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Application of Generative AI for Waste Reduction in Construction - A Systematic Review

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The construction industry significantly contributes to material waste and greenhouse gas emissions, making sustainability essential. Artificial intelligence (AI), especially Generative AI (GenAI), offers new opportunities to improve efficiency and reduce waste in the Architecture, Engineering, and Construction (AEC) sector. This study conducts a systematic literature review (SLR) of GenAI applications in construction waste management from 2020–2025. Using PRISMA 2020 guidelines, 29 peer-reviewed studies from databases such as Web of Science, Scopus, Engineering Village, and Google Scholar were analysed. Results show GenAI is advancing in design optimization to prevent waste, robotic sorting of demolition debris, and lean construction workflows. Key benefits include enhanced design accuracy, real-time decision support, and material reuse. However, challenges like data scarcity, computational costs, model hallucination, and lack of regulations persist. The study proposes future research on hybrid AI-human collaboration, model validation, and natural language interfaces for efficient waste management.

Keywords: Generative AI, Waste Reduction, Systematic Literature Review, Artificial Intelligence

Introduction and Background

Construction is resource- and emission-intensive: buildings alone account for large shares of global energy use and CO_2 emissions (Adewale et al., 2024; Regona et al., 2022). Estimates indicate up to 30% of construction materials become unused or wasted due to design inefficiencies, rework, procurement mismatches, and demolition streams (Adewale et al., 2024; Dagadkar et al., 2024). Meeting sustainability goals demands new methods to prevent waste across project phases. Generative AI (GenAI) extends conventional AI by creating novel outputs—design alternatives, synthetic datasets, or scenario simulations—using models such as transformers, GANs, diffusion models, and multimodal LMMs (Rad & Ilbeigi, 2025). In construction, GenAI promises low-cost exploration of design spaces, robust augmentation for scarce data, automated upcycling ideas, and conversational copilots tied to IoT/BIM for operational decisions (Liao et al., 2024; Rehman et al., 2024; Gharib & Moselhi, 2025). Yet the field is nascent and fragmented.

Significance of the Study

This study is significant because it addresses the critical gap between the rapid evolution of Generative AI technologies and their practical implementation in the construction sector. While traditional AI has been widely studied, the specific potential of Generative AI to proactively design out waste and autonomously optimize resource loops remains fragmented across isolated pilot studies. By synthesizing this emerging body of knowledge, this review not only validates the efficacy of current tools but also provides a necessary roadmap for practitioners and researchers. It identifies the systemic barriers—such as data scarcity and interoperability—that must be overcome to transition from theoretical models to scalable, net-zero construction solutions.

The Construction Industry Waste Management

The construction industry, one of the world's largest sectors, is resource-intensive and environmentally harmful. Buildings and infrastructure account for over 40% of global energy use and 30% of greenhouse gas emissions (Adewale et al., 2024). About 30% of materials become waste due to rework and inefficiencies, with 11–15% discarded before use (Adewale et al., 2024; Dagadkar et al., 2024). Excessive energy use, embodied carbon, and poor planning worsen impacts (Labib & Alhasan, 2025). Construction and demolition waste forms over one-third of municipal solid waste (Dodampegama et al., 2024), while recycling remains limited by contamination, costs, and poor infrastructure (Liu et al., 2024). In addition, oversized or inefficient energy systems cause further fuel waste and emissions (Adewale et al., 2024; Labib & Alhasan, 2025). Sustainable waste management must therefore integrate materials, energy, and lifecycle efficiency through digital and automated solutions (Regona et al., 2022; Labib & Alhasan, 2025).

Construction Phased Waste Management

The pre-construction, construction, and post-construction stages of a project lifecycle are critical phases for examining and understanding construction waste, as each stage presents distinct opportunities for intervention and contributes differently to overall inefficiencies.

Pre-construction phase: This stage shapes most future waste through poor design, planning, and procurement. Up to one-third of construction waste originates here due to over-specification and lack of sustainability focus (Adewale et al., 2024; Liao et al., 2024). AI-integrated BIM and generative design tools can optimize materials and reduce embodied carbon before construction begins (Dagadkar et al., 2024;Desai et al., 2023).

Construction phase: The construction phase generates the most visible waste from rework, damage, and poor coordination among stakeholders (Gopi Krishna & Dinesh Kannaa, 2024). AI-based monitoring and automation—like 3D printing and robotic bricklaying—can cut waste by up to 40%, improving precision and efficiency (Adewale et al., 2024; Alshamrani et al., 2024). However, high costs and skill shortages limit adoption.

Post-construction phase: Post-construction waste mainly comes from inefficient building operations and demolition. AI-managed HVAC and lighting systems reduce energy use by 20–30% (Adewale et al., 2024). Vision-based robots also improve sorting of C&D waste, increasing recycling despite challenges with irregular debris and limited datasets (Dodampegama et al., 2024).

AI Use Cases in Construction Waste Management

Artificial Intelligence (AI) has become a key tool for fixing problems that happen throughout the construction lifecycle. There are 4 ways that AI can be used in waste management: tracking materials and optimizing logistics, optimizing energy use, using robots and additive manufacturing, and predictive maintenance.

Real-time material tracking and logistics optimization: AI uses RFID tags, IoT sensors, and predictive algorithms to monitor and forecast material flows on sites. These systems detect discrepancies between deliveries and usage, reducing material waste by up to 40% (Adewale et al., 2024). Predictive models also enhance just-in-time procurement, minimizing excess inventory and transport-related emissions (Dagadkar et al., 2024).

Energy optimization: AI improves energy efficiency by adjusting HVAC, lighting, and temporary power based on occupancy and weather, cutting energy costs by 20–30% (Adewale et al., 2024). Digital twins allow real-time energy monitoring and predictive control (Lucchi, 2023), while surrogate-assisted

models enable near-instant configuration decisions (Manmatharasan et al., 2025). However, high costs and integration issues with older systems remain challenges (Dagadkar et al., 2024).
Robotics, automation, and additive manufacturing: AI-driven robots perform precise, repetitive tasks such as welding, bricklaying, and prefabrication, reducing rework and material loss (Gopi Krishna & Dinesh Kannaa, 2024). AI-guided 3D printing optimizes geometry and material use, while using fly ash and slag further lowers embodied carbon (Baduge et al., 2022). Adoption, however, is limited by high costs and skill gaps (Gopi Krishna & Dinesh Kannaa, 2024).
AI-driven predictive maintenance and asset management: AI predicts equipment failures through sensor data, minimizing downtime and conserving materials and energy (Dagadkar et al., 2024). Predictive maintenance extends machinery lifespan and reduces wasted fuel, spare parts, and emissions, creating both economic and environmental benefits (Adewale et al., 2024).
This systematic review answers three questions: *RQ1* — What GenAI applications for construction waste reduction are documented (2020–2025)? *RQ2* — What benefits, challenges, and barriers are reported? *RQ3* — Which research directions are most promising?

Methodology

Research Design

This study employs a Systematic Literature Review (SLR) to synthesize knowledge on the application of generative artificial intelligence (AI) for waste reduction in construction. The SLR method was chosen as it provides a transparent, replicable, and evidence-based framework for collecting, screening, and analysing research while minimizing bias. The review follows the PRISMA 2020 guidelines to ensure methodological rigor and reporting quality (Page et al., 2021).

Search Strategy

Four major databases were searched to capture relevant research: Web of Science, Engineering Village, Scopus, and Google Scholar. These databases were selected for their broad coverage of engineering, construction management, and computer science literature. A comprehensive search string was developed to combine terms related to artificial intelligence, waste management, energy optimization, and construction practices. Boolean operators (AND, OR) were used to refine retrieval. The final search string applied across databases was:

TITLE-ABS-KEY
(“Generative AI” OR “Generative Artificial Intelligence”) AND
(“Waste” OR “Waste Management”) AND
(“Construction”)

The search was limited to peer-reviewed publications written in English and published between 2020 and 2025, in alignment with the timeframe of the research questions. The timeframe was restricted to 2020–2025 to align with the technological inflection point that defines modern Generative AI. The release of foundational transformer models (such as GPT-3 in mid-2020) and advanced diffusion models marked a distinct paradigm shift from traditional, predictive machine learning to true generative capabilities. Literature published prior to 2020 predominantly focuses on discriminative AI methods (e.g., regression, standard computer vision), which lack the content-creation capabilities central to this review. Limiting the scope to this period ensures that the analysis captures only the most relevant, state-of-the-art applications while excluding obsolete methodologies.

Inclusion and Exclusion Criteria

The research team conducted the screening process in multiple stages, as illustrated in *Figure 1*, with strict application of specific inclusion and exclusion criteria at each step. To be eligible for inclusion, studies were required to be peer-reviewed journal articles or conference papers published in English between 2020 and 2025. Thematically, the primary focus of the research had to be the application or proposal of a Generative AI technique—such as LLMs, GANs, or Generative Design—situated within the Architecture, Engineering, and Construction (AEC) industry or the construction and demolition (C&D) waste management sectors. Furthermore, selected papers were required to explicitly discuss waste reduction, sustainability, the circular economy, or lean principles as a tangible outcome or goal. Conversely, the team applied exclusion criteria to filter out non-peer-reviewed content, including books, book chapters, editorials, patents, and theses, as well as works not written in English or published outside the designated 2020–2025 timeframe. Studies utilizing only traditional AI methods, such as predictive computer vision or regression, were excluded if they lacked a generative component. Additionally, papers were removed if they referenced "waste" only in passing or in an irrelevant context (e.g., data waste) rather than physical construction or process waste.

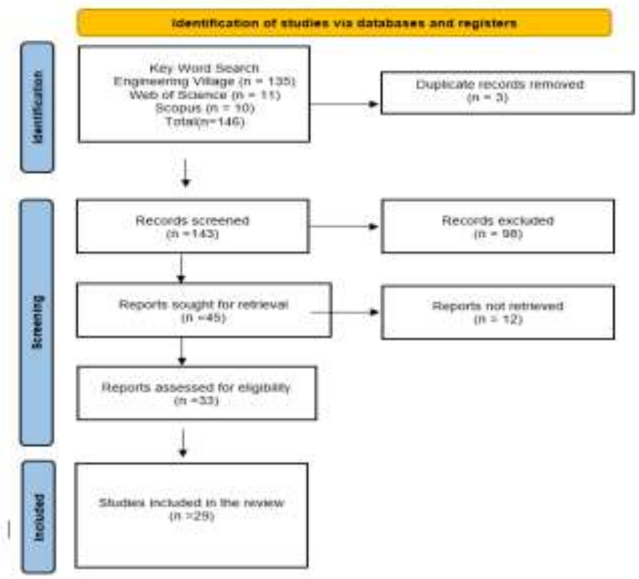

Figure 1: PRISMA Flow Chart

Data Extraction

Data from the included studies were systematically recorded in a structured Excel extraction sheet to ensure transparency and comparability. The extraction template (see *total paper review* sheet) captured the following information for each article:

- Bibliographic details: Article title, publication year, and source database (Scopus, Web of Science, and Engineering Village).
- Screening decisions: Title review outcome and abstract review outcome.
- Content summary: Abstract text.
- Eligibility status: Inclusion or exclusion in the final set of studies.

This structured process ensured that all relevant metadata were consistently documented and traceable across the review stages. The included studies were analysed through thematic synthesis, structured around the research questions:

- RQ1: Mapping current applications and findings of generative AI in waste reduction across construction activities (2020–2025).
- RQ2: Identifying benefits, challenges, drivers, and barriers reported in the literature.

- RQ3: Highlighting opportunities and directions for future research in generative AI–enabled construction waste reduction.

Quantitative patterns (e.g., frequency of methods, areas of application) were combined with qualitative synthesis of insights to provide a balanced review.

Ethical Considerations

This study is based entirely on secondary data from published sources. Therefore, no direct ethical risks to human participants were involved. However, methodological transparency was maintained by adhering to PRISMA guidelines and ensuring unbiased representation of all reviewed studies.

Results

Distribution of methods and focus

From the 29 included studies:

- 45%: Generative design / LLM / multimodal methods (pre-construction emphasis).
- 27%: Robotic automation and computer vision (construction & MRFs).
- 18%: GenAI–digital twin integration (post-construction energy and lifecycle optimization).
- 10%: GANs/diffusion for data augmentation supporting perception and mix design.

Pre-construction findings

GenAI-driven generative design and synthetic-data augmentation target early waste drivers: over-specification and excessive trial mixes. Representative results: embodied carbon reductions reported up to ~23% in simulated optimization studies (Liao et al., 2024); DGAN-augmented mix-predictors achieved $R^2 \approx 0.98$, reducing trial-and-error for 3D print mixes (Rehman et al., 2024). Mechanisms: (i) rapid virtual design-space exploration, (ii) data augmentation reducing physical experiments, and (iii) automated upcycling concept generation (Liu et al., 2024). Caveats: many studies are simulations or small-scale and use heterogeneous KPI definitions, affecting generalizability.

Construction-phase findings

Key applications include vision-based sorting, AI-IoT material tracking, robotic fabrication, and Lean+AI operational redesign. Perception models often achieve>90% accuracy on curated datasets; however, field performance commonly drops by 5–15 percentage points due to domain shift (Langley et al., 2025; Dodampegama et al., 2024). Integrated systems (AI + Lean workflows + human-in-the-loop + robotics) yield the largest on-site material outcomes: aggregated waste reductions between ~20–40% in coordinated pilots (Berroir et al., 2023; Kazeem et al., 2023). Isolated perception improvements yield modest gains (~5–10%). Hardware constraints (robotic grasping), contamination/occlusion, and socio-technical mismatches (unclear human roles for AI alerts) are frequent failure modes.

Post-construction findings

GenAI augments MRF throughput via synthetic labeling and assists operational energy reduction using GenAI-augmented digital twins (Adewale et al., 2024; Langley et al., 2025). Reported energy savings with DT-based GenAI controllers cluster at ~20–30% compared to static setpoints, though head-to-head benchmarks versus advanced MPCs are limited. MRF pilot results are promising but often measured in controlled conditions; full-scale plant evidence is scarce.

Quantitative effect patterns

Across studies reporting numeric outcomes:

- Material waste reductions typically range ~15–40%, with a central tendency near 25–30% when GenAI is part of integrated processes.
- Energy reductions are commonly 20–30% in GenAI-augmented buildings.

- Perception accuracy: >90% on curated tests; field accuracy commonly 75–88% absent domain adaptation.
  Drivers of heterogeneity: study maturity (lab vs. field), KPI definitions, integration depth (component vs. system), material stream complexity, and data freshness.

Limitations of the Analysis

- Non-comparable metrics across studies limited the ability to run meta-analytic pooling; we therefore used descriptive synthesis and cross-study triangulation. This reduces the statistical precision of pooled effect estimates.
- Publication bias: The review may over-represent positive pilot results published in peer-reviewed venues; negative or failed deployments often remain unreported in academic literature.
- Temporal concentration: The 2020–2025 window captures an era of rapid GenAI change; early 2025 conference papers may report prototypes that quickly evolve — findings should be considered a snapshot subject to rapid technical change.

Discussion

This section synthesizes evidence from 29 peer-reviewed studies (2020–2025) on Generative AI (GenAI) for construction waste reduction, noting benefits, failure modes, and literature limits. Overall, GenAI shows promise when embedded in socio-technical systems, but most evidence is pilot-scale or simulation-based. Measurement heterogeneity, limited lifecycle and cost accounting, and probable publication bias reduce generalizability. To scale confidently, the field needs standardized KPIs, more field trials, transparent reporting, and reproducible benchmarks (Langley et al., 2025; Gharib & Moselhi, 2025; Rampini & Cecconi, 2022).

RQ1. Current Findings on Applications of Generative AI for Waste Reduction (2020–2025)

Between 2020 and 2025, GenAI applications span pre-construction generative design and data augmentation, construction-phase vision/robotics and AI–IoT workflows, and post-construction digital twin and MRF augmentation (Zhang & Zhang, 2024). Reported impacts vary, with material reductions often falling in the ~15–40% range when GenAI is part of integrated processes, and perception models exceed 90% on curated sets but decline in field use. Benefits and effect sizes depend strongly on integration depth, dataset quality, and deployment scale (Liao et al., 2024; Rehman et al., 2024; Langley et al., 2025; Adewale et al., 2024).

Pre-construction

Pre-construction studies show that GenAI reduces embodied waste and trial-and-error by enabling extensive virtual design exploration and synthetic data augmentation. Examples include scrap upcycling with Stable Diffusion and CV that improves recognition and stacking (Liu et al., 2024), LLM-driven lean workflow assistance (Rad & Ilbeigi, 2025), DGAN mix-design for 3D printing with $R^2 \approx 0.98$ (Rehman et al., 2024), symbolic planning for printability (Barjuei et al., 2024), and large multimodal scraping for reuse-tracking with high metadata accuracy (Gharib & Moselhi, 2025), though many results are simulation-oriented and need broader field validation.

Construction

Construction-phase work centres on vision-based sorting, AI–IoT predictive monitoring, robotics, and Lean+AI reorganization. Lean+AI synergies improved sorting and reduced mixed waste where standalone AI failed (>90% lab accuracy in integrated pilots) (Berroir et al., 2023). Spectral sensors, combined with GenAI, enable excavation reuse (Hauzinger et al., 2025; Zhang & Zhang, 2024). Synthetic-data augmentation improves detectors (Langley et al., 2025), while AI–IoT predictive systems cut idle time (~15–20%) and flag inefficiencies for GenAI “what-if” simulation (Kazeem et al., 2023). Common field challenges include contamination, hardware limits, and socio-technical mismatches.

Post-construction

Post-construction GenAI work targets MRF augmentation, lifecycle energy optimization, and continuous O&M improvements. Synthetic labelling (diffusion + LLMs) boosts detection mAP and throughput in sorting facilities (Langley et al., 2025). GANs, DRL, and digital twins support predictive maintenance and lifecycle energy reductions (Rampini & Cecconi, 2022), while GenAI+DT frameworks promise ongoing optimization of carbon and waste KPIs (Labib & Alhasan, 2025). However, many MRF and DT results are pilot scale; full-scale validations and head-to-head benchmarks versus established controls are limited.

Table 1: Summary of RQ1 – Applications and Findings (2020–2025)

This table maps the specific applications of Generative AI across the construction lifecycle and their documented quantitative findings.

Project Phase	GenAI Application	Techniques Used	Key Findings & Quantitative Outcomes
Pre-Construction	**Generative Design & Data Augmentation**	• Generative Design • Large Language Models (LLMs) • Diffusion Models • DGANs	• **Embodied Carbon:** Reduced by up to **~23%** in simulation studies. • **Material Mix:** DGAN-augmented predictors achieved **$R^2 \approx 0.98$** for 3D print mixes, reducing trial-and-error. • **Scrap Reuse:** Automated upcycling concept generation using Stable Diffusion.
Construction	**Vision, Robotics & AI-IoT**	• Computer Vision (CV) • AI-IoT integrated systems • Spectral Sensors • Robotics	• **Waste Reduction:** Integrated systems (Lean + AI + Robotics) reduced waste by **20–40%**. • **Sorting Accuracy:** Perception models >90% in labs; drops **5–15%** in the field due to domain shift. • **Efficiency:** Predictive monitoring reduced equipment idle time by **~15–20%**.
Post-Construction	**MRF Augmentation & Digital Twins**	• Synthetic Labelling • Digital Twins (DT) • GenAI Controllers	• **Energy Optimization:** DT-based GenAI controllers achieved **20–30%** energy savings compared to static setpoints. • **Sorting:** Synthetic labelling (using diffusion + LLMs) improved detection mean Average Precision (mAP) and throughput in Material Recovery Facilities (MRFs).

RQ2 – Benefits, Challenges, Drivers and Barriers (2020–2025)

From 2020–2025 GenAI demonstrated benefits such as rapid design-space exploration, fewer physical trials, improved sorting accuracy, and operational energy savings via DTs (Barjuei et al., 2024; Rehman et al., 2024; Adewale et al., 2024). Barriers include dataset scarcity, domain shift, high compute and hardware costs, interoperability and skills gaps with BIM/IoT, inconsistent metrics, limited lifecycle cost studies, and LLM hallucination and governance risks. Overcoming these requires standardization, open datasets, workforce training, and ethical oversight (Gharib & Moselhi, 2025; Langley et al., 2025; Rampini & Cecconi, 2022; Rad & Ilbeigi, 2025).

Table 2: Summary of RQ2 – Benefits, Challenges, and Barriers
This table categorizes the positive impacts alongside the technical and operational hurdles identified in the literature.

Category	Key Aspects	Description & Evidence
Benefits	**Process Optimization**	• Rapid exploration of design spaces. • Significant reduction in physical trial-and-error (e.g., concrete mixes).
	Material & Energy Efficiency	• Enhanced sorting accuracy leads to higher material reuse. • Real-time decision support via Digital Twins yields operational energy savings.
Technical Challenges	**Data & Compute**	• **Data Scarcity:** Lack of open, standardized datasets for training. • **Computational Cost:** High cost of training and maintaining large models. • **Domain Shift:** High accuracy in labs fails to transfer perfectly to messy, real-world sites.
	Reliability	• **Hallucination:** Risk of LLMs generating plausible but incorrect data. • **Validation:** Difficulty in validating generative outputs against professional standards.
Barriers	**Socio-Economic & Structural**	• **Skills Gap:** Shortage of workforce trained in both Construction and AI. • **Interoperability:** Poor integration with existing BIM and IoT legacy systems. • **Regulation:** Lack of clear governance, ethical oversight, and liability frameworks for AI decisions.

RQ3 – Opportunities for Future Research

Priority opportunities include creating large-scale synthetic C&D datasets (diffusion, DGANs, LMM auto-labellers) to improve transferability (Dodampegama et al., 2024; Gharib & Moselhi, 2025), building real-time AI copilots that link BIM, IoT and DTs (Rad & Ilbeigi, 2025), developing GenAI–DT hybrids for rapid what-if sustainability analysis (Manmatharasan et al., 2025; Labib & Alhasan, 2025), designing AI–sensor hybrid frameworks for excavation reuse (Hauzinger et al., 2025), and advancing human–AI–robot collaboration and autonomous multimodal sorting (Liu et al., 2024; Dodampegama et al., 2024), alongside open benchmarks, KPI standards and lifecycle cost analyses for reproducibility and governance.

Limitations of Current Research

Although the reviewed studies highlight the strong potential of Generative AI (GenAI) in minimizing construction waste, several limitations restrict the practical application and generalizability of these findings.

- Overreliance on Simulations: Most studies rely on controlled lab settings, where AI systems perform well but lose accuracy in real-world conditions such as lighting changes and mixed debris (Langley et al., 2025; Dodampegama et al., 2024).
- Lack of Lifecycle and Cost Analyses: Few studies assess the full environmental or financial trade-offs of GenAI, ignoring the energy and carbon costs of training and maintaining large models.
- No Standardized Datasets or Metrics: Research uses inconsistent data and waste definitions, limiting comparability; standardized, open-access datasets are needed for reproducibility.

- Integration and Skills Gaps: Limited AI expertise among professionals and poor interoperability with BIM and IoT hinder practical implementation (Rampini & Cecconi, 2022).
- Ethical and Governance Issues: Transparency, accountability, and privacy remain unaddressed, leaving unclear liability for biased or inaccurate AI decisions.

Future Opportunities

Despite current limitations, the rapid evolution of GenAI presents transformative opportunities to advance waste reduction and sustainability in the construction industry. For practitioners and policymakers, there is need to:

- Embed GenAI outputs into procurement and design processes as probabilistic forecasts rather than deterministic orders to reduce over-ordering.
- Require GenAI-generated alternative sets at early design checkpoints.
- Invest in on-site labeled datasets and domain-adaptation methods.
- Implement human-in-the-loop protocols that define responsibility for AI alerts.
- Favor outcome-based contracts (e.g., kg CO_2e avoided) to align incentives with GenAI-enabled performance.
- Support open synthetic dataset repositories and standard KPI reporting.

Conclusion

This review synthesized 29 studies (2020–2025) to explore how Generative AI (GenAI) reduces construction waste across all project phases. Key applications include generative design for material efficiency, LLM-based systems for lean workflow automation and compliance, and AI-driven robotics for sorting and recycling (RQ1). Main benefits include better decision-making, proactive waste prevention, and material circularity, though data scarcity, high costs, LLM unreliability, and limited skills remain barriers (RQ2). Future directions focus on fact-checked AI (RAG), Human-in-the-Loop systems, explainable AI, and multimodal models integrating VR/AR for collaboration (RQ3). Overall, GenAI represents a major shift from reactive waste management to proactive prevention—serving as a collaborative "co-pilot" that empowers AEC professionals to enhance sustainability and advance toward a circular, low-waste built environment.

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