. J-PR: Resources, Funding acquisition, Visualization, Project administration, Validation, Writing – review and editing, Supervision, Conceptualization, Methodology.

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Conflict of interest

The author(s) declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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