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Grey-box model–integrating tribology descriptor for tool wear prediction in milling

Amirmohammad Jamali[a], Amod Kashyap[b,c], Finn Rümenapf[d], Nelson Filipe Lopes Dias[d], Wolfgang Tillmann[d], Johannes Schneider[b,c], Michael Stüber[e], Volker Schulze (1)[a,*]

[a] *Institute of Production Science (wbk), Karlsruhe Institute of Technology, Karlsruhe 76131, Germany*
[b] *Institute of Applied Materials (IAM-ZM), Karlsruhe Institute of Technology, Karlsruhe 76131, Germany*
[c] *Micro-Tribology Centre (μTC), Karlsruhe Institute of Technology, Karlsruhe 76131, Germany*
[d] *Institute of Materials Engineering (LWT), TU Dortmund University, Dortmund 44227, Germany*
[e] *Institute of Applied Materials (IAM-AWP), Karlsruhe Institute of Technology, Karlsruhe 76131, Germany*

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ABSTRACT

Tool wear prediction in milling often relies on extensive experiments or data-driven models, limiting efficiency and interpretability. This study introduces a process–tribology descriptor linking a coating-specific tribological wear parameter from model tests to time-dependent tool wear. A coating-specific wear rate is embedded within a structured wear formulation to describe coating-dependent behavior across machining conditions. A physics-informed grey-box model further incorporates machining parameters and thermo-mechanical effects, enhancing predictive robustness. The approach preserves the relative wear ranking of coatings and enables efficient, transferable, and physically interpretable tool wear modeling within the tested machining parameter range.
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1. Introduction

Tool wear remains one of the critical limiting factors in milling operations, directly affecting productivity, dimensional accuracy, surface integrity, and sustainability in manufacturing. Progressive wear of the cutting edge leads to an increase of the cutting forces, elevates temperature, and deteriorates the surface quality, ultimately making it necessary to replace the tool combined with production downtime. In modern milling, coated cemented carbide tools are indispensable to withstand extreme thermo-mechanical loads and severe tribological conditions at the tool–workpiece interface. Advanced hard coatings such as TiN and TiAlN are widely employed and enhance tool life by modifying interfacial contact conditions and heat partitioning during cutting [1,2].

The wear behavior of coated milling tools stems from intricate interactions among process parameters, coating composition/microstructure, and local tribological mechanisms (friction, adhesion, abrasion) at tool–chip/workpiece interfaces, which drive heat generation and material transfer [1]. Milling's dynamic cyclic loading and steep stress/temperature gradients further challenge accurate prediction of time-dependent wear evolution [3–5]. Extensive experimental and numerical studies have addressed coating performance and wear mechanisms, but a robust approach of wear prediction across varying machining conditions and coatings still remains challenging [6,7].

Existing approaches to tool wear prediction can be broadly categorized into machining experiments, data-driven models, and physics-based simulations, each associated with their own fundamental limitations. Direct machining tests provide realistic wear data but are time-consuming, resource-intensive, and strongly coating and process-specific, limiting their transferability to new coating concepts or operating conditions [4,8]. Data-driven and black-box machine learning models can capture nonlinear dependencies between process variables and wear signals but require large datasets and often lack physical interpretability, resulting in limited extrapolation capability across coatings and process parameters [7,9]. Physics-based or white-box models provide insights into thermo-mechanical and tribological mechanisms but rely on simplified assumptions and require extensive calibration for each coating–workpiece system, which limits their industrial applicability in milling [4,9]. In recent years, hybrid modeling approaches that combine physical process knowledge with data-driven methods have gained increasing attention. Physics-informed machine learning (PIML) integrates physically meaningful descriptors or simulation-derived quantities into data-driven models to improve prediction robustness and reduce dependence on purely empirical data [10,11]. Several studies have demonstrated the potential of combining process simulations, experimental data, and machine learning for modelling complex machining phenomena, including tool wear prediction, process monitoring, and the prediction of thermo-mechanical and frictional behavior under varying cutting conditions [10,12].

Across these approaches, tribology is widely recognized as one of the major governing factors for tool wear, yet it is typically treated either implicitly within machining experiments or in isolated laboratory-scale tribological tests. While tribological model tests enable accelerated and controlled assessment of coating's friction and wear behavior, their

* Corresponding author.
E-mail address: volker.schulze@kit.edu (V. Schulze).

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systematic integration into machining-scale wear prediction frameworks remains limited. The missing linkage between coating-specific tribological behavior and time-dependent tool wear evolution therefore represents a critical gap in the current methodologies.

To address this gap, the present study introduces a process–tribology descriptor that links coating-specific tribological wear behavior obtained from simplified model tests to the time-dependent evolution of tool wear during milling. The concept builds upon the experimental and simulation framework previously established in Jamali et al. [4], where grey-box modelling was applied using machining signal features extracted from cutting force and vibration measurements together with simulation-derived thermo-mechanical quantities. In contrast, the central contribution of the present work is the introduction of a compact coating-specific tribological descriptor *Ws*, which replaces the large set of machining signal features and directly represents the intrinsic wear behavior of the coating. By embedding this descriptor into a structured wear formulation and combining it with process parameters and physics-based simulation outputs, the proposed framework enables coating-dependent wear prediction with significantly reduced experimental effort while preserving physical interpretability.

2. Process–tribology descriptor and grey-box framework

This section establishes a process–tribology descriptor that relates the time-dependent evolution of tool flank wear land width *VB* to a coating-specific wear rate W_s obtained from a tribological model test and demonstrates how physics-informed grey-box modeling improves predictive robustness across machining conditions.

2.1. Core concept and workflow

The proposed framework integrates machining experiments, tribological model tests and characterization, and numerical simulations into a process–tribology descriptor for tool wear evolution. Milling experiments provide the machining parameters cutting speed v_c, feed rate v_f, and cutting time t, together with the measured flank wear *VB* Independently, tribological model tests are conducted for each coating, yielding a coating-specific descriptor in the form of W_s. In addition, white-box physics-based simulations are used to extract physically meaningful process variables, namely the maximum interface temperature T_{max}, maximum sliding velocity $v_{slide.\max}$, and maximum normal stress $\sigma_{n,\max}$, which represent dominant thermo-mechanical drivers at the tool–workpiece interface. Details of the machining setup and simulation methodology are reported in [4].

The hybrid modeling strategy is illustrated in Fig. 1. The experimentally measured flank wear $VB_{(real)}$ was assessed after each cutting pass by evaluating the tool flank using high-resolution digital light microscopy (VHX 6000, Keyence®, Japan). A black-box model is first employed to describe the dominant trend of time-dependent tool wear. This model uses the process parameters (v_c, v_f, t) together with the coating-specific tribological wear descriptor W_s as inputs, yielding an initial wear prediction denoted as $VB_{(B)}$. The black-box model captures the global wear evolution and the coating-dependent tribological behavior but does not explicitly resolve the local thermo-mechanical load states.

To further enhance physical consistency and predictive accuracy, a grey-box learning model is subsequently applied. The grey-box model directly receives the black-box wear prediction $VB_{(B)}$, the process

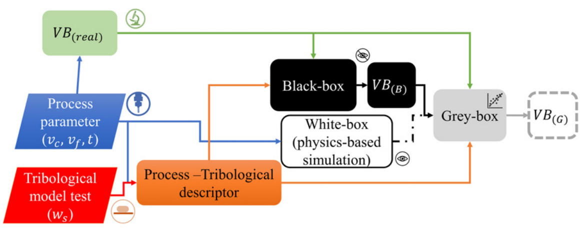

Fig. 1. Conceptual workflow of the proposed process–tribological descriptor and grey-box framework for tool wear prediction.

parameters (v_c, v_f, t), the process–tribology descriptor, and white-box simulation-derived thermo-mechanical quantities, namely the maximum temperature T_{max}, maximum sliding velocity $v_{slide.\max}$, and maximum normal stress $\sigma_{n,\max}$, as inputs. By jointly exploiting data-driven learning and physics- and tribology-informed descriptors, the grey-box model produces an improved and physically informed prediction of tool wear, denoted as $VB_{(G)}$. This quantity represents the final output of the proposed hybrid grey-box modeling framework.

2.2. Machining experiments, tribological model test and coating-specific wear descriptor

Machining experiments were carried out under dry (unlubricated) conditions using indexable cutting inserts based on a cemented carbide substrate consisting of tungsten carbide (WC) particles embedded in a cobalt (Co) binder with a cobalt content of 10 *wt%*. The inserts were Gühring CCHT CCHX09T304E L-116 type tools. The clearance angle was set to 7°, while the rake angle was 10° across all inserts**.** The cutting-edge radius varied between 40 and 45 µm depending on the coating thickness. The workpiece material was normalized AISI 1045 (C45) carbon steel with dimensions of 100 mm × 100 mm × 150 mm. The defined tool material composition and cutting-edge geometry served as input parameters for the white-box chip formation simulations, enabling a direct transfer of experimentally validated boundary conditions to the numerical model. All machining tests were performed on a POSmill CE 1000 machining center (POS, Germany), using cutting speeds of 112 and 132 m/min and feed rates of 150 and 200 mm/min with 3 repetitions for each process parameter set (detailed parameters provided in Supplementary File, Table S1).

To obtain a coating-specific wear descriptor independent of machining experiments, tribological model tests were conducted for all investigated coatings under controlled and reproducible contact conditions. The purpose of these model tests is not to reproduce the full complexity of the load scenario of a machining process, but to provide a rapid and comparable characterization of coating's wear behavior under simplified test conditions. In this study, W_s represents a coating-specific descriptor under a fixed and well-defined tribosystem, i.e., identical substrate material (coated cemented carbide cylinders with a diameter of 12 mm), and flat counter body material (normalized AISI 1045 carbon steel), resulting in a line contact between the tribopair. A normal load of 15 *N*, an ambient temperature of 100°C and a sliding speed of 0.25 m/s and test time of 2000 s were used as test parameters (Fig. S2). The parameters were selected such that only the coatings underwent wear and wear mechanisms remain similar to the milling experiments, while W_s remained unaffected by wear of the substrate material. W_s is determined from the measured wear volume normalized by the applied normal load and the sliding distance. As such, W_s represents a compact measure of the intrinsic tribological wear behavior of the coating, which can be related to the evolution of tool wear under machining conditions.

The investigated coatings were deposited on both cylindrical tribological test specimens and cutting inserts. The coating set comprised conventionally DC magnetron-sputtered TiN (4.9 µm, Type I), as well as TiAlN coatings with Ti/Al ratios of 75/25 (4.4 µm, Type II) and 50/50 (5.5 µm, Type III), all produced at IAM-AWP. In addition, a HiPIMS-deposited TiAlN coating with a Ti/Al ratio of 45/55 (2.5 µm, Type IV) was manufactured at LWT, TU Dortmund University (detailed coating parameters provided in Supplementary File Table S2). An industrial TiAlN reference coating (2.0 µm, Type V) was also included for comparison. The industrial reference corresponds to a commercially available TiAlN-coated insert (6676, Gühring®, Germany), representing a high-performance coating system optimized for milling applications.

For each coating, four machining parameter sets were investigated. Fig. 2(a) summarizes the flank wear progression of all investigated coated milling tools as a function of machining time for one representative machining condition (v_f = 200 mm/min, v_c = 132 m/min). Similar experiments with 20 points of wear within the steady-state stage were also determined for 3 other combinations of the process parameters. Fig. 2(b) represents the W_s obtained for the five investigated coating types in tribological contact with the normalized

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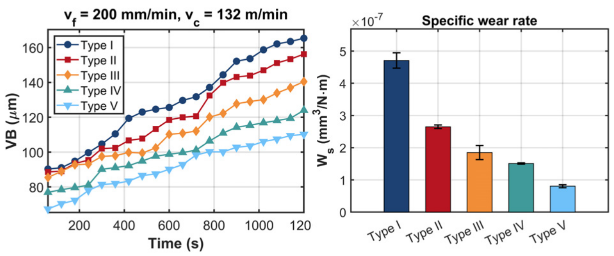

Fig. 2. a) Wear progression of coated milling tools with milling time, and b) W_s obtained from tribological tests for the investigated coatings, serving as coating-specific tribological wear descriptors (as long as the coating layer remains intact and governs the contact behavior).

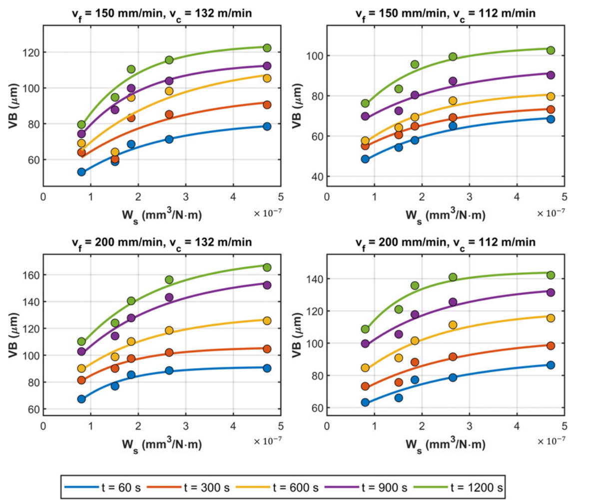

Fig. 3. Relationship between tool wear VB and coating-specific wear rate W_S at different cutting times for representative machining conditions.

plain carbon steel C45. Distinct differences in W_s are observed between the coatings, reflecting variations in coating synthesis route, composition, microstructure, and resulting tribological properties. These differences in W_s behavior form the basis for analyzing correlations between tribological wear behavior and the time-dependent evolution of tool flank wear measured during milling (Fig. 3).

2.3. Correlation between the specific tribological wear rate and tool wear evolution

To establish a quantitative correlation between the coating-specific tribological wear behavior and the time-dependent evolution of tool wear in milling, the measured wear $VB_{(real)}$ is analyzed as a function of W_s obtained from the tribological tests. For fixed machining conditions and discrete cutting times, the wear exhibits a monotonic dependence on W_s for all investigated coatings. This observation indicates that coatings characterized by lower tribological wear rates consistently show reduced wear during machining, across different wear levels.

$$VB = a - b \cdot e^{(-c \cdot Ws)} \tag{1}$$

where the coefficients *a*, *b*, and c depend on the machining parameters (v_c, v_f) and the cutting time *t*. While the functional form remains unchanged, the coefficients capture the influence of process conditions and wear progression. This formulation allows the tribological wear rate W_S, to be embedded into a time-resolved description of tool wear evolution

The parameters *a*, *b*, and *c* are identified from the experimental data collected across all coatings and machining conditions and fit to a second-order regression equation. A polynomial model incorporating second-order terms and interaction terms is used to represent nonlinear dependencies observed in the experimental data using 24 parameters in total. Their variation with cutting time reflects the progression of wear within the steady wear regime in milling, where wear evolves approximately linearly with time, which corresponds to the dominant wear regime investigated in this study. In this context, the exponential form provides a compact representation of how coating-dependent tribological properties modulate the absolute wear level reached during machining.

By combining a fixed functional relationship with process- and time-dependent coefficients, the proposed formulation defines a process–tribology descriptor that relates the coating-specific tribological parameter to the evolution of tool wear. This descriptor forms the basis for the subsequent black-box modeling and grey-box model introduced in the following section.

2.4. Black-box formulation of the process–tribology wear relationship

Building on the link between model-test wear rate *Ws* and machining tool wear (Section 2.3), a black-box model uses *Ws* as input within the fixed structure of Eq. (1). Coefficients *a*, *b*, and *c* vary explicitly with cutting speed, feed rate, and time to capture process and wear progression effects; explicit forms are omitted for brevity, emphasizing predictive capability.

The black-box models are identified using experimental data from all investigated coatings and machining conditions. The available data are partitioned into training and validation subsets on a coating-wise basis, where each coating is treated as an indivisible data entity. Specifically, the entire dataset of a coating, including all machining conditions and time-dependent wear measurements, is assigned either to the 80% training set or to the independent 20% test set omitting one of the coatings. Model performance is evaluated by comparing the predicted wear $VB_{(B)}$ of the black-box modeling with the experimentally measured values $VB_{(real)}$, focusing on systematic deviations rather than local fitting accuracy.

2.5. Grey-box learning and prediction refinement

While the black-box formulation captures the dominant trends of tool wear evolution, local thermo-mechanical effects are not explicitly represented.

To account for local thermo-mechanical effects not explicitly represented in the black-box formulation, an additional white-box model was added. It is based on physics-based finite element chip formation simulations for milling. The approaches used there were basically described in Jamali et al. [4]. Here they were used to provide the thermo-mechanical quantities maximum interface temperature, maximum sliding velocity, and maximum normal stress at the tool–workpiece interface for all process parameter sets used in this study. This provides another 12 white-box-characteristics for the wear modeling. Together with the 24 characteristics of the black-box model and the coating-specific descriptors they were employed for the grey-box modeling of all wear data. Gradient Boosting Regression (GBR), as employed in Jamali et al. [4], and CatBoost as a more sophisticated approach are considered as regression models. While GBR provides robust baseline performance, CatBoost offers improved robustness to noise and short-term fluctuations, resulting in enhanced prediction accuracy. Therefore, CatBoost is adopted for the grey-box modeling stage. Grey-box model training and validation follow the same data partitioning strategy as applied for the black-box model to ensure a fair and consistent comparison. As a result, the predictive trends observed for the grey-box model on the test data can be directly compared to those of the black-box model under identical validation conditions.

3. Results and discussion

The results shown in Fig. 4 exemplarily for v_f = *150* mm/min, v_c=*112* m/min confirm that the proposed process–tribology descriptor provides a consistent and physically meaningful basis for describing tool wear evolution across different coatings and machining conditions. Despite the simplified nature of the tribological test, the coating-specific wear rate preserves the relative ranking of coatings with respect to wear over time. For all investigated cutting speeds and feed rates, coatings characterized by lower W_s values show reduced wear during milling, indicating that the tribological

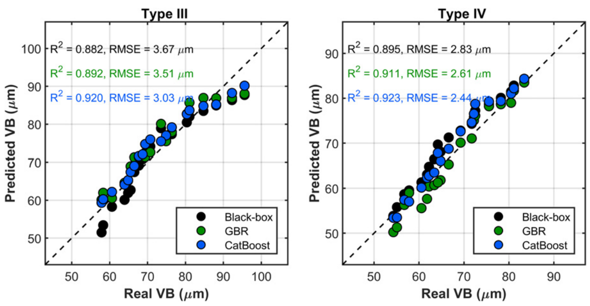

Fig. 4. Comparison of black-box and grey-box wear predictions for TiAlN coatings with almost identical composition under the same machining conditions (v_f=*150* mm/min, v_c=*112* m/min). Results are shown for a DC magnetron-sputtered deposited TiAlN coating (a, Type III) and a HIPIMS-deposited TiAlN coating (b, Type IV). The trends illustrated here are representative of the entire dataset, and results for other coatings are shown in Figure S3 of the Supplementary File.

descriptor captures essential aspects of coating wear behavior relevant to the machining process.

The robustness of the descriptor is further demonstrated by the monotonic relationship between tool wear *VB* and W_s observed at different cutting times. Although the absolute wear level increases with time, the relative influence of the coating-specific tribological wear rate remains consistent, allowing a descriptor value per coating to be embedded into a time-resolved description of wear evolution. This indicates that the tribological test can be used to position coatings within a common wear evolution framework without requiring extensive machining experiments for each coating variant.

Fig. 4 shows predicted versus measured wear for Type III and Type IV coatings under one representative machining parameter set. For this condition, the black-box model captures the dominant wear trends (Type III: R^2 = 0.920, RMSE = 3.03 µm; Type IV: R^2 = 0.923, RMSE = 2.46 µm), while the grey-box formulations yield comparable accuracy (Type III: R^2 = 0.882–0.898, RMSE = 3.51–3.67 µm; Type IV: R^2 = 0.895–0.911, RMSE = 2.61–2.83 µm) with improved consistency across wear levels. Beyond this representative condition, evaluating the Type III coating across all four-machining parameter sets yields an overall performance of R^2 = 0.917 and RMSE = 3.09 µm for the CatBoost-based grey-box model, compared to R^2 = 0.886 and RMSE = 3.61 µm for the black-box formulation, indicating that physics-based thermo-mechanical descriptors capture systematic effects not represented by the process–tribology descriptor alone.

Representative results for TiAlN coatings with almost identical nominal composition, type III and IV, but different synthesis routes demonstrate that the W_s also accounts for the change in mechanical properties arising from microstructural differences despite having similar chemical composition (Fig. 4). Beyond coating composition, microstructural characteristics induced by the deposition process are expected to influence both tribological and machining wear behavior. HiPIMS-deposited TiAlN coatings (Type IV) are commonly associated with a denser microstructure, reduced columnar porosity, and improved coating–substrate adhesion compared to conventionally direct DC magnetron-sputtered coatings. Such microstructural differences are commonly associated with enhanced resistance to abrasive and adhesive wear mechanisms, which is reflected in differences in specific wear rate and wear evolution despite identical nominal chemistry.

For the Type III coating, the larger deviations observed at progressive wear levels within the investigated steady wear regime signify the onset of substrate wear (cemented carbide) due to coating failure. Since the modeling framework is primarily calibrated in the steady wear regime, predictive accuracy decreases when dominant wear mechanisms change during the final stages of tool degradation (distinct from those governing the coatings). In contrast, the Type IV coating, which exhibits a denser and more homogeneous microstructure because of HiPIMS deposition exhibits a more stable wear progression for a longer duration than the Type III coating. This behavior is consistent with the adjusted quality data and highlights the influence of microstructure-dependent damage mechanisms on wear evolution.

Overall, the results demonstrate that combining a compact tribological descriptor with physics-informed modeling improves R^2, reduces RMS, and yields an efficient and transferable approach for tool wear modeling. The framework enables rapid coating assessment based on minimal tribological input, reduces experimental effort in machining tests, and provides a structured pathway for integrating tribology, process parameters, simulation-derived information, and microstructure-sensitive effects into predictive wear models.

4. Conclusions and outlook

This study successfully introduced a process–tribology descriptor that links a coating-specific tribological wear parameter (*Ws*) from simplified model tests to the time-dependent evolution of tool flank wear (*VB*) in milling operations. By embedding *Ws* into an exponential wear formulation with process-dependent coefficients, the descriptor enables compact, coating-dependent wear prediction across the investigated machining conditions within the steady wear regime ($VB \leq 0.16$ mm). The results confirm that the descriptor consistently preserves the relative ranking of coatings according to their tribological wear resistance, while the physics-informed grey-box framework - combining process parameters, *Ws*, and simulation-derived thermo-mechanical quantities - demonstrates improved predictive robustness over the purely process-based black-box formulation.

Importantly, the present work establishes a complete and validated modelling framework specifically for the steady wear regime dominating practical tool life in industrial milling applications. The achieved prediction accuracy ($R^2 > 0.89$, RMSE < 3.7 µm across coating-withheld validation) confirms the effectiveness of this coating-focused approach for efficient wear prediction and ranking within the calibrated parameter range (cutting speeds 112–132 m/min, feed rates 150–200 mm/min). Extension of the framework to initial wear, coating failure, and accelerated wear phases ($VB > 0.16$ mm up to industrial end-of-life criteria of ~0.3 mm) will be addressed in future work by incorporating regime-specific model switching based on measurable indicators such as wear rate changes or force signatures.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

Amirmohammad Jamali: Writing – original draft, Resources, Methodology, Formal analysis, Data curation, Conceptualization. **Amod Kashyap:** Writing – review & editing, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Finn Rümenapf:** Writing – review & editing, Resources. **Nelson Filipe Lopes Dias:** Writing – review & editing, Resources. **Wolfgang Tillmann:** Writing – review & editing, Resources. **Johannes Schneider:** Writing – review & editing, Visualization, Supervision, Resources. **Michael Stüber:** Writing – review & editing, Visualization, Supervision, Resources. **Volker Schulze:** Writing – review & editing, Visualization, Supervision, Resources, Conceptualization.

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Supplementary materials

Supplementary material associated with this article can be found in the online version at doi:10.1016/j.cirp.2026.04.087.

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