Life Cycle Assessment for the Unconventional Construction Materials in Collaboration with a Large Language Model

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In this paper, developing an online tool for the Life Cycle Assessment (LCA) of unconventional construction materials in collaboration with Large Language Models (LLMs) is proposed. The LCA provides information on the environmental impact of a product throughout its entire life cycle, from the extraction of raw materials to disposal or recycling. The LLMs are neural network architectures, typically utilizing variants of recurrent neural networks such as the transformer, which are trained on large bodies of textual data using techniques such as pre-training and fine-tuning. This study focuses on the use of bacterial cellulose composites as a biobased unconventional construction material. The methodology of developing an LLM-aided LCA tool is divided into five stages: Defining the functional unit; identifying the life cycle stages; collecting environmental and social impact data; interpreting and evaluating; developing a web-based tool. The results of this study have shown that the designers can incorporate sustainable thinking in the design process by using LLMs integrated to LCA, ultimately contributing to a more sustainable future against the impacts of the Anthropocene. Overall, the outcomes demonstrated the value of human-computer interaction (HCI) as a tool for exploring new possibilities with biobased materials and for inspiring designers to reconsider the material evaluation in their work. Future studies can delve into the integration of this tool into building information modeling software or computational design software in order to perform LCA for 3D structures. Different scales of such applications in design practices, such as fashion design, product design or service design can also be conducted by questioning how LCA can be combined with LLMs to leverage novel sustainable design solutions.

Keywords: *Machine Learning (ML), Large Language Models (LLMs), Human-computer Interaction (HCI), Life Cycle Assessment (LCA)*

INTRODUCTION

Life cycle assessment (LCA) is a comprehensive and multi-disciplinary approach to evaluate the environmental impact of a product, process, or service from the cradle to the grave (Vieira, Calmon and Coelho, 2016). It aims to provide a thorough understanding of the environmental implications associated with the entire lifecycle of a product, including the extraction of raw materials, production, use, and disposal (Buyle, Braet and Audenaert, 2013). The rigorous methodology of LCA ensures that all relevant environmental impacts are considered, providing a holistic and reliable assessment of the environmental footprint of a product or system.

LCA is applicable across a wide range of industries and sectors, including manufacturing, construction, transportation, and consumer goods (Hellweg, Mila and Canals, 2014). It provides valuable insights for designers, policymakers, and businesses to make informed decisions about the environmental impact of their products and processes (Zhang et al., 2020). LCA can inform the development of new products, help improve existing products and processes, and support the implementation of sustainable practices. It is used to evaluate the trade-offs between different materials, technologies, and design alternatives, as well as to compare and evaluate the environmental performance of competing products (Bishop, Styles and Lens, 2021). In recent years, LCA has become increasingly important for companies to demonstrate their commitment to sustainability and meet the growing demand for environmentally-friendly products from consumers (Roos et al., 2016).

In the field of architectural design and construction, LCA provides a framework to consider the environmental impact of buildings and infrastructure over their entire life cycle (Evangelista et al., 2018). It enables architects, engineers, and construction professionals to make informed decisions about materials selection, construction methods, and building operations that minimize environmental impact (Basbagill et al. 2013). The benefits of LCA in architectural design and construction are numerous. It can inform the selection of materials that are not only aesthetically pleasing but also environmentally responsible (Pollini and Rognoli, 2021). It can also help to optimize building operations, such as energy and water usage, to minimize environmental impact (Zabalza et al., 2013). Additionally, LCA can help identify opportunities for waste reduction, recycling, and other sustainability initiatives (Maria, Eyckmans and Acker, 2020).

The implications of LCA in architectural design and construction have the potential to drive innovation in sustainable building practices and materials, support the transition to a low-carbon built environment, and promote environmentally responsible design. LCA can also help to educate design and construction professionals about the environmental impact of their decisions and raise awareness about the role of the built environment in addressing global sustainability challenges (Malkki and Alanne, 2017). By integrating LCA into the design process, designers and builders can contribute to a more sustainable future by creating buildings and infrastructure that are environmentally responsible, economically viable, and socially responsible. There are several technologies and tools associated with LCA that support the collection and analysis of data and help make the LCA process more efficient and accessible. Life Cycle Inventory (LCI) databases such as Ecoinvent and the GaBi databases provide pre-existing information about the environmental impact of various materials, products, and processes, allowing for a faster and more accurate assessment of a product's life cycle (Pauer, Wohner and Tacker, 2020). Software such as SimaPro and GaBi, automates the LCA process, allowing users to perform assessments with a high degree of accuracy and consistency (Herrmann and Moltesen, 2015). Environmental Product Declarations (EPDs) provide a standardized and independently verified report on the environmental impact of a product, allowing for the comparison of products across different categories (Rasmussen et al., 2021). Carbon footprint calculators allow users to calculate the carbon emissions associated with a product or process and can be used as a simplified form of LCA (Zhong et al., 2019). These technologies and tools make it easier for designers, builders, and manufacturers to understand and reduce the environmental impact of their products and processes and support the transition to a more sustainable future.

On top of these technologies, recently released Large Language Models (LLMs) have the potential to

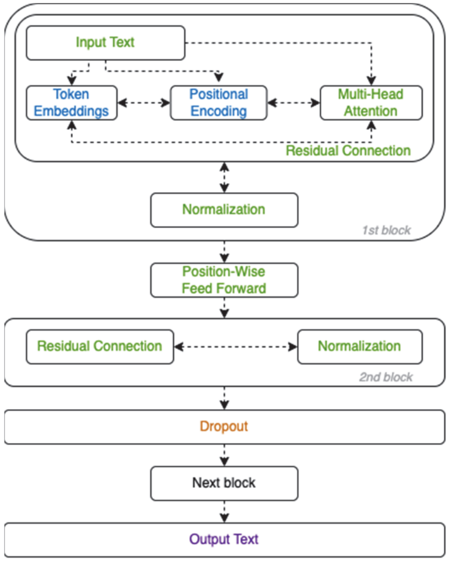

Figure 1
The architecture of Generative Pre-trained Transformer 3 (GPT-3)

revolutionize various industries, including the field of LCA. LLMs can be integrated with LCA to enhance the accuracy and speed of the assessment process, as well as to provide a more comprehensive understanding of the environmental impact of building materials, processes, and products. LLMs can automate the data collection and analysis process by extracting and analyzing data from a variety of sources, including product specifications, product databases, and scientific articles (Trummer, 2022). They can provide insights into product sustainability by analyzing product specifications and assessing the environmental impact of different materials, products, and processes, allowing designers, builders, and manufacturers to make informed decisions about product selection. LLMs can support the development of new materials and products by analyzing product specifications and suggesting alternative materials and products that have a lower environmental impact. LLMs can streamline the communication of LCA results by generating reports and summaries of LCA results, making the results more accessible and understandable to a wider audience. Overall, the integration of LLMs with LCA has the potential to transform the way that the environmental impact of building materials, processes, and products is assessed, enabling more informed and sustainable decision-making in the field of architectural design and construction.

LARGE LANGUAGE MODELS (LLMs)

The LLMs are neural network architectures, typically utilizing variants of recurrent neural networks such as the transformer, which are trained on large corpora of textual data using techniques such as unsupervised pre-training and fine-tuning (Veres, 2022). These models learn to generate text by predicting the next word in a sequence based on the contextual information provided by the previous words and are able to produce coherent and fluent sentences that resemble human-written text (Aliyu and Kotzee, 2022) with potential applications in architectural design and construction and related design fields. The architecture of large language models (LLMs) typically consists of several layers of neural networks (Arnold, Paugam-Moisy and Sebag, 2010). These layers may include attention mechanisms, transformer blocks, or other specialized modules depending on the specific model (Bahdanau, Cho and Bengio, 2014).

One key aspect of LLM architecture is the use of self-attention mechanisms, which allow the model to attend to different parts of the input text when making predictions enabling the model to capture complex dependencies between words and phrases, which is particularly useful for tasks like language modeling and machine translation (Skrlj et al., 2021). Another important component of LLM architecture is the use of pre-training, where the model is first trained on a large corpus of text using unsupervised learning techniques enabling the model to learn a rich representation of the underlying structure of language, which can then be fine-tuned on specific downstream tasks (Zhang et al., 2020).

Overall, the architecture of LLMs is designed to enable the model to learn high-level representations of language that can be used for a wide range of natural language processing (NLP) tasks, from simple text classification to more complex tasks like question answering and text generation. LLMs can do a variety of tasks beyond just predicting the next word in a sequence when combined with different methods and tools. The capabilities of LLMs and their area of use include language understanding, text-to-text translation, text-to-image generation, text completion, reinforcement learning etc. (Zhou et al., 2021).

In order to have a better understanding of the process, the architecture of Generative Pre-trained Transformer 3 (GPT-3) was investigated (Figure 1). It is a deep neural network (DNN) that consists of multiple transformer blocks, which are a type of neural network module specifically designed for NLP tasks (Gillioz et al., 2020). At a high level, GPT-3 takes as input a sequence of text, such as a sentence or paragraph, and processes it through a series of transformer blocks to generate a corresponding sequence of output text.

In Figure 1, the blue components represent the input text and the related encodings. The input text is tokenized (i.e., split into individual words or tokens) and then passed through various encoding layers to convert it into a numerical representation that the model can work with. These layers typically include a token embedding layer that maps each token to a vector representation and a positional encoding layer that adds information about the position of each token in the input sequence. The green components represent the layers of the transformer model that comprise the bulk of the GPT-3 architecture. These layers include multiple levels of self-attention (or multi-head attention) and feed-forward networks, which enable the model to capture complex patterns in the input text and generate high-quality output. The green components also include residual connections and normalization layers, which help to prevent vanishing gradients and stabilize the training process. The orange components represent the dropout layers used for regularization. Dropout is a technique used to prevent overfitting in deep learning models by randomly "dropping out" some of the neurons in a layer during training. This helps to prevent the model from becoming too reliant on any one feature and can improve its generalization performance on new data. The purple component represents the output text generated by the model. This is the final result produced by the GPT-3 architecture, which is based on the input text and the context provided to the model.

Some of the components that have been identified as particularly important for the performance of the LLMs include the self-attention mechanism, the use of pre-training on large datasets, and the size and depth of the model architecture. Additionally, the quality and quantity of the training data used to train the model can also be a critical factor in the performance of the model. The recently released ChatGPT, developed by OpenAI, is an implementation of the GPT architecture specifically designed for the tasks of generating natural language texts (Mijwil, Aljanabi and Ali, 2023). The architecture consists of multiple layers of self-attention and feed-forward neural networks, similar to the original GPT architecture.

In the ChatGPT, the components mentioned earlier are crucial in the sense that they allow the model to process and understand the input text and generate coherent and contextually relevant responses. The token embedding layer is responsible for converting each word in the input text into a numerical representation. The positional encoding layer helps the model to understand the position of each word in the input text, which is important for maintaining the context. The multi-head self-attention layer allows the model to attend to different parts of the input text and gather information from them. The residual connection and normalization layers improve the flow of information through the layers and prevent the model from losing information. The position-wise feed-forward layer processes the information further and adds additional context. Finally, the dropout layer is used for regularization, which helps prevent the overfitting of the model. Overall, these components work together to allow the ChatGPT to understand and generate natural language text, making it a powerful tool for various natural language processing tasks such as chatbot development and language translation.

As an open-source language model, ChatGPT's architecture and pre-trained models are publicly available for developers to build upon for specific applications. The pre-trained models can be fine-tuned on a specific dataset to specialize the model for a specific task, such as sentiment analysis or chatbot development. This allows for the development of highly customized language models that can perform specific tasks at a high level of accuracy.

In addition to the pre-trained models, ChatGPT provides an API that can be used for integrating the language model into specific tools or applications. The API allows for easy integration of ChatGPT's natural language processing capabilities into existing software, such as chatbots or virtual assistants. Furthermore, ChatGPT can be integrated with a wide variety of open-source tools, libraries, and frameworks, such as TensorFlow and PyTorch, which makes it easy for developers to incorporate ChatGPT into their existing workflows. This flexibility allows for a wide range of use cases and enables developers to create highly customized language models that meet specific requirements. There are many software and tools that have been built on top of the ChatGPT architecture. Some examples include Copy.ai, a web application that generates marketing copy, taglines, and slogans using GPT-3 language models; Jarvis, a mobile application that uses GPT-3 to generate natural language responses to user queries; Hugging Face, a platform that provides a suite of natural language processing tools, including transformers and language models, that can be used for a wide range of applications; AI Dungeon: a web-based game that uses GPT-3 to generate interactive stories and game scenarios based on user input; GPT-3 Sandbox, a web-based playground that allows developers to experiment with GPT-3 models and build their own applications. These are just a few examples of the many applications and tools that have been built using the ChatGPT architecture. With the open-source nature of the platform and the availability of APIs, there is virtually no limit to the kinds of tools and applications that can be built on top of this technology. The first step is to tokenize the input text, breaking it down into a series of individual tokens or words. These tokens are then passed through a layer of positional embeddings, which encode the position of each token in the sequence. The token embeddings are then processed through a series of encoder and decoder layers, each consisting of multiple transformer blocks. The encoder layers analyze the input text and generate a series of hidden representations that capture the meaning and context of each word or phrase, while the decoder layers use these representations to generate the corresponding output text. The final output of GPT-3 is a sequence of tokens corresponding to the generated text. This architecture enables GPT-3 to generate high-quality text that is fluent and coherent and can be used for a wide range of NLP tasks.

LEVERAGING LIFE CYCLE ASSESSMENT (LCA) THROUGH LLMs

The architecture of ChatGPT, namely GPT-3, has the potential to be used as a “text-to-LCA” bot in evaluating materials' sustainability. One possible application is through analyzing the language used in materials' specifications and comparing it against established sustainability standards. For example, GPT-3 could be used to identify the use of materials that are known to be unsustainable, such as those with high carbon footprints or that are non-renewable. GPT-3 could also be used to assess the sustainability of a given design or construction project by analyzing text descriptions of the project's materials, energy usage, and other factors. The model could be trained to recognize patterns and associations that are indicative of environmentally friendly design and construction practices, such as the use of renewable energy sources or low-impact building materials. Another potential use of GPT-3 in evaluating materials' sustainability is through analyzing text descriptions of materials themselves, such as their composition, production processes, and expected lifespan. By analyzing this information, the model could identify materials that are likely to be more sustainable or environmentally friendly, such as those that are recyclable or biodegradable. Overall, GPT-3's ability to analyze and understand natural language could be harnessed to support efforts in evaluating materials' sustainability, as well as in other areas of sustainable design and construction.

Conventional construction materials, such as concrete, steel, and wood, are widely used in the building industry. However, producing these materials can have significant environmental impacts, including greenhouse gas emissions, water, and air pollution, and the depletion of natural resources. Their LCA studies have been widely conducted, and these environmental challenges have been reported. These LCA studies have provided valuable insights into the environmental impact of conventional construction materials, and have supported the development of more sustainable building materials and construction practices. The results of these studies have also been used to develop sustainability standards, such as the ISO 14040 series for Life Cycle Assessment, which provides guidelines for conducting LCA studies and comparing the sustainability of different materials and products.

On top these materials, biologically active materials are a relatively novel class of biobased materials that have recently gained attention for their potential applications in building construction. These materials incorporate living microorganisms, such as bacteria, fungi, and algae, into building materials to enhance their functional properties and create new opportunities for sustainable design. Examples of biologically active biobased materials include bio-concrete, a type of concrete that incorporates bacteria into the mixture, which produces calcium carbonate in the presence of water. This process helps to heal cracks and extend the life of the concrete, reducing the need for repairs and maintenance; algae-based building materials that incorporate living algae into building materials, such as insulation and wall panels, to provide insulation and improved air quality; mycelium-based materials that are made from the fast-growing underground network of fungal filaments known as mycelium. These materials have high insulation and thermal performance, and can be used as an alternative to conventional insulation materials.

In contrast to various databases for conventional building construction materials, these biologically active materials as construction materials do not have any databases. The reason is that these materials have emerged with the application of different material formulations, and the production is often altered based on the desired qualities, such as increasing the tensile strength or coloring. This study aims to leverage the LCA of biobased materials through LLMs, focusing on evaluating a bacterial cellulose-based (BC-based) partition wall as a case study. Since the traditional LCA processes can be time-consuming and resource-intensive, especially when dealing with complex and living materials w,th intricate processes such as the growth and production of bacterial cellulose (BC). LLMs, on the other hand, have shown promising results in streamlining and automating various tasks, including data gathering and analysis.

METHODOLOGY

This methodology (Figure 2) aims to integrate the capabilities of LLMs into the LCA process, to enhance its efficiency and accuracy. The methodology is divided into five main stages: Defining the functional unit; identifying the life cycle stages; collecting environmental and social impact data; interpreting and evaluating; building a web-based tool.

Stage 1: Defining the Functional Unit. The first stage of the methodology involves defining the functional unit, which is the unit of product or process that will be evaluated in the LCA. In this case, the functional unit is defined as a 1x2 square meter of BC-based partition wall surface.

Stage 2: Identifying the Life Cycle Stages. The second stage of the methodology involves identifying the life cycle stages of the partition wall. The life cycle stages are divided into the following phases based on the ISO 14040 and ISO 14044: Raw material production and processing, manufacture of the partition wall, transportation and distribution, installation and use of the partition wall, disposal or end of life.

Stage 3: Collecting Environmental and Social Impact Data. The third stage of the methodology involves collecting environmental and social impact data for each life cycle stage identified in stage 2. This data can be gathered through a combination of primary and secondary sources, including database searches and academic articles. LLMs is used to automate the data collection process, and to identify the relevant and up-to-date data sources.

Stage 4: Interpreting and Evaluating. The fourth stage of the methodology involves interpreting and evaluating the environmental and social impact data collected in stage 3 based on CML 2001. This can be done using a variety of impact assessment methods and tools, such as life cycle impact assessment (LCIA), sustainability assessment, and life cycle costing (LCC). LLMs is used to automate the impact assessment process, and to provide more accurate and comprehensive results.

Stage 5: Building a web-based tool. The final stage of the methodology involves ChatGPT API integration to Superblock in order to analyze the environmental impact potentials of the products and suggest improvements based on the results. The ChatGPT was trained on the available qualitative and quantitative data for the first three steps in a feedback-based conversational way, then it was asked to interpret and evaluate the data in the fourth step, while generating results on defining optimization potentials in the last step.

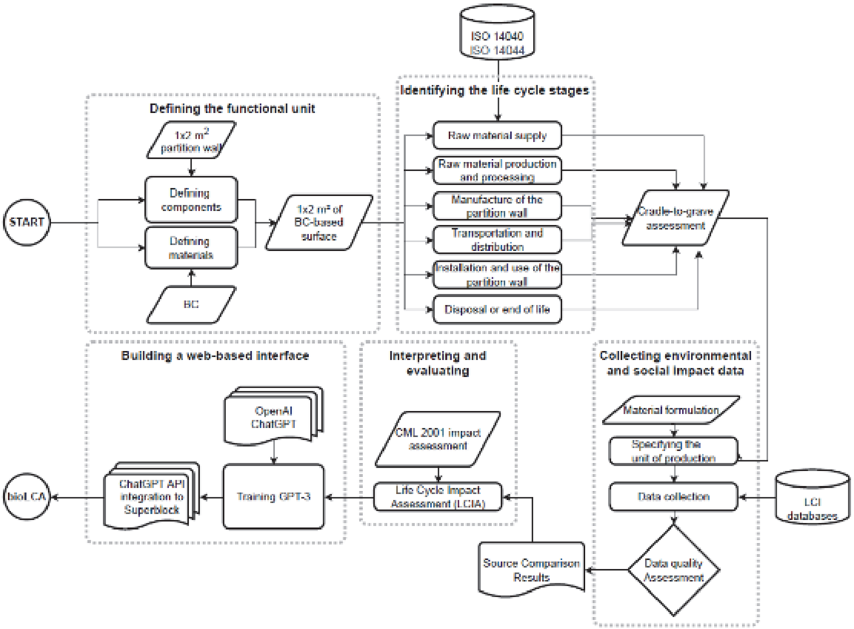

Figure 2
Methodology

IMPLEMENTATION

After specifying the unit of production, which was defined as 1x2 m2 of a partition wall, data was collected from the life cycle inventory databases, academic articles and project reports. The collected data was assessed in terms of quality and reliability through multiple comparisons. The environmental and social impacts of the product was then analyzed through CML 2001 impact assessment method. CML 2001 impact assessment method, which is a widely used life cycle impact assessment method for environmental analysis of products, services and processes. It was developed by the Center for Environmental Science at Leiden University in the Netherlands. The CML 2001 method (Table 2) covers a wide range of impact categories related to the environment, such as climate change (GWP100a), ozone layer depletion (ODP), human toxicity (HTP), freshwater aquatic ecotoxicity (FWAETP), marine aquatic ecotoxicity (MAETP), terrestrial acidification (TAP), terrestrial eutrophication (TEP), photochemical ozone creation (POCP), and particulate matter formation (PMFP). It is often used in the construction sector for the environmental assessment of building materials, products, and systems, as well as for the assessment of infrastructure projects. The whole qualitative and quantitative data collected since the beginning of the study, which covers the process from the production of BC biofilm to its disposal, was introduced to OpenAI's generative pre-trained transformer ChatGPT for training on the desired data sets. The model required a context and was constantly in need of more information on each step to generate values for each impact category.

Impact Category	Unit	Raw material supply	Raw material processing	Manufac-ture	Transport. and distrib.	Installa-tion and use	Disposal
GWP100a	kgCO2 eq	0.02	0.24	2.82E-03	1.16E-04	0.00	3.23E-05
ODP	kgR-11 eq	1.85E-07	6.92E-06	1.29E-09	1.53E-09	0.00	0.00
HTP	kg	0.02	0.10	0.00	0.00	0.10	0.00
FWAETP	kg 1,4-DB eq	7.90E-05	4.75E-04	0.00	0.00	4.90E-04	0.00
MAETP	kg 1,4-DB eq	2.08E-04	1.24E-03	0.00	0.00	1.28E-03	0.00
TAP	kg SO2 eq	5.27E-05	1.24E-04	0.00	0.00	1.10E-04	0.00
TEP	kg PO4 eq	4.22E-06	4.85E-05	0.00	0.00	4.66E-05	0.00
POCP	kg ethene eq	7.48E-06	1.00E-04	0.00	0.00	9.90E-05	0.00
PMFP	kg PM2.5 eq	3.41E-07	2.06E-06	0.00	0.00	2.12E-06	0.00

Table 2
LCA of BC-based partition walls based on CML 2001 impact categories

RESULTS

Based on the results obtained from the LCA analysis it can be observed that the BC-based partition wall has a lower environmental impact compared to a conventional partition wall made of wood. The production and transportation of wooden partitions have higher impacts on climate change, fossil fuel depletion, and water consumption. For instance, the GWP100a of the BC-based partition wall is 0.02 kg CO_2 eq/m^2, while the GWP100a of the wood partition wall is around 3.08 kg CO_2 eq/m^2. The difference in impact can also be observed in other categories as well.

After the results were retrieved successfully, an online browser-based platform (Figure 3) was developed by using Superblocks, a blockchain platform that allows developers to create decentralized applications, by integrating the API of ChatGPT to retrieve LCA for biobased materials. Once the smart contracts are deployed, the API provides a range of endpoints that allow developers to read and write data to the blockchain, as well as to interact with smart contracts.

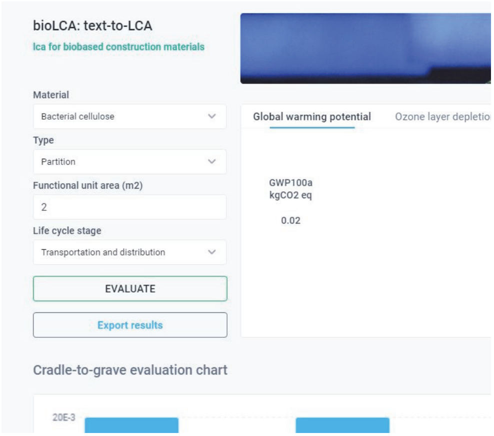

Figure 3
Online browser-based platform bioLCA

CONCLUSION AND DISCUSSION

The results of this study have shown that the designers can incorporate sustainable thinking in the design process by using LLMs integrated to LCA, ultimately contributing to a more sustainable future against the impacts of the Anthropocene. The proposed implementation of an online interface can also be integrated into Building Information Modeling (BIM) software such as Autodesk Revit and ArchiCAD to streamline the process of data collection and analysis in building design and construction.

Future studies can delve into the integration of this tool into building information modeling software or computational design software in order to perform LCA for 3D structures. Different scales of such applications in design practices, such as fashion design, product design or service design can also be conducted by questioning how LCA can be combined with LLMs to leverage novel sustainable design solutions.

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