

Review

ML-Based Materials Evaluation in 3D Printing

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Featured Application: ML-based systems supporting material selection and evaluation for 3D printing purposes.

Abstract: Machine learning (ML) is transforming the evaluation of 3D printing materials, enabling more efficient and accurate assessment of material properties, including their sustainable life cycle. ML algorithms can analyze vast amounts of data from previous printing processes to predict the performance of different materials (including those used in multi-material printing) under different conditions. This predictive ability helps in selecting the most suitable materials for specific printing tasks, optimizing the mechanical, chemical, and overall quality of the final product. Furthermore, by integrating real-time data from sensors during the printing process, ML can continuously monitor and adjust parameters, ensuring optimal material utilization and reducing waste. ML models can identify and correct defects in printed materials by recognizing patterns associated with defects, thus improving the reliability of 3D-printed objects. This approach reduces the need for expensive and time-consuming physical tests. This accelerates the pace of 3D printing development but also increases the precision of material selection and processing, contributing to more efficient use of materials and energy for printing.

Keywords: artificial intelligence; machine learning; material selection; materials evaluation; 3D printing



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1. Introduction

The emergence of machine learning (ML)-based materials evaluation in 3D printing is the result of a combination of advances in 3D printing technologies, materials science, and computer science (AI). Early 3D printing research focused largely on using trial-and-error to optimize material properties and printing parameters. As 3D printing became more sophisticated, researchers recognized the limitations of traditional approaches, particularly in terms of time, cost, and scalability.

The rapid development of ML algorithms in the 2010s provided a fast track to addressing these challenges by leveraging insights from historical and current 3D printing processes [1–3]. Initial applications of ML in materials science involved predicting the properties of conventional materials, such as metals and polymers, based on data focused on material composition and how it changed during manufacturing and processing. These successes inspired researchers to apply similar techniques to the emerging field of 3D printing. One of the earliest applications of ML in 3D printing involved optimizing process parameters, such as temperature, speed, and layer height, to improve print quality and material performance [4]. Over time, advances in computing power (including the emergence of cloud technologies) and the availability of larger sets of historical and real-time

data (thanks to the Internet of Things) have enabled the development of more complex ML models tailored to the needs of 3D printing. Scientists have begun to integrate ML with advanced characterization techniques, such as scanning electron microscopy and spectroscopy, to analyze and predict the behavior of materials at the micro- and nano-scale [5]. In the mid-2010s, the emergence of generative models enabled the virtual design of new 3D printing materials with specific properties (mechanical, chemical) [6]. Collaborations between academia and industry have further accelerated the adoption of ML in 3D printing materials analysis, as companies continue to improve product and material development cycles; supply chain issues related to the pandemic and political crises around the world have played a role [7,8]. Interdisciplinary approaches have begun to emerge, with physicists, chemists, and computer scientists working together to build hybrid ML–physics models to achieve more accurate classifications and predictions [9]. Open-source platforms and initiatives have democratized access to ML tools, encouraging scientists and engineers to experiment and innovate more widely in materials evaluation. The late 2010s also saw the emergence of real-time ML applications in 3D printing, focusing on defect detection and adaptive control during the printing process. Sustainability concerns have also influenced the adoption of ML, as it has proven effective in evaluating recyclable and bio-based materials for 3D printing [10].

ML-assisted materials evaluation in 3D printing allows for the prediction of material properties before printing begins. This allows for the optimization of the production process through better selection of parameters and materials. ML models analyze data from previous prints, allowing for automatic adjustment of settings to obtain the best quality. Such optimization shortens experimentation time, reduces costs, and increases efficiency. As a result, ML becomes a key tool supporting continuous improvement of the 3D printing process. Today, ML-based materials evaluation is a key tool in advancing 3D printing capabilities, combining computational intelligence with manufacturing technologies. As part of predictive maintenance, ML algorithms help predict when 3D printer components are likely to fail or require maintenance, which helps reduce material waste, avoid print quality degradation, reduce downtime, and increase productivity. This evolution reflects the synergy between traditional scientific research and modern data-driven methodologies, setting the stage for further breakthroughs in 3D printing [11–13].

Currently observed research gaps in the evaluation of ML-based materials for 3D printing are as follows:

- The number of high-quality, diverse datasets for training ML models is limited, which makes it difficult to develop robust predictive models [14,15];
- The lack of standardized protocols for data collection and reporting results in inconsistent datasets that are difficult to integrate or compare;
- Many ML models act as black boxes, making it difficult for researchers to understand and verify their predictions in the context of materials science [16];
- The computational requirements of ML models, especially for large-scale or real-time applications, still constitute a significant barrier to industrial implementation even using cloud technologies—recently, these are increasingly often limitations related to the cost of electricity required for computation [17];
- ML models trained on specific materials, technologies, or printing conditions often fail to generalize to other materials, systems, or environments, which limits their usefulness [18];
- The integration of the knowledge of physics, chemistry, and mechanics specific to a given 3D printing technology and related printing materials with ML algorithms is still underdeveloped, leading to gaps in the accuracy and reliability of predictions;

- Although real-time ML frameworks exist, they often lack the precision or speed needed for dynamic adjustments in complex printing processes [19–21];
- Predicting interactions and optimizing parameters for multi-material or composite 3D printing remains a major challenge;
- Limited research has investigated the role of ML in assessing the environmental impact, recyclability, and life cycle of 3D printing materials;
- The cost of implementing ML solutions, including hardware and expertise, remains prohibitive for smaller organizations and research labs, even with the advent of cloud solutions [1,5,22,23].

These gaps underscore the need for further research and innovation to fully leverage the potential of ML in 3D printing materials evaluation.

It is important to note that it is necessary to accelerate research into 3D printing materials and their targeted dynamization. New materials (with improved and specialized properties, e.g., antibacterial properties, etc.) are revolutionizing 3D printing, expanding the range of possible properties and applications beyond traditional plastics, metals, and ceramics. Materials such as carbon fiber composites increase mechanical strength and reduce weight, making them invaluable in the aerospace, automotive, and high-performance sports equipment industries [24,25]. Conductive polymers and graphene-based materials enable the creation of electronic components, flexible circuits, and 3D-printed smart devices (e.g., clothing items) directly through 3D printing. Biocompatible materials such as hydrogels and medical-grade polymers (according to the Medical Devices Regulation) are facilitating advances in bioprinting for the creation of custom implants, tissue engineering, and drug delivery systems. Ceramic and glass materials open up applications in electronics, optics, and high-temperature environments where conventional plastics would fail. Shape-memory alloys and polymers offer capabilities such as self-healing, supporting applications in robotics, medical devices, and responsive structures. Sustainable materials, including bio-based plastics and recycled composites, address environmental concerns, making 3D printing more environmentally friendly and attractive for large-scale implementation [26]. Multi-material printing enables the integration of different materials within a single structure, enabling the creation of complex, multifunctional objects such as sensors with embedded electronics. Advanced material formulations tuned for high precision or specific thermal, chemical, or electrical properties are key to industries such as semiconductors, energy, and aerospace [27–29]. Continuous innovations in materials science not only provide new functionalities for 3D-printed objects, but also push the boundaries of design freedom, change the face of industries, and enable the creation of completely new products, services, and industrial processes, developing economies and providing new opportunities for societies, e.g., in the area of healthcare. ML-based material optimization integrates with connected systems, enabling smart factories to autonomously select and customize materials for specific 3D printing applications. ML leverages big data analytics to process information from sensors and IoT devices in real time, ensuring that materials are optimized for performance, sustainability, and efficiency in the manufacturing process. ML-based predictive models improve supply chain management by forecasting material demand, reducing waste, and ensuring timely availability of customized materials [30]. ML supports human- and environment-centric manufacturing by enabling the co-creation of materials that meet both functional requirements and ethical or aesthetic preferences. Human–AI collaborative systems enable rapid prototyping and iterative development of materials with unique characteristics, such as biocompatibility or multifunctionality, tailored for personalized applications. ML-based optimization enables sustainability by facilitating closed-loop material systems, the efficient recycling of input materials, and the design of materials with reduced environmental impact. Real-time defect detection and

correction, enabled by ML, aligns with the goals of zero-defect manufacturing, delivering high-quality results with optimized material utilization. ML algorithms also support decentralized manufacturing, where local units can customize material formulations based on specific requirements without centralized oversight. Combining machine learning-based material optimization with interconnected, sustainable, and human-centric principles creates a transformative ecosystem for advanced manufacturing that combines efficiency, innovation, and responsibility [5,30].

The aim of this article is to assess to what extent ML-based issues regarding materials evaluation in 3D printing are present in scientific research and to identify possibilities for further investigation.

2. Materials and Methods

2.1. Dataset

This bibliometric analysis aims to investigate the state of knowledge and practice in the area of planning and implementing ML for the optimization of 3D printing materials and technologies. For this purpose, we used bibliometric methods to analyze recently published (i.e., up to five years back) scientific publications with a global reach. The analysis is guided by the following research questions (RQs) to identify key areas that encompass the current state of research:

- RQ1: what is the most common origin of publications (institutions, country, if possible, funding mode)?
- RQ2: who are the most influential authors and what are their articles?
- RQ3: what are the most popular topics, and, if possible, how are the research topics evolving?

When possible, we tried to answer RQ4:

- RQ4: what Sustainable Development Goals (SDGs) are related to the publications included in the review?

Our approach allows for a more comprehensive understanding of current research and industry trends, strategies, and business practices based on ML in the development of 3D printing. It is necessary to understand and plan the necessary further developments in this field and to strengthen its potential. The interpretation of bibliometric data will thus enrich current discussions and provide a solid basis for future research.

In the context of ML-based materials evaluation in 3D printing, it is crucial to use consistent technical terminology to avoid confusion—especially with terms that are often used interchangeably, such as FDM (Fused Deposition Modeling) and FFF (Fused Filament Fabrication). Consistency in terminology requires that FFF (Fused Filament Fabrication) be used when referring to the open or generic term for extrusion-based printing, and FDM (Fused Deposition Modeling) only when referring to the trademarked version (owned by Stratasys, Waltham, MA, USA).

2.2. Methods

In this study, we searched four bibliographic databases: Web of Science (WoS), Scopus, PubMed, and dblp. This selection was dictated by the wide range of publications they indexed and the rich metadata of global importance (Table 1). We applied filters to focus on the relevant literature, narrowing the search to articles in English. After filtering, we manually reviewed each article to ensure that it met the inclusion criteria, which helped determine the final sample size. We then analyzed the main features of the dataset, including the most frequent authors, research groups/institutions, countries, topic groups, and emerging trends. This allowed us to map key terminology and its evolution, as well as

the main research developments in the study area. Where possible, we tracked temporal trends to monitor changes in the research landscape over time and grouped publications into topic clusters that showed relationships between different research areas. This process highlighted important themes and subfields emerging within the research area.

Table 1. Bibliometric analysis procedure (own approach).

Stage Name	Tasks
Defining research objectives	Defining goals of the bibliometric analysis
Selecting data bases and data collections	Choosing appropriate dataset(s) and developing research queries according to the study goals
Data preprocessing	Cleaning the collected data to remove duplicates and irrelevant records
Bibliometric software selection	Choosing suitable bibliometric software/tools for analysis
Data analysis	Description, author, journal, area, topics, institution, country, etc.
Visualization (if possible)	Visualizing the analysis results to present insights
Interpretation and discussion	Interpreting findings in the context of the research goals

The study used selected elements of the PRISMA 2020 guidelines for bibliographic reviews [31], focusing on the following aspects: rationale (item 3), objectives (item 4), eligibility criteria (item 5), information sources (item 6), search strategy (item 7), selection process (item 8), data collection process (item 9), synthesis methods (item 13a), synthesis results (item 20b) and discussion (item 23a). Partial PRISMA 2020 checklist is attached as Supplementary File. For the bibliometric analysis, we used tools embedded in the databases Web of Science (WoS), Scopus, PubMed and dblp. The selected review methodology supports bibliometric and scientometric studies, often enabling refined classification by concepts, research areas, authors, documents, and sources. The results are presented in a table, which allows for further flexible analysis and visualization options. Given the interdisciplinary scope and complexity of the topic, we have summarized the most important results of the review in a summary table.

3. Results

3.1. Data Sources

To refine the search, advanced filtered queries were used, limiting the results to articles in English. Searches were performed as follows: in WoS using the “Subject” field (consisting of the title, abstract, KeyWords Plus, and other keywords); in Scopus using the article title, abstract, and keywords; and in PubMed and dblp using manual sets of keywords. The databases were searched for articles using keywords such as “machine learning”, “3D print” or “3D printing”, and “material” (Table 2).

Table 2. Detailed database search query (own version).

Parameter/Feature	Detailed Description
Inclusion criteria	Books (and chapters in books), articles (original, reviews, communication, editorials), and conference proceedings, in English
Exclusion criteria	Books older than 10 years, letters, conference abstracts without full text, other languages than English
Keywords used	deep learning, energy optimization/optimization, smart city
Used field codes (WoS)	“Subject” field (consisting of title, abstract, keyword plus and other keywords)

Table 2. Cont.

Parameter/Feature	Detailed Description
Used field codes (Sopus)	article title, abstract and keywords
Used field codes (PubMed)	manually
Used field codes (dblp)	manually
Boolean operators used	Yes, e.g., “3D print” AND (“optimization” OR “optimization”) AND “machine learning”
Applied filters	Results refined by publication year, document type (e.g., articles, reviews), and subject area (e.g., industry, engineering).
Iteration and validation options	Queries are run iteratively, refined based on results, and validated by ensuring that relevant publications appear among the top results
Leverage truncation and wildcards used	Used symbols like * for word variations (e.g., “3D print*” for “3D print” or “3D printing”) and ? for alternative spellings (e.g., “optimi?ation” for “optimisation” or “optimization”)

The selected set of publications was then further refined (Figure 1) by manually re-screening articles, removing irrelevant publications and duplicates to determine the final sample size.

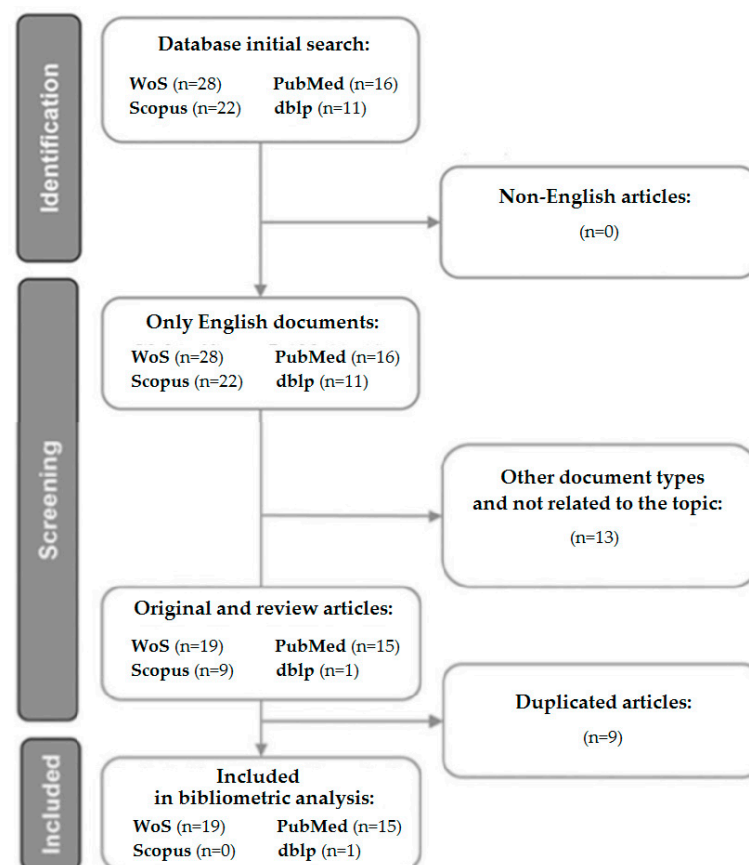


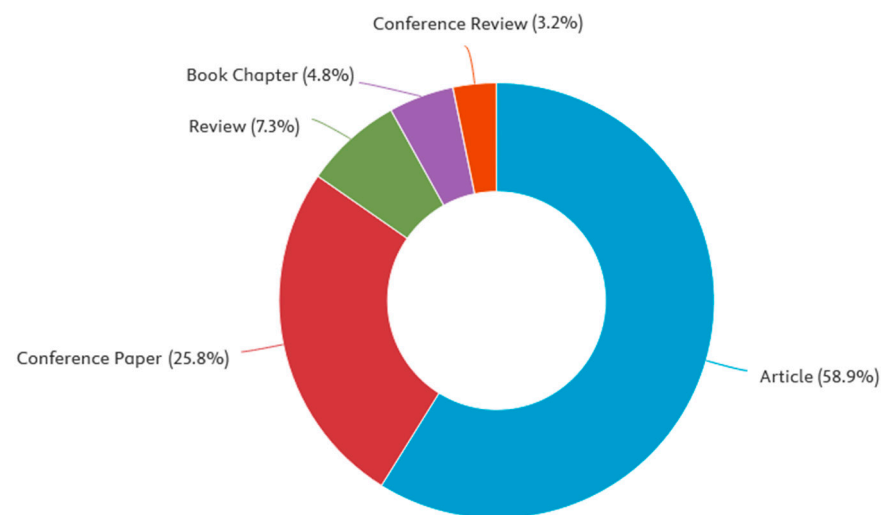
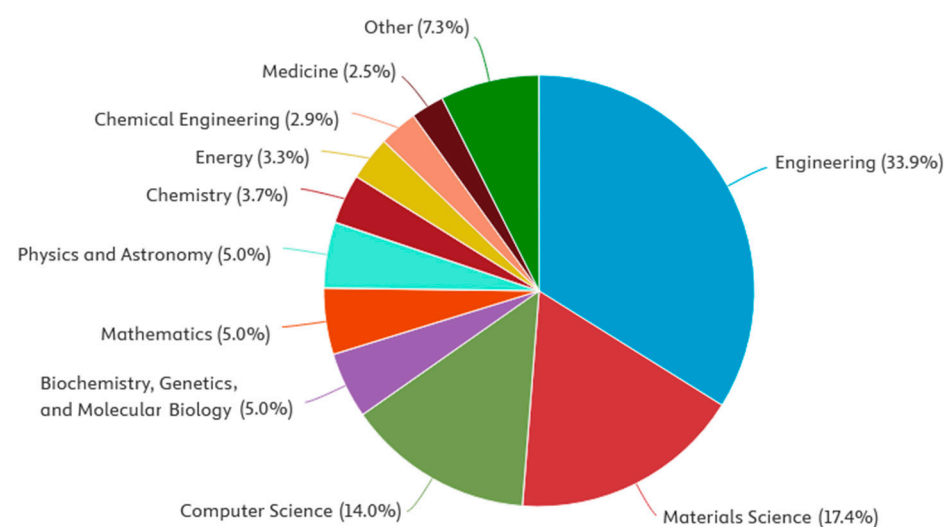
Figure 1. PRISMA flow diagram of review process using selected PRISMA 2020 guidelines [31].

3.2. General Results of Analysis

The summary of the bibliographic analysis results is presented in Table 3 and Figures 2–5. A total of 35 articles published in the last five years were analyzed (older articles were not included due to rapid knowledge advances in the field).

Table 3. Summary of bibliographic analysis results (WoS, Scopus, PubMed, dblp).

Parameter/Feature	Value
Leading types of publication	Article (58.9%), proceeding paper (25.8%), review (7.3%) (Figure 2)
Leading areas of science	Engineering manufacturing (33.9%), Materials science (17.4%), Computer science (14.0%) (Figure 3)
Leading topics	Nanofibers, scaffolds and fabrication, Mechanics
Leading countries	USA, India, China (Figure 4)
Leading scientists	Baldwin M., McComb C.; Meisel N.A.
Leading affiliations	Pennsylvania State University, Carnegie Mellon University, Georgia Institute of Technology
Leading funders (where information available)	National Science Foundation, United States Department of Defence, United States Department of Energy, European Commission (Figure 5)
Sustainable development goals	Industry innovation and infrastructure, Good health and well being

**Figure 2.** Documents by type.**Figure 3.** Documents by subject area.

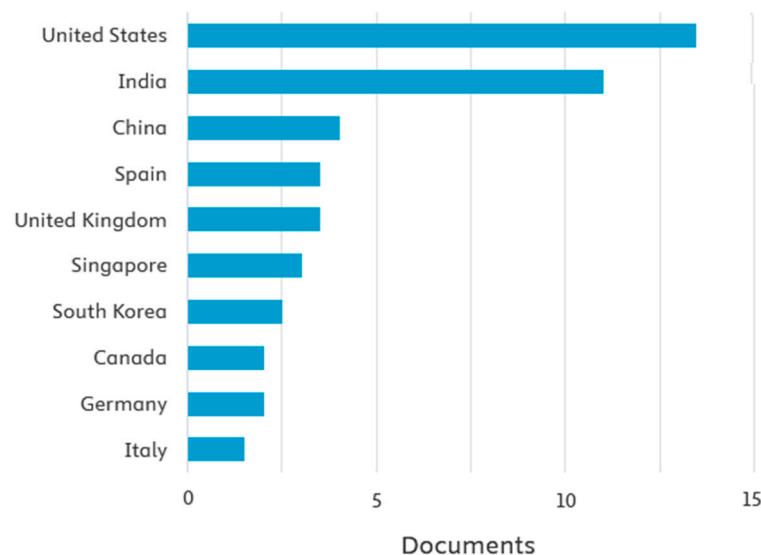


Figure 4. Documents by country/territory.

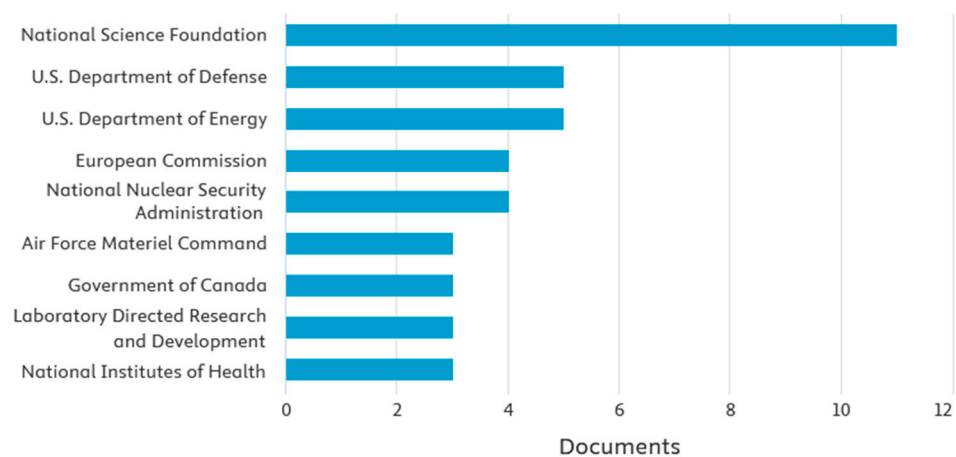


Figure 5. Documents by foundation (where available).

3D printing is currently a well-researched method for manufacturing structural elements from various materials, mainly polymers, metals, and ceramics. Research on 3D printing materials focuses on three main areas:

- The better or alternative use of existing materials, including improving material preparation procedures to improve the quality, efficiency, and sustainability (energy costs, waste, gases) of printing;
- The development of currently used materials (bio-ink, composites, multi-material printing materials);
- The development of completely new materials (e.g., nanomaterials), complementary or alternative to the current ones.

ML is slowly transforming 3D printing materials evaluation towards AI-driven methods, enabling real-time analysis and optimization of material properties, reducing waste and increasing efficiency. Advanced ML models can predict how materials will behave under different conditions, such as stress, temperature, or load, increasing the reliability of printed parts. By analyzing large datasets, ML algorithms can identify correlations between material composition and performance, paving the way for the development of innovative materials tailored to specific applications. ML-based tools can automate quality assurance processes by detecting microscopic flaws or inconsistencies in 3D-printed materials that traditional methods might miss. The technology facilitates adaptive printing strategies, where

changes in printing parameters are dynamically introduced to compensate for material variability or environmental changes. With ML, manufacturers can simulate and optimize material deposition patterns, leading to stronger, lighter, and more efficient structures. ML-based predictive maintenance ensures printers operate with consistent material quality, minimizing downtime and preventing costly breakdowns. Scientists can use machine learning to explore vast areas of chemical and materials design, accelerating the discovery of new materials with desirable mechanical, thermal, or chemical properties [1]. Integrating ML with 3D printing improves multi-material manufacturing by optimizing interfaces, which is crucial when creating complex, functional devices [4]. In this way, ML democratizes materials evaluation by making advanced analytics accessible to non-experts, supporting innovation across industries and applications (Figure 6).

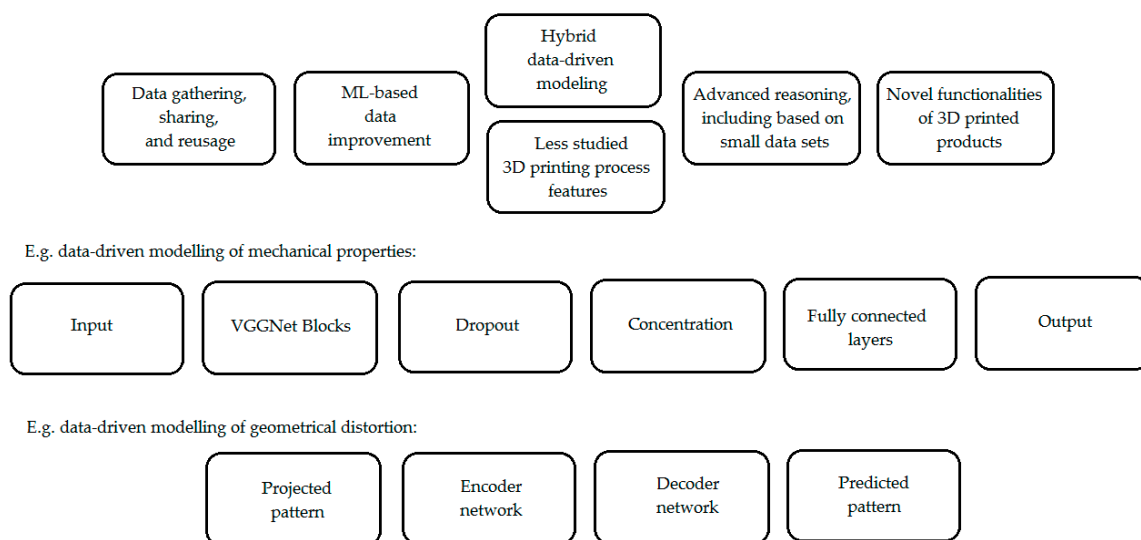


Figure 6. ML model applications in materials evaluation in 3D printing.

Figure 6 shows the main areas of ML application at different stages of product development, from data collection to the development of new materials and related functionalities. The use of ML is shown here in two examples:

- The modeling of mechanical properties of products, combining the actual microstructure (as input to the network) with descriptors of the structure properties within the network;
- The modeling of geometrical distortions, where a convolutional neural network with an encoder and decoder allows for explicit modeling of geometric distortions of the entire printable shape.

The aforementioned ML-based models provide new possibilities compared to traditional analytical methods.

3.3. Detailed Results of Review

In light of the review, current research on the use of ML in the area of material selection and adapting 3D printing parameters to the selected material is fruitful. Already, factors influencing the number and types of defects in 3D printing (unexpected material flow, machine setting errors) are analyzed using anomaly detection systems based on, for example, image recognition by a DL model with a variational autoencoder. On this basis, the autocalibration algorithm corrects defects. It is also possible to use a set of simulated parameters that maximize printing speed while minimizing deflection-related failures throughout the 3D printing process in terms of material properties and geometry, ensuring high process efficiency [32]. In the case of multi-material 3D printing, the 3D printing of active electronics

(photodetectors, light-emitting diodes) has been shown, but this process is sensitive to printing parameters, ink concentration, and composition, and environmental disturbances. This is due to the fact that the assembly process is governed by multi-step interactions between solutes, solvents, and the microenvironment. Any instabilities can cause deviations from the target printing patterns. The integration of a multi-scale microfluidics-driven 3D printer with an ML algorithm can classify and optimize complex sets of internal features (explore the multidimensional parameter space) by modulating ink composition [33]. In the case of inkjet 3D printing, this challenge has been the ability to continuously jet different materials from print heads. Active ML is used to construct detailed jetting diagrams that identify complex regions rather than just individual jet points. The method requires more than 200 experiments for each fluid, but still reduces the number of experiments by 80%, achieving an accuracy of more than 95% in predicting useful jet zones for the tested fluids. This will accelerate the development of new inks and jet heads for 3D printing [34]. Recent years have shown that the availability of polymer materials for 3D printing is limited, and the experimental determination of resin compositions is time-consuming and expensive. For the above reasons, an active ML approach was used to select the composition in the space of ternary monomers with specific parameters (from rigid to elastomeric, based on, among others, Young's modulus, peak stress, ultimate strain, or Shore hardness) in successive rounds of tests. This allows the selection of the composition of materials within, for example, 10% of the target value of Young's modulus. This allows for better adjustment of the properties of the 3D-printed product to the user's requirements, accelerates material discovery, and limits the space of monomers to those currently available [35]. The 3D printing filaments and polymer composites (e.g., acrylonitrile-butadiene-styrene—ABS) are increasingly combined with electrically conductive carbon nanostructures. Here, ML models can be used to predict tensile strength and resistance values in real time. Gaussian Process Regression and Support Vector Machine models confirmed the linear dependence of electrical resistance on the length of ABS products and the influence of the method on producing strength values [36]. The widespread use of 3D printing technology is increasing the need for non-destructive inspection methods that can assess and quantify build quality with high certainty. To this end, a solution is proposed for automatic defect recognition in 3D-printed parts using X-ray computed tomography scans and ML, assuming no a priori information about defect appearance, size, and/or shape. Processing times of several minutes and low false positive rates are achieved [37]. The research also aims to introduce machine learning-based models that predict the tensile strength of 3D-printed parts using the Fused Filament Manufacturing (FFF) method and develop a tool that optimizes printing conditions according to user requirements. This helps to generalize the results obtained during the 3D printing of samples with different materials and properties to new cases [38]. Hierarchical ML is also being applied to the 3D printing of silicone elastomer using free-form reversible deposition (FRE). It can predict the behavior of complex physical systems using distributed datasets by integrating physical modeling into statistical learning and optimizing material, formulation, and processing variables. This has increased printing speeds by up to 2.5 times while maintaining print fidelity [39]. Melt electrowriting enables high-resolution 3D printing without solvents, sensitive to changes in printing parameters. An ML-based Gaussian process regression model yielded 93% accuracy, reducing printing time and material waste, and does not require users to have ML skills [40]. A hybrid variational geometry/property autoencoder was used to generate multi-lattice transition regions. This provided improved performance in maintaining stiffness continuity across transition regions in designs requiring smooth mechanical properties. Thus, integrating mechanical properties added to the geometric data improves ML capabilities in designing such spatial structures for 3D printing [41,42]. Material defect mitigation in 3D printing

processes is also becoming available. This is based, among other things, on the use of ML to predict mechanical properties. This is demonstrated on the example of Ti-6Al-4V produced by laser powder bonding. A wide range of microstructure and property changes in the samples were investigated depending on the production parameters, laser power, and scanning speed using photodiodes. The images from the photodiodes were assembled into a comprehensive matrix and extracted into high-density information vectors using convolutional neural networks with pre-trained weights. The regression models for mechanical properties achieved an average accuracy of 98.7%. This provides the possibility of real-time closed-loop control and optimization of the above-mentioned 3D printing processes in industrial applications [43]. The transparency of some printing materials blurs the color texture details; hence, research has emerged on how to quickly prepare color-accurate 3D prints. Previous methods have been computationally expensive. A 100-fold less computationally expensive approach is the ML-based approach derived from atmospheric cloud rendering, realized in a time frame corresponding to the actual printing time [44]. Changing a bit or a group of bits in a digital data file intended for 3D printing is enough to compromise its integrity, but it is easily detected (e.g., by hash functions), and the printing process (and then the printed object) remains compliant within the parameter tolerance zones (if they are different from zero). So far, four possible cyberattacks have been identified based on changing physical parameters within the tolerances of 3D printing parameters in order to sabotage the mechanical properties of printed elements. These attacks did not cause any visible deformation of the dimensions and mass of printed elements (e.g., rods), but nevertheless changed their tensile and bending strength by up to 25%. What is worse, these attacks were not detected at all or were detected with a significantly high false negative rate [45]. Structural innovations also apply to 3D printing: CNN and digital morphogenesis research methods have been used to perform biomimetic design of 3D-printed material morphologies. These approaches transfer the material properties of structural natural 2D biological forms to 3D models while maintaining their structural performance advantages observed in nature (e.g., spider webs). This allows for the selection, reconstruction, and testing of various biomimetic 3D structures, including for sustainable development [46]. Techniques in 3D printing are usually limited to printing in flat environments with a fixed orientation of a single nozzle. The challenge is to attach new structures to existing structures that may have non-planar surfaces in unconventional orientations. This can be accomplished, for example, by extruding conformal material using a robotic arm that uses an algorithm to generate layers consisting of the spatial (3D) coordinates of the print path and a nozzle oriented along the substrate's normal direction. This allows, for example, the reconstruction, repair, or reinforcement of existing structures, including in spaces with difficult access or limited volume [47]. There has also been a suggestion to use realistic 3D-printed copies of ancient artifacts in university teaching to avoid damage to the originals [48]. This requires 3D printing materials that provide not only an accurate representation of shape, but also texture, material type, and cohesion. This requires a relative reduction in scanning quality in order to accurately interpret the original for 3D printing, especially in the case of small details [49]. The literature review [50] showed that ML models and algorithms are already used for decision-making related to the extrusion process of polymer materials, in detecting quality defects or flaws of 3D-printed parts. The most studied aspect here is the relationship between the mechanical properties of materials and anisotropy. Sensors (digital cameras, thermal cameras, thermocouples, accelerometers, etc.) have been integrated to obtain data. Despite efforts, there is still no system on the market that could provide integral feedback control and real-time process regulation, which presents an opportunity and space for further research and technological development [50]. A similar challenge is the integration of multiple materials during printing (e.g., sensors),

and there may be many different reasons for this. The process of separating conductive from non-conductive parts may still require manual intervention using a stencil and metallic spray to obtain sufficient contact area and insulation efficiency [51]. A similar challenge is the 3D printing of soft magnetic materials (e.g., Fe-6.5 wt.% Si steel) for topologically optimized electrical machines. The production of this steel by cold rolling is not possible due to its brittleness, but laser powder fusion (L-PBF) offers a solution to this problem [52].

Also in demand are ceramic materials for 3D printing, made for example from a mixture of stoneware clay and biomaterial dough, which better correlates shrinkage, density, strength, and porosity with the amount of dough in the recipe. In a study, the shrinkage of the clay dough was used in a material-oriented approach to create ceramic molds, where the form was dictated by the pattern in which the clay dough materials were loaded for 3D printing [53]. Similarly, current methods of creating 3D-printed displays either require specialized post-production processes or use passive elements that respond to environmental factors (e.g., body temperature, etc.). These passive displays offer limited control over when, where, and how colors change. ThermoPixels may be a breakthrough as a method for designing and 3D printing actively controlled and visually rich thermochromic displays embedded in arbitrary geometries [54]. The development of new, cost-effective 3D-printed ground contact sensors improves proprioceptive capabilities in small legged robots, using multiple materials, including conductive ones, to provide improvements in responsiveness, ease of integration, and cost-effectiveness [55]. The real data (on sliding friction, rolling friction, and coefficient of restitution) of 3D-printed materials will be used to create simulation models in which the interaction between grinding bodies and grinding media takes place in order to improve the accuracy of simulation models [56].

The incorporation of recycled materials into multi-material 3D printing offers the potential to enhance the performance of 3D printing materials in practical industrial applications. Research is ongoing regarding the multi-material 3D printing of pure polylactic acid (PLA) with recycled polylactic acid (rPLA) using FDM to obtain desired material properties by exploring different percentages and layer arrangements of recycled material in combination with pure PLA [57].

For many applications related to the interface of equal environments (industrial, clinical), the key role is played by the reactivity of 3D printing materials related to the processes and interactions at the interface of surfaces, one of which is printed. Relationships of chemical functions and their spatial arrangement are sought, as well as new ways of modifying the surface of micro- and nanomaterials, which will allow for the design of specific interactions at the interface or their absence at the stage of selecting a material for 3D printing [58]. The degree of complexity of the research makes it necessary to include ML at the initial stages of the study. The process of 3D printing is increasingly supporting the 3D printing itself by measuring its parameters, generating new data useful for further AI/ML analysis of the material preparation processes, the 3D printing process itself, and the finishing of the printed surfaces [59].

3D printing systems are emerging for the precise deposition of continuous filament materials (from spools) into thermoplastic 3D prints during the FFF printing process, improving tensile strength, force transfer, and aesthetic/tactile characteristics (FFF) [60]. The integration of stiffness and softness in 3D prints can increase their versatility in applications such as robotics, but the challenges of forming durable interfaces between soft and rigid materials remain significant (e.g., insufficient extrusion with increased resistance to lap shear and peel) [61].

New algorithms also allow for the generation of a 3D extruder path combining planar and non-planar layers to improve the accuracy of printed parts and their surface quality (avoiding the step effect). A hybridization effect is achieved: non-planar 3D layers are used

to print “difficult” surfaces, and planar layers are used for the remaining areas of a specific 3D print [62]. This will perhaps become a standard based on the use of ML to reconcile the speed and quality of 3D printing.

Environments such as FRoMEPP [63] or the TODIM-TOPSIS method based on PIVHFS [64] are being created that generate technical guidelines and compliance criteria for critical parameters (including material and cybersecurity) of 3D printing based on historical and current data. They identify, for example, potential thermal profile manipulation, internal voids, and lack of print time integrity resulting from incorrect material selection or preparation, incorrect process parameters, or attacks [63]. This also applies to the quantification of property changes in uncertain environments, e.g., in hygrothermal ageing, which plays an important role in material selection and solving related problems by optimizing the material and/or its structure, e.g., through 3D printing reinforced with separately stacked continuous glass fiber layers [64].

4. Discussion

4.1. State-of-the-Art Summary

Research into ML-based materials evaluation in 3D printing has gained momentum as 3D printing evolves toward smarter, data-driven methodologies. ML techniques are already being used to predict material properties (tensile strength, elasticity, thermal resistance, etc.) based on input parameters such as material composition and printing conditions. Research often uses supervised machine learning models such as neural networks or decision trees trained on datasets containing experimental or simulated material data. The pro-growth and pro-ecological opportunities offered by ML-based optimization in 3D printing include rapid innovation, cost-effectiveness, and sustainability, while risks include data challenges, safety concerns, and ethical considerations [65,66]. Balancing these aspects in further research will be key to realizing the full potential of ML in this field [67,68]. The opportunities are as follows:

- ML can rapidly analyze data to discover new materials, reducing development time from years to months;
- By tailoring material properties to specific applications, ML enables highly specialized solutions in various industries such as aerospace and healthcare;
- ML optimizes material usage, minimizing waste and promoting the development of recyclable or bio-based materials;
- Algorithms optimize printing parameters in real time, leading to fewer defects and higher quality results;
- Automated optimization reduces trial-and-error experiments, lowering material and energy costs;
- ML helps create multifunctional composites and materials with unique properties, such as conductivity or biocompatibility [67–69];
- ML models can predict failures in material performance or printer operations, reducing downtime [70,71];
- ML supports local material optimization, enabling on-demand manufacturing in remote locations [1,5,72,73].

ML accelerates the design of multifunctional composites by predicting how combinations of materials and structures affect multiple properties, such as strength, conductivity, and elasticity. For example, ML models can learn from experimental data to suggest optimal proportions of carbon nanotubes in polymers to maximize both electrical and mechanical performance. Techniques such as neural networks and genetic algorithms enable inverse design, where a target set of properties leads to suggestions for composite formulations. ML also supports microstructure optimization by analyzing image data to correlate internal

geometry with macroscopic behavior. Reinforcement learning can be used to discover new manufacturing strategies, such as layer-by-layer deposition paths that simultaneously increase thermal and acoustic insulation [67–69].

The following risks are also defined:

- ML requires vast amounts of high-quality data that can be difficult or expensive to acquire and maintain;
- Poorly trained models can introduce biases or inaccuracies, leading to suboptimal material properties or printing failures;
- As ML integrates with IoT and cloud systems, security flaws can expose proprietary material designs to cyberattacks;
- Models optimized for narrow scenarios may not generalize well to other applications, limiting versatility;
- ML integration requires skilled personnel and advanced infrastructure, which is a challenge for smaller companies;
- The automated development of advanced materials raises concerns about misuse in areas such as weapons or surveillance;
- While ML promotes sustainability, the computational resources required for training and optimization can have a significant carbon footprint [1,5,72,73].

In ML-based materials evaluation for 3D printing, one of the main challenges is limited and noisy datasets, which can be solved by transfer learning or Bayesian inference using frameworks such as PyTorch 2.7.0 (Meta AI, New York, NY, USA) or scikit-learn 1.6.1 (open source). High-dimensional input spaces from process and material parameters require dimensionality reduction techniques such as principal component analysis (PCA) or autoencoders, often implemented in TensorFlow 2.16.1 (Google Brain Team, Mountain View, CA, USA) or PyTorch. To predict complex properties such as mechanical strength or microstructure, deep neural networks are effective, especially when integrated with image data, implementing Keras 3.9.2 (ONEIROS project, open source) or PyTorch. Gaussian process regression in GPyTorch can help interpolate material behavior when data are scattered, but precision is key. Optimizing process parameters to achieve the desired performance is another challenge, commonly solved by Bayesian optimization or genetic algorithms, supported by solutions such as the automatic hyperparameter optimization software framework Optuna (Preferred Networks Inc., Tokyo, Japan). For real-time control and in situ adaptation, online and active approaches are useful, enabled by frameworks such as scikit-multiflow (open source). Digital twins built using ML can accelerate virtual experiments, thus helping to reduce the cost and time of materials testing.

4.2. Limitations

This multidisciplinary field continues to combine materials science, data analysis, and manufacturing technologies, promising innovative advances in 3D printing. Scientists face challenges in obtaining large, high-quality datasets due to the high cost and time-consuming nature of experimental 3D printing studies [71]. At the current stage of development, it is difficult to clearly select an ML method for an application. Transfer learning has been explored to overcome the data shortage by using pre-trained models on similar material datasets [74]. Reinforcement learning is used to dynamically optimize printing parameters, with the goal of improving material performance during the printing process itself. Advanced imaging techniques such as X-ray microtomography are combined with ML to assess material porosity and defects in real time [75,76]. Generative models such as GANs are used to simulate the microstructural properties of new materials, reducing the need for extensive physical testing. Scientists have used clustering algorithms to classify materials based on their printability and compatibility with different 3D printing

techniques [77]. Hybrid approaches that combine ML with physics-based models provide a deeper understanding of material behavior under complex printing conditions. Active learning frameworks allow researchers to iteratively improve models by selecting the most informative data points for further testing [78]. Integrating ML models with digital twins has enabled real-time monitoring and prediction of material properties during the printing process. Some studies focus on multi-material 3D printing, using ML to predict material interactions and optimize the mixing of different materials [79]. Researchers are investigating the role of ML in assessing the environmental impact of 3D printing materials, such as recyclability and carbon footprint. Despite significant progress, challenges remain in model interpretability, as many ML models act as black boxes, complicating the validation of predictions [80].

Data heterogeneity is a major limitation in evaluating ML-based materials for 3D printing, as data often come from different sources (different machines, materials, and measurement methods) which can lead to inconsistencies in format, quality, and scale. This variability can confuse ML models, resulting in poor generalization and uncertain predictions across different printing setups. In turn, model robustness becomes a challenge, as models trained on limited or unrepresentative datasets can fail when exposed to unseen materials, geometry, or environmental conditions. Robustness also suffers when models lack interpretability, making it difficult to diagnose or correct prediction errors in high-stakes engineering applications. In contrast, physics-based models or finite element simulations offer greater consistency and explainability because they rely on well-understood principles rather than data correlations. However, these alternatives are computationally expensive and less flexible for complex or new materials. Combining both approaches, i.e., hybrid ML–physics models, seems to be a promising direction that aims to balance accuracy, efficiency, and robustness.

4.3. Directions for Further Studies

Further research on machine learning-based materials evaluation in 3D printing aims to address existing challenges and explore new opportunities to improve the technology. Developing large, high-quality, and diverse datasets is a key direction to enable more accurate and generalizable machine learning models for materials evaluation. Incorporating multimodal data such as mechanical, thermal, and chemical properties along with printing conditions can improve model predictions and insights [81,82]. Integrating physics-based ML models to combine domain knowledge with data-driven methods is promising for increased model robustness and interpretability. Advanced generative models, such as diffusion models, can be explored to design new materials tailored to specific 3D printing applications [83]. Extending the application of transfer learning to adapt models trained on one type of material or process to others can reduce the reliance on expensive experimental data. An improved real-time machine learning framework for in situ material monitoring during the printing process can enable dynamic adjustments to prevent defects and optimize results [84]. Expanding the use of reinforcement learning can help autonomously discover optimal printing parameters and material formulations [85]. Research into explainable AI (XAI) methods will help improve the interpretability of ML predictions, making them more accessible to materials scientists and engineers [86]. Developing ML algorithms for multi-material systems can address the complexities of material interactions in composite and hybrid 3D printing. Exploring the use of ML in sustainability, such as in predicting the recyclability and life cycle performance of 3D-printed materials, will support environmentally friendly manufacturing practices [87]. Research into integrating ML with advanced imaging and nondestructive assessment techniques can improve the detection of microscopic defects and improve material consistency. ML-based optimization

of bio-based and biodegradable materials for 3D printing offers opportunities for developing sustainable technologies [88–90]. Expanding the use of digital twins in combination with ML to simulate the performance and degradation of materials over time can increase predictive capabilities [91]. Addressing issues related to model scalability and computational efficiency will be critical to implementing ML in industrial 3D printing environments. Collaborative research between academia, industry, and government agencies could lead to the creation of standard benchmarks and protocols for evaluating ML-based materials in 3D printing [92,93]. These research directions aim to push the boundaries of what is possible in ML-based materials science, contributing to smarter, more efficient, and innovative 3D printing technologies [94,95]. Future research on ML-based materials evaluation in 3D printing should:

- prioritize the development of large, standardized datasets that integrate material properties, printing parameters, and results to enable more robust and transferable models;
- develop physics-based machine learning that combines domain knowledge with data-driven methods to improve accuracy and interpretability;
- improve real-time monitoring and adaptive control using machine learning can enable dynamic tuning of printing parameters to achieve consistent material quality;
- develop multimodal learning that combines imaging, sensor data, and numerical simulations and can help to more holistically assess complex material behaviors;
- focus on interpretable AI to ensure that materials scientists can trust and understand machine learning-based insights;
- develop scalable inverse design framework to automate the discovery of new materials with tailored multifunctional properties;
- integrate sustainability metrics with machine learning assessment can promote eco-friendly materials and reduce waste in 3D printing within all three main stages of ML-modeling: input features, data-driven models, and output (quantity of interests) [96].

5. Conclusions

Our review confirms that the ML approach to materials evaluation in 3D printing has gained significant research attention, especially in the areas of printing parameter optimization, mechanical property prediction and defect detection. The original contribution of our review shows that ML-based materials evaluation in 3D printing brings significant new benefits, such as increased efficiency in predicting and optimizing material properties (up to 95% within minutes), reduced reliance on costly and time-consuming experiments, real-time monitoring and dynamic adjustments during the printing process, improved material performance, and reduced probability of defects. The added value beyond the existing literature is the belief that ML promotes innovation in 3D printing by discovering previously unexplored relationships between material and process parameters, designing new material combinations and multi-material systems with greater precision. However, despite promising advances, ML methods in 3D printing are still in the relatively early stages of widespread implementation. Current research often focuses on specific materials or printing techniques, limiting generalization across the diverse 3D printing landscape. A major challenge remains the standardization and availability of high-quality datasets required to effectively train ML models. However, interdisciplinary collaborations between materials scientists, computer scientists, and engineers are fostering innovative solutions and broadening research horizons. With increasing computing power and improved data collection tools, there is great potential to increase and diversify ML-based research in this area. Future efforts should prioritize the creation of open-access databases and the development of robust, portable models to accelerate adoption in both academia and in-

dustry. Challenges in this area include the need to consistently acquire large, high-quality datasets that are often expensive to obtain, and the black-box nature of many machine learning models that limits interpretability in the world of eXplainable Artificial Intelligence (XAI) development. Scalability and computational requirements are also barriers to industrial implementation, underscoring the need for continued development of more efficient algorithms and computational infrastructure.

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Abbreviations

The following abbreviations are used in this manuscript:

ABS	Acrylonitrile-butadiene-styrene
AI	Artificial intelligence
FDM	Fused deposition modeling
FFF	Fused filament fabrication
FRE	Free-form reversible deposition
L-PBF	Laser powder fusion
ML	Machine learning
PLA	Poly lactid acid
rPLA	Recycled poly lactid acid
XAI	eXplainable artificial intelligence

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