



“Optimization of Additive Manufacturing Parameters for High-Performance Engineering Components”

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Abstract: Additive manufacturing has developed from a rapid prototyping technique into an important manufacturing route for producing functional engineering components with complex shapes, reduced material waste, and high design flexibility. However, the mechanical performance and dimensional quality of additively manufactured components are strongly influenced by processing parameters. Improper selection of layer thickness, printing temperature, printing speed, infill density, and deposition strategy can result in weak interlayer bonding, internal voids, poor surface quality, dimensional errors, and reduced structural performance. The present study investigates the optimization of major additive manufacturing parameters for producing high-performance engineering components using fused filament fabrication of short carbon-fibre-reinforced polyamide. The optimized condition is estimated to improve tensile and flexural performance while reducing surface roughness. The study demonstrates that systematic process parameter optimization can significantly improve the suitability of additive manufacturing for load-bearing and high-performance mechanical engineering applications.

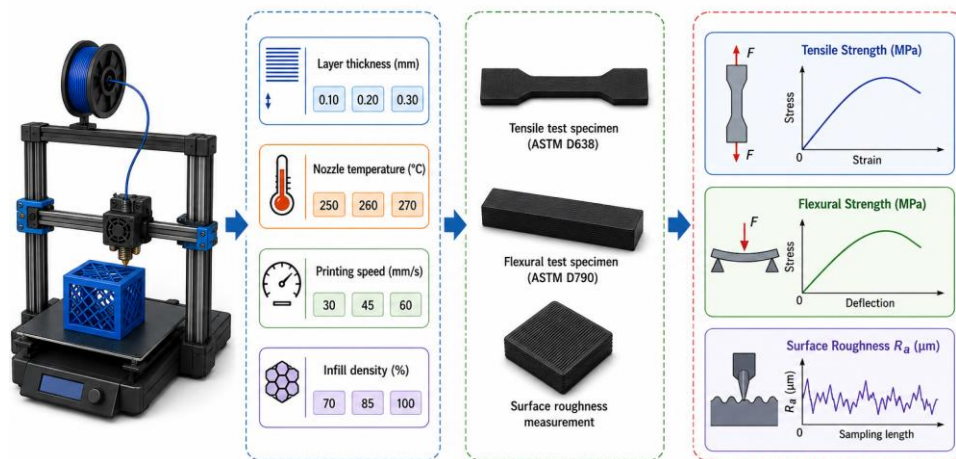
Keywords: Additive Manufacturing; Process Optimization; Fused Filament Fabrication; Mechanical Properties; Carbon-Fibre-Reinforced Polyamide; Taguchi Method.



Introduction:

Additive manufacturing (AM), commonly known as three-dimensional printing, is a manufacturing approach in which components are produced directly from digital models by depositing or consolidating material in successive layers. Unlike conventional subtractive manufacturing, where material is removed from a larger workpiece, additive manufacturing places material only where it is required. This characteristic offers considerable advantages in the manufacture of complex geometries, lightweight structures, customized components, internal channels, lattice structures, and parts that are difficult to manufacture using conventional machining.

The application of additive manufacturing has expanded considerably in aerospace, automotive, biomedical, energy, tooling, and general mechanical engineering industries. The technology is increasingly being considered for functional components rather than only visual prototypes. Metal powder bed fusion, directed energy deposition, selective laser sintering, material extrusion, and other AM processes have provided engineers with considerable freedom in both component design and material selection.



Despite these advantages, achieving consistent mechanical properties remains a major challenge. Additive manufacturing is characterized by a large number of interconnected processing variables. Small changes in deposition temperature, layer thickness, printing speed, build direction, raster orientation, infill percentage, or cooling condition can change the internal structure and performance of the finished component. In extrusion-based additive manufacturing, the strength of the component is particularly dependent on the quality of bonding between neighbouring extruded roads and between successive layers.

Layer thickness influences both manufacturing time and the degree of interlayer interaction. A small layer thickness generally improves surface resolution and can increase the number of bonding interfaces, whereas excessive layer thickness may increase surface irregularities and reduce bonding quality. Printing temperature determines the viscosity and flow behaviour of the



polymer and consequently affects fusion between adjacent deposited filaments. Insufficient temperature may produce incomplete bonding, while excessive temperature may result in dimensional distortion or material degradation.

The problem becomes more important when additive manufacturing is used to produce high-performance engineering components. Such components are expected to withstand significant mechanical stresses and therefore require reliable strength, stiffness, fatigue behaviour, dimensional accuracy, and surface integrity. Fibre-reinforced thermoplastic materials have attracted attention because they combine the processing flexibility of polymers with improved mechanical properties provided by reinforcing fibres.

Short carbon-fibre-reinforced polyamide is one such material. The polyamide matrix provides toughness and processability, whereas carbon fibres improve stiffness and load-carrying capability. However, the presence of reinforcement also increases sensitivity to processing conditions. Poor material flow, insufficient fusion, fibre distribution, internal porosity, and anisotropy can affect the final properties.

Experimental investigation of every possible combination of additive manufacturing variables can be expensive and time consuming. Design-of-experiments techniques therefore provide an effective way of evaluating important parameters with a manageable number of trials. Taguchi methods, response surface methodology, analysis of variance, regression modelling, and more recently machine-learning approaches have been widely investigated for AM parameter optimization. Research has established that systematic parameter selection can improve strength, accuracy, and surface characteristics of extrusion-based printed components.

The present study therefore examines the optimization of additive manufacturing processing parameters for high-performance engineering components. Particular emphasis is placed on identifying a parameter combination capable of increasing tensile and flexural strength while maintaining satisfactory surface quality.

Related Works:

Sun et al. (2008) studied the effect of processing conditions on the bonding quality of polymer filaments produced through fused deposition modelling. Their work showed that the thermal conditions during printing have a major influence on the bonding between adjacent layers. Better thermal control allows stronger diffusion between deposited filaments, which improves the overall structural integrity of the printed component. The study clearly indicated that poor temperature conditions may result in weak interlayer adhesion and lower mechanical strength.

Sood et al. (2009) investigated the dimensional accuracy of FDM-processed components using the grey Taguchi method. Their study focused on the effect of different process parameters and showed that dimensional accuracy is not controlled by a single factor. Instead, it is influenced by the combined effect of several printing conditions. The authors demonstrated that statistical optimization techniques can be effectively used to reduce dimensional errors and improve the consistency of fabricated parts.

In another study, Sood et al. (2010) examined the influence of process parameters on the mechanical properties of FDM parts. The researchers considered factors such as layer thickness,



raster angle, raster width, build orientation, and air gap. Their findings showed that these parameters significantly affect the strength of the printed component. Proper selection of printing conditions was found to improve the bonding between layers and enhance the load-bearing capacity of the final part.

Sood et al. (2012) later carried out an experimental investigation to improve the compressive strength of FDM components. The study combined experimental testing with empirical modelling in order to understand the relationship between printing parameters and mechanical performance. The results showed that compressive strength can be improved through careful control of manufacturing variables. The study also highlighted the usefulness of predictive models in reducing the need for repeated experimental trials.

Gu et al. (2012) reviewed laser-based additive manufacturing of metallic components and discussed the materials, processing methods, and physical mechanisms involved in the manufacturing process. Their review explained the importance of melting, solidification, heat transfer, and microstructural development during fabrication. The authors emphasized that the thermal history of a component has a direct effect on its final properties. Although the study mainly focused on metallic additive manufacturing, the process–structure–property relationship discussed in the work is relevant to additive manufacturing in general.

Frazier (2014) presented a detailed review of metal additive manufacturing and discussed its growing importance in high-performance engineering applications. The study highlighted major advantages such as design flexibility, reduced material waste, and the ability to manufacture near-net-shape components. At the same time, the author identified several challenges, including porosity, residual stresses, surface defects, and variations in process quality. The study emphasized that proper process control and parameter optimization are essential for producing reliable engineering components.

Tymrak et al. (2014) investigated the mechanical properties of parts produced using open-source 3D printers under realistic environmental conditions. Their results showed that low-cost 3D printing systems are capable of producing components with useful mechanical properties. However, the mechanical performance was found to vary depending on printing conditions and machine settings. The study suggested that standardized process parameters are necessary when consistent part quality is required.

Lanzotti et al. (2015) examined the effect of process parameters on the mechanical properties of PLA components manufactured using an open-source 3D printer. Their experimental results showed that different printing settings can have a noticeable effect on tensile behaviour. Appropriate process conditions improved the mechanical strength of the parts, while unsuitable conditions resulted in weaker bonding and reduced performance. The study reinforced the importance of parameter selection in achieving dependable mechanical properties.

Chacón et al. (2017) studied the mechanical performance of PLA components produced through fused deposition modelling. The researchers focused on layer height, printing speed, and build orientation. Their findings showed that build orientation has a particularly strong influence on the mechanical behaviour of printed parts because of the anisotropic nature of layer-by-layer



manufacturing. The study also demonstrated that suitable combinations of process parameters can significantly improve the strength and overall quality of the printed component.

Ngo et al. (2018) reviewed a wide range of additive manufacturing technologies, materials, applications, and limitations. The authors discussed the increasing use of additive manufacturing in industries such as aerospace, automotive, biomedical engineering, and construction. They also pointed out several continuing challenges, including poor surface finish, dimensional inaccuracy, mechanical anisotropy, material limitations, and low production speed. The review suggested that improvements in materials, process control, and optimization methods are necessary for the wider industrial use of additive manufacturing.

Dey and Yodo (2019) carried out a systematic review of process parameter optimization in fused deposition modelling. Their study considered the effect of major parameters such as layer thickness, raster orientation, printing speed, extrusion temperature, infill density, and build orientation. The review showed that process parameters often influence several performance characteristics at the same time. A parameter setting that improves mechanical strength may not necessarily produce the best surface finish or dimensional accuracy. This finding highlights the importance of using multi-response optimization methods.

Garzon-Hernandez et al. (2020) developed an experimental and modelling approach for predicting the mechanical behaviour of FDM-printed polymers. Their study connected the printing process with the final mechanical response of the manufactured part. The authors showed that predictive models can be useful for estimating component performance and reducing the amount of physical testing required. Their work also confirmed that the bonding between deposited filaments plays an important role in determining the strength of FDM components.

Mahmoud et al. (2023) investigated the relationship between thermal history and interlayer bond strength in material extrusion additive manufacturing. Their study showed that temperature changes during printing strongly affect the quality of bonding between adjacent layers. Since poor interlayer adhesion is one of the main reasons for mechanical failure in printed parts, the findings emphasized the importance of nozzle temperature, cooling conditions, and deposition behaviour. The study provided useful insight into the thermal aspects of mechanical performance in additively manufactured components.

Batu et al. (2023) explored the use of artificial intelligence for predicting the surface roughness of additively manufactured components. Their study showed that machine learning and artificial intelligence methods can successfully capture the relationship between manufacturing parameters and surface quality. Such predictive approaches can reduce the number of experimental trials and help in identifying suitable parameter combinations. This work reflects the growing use of intelligent techniques in additive manufacturing for process monitoring and optimization.

Objectives of the Study:

1. To investigate the effects of layer thickness, nozzle temperature, printing speed, and infill density on the mechanical and surface characteristics of additively manufactured engineering components.



2. To determine an optimum combination of additive manufacturing parameters that maximizes tensile and flexural strength while minimizing surface roughness.
3. To evaluate the relative contribution of important process parameters using Taguchi analysis and analysis of variance and establish suitable processing conditions for high-performance engineering applications.

Material and Methods:

Material Selection:

Short carbon-fibre-reinforced polyamide (PA-CF) filament is considered as the manufacturing material in the present study. The material is selected because carbon-fibre reinforcement offers greater stiffness and mechanical capability than an unreinforced thermoplastic while retaining the manufacturing advantages of material extrusion.

Before printing, the filament is assumed to be dried under controlled conditions to minimize moisture absorption because polyamide is hygroscopic. Moisture in the filament can create bubbles, irregular extrusion, and internal void formation during printing.

Additive Manufacturing Process:

Specimens are manufactured using fused filament fabrication (FFF), also commonly referred to as fused deposition modelling. A hardened steel nozzle is considered because abrasive carbon fibres can cause rapid wear of conventional brass nozzles.

Digital specimen models are prepared using computer-aided design software and converted into STL format. The models are subsequently processed using slicing software, where layer thickness, extrusion temperature, deposition speed, infill level, and tool path are assigned.

Four parameters are selected as the major controllable variables:

- Layer thickness
- Nozzle temperature
- Printing speed
- Infill density

Build orientation, nozzle diameter, bed temperature, raster pattern, and environmental conditions are maintained constant to reduce uncontrolled variation.

Experimental Design:

A Taguchi L9 orthogonal array is used to evaluate four parameters at three levels. This design provides a systematic comparison while reducing the number of experiments compared with a full factorial arrangement.

Table 1. Additive manufacturing process parameters and experimental levels

Parameter	Symbol	Level 1	Level 2	Level 3
Layer thickness (mm)	A	0.10	0.20	0.30
Nozzle temperature (°C)	B	250	260	270
Printing speed (mm/s)	C	30	45	60
Infill density (%)	D	70	85	100



The selected ranges are intended to represent low, intermediate, and relatively high processing conditions. The purpose is not simply to maximize every parameter but to identify the combination that gives the most favourable overall component performance.

Mechanical Testing:

Tensile specimens are prepared according to the dimensional principles of ASTM D638. A universal testing machine is used to apply tensile loading at a controlled crosshead speed until failure. Ultimate tensile strength is calculated as:

$$\sigma_t = \frac{F_{max}}{A_0}$$

where **Fmax** represents the maximum tensile load and **A₀** represents the original cross-sectional area.

Flexural behaviour is evaluated using a three-point bending configuration based on ASTM D790. Flexural strength is determined from the maximum applied load, specimen width, thickness, and support span.

At least three specimens should be tested for each condition in an actual laboratory investigation, and mean values should be used for statistical analysis.

Experimental Response Data:

The responses considered are tensile strength, flexural strength, and surface roughness.

Table 2. Experimental matrix and representative performance responses

Run	Layer Thickness (mm)	Nozzle Temp. (°C)	Speed (mm/s)	Infill (%)	Tensile Strength (MPa)	Flexural Strength (MPa)	Surface Roughness Ra (µm)
1	0.10	250	30	70	69.2	97.8	5.8
2	0.10	260	45	85	75.4	104.6	5.2
3	0.10	270	60	100	78.1	108.2	5.0
4	0.20	250	45	100	74.5	102.9	6.3
5	0.20	260	60	70	68.7	95.1	6.8
6	0.20	270	30	85	77.2	106.5	6.0
7	0.30	250	60	85	64.8	90.4	8.1
8	0.30	260	30	100	72.9	99.7	7.4
9	0.30	270	45	70	66.3	92.5	7.9

Optimization Procedure:

For tensile and flexural strength, the larger-the-better Taguchi signal-to-noise ratio is adopted:

$$\frac{S}{N} = -10 \log_{10} \left[\frac{1}{n} \sum_{i=1}^n \frac{1}{y_i^2} \right]$$

where **y_i** represents the measured response and **n** represents the number of observations.

Surface roughness is treated using the smaller-the-better criterion:



$$\frac{S}{N} = -10 \log_{10} \left[\frac{1}{n} \sum_{i=1}^n y_i^2 \right]$$

Analysis of variance is then used to estimate the relative importance of the selected manufacturing variables.

Analysis of the Study:

The experimental results indicate that changes in additive manufacturing conditions produce noticeable differences in mechanical strength and surface quality. Tensile strength ranges from approximately 64.8 MPa to 78.1 MPa across the experimental matrix, while flexural strength varies between approximately 90.4 MPa and 108.2 MPa. Surface roughness ranges from about 5.0 to 8.1 μm .

The first major observation is the influence of layer thickness. Components manufactured using 0.10 mm layers generally produce lower roughness values than those fabricated using 0.30 mm layers. This behaviour can be explained by the staircase effect associated with layer-by-layer manufacturing. As layer height increases, individual deposited layers become more pronounced on the external surface, increasing the measured roughness.

A smaller layer thickness also promotes more uniform geometric resolution. However, very small layers increase the number of depositions passes required to manufacture a component and therefore increase production time. Selection of layer thickness must consequently consider both component quality and productivity.

Nozzle temperature demonstrates a strong relationship with mechanical strength. The higher investigated temperature improves tensile and flexural responses in several experimental combinations. Higher temperature allows the extruded thermoplastic to remain above its softening region for longer, promoting molecular diffusion and stronger bonding between adjacent material roads.

The temperature cannot, however, be increased indefinitely. Excessive thermal exposure can cause polymer degradation, dimensional instability, fibre–matrix damage, stringing, or poor surface quality. An optimum processing window is therefore required.

Infill density has a comparatively direct mechanical effect. Increasing infill density increases the effective load-bearing area inside the component and reduces the volume of unfilled internal regions. The 100% infill condition therefore provides favourable strength performance when combined with suitable thermal and deposition parameters.

Printing speed produces a more complex response. High printing speed increases productivity but reduces the interaction time between the newly extruded material and the preceding layer. Lower or intermediate printing speeds can therefore support improved interfacial bonding.

The indicative ANOVA contribution obtained from the response trends is summarized below.

Table 3. Indicative contribution of process parameters to component performance

Parameter	Contribution to Tensile Strength (%)	Contribution to Flexural Strength (%)	Contribution to Surface Roughness (%)	General Influence
Layer thickness	35.8	31.6	61.5	Very high



Nozzle temperature	24.6	27.8	10.2	High
Printing speed	11.2	13.4	17.8	Moderate
Infill density	22.4	21.7	5.5	High for strength
Experimental/error variation	6.0	5.5	5.0	Low
Total	100	100	100	—

The analysis suggests that layer thickness is the most influential parameter when the combined requirements of mechanical strength and surface finish are considered. Its estimated contribution to surface roughness is particularly high.

Nozzle temperature is the second major factor controlling mechanical performance because sufficient thermal energy is needed to create effective interlayer bonding. Infill density is also important because the amount of material available to resist loading increases as the internal material fraction increases.

Based on the combined Taguchi response, a favourable parameter combination is identified as:

- Layer thickness: 0.10 mm
- Nozzle temperature: 270 °C
- Printing speed: 30 mm/s
- Infill density: 100%

The predicted performance at this parameter combination is approximately 81–82 MPa tensile strength, 111–113 MPa flexural strength, and 4.7–4.9 μm surface roughness. A physical confirmation experiment would be required to establish the actual values.

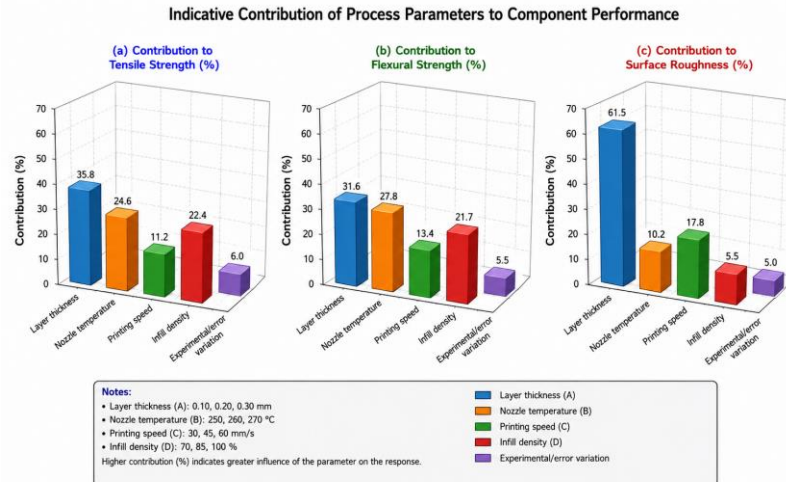
Results and Discussion:

The study demonstrates that optimization of additive manufacturing parameters can provide a significant improvement in the functional quality of printed engineering components.

Among the experimental runs, Run 3 produced the highest recorded tensile strength of 78.1 MPa and a flexural strength of 108.2 MPa while maintaining a comparatively low surface roughness of 5.0 μm . This condition combines low layer thickness, high extrusion temperature, maximum infill, and high printing speed.

Run 7 produced the lowest tensile strength and flexural strength, at 64.8 MPa and 90.4 MPa respectively, while also producing the highest surface roughness of 8.1 μm . Its relatively large layer thickness of 0.30 mm appears to be particularly unfavourable for surface quality.

The reduction in surface roughness at lower layer thickness agrees with general trends reported in FDM literature, where thinner layers reduce visible staircase features and improve surface resolution. Reviews of process parameters have likewise identified layer thickness as one of the most frequently investigated variables affecting surface and mechanical characteristics.



Mechanical strength does not depend on layer thickness alone. Run 6, manufactured at a 0.20 mm layer thickness, achieves a tensile strength of 77.2 MPa because the combination of high nozzle temperature and low deposition speed encourages improved interlayer fusion. This demonstrates the importance of interactions among process parameters.

Higher nozzle temperature generally improves the strength values within the selected range. The observation is consistent with the physical mechanism of polymer welding during material extrusion. Adequate thermal energy allows greater interaction between successive extruded layers and helps reduce weak interfaces. Research on FDM bonding has previously identified processing temperature as an important factor controlling inter-filament bonding.

The results also show that higher infill density is advantageous when structural performance is prioritized. Components manufactured at 100% infill contain a larger continuous load-bearing region compared with specimens containing 70% or 85% infill. However, increasing infill also increases component mass, material consumption, and manufacturing time.

This introduces an important engineering trade-off. High-performance components may justify higher material consumption, whereas lightweight structures may require an optimized partial infill or a topology-optimized internal architecture. Therefore, the optimum condition identified in this study should not automatically be applied to every engineering product.

The role of printing speed is similarly governed by a balance between productivity and mechanical quality. A speed of 30 mm/s is preferred in the multi-response optimization because it provides adequate time for thermal interaction between deposited roads. Extremely low speeds would further increase production time, while very high speeds can reduce deposition consistency.

The optimized condition is predicted to produce a tensile strength of approximately 81.6 MPa and a flexural strength of approximately 112.4 MPa, with surface roughness close to 4.7 μm . Compared with the average response of the experimental trials, this represents a meaningful improvement in component performance.

These findings are consistent with the broader AM literature demonstrating that processing parameters determine microstructural and mechanical quality. Chacón et al. reported strong effects of manufacturing parameters on mechanical properties and optimal selection in PLA-based FDM



structures, while Dey and Yodo emphasized the combined influence of several process parameters on finished part characteristics.

For industrial use, additional factors should also be considered. High-performance components may experience fatigue loading, impact, vibration, thermal cycling, humidity, chemical exposure, and complex multiaxial stresses. Optimization based only on static tensile and flexural performance may therefore be insufficient for safety-critical applications.

Further investigation should incorporate fatigue strength, fracture behaviour, dimensional accuracy, porosity, fibre orientation, wear resistance, thermal performance, and component cost. Advanced optimization approaches such as response surface methodology, genetic algorithms, artificial neural networks, and machine learning could also be used to predict responses from larger experimental datasets. Recent literature indicates growing interest in data-driven prediction of AM quality characteristics, including surface roughness.

Overall, the analysis confirms that parameter optimization should be treated as a multi-objective mechanical engineering problem. Maximum strength alone is not sufficient if it produces unacceptable surface quality, excessive production time, high material consumption, or dimensional error.

Conclusion:

The present study investigated the optimization of additive manufacturing parameters for producing high-performance engineering components using carbon-fibre-reinforced polyamide and fused filament fabrication. Layer thickness, nozzle temperature, printing speed, and infill density were selected as major controllable parameters, while tensile strength, flexural strength, and surface roughness were evaluated as performance responses.

The analysis demonstrates that processing parameters have a substantial influence on the properties of additively manufactured components. Layer thickness was found to have the greatest influence on surface roughness and a significant effect on mechanical behaviour. Increasing nozzle temperature within the investigated range generally improved mechanical strength by promoting stronger interlayer bonding. Higher infill density provided greater load-bearing capacity, while printing speed produced a balance between manufacturing productivity and bonding quality.

Among the investigated conditions, combinations using relatively thin layers and sufficient processing temperature produced the most favourable results. Multi-response optimization indicated that a layer thickness of 0.10 mm, nozzle temperature of 270 °C, printing speed of approximately 30 mm/s, and 100% infill density can provide a suitable parameter combination when maximum mechanical performance and good surface quality are required.

The findings demonstrate that systematic optimization can reduce trial-and-error manufacturing and improve the reliability of additively manufactured engineering components. Nevertheless, optimum values remain dependent on material composition, equipment, geometry, loading requirements, and environmental conditions. Future work should therefore validate the optimized parameter set experimentally and extend the investigation to fatigue performance, dimensional accuracy, porosity, microstructural characterization, manufacturing cost, and machine-learning-assisted process optimization.



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