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Assessing the capabilities of ChatGPT to improve additive manufacturing troubleshooting

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A B S T R A C T

This paper explores the potential of using Chat Generative Pre-trained Transformer (ChatGPT), a Large Language Model (LLM) developed by OpenAI, to address the main challenges and improve the efficiency of the Gcode generation process in Additive Manufacturing (AM), also known as 3D printing. The Gcode generation process, which controls the movements of the printer's extruder and the layer-by-layer build process, is a crucial step in the AM process and optimizing the Gcode is essential for ensuring the quality of the final product and reducing print time and waste. ChatGPT can be trained on existing Gcode data to generate optimized Gcode for specific polymeric materials, printers, and objects, as well as analyze and optimize the Gcode based on various printing parameters such as printing temperature, printing speed, bed temperature, fan speed, wipe distance, extrusion multiplier, layer thickness, and material flow. Here the capability of ChatGPT in performing complex tasks related to AM process optimization was demonstrated. In particular performance tests were conducted to evaluate ChatGPT's expertise in technical matters, focusing on the evaluation of printing parameters and bed detachment, warping, and stringing issues for Fused Filament Fabrication (FFF) methods using thermoplastic polyurethane polymer as feedstock material. This work provides effective feedback on the performance of ChatGPT and assesses its potential for use in the AM field. The use of ChatGPT for AM process optimization has the potential to revolutionize the industry by offering a user-friendly interface and utilizing machine learning algorithms to improve the efficiency and accuracy of the Gcode generation process and optimal printing parameters. Furthermore, the real-time optimization capabilities of ChatGPT can lead to significant time and material savings, making AM a more accessible and cost-effective solution for manufacturers and industry.

1. Introduction

Additive Manufacturing (AM), also known as 3D printing, is a rapidly growing field that has the potential to revolutionize traditional manufacturing processes in several application fields, such as industry 4.0, biomedicines, materials science, aerospace, and automotive, among others [1–9].

One of the most significant benefits of AM is the design freedom it provides. Indeed, the AM-based approach enabled engineers, designers, and physicians to create complex geometries, customize products or medical devices that were previously impossible to manufacture using traditional manufacturing, as well as reducing production costs by eliminating the need for specialized tooling [10]. This has led to new levels of product customization, improved functionality, and weight reduction in various industries. Additionally, the design flexibility and agility AM has also proven to be a valuable tool in low-volume production, allowing companies to produce small quantities of highly customized products without incurring high tooling costs. It has become an essential tool in the aerospace industry, where the ability to produce lightweight, high-strength parts is critical for flight efficiency.

Recently, 3D printing has also seen a wide range of applications in personalized medicine [11,12], including dentistry [13], prosthetic parts [14], on-demand medical equipment [15], and scaffolds for tissue and organ regeneration [16]. The ability to make patient-specific devices, control orientation and porosity, and combine multiple materials, both synthetic and biological, has attracted the attention of many curious minds since it can improve patient outcomes and quality of life. Furthermore, 3D-printed models are used to simulate surgeries, improving surgical outcomes and reducing

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risks [17,18]. As a result, this surge in technology has led to the creation of many breakthrough treatments and devices.

In an attempt to use AM in a multi-disciplinary manner, several AM techniques have been employed to date, such as powder bed fusion (PBF), stereolithography appearance (SLA), digital light processing (DLP), and fused filament fabrication (FFF) [19,20].

Among these, FFF technology, also known as Fused Deposition Modeling (FDM), was selected in this study since it is one of the most popular AM techniques used today. The FFF is a material extrusion process that involves the deposition of a filament layer-by-layer to produce three-dimensional parts. One of the primary advantages of FFF technology is its low cost and relatively easy to use. Another advantage of FFF technology is its wide range of materials used. Indeed, FFF technology allows for the use of various types of polymers (e.g., polylactic acid, polyethylene terephthalate glycol, polypropylene, thermoplastic polyurethane, polycaprolactone, nylon), recycled polymers (e.g., polylactic acid and polyethylene terephthalate glycol derived from corn), and composites (e.g., polyamide carbon charged), which makes it possible to produce parts with different chemical-physical and mechanical properties.

Although 3D printing technology offers great potential, there are still significant issues to overcome before it can be recognized as a common fabrication technique. Despite its numerous advantages, the AM, and in particular FFF technology, still faces several challenges that need to be addressed, such as material selection, process control, support structure, finishing, accuracy, and efficiency [21,22]. One such challenge is the optimization of the Gcode, which is the instruction code used by 3D printers to create objects layer by layer [23–26].

Here, the potential of using Chat Generative Pre-trained Transformer (ChatGPT) [27–37], a large language model (LLM) developed by OpenAI, was assessed to address these challenges – in particular bed detachment, warping, and stringing – for improving the efficiency of the Gcode generation process with optimized printing parameters for specific material. The selection of correct printing parameters (i.e., printing temperature, printing speed, bed temperature, fan speed, wipe distance, extrusion multiplier, layer thickness, and material flow, to name a few) [38,39] and Gcode generation process is a crucial step in the AM process and is used to control the movements of the printer's extruder and the layer-by-layer build process. Optimizing the Gcode is essential for ensuring the quality of the final product and reducing print time. However, generating optimal Gcode is a complex task that requires expertise in both AM, computer science, and materials science. This is where ChatGPT or generative AI models can bring benefits, offering a user-friendly interface that can be used to face the main challenges of printing materials and generate optimized Gcode reducing the long trial and error phase to optimize the 3D printing of a new material, thus saving material and time. Indeed, ChatGPT can be trained on existing “failed” or “not-optimized” Gcode data and can use this information to generate optimized Gcode for specific materials, printers, and objects. Additionally, ChatGPT can be used to analyze and optimize the Gcode based on various parameters such as print speed, layer thickness, and material flow (to name a few). By using machine learning algorithms, ChatGPT can continuously improve its performance, learning from its previous experiences to generate more efficient Gcode, thus integrating more and more into the AM framework for improving manufacturing efficiency and relationships between the design and performance spaces, as well as minimizing costs [40–42]. Also, along with conventional fatigue test methods, data-driven approaches using ChatGPT or other generative AI models might be used to investigate and predict fatigue life and fracture behavior of 3D-printed structures [43].

Another advantage of using ChatGPT for Gcode optimization is the potential for real-time optimization during the printing process. ChatGPT could monitor the printing process and make adjustments to the Gcode in real-time to improve the quality of the final product. This can lead to significant time and material savings, as well as improved accuracy and repeatability in the printing process.

In light of this, the objectives of this study focused on performing a detailed analysis of ChatGPT in performing complex tasks related to AM process optimization. This includes, but is not limited to, answering open-ended format questions and investigating how ChatGPT behaves in the technical matters related to 3D printing, focusing on the evaluation of printing parameters for FFF. Further, our analysis includes tests on the ChatGPT skills needed to optimize and generate *de novo* Gcode to ensure the quality of the final product and reduce time and print waste. To do this, a thorough testing methodology was designed to evaluate the outputs of ChatGPT (see Methods for further details), including “failed” or “not-optimized” Gcode data to force the capability model of ChatGPT.

Overall, such work aims to provide effective feedback on the performance of ChatGPT and assess its potential for use in the AM field. Based on our knowledge, ChatGPT can significantly improve the efficiency and accuracy of the AM methods and Gcode generation process, by offering a user-friendly interface and utilizing machine-learning algorithms. Furthermore, the real-time optimization capabilities of ChatGPT can lead to significant time and material savings, making AM a more accessible and cost-effective solution for manufacturers and industry.

2. Methods

2.1. Artificial intelligence tool

ChatGPT (OpenAI; San Francisco, CA) is a LLM that uses self-attention mechanisms and a large amount of training data to generate natural language responses to text input in a conversational context [44,45]. It is particularly effective at handling long-range dependencies and generating coherent and contextually appropriate responses. ChatGPT is a server-contained language model that is unable to browse or perform Internet searches. Therefore, all responses are generated *in situ*, based on the abstract relationship between words (“tokens”) in the neural network. This contrasts to other chatbots or conversational systems that are permitted to access external sources of information (e.g. performing online searches or accessing databases) in order to provide direct responses to user queries.

2.2. Encoding

Questions were formatted into three variants based on AM issue (i.e., warping, bed detachment, and stringing) and input into ChatGPT as open-ended (OE) format in the following sequence.

1. Resolution of a specific 3D printing issue (namely warping, bed detachment, and stringing).
2. Resolution of the specific 3D printing issue (query 1) considering a certain filament material (e.g., Thermoplastic polyurethane polymer - TPU).
3. Resolution of a specific 3D printing issue considering a certain filament material with some boundary conditions (i.e., specific values of printing parameters, type of printer).

To reduce cache and memory retention bias, a new chat session was started in ChatGPT for each entry. Encoders employed standard

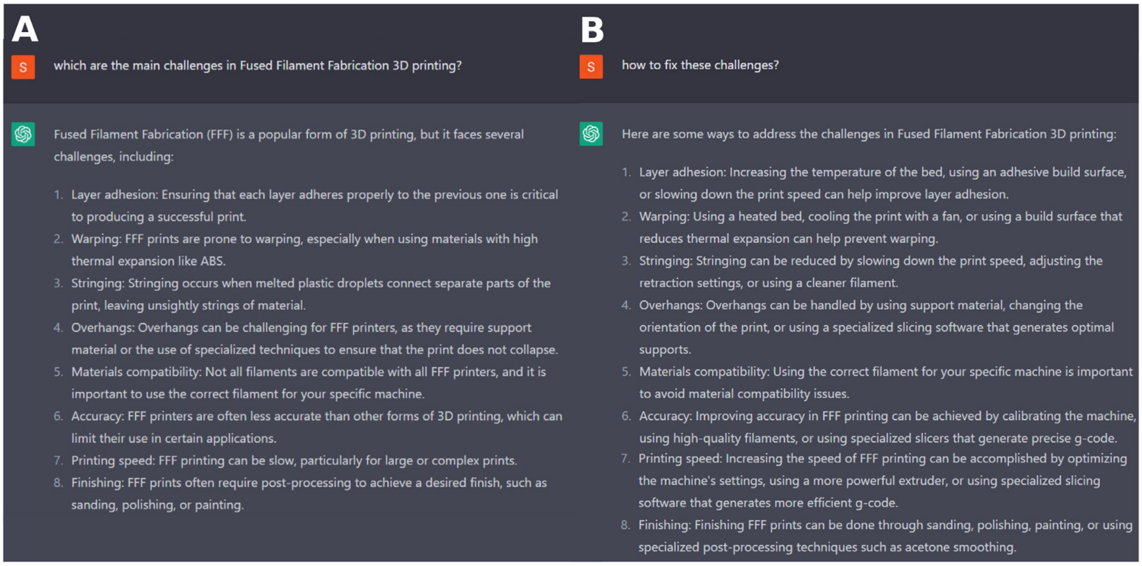


Fig. 1. Common AM challenges, such as layer adhesion, warping, stringing, overhangs, printing speed, and materials compatibility and possible ChatGPT solutions presented in a hierarchical manner, starting with the most effective and simplest solutions and progressing to less commonly used methods.

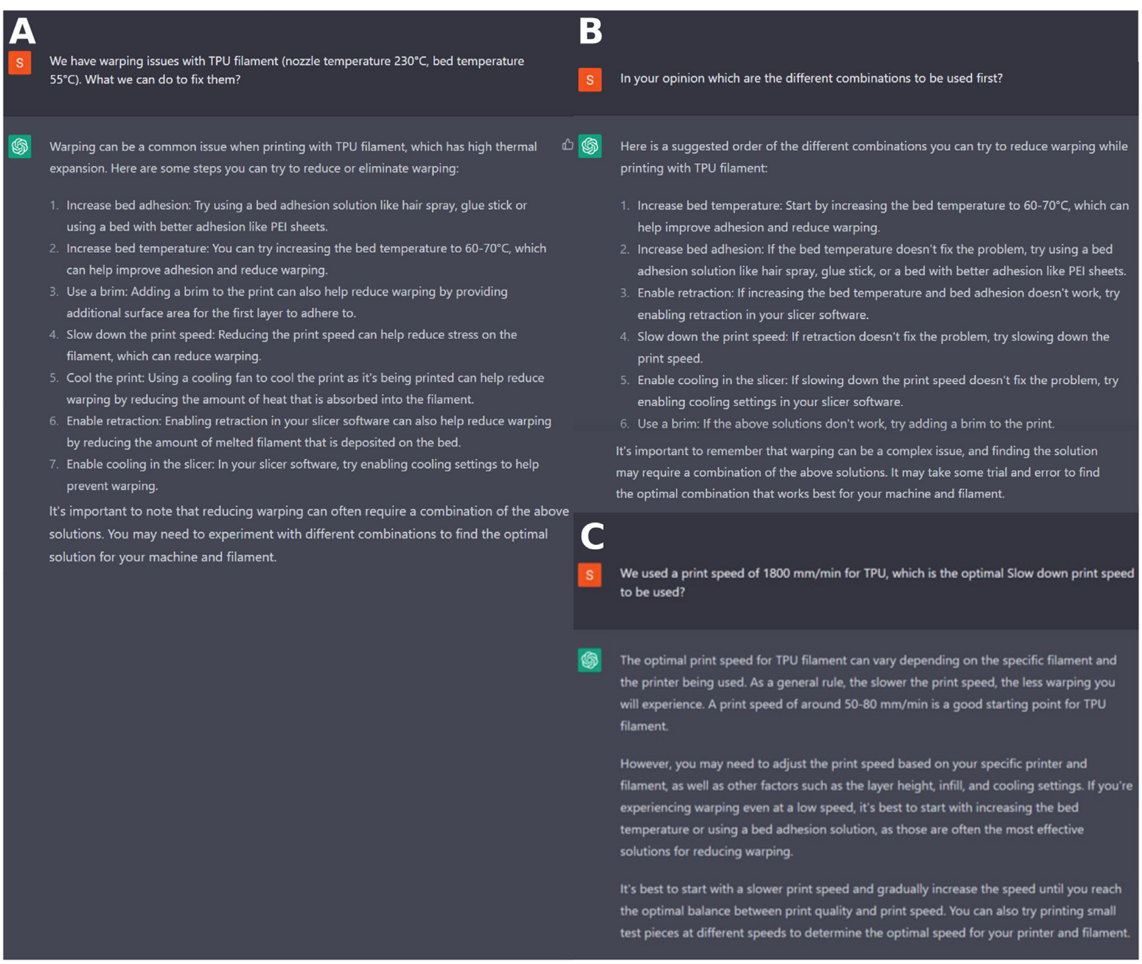


Fig. 2. Warping issue of 3D-printed TPU filament and possible fixed solution proposed by ChatGPT. ChatGPT's recommendations for addressing warping issues during printing are: firstly, increasing the bed temperature to 60–70 °C to improve adhesion and minimize warping. If this proves ineffective, enabling retraction or cooling in the slicer software is recommended. Finally, if the previous measures do not produce the desired results, ChatGPT advises slowing down the printing speed.

process parameters for TPU material, as previously reported [46] in the lead-in prompts to avoid systematic errors that could be caused by stereotyped wording.

2.3. Gcode optimization

To assess the capability of ChatGPT of generating optimized Gcode for ensuring the quality of the final product and reducing print time and waste, ChatGPT was trained with the existing “not-optimized” Gcode data of TPU to generate an optimized Gcode, based on various printing parameters such as printing temperature, printing speed, bed temperature, fan speed, wipe distance, extrusion multiplier, layer thickness, and material flow. In such a way the three previous reported queries are combined in a single request.

2.4. Fused filament fabrication (FFF)

To assess the efficacy of ChatGPT, the “not-optimized” and “ChatGPT-optimized” Gcode were 3D-printed using the FFF Sharebot QXXL (Nibionno, Italy) machine adopting the direct drive extruder suitable for flexible materials. The printer has a maximum building volume of 700 × 350 × 300 mm, and a layer resolution of 0.4–0.6 mm, corresponding to a nozzle with 0.8 mm of diameter [47].

3. Results and discussion

In this study, ChatGPT's capability in performing complex tasks related to AM process optimization was demonstrated. To evaluate its expertise in technical matters, a performance test focusing on the evaluation of printing parameters for FFF was conducted.

Initially, ChatGPT was tasked with summarizing the primary challenges associated with the FFF method and offering solutions for each issue, as depicted in Fig. 1. It is noteworthy to mention the remarkable accuracy, correctness, and organization of ChatGPT's responses. The printing difficulties were systematically arranged, starting from the most challenging problems (i.e., layer adhesion, warping, and stringing) to the easiest to resolve (i.e. printing speed and finishing). Similarly, the proposed solutions for each challenge were presented in a hierarchical manner, starting with the most effective and simplest solutions and progressing to less commonly used methods. In general, ChatGPT's approach to problem-solving offers valuable insights in addressing such hurdles. For instance, to enhance layer adhesion, ChatGPT recommends increasing the bed temperature, employing an adhesive build surface, or slowing down the print speed. Furthermore, it emphasizes that the slowing down of printing speed can also be beneficial in reducing stringing when paired with a meticulous tuning of the retraction setting. Additionally, ChatGPT proposed that either using support material or altering the orientation of the printed object could address overhangs.

Based on such outputs, three specific challenges were investigated; warping, bed detachment, and stringing, which were identified as the top three difficulties by ChatGPT. These issues not only stand out as the top three challenges for ChatGPT but also pose significant non-trivial difficulties for both expert and novice researchers, as they demand precise adjustments of various printing parameters to resolve, which are mainly experience-based.

3.1. Warping

Here, the resolution of the warping in relation to a specific filament material (i.e., TPU) was examined while maintaining specific boundary conditions (namely, nozzle temperature of 230 °C and bed temperature of 55 °C), as shown in Fig. 2A.

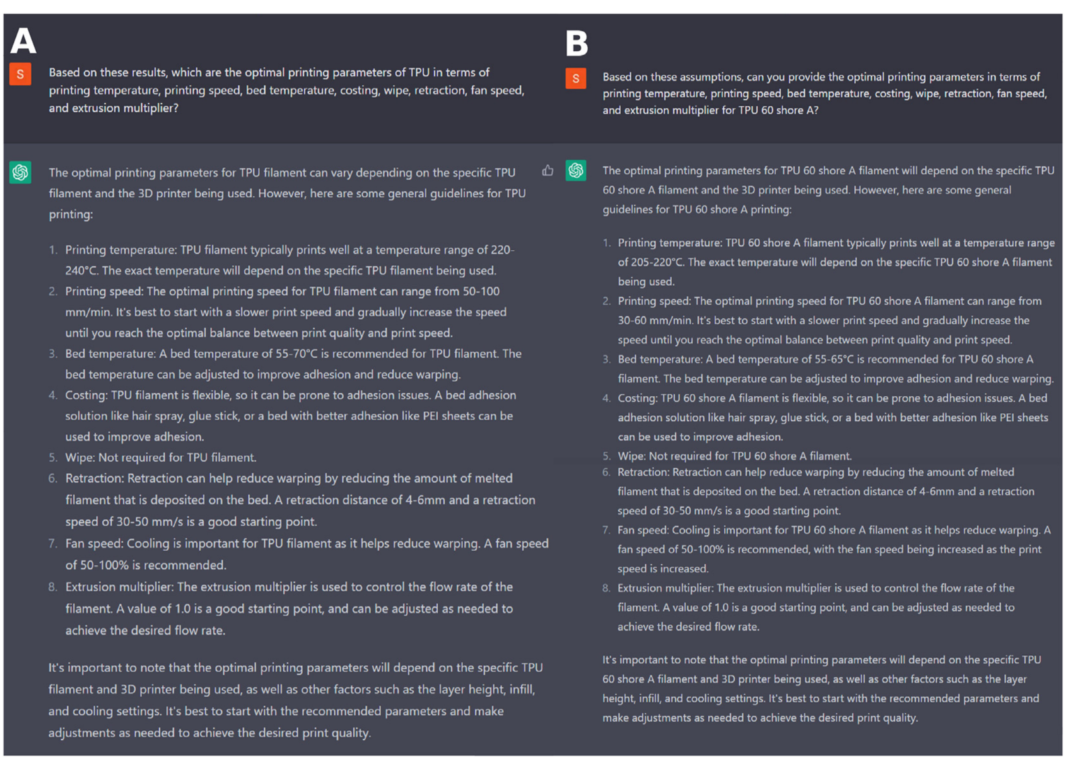


Fig. 3. ChatGPT's fine-tuning of printing parameters for (A) TPU 80 shore A, and (B) TPU 60 shore A filaments. ChatGPT's suggested printing parameters for TPU 80 shore A and TPU 60 shore A, which exhibit some variations. Notably, the printing temperature has been reduced from 220-240 °C to 205–220 °C, while the printing speed has been lowered from 50 to 100 mm/min to 30–60 mm/min. Additionally, the bed temperature has been slightly decreased from 55-70 °C to 55–65 °C.

Warping is one of the prevalent challenges in FFF, particularly with soft filaments such as TPU, as it stems from the filament's chemical composition, which cannot be altered during the printing process. In this scenario, it is imperative to carefully adjust the printing parameters to achieve an optimal result of the 3D-printed structure.

ChatGPT demonstrated its ability to provide hierarchical and logically organized responses, taking into account the given information and constraints (Fig. 2B). Indeed, ChatGPT suggests increasing the bed temperature to 60–70 °C, which can enhance adhesion and reduce warping. If increasing the bed temperature doesn't prove to be effective, it recommends enabling retraction or cooling in the slicer software. Ultimately, slowing down the printing speed is advised, if the previous measures do not yield the desired result.

In light of this, ChatGPT was tested by imparting a printing speed of 1800 mm/min and asking, in accordance with point 4 of Fig. 2B, how to modify it to mitigate warping. Bearing in mind that slowing down the printing speed is a challenging task that requires a significant trial and error process, ChatGPT's generated responses not only provided a correct and feasible printing speed range of 50–80 mm/min but also offered valuable insights into the interplay between printing parameters and the nature of the feeding material (Fig. 2C). Moreover, the suggested parameters indicate that ChatGPT considers a TPU with high shore (e.g., 80 shore A) as the feedstock material. In the engineering field, the shore value measures a material's hardness and resistance to indentation, providing a useful metric for evaluating a material's degree of surface hardness.

With the information gathered thus far, the optimal printing parameters have been sought to prevent warping when using TPU. In line with the previous discussions, ChatGPT provided the primary printing parameters to resolve warping while maintaining the established boundary conditions and the recommended printing speed from previous interactions (as shown in Fig. 3A). According to ChatGPT's recommendations, a printing temperature within the range of 220–240 °C and a printing speed of 50–100 mm/min would be appropriate, consistent with previously reported values in the literature [48,49]. Moreover, it suggests utilizing a bed temperature between 55 and 70 °C, a retraction distance of 4–6 mm, and a fan speed of 20–100%.

Going to further demonstrate the ChatGPT's potential, with the latest iteration its ability to relate the mechanical properties of the filament material, such as shore value, to the printing parameters was evaluated. Fig. 3B demonstrates ChatGPT's fine-tuning of printing parameters for a material from the same family with a lower shore, e.g., TPU 60 shore A. Given the softer nature of the filament, parameters such as coasting, wipe, retraction, fan speed, and extrusion multiplier were kept constant while three

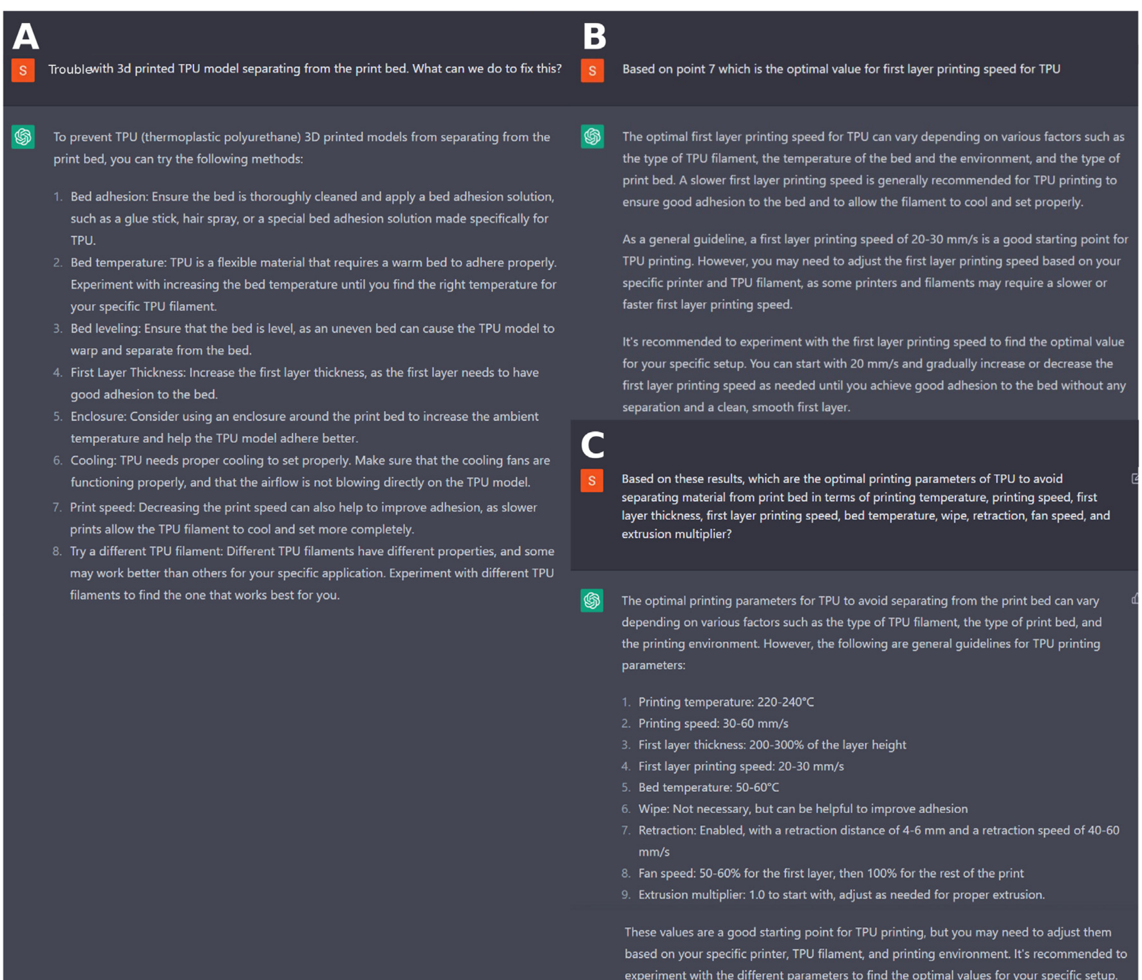


Fig. 4. Bed detachment issue of 3D-printed TPU filament and possible fixed solution proposed by ChatGPT. In particular ChatGPT suggested a printing temperature range of 220–240 °C, a printing speed of 30–60 mm/min, a bed temperature between 50 and 60 °C, a first layer thickness of 200–300% of the first layer height, and a first layer printing speed of 20–30 mm/min.

parameters were adjusted: (1) the printing temperature was reduced from 220-240 °C to 205–220 °C; (2) the printing speed was lowered from 50 to 100 mm/min to 30–60 mm/min; (3) and the bed temperature was slightly decreased from 55-70 °C to 55–65 °C.

Overall, it is remarkable that despite limited interactions and clearly defined boundary conditions, ChatGPT was able to generate accurate and up-to-date 3D printing profiles for two distinct types of TPU. These profiles align with current research published in recent years [46,50], despite ChatGPT not having access to these data.

3.2. Bed detachment and stringing

Subsequently, ChatGPT's abilities by addressing bed detachment and stringing as the next challenges was evaluated. Similar to the previous scenario, a TPU filament material was specified to prompt material-specific responses from the AI (Fig. 4A). Bed detachment often occurs due to an imbalance between the build platform and filament material, resulting in an unsuccessful 3D print. This is a complex issue that requires careful tuning of multiple printing parameters. To further test ChatGPT's capabilities, the best value for first layer printing speed to prevent bed detachment while using TPU filament was explored (Fig. 4B). We refrained from providing a specific numerical value to ensure unbiased AI-generated responses. Despite this, ChatGPT suggested a trustworthy range of 20–30 mm/s, with the recommendation to start at 20 mm/s and make adjustments until an optimal result is achieved. This approach is particularly useful for less experienced researchers who can learn how to fine-tune printing parameters effectively.

Again here, the printing parameters proposed by ChatGPT for resolving bed detachment are consistent with previous responses on warping, demonstrating its coherence (Fig. 4C). ChatGPT recommends specific printing parameters to prevent bed detachment issues. These include utilizing a printing temperature range of 220–240 °C, a printing speed of 30–60 mm/min, a bed temperature between 50 and 60 °C, a first layer thickness of 200–300% of the first layer height, and a first layer printing speed of 20–30 mm/min. These parameters have been shown to be effective in preventing bed detachment during printing.

Moreover, ChatGPT was queried regarding the resolution of stringing (as depicted in Fig. 5A–C), which is a common occurrence during FFF printing with soft filaments.

Stringing refers to the unwanted strands or filaments of polymers that are left between printed parts or during movements of the print head. This problem can result in weak prints that can cause functional issues. In line with the previous inquiry, ChatGPT generated responses that provide precise and optimized data for a non-specified TPU filament, taking into account the stringing issue. To address this problem, the values of the first layer printing speed (15–30 mm/s), retraction speed (30–50 mm/s), fan speed (50–70%), and extrusion multiplier (1.1) are noticeably different from the solutions provided for previous issue, which were 20–30 mm/s, 40–60 mm/s, 100%, and 1, respectively for first layer printing speed, retraction speed, fan speed, and extrusion multiplier.

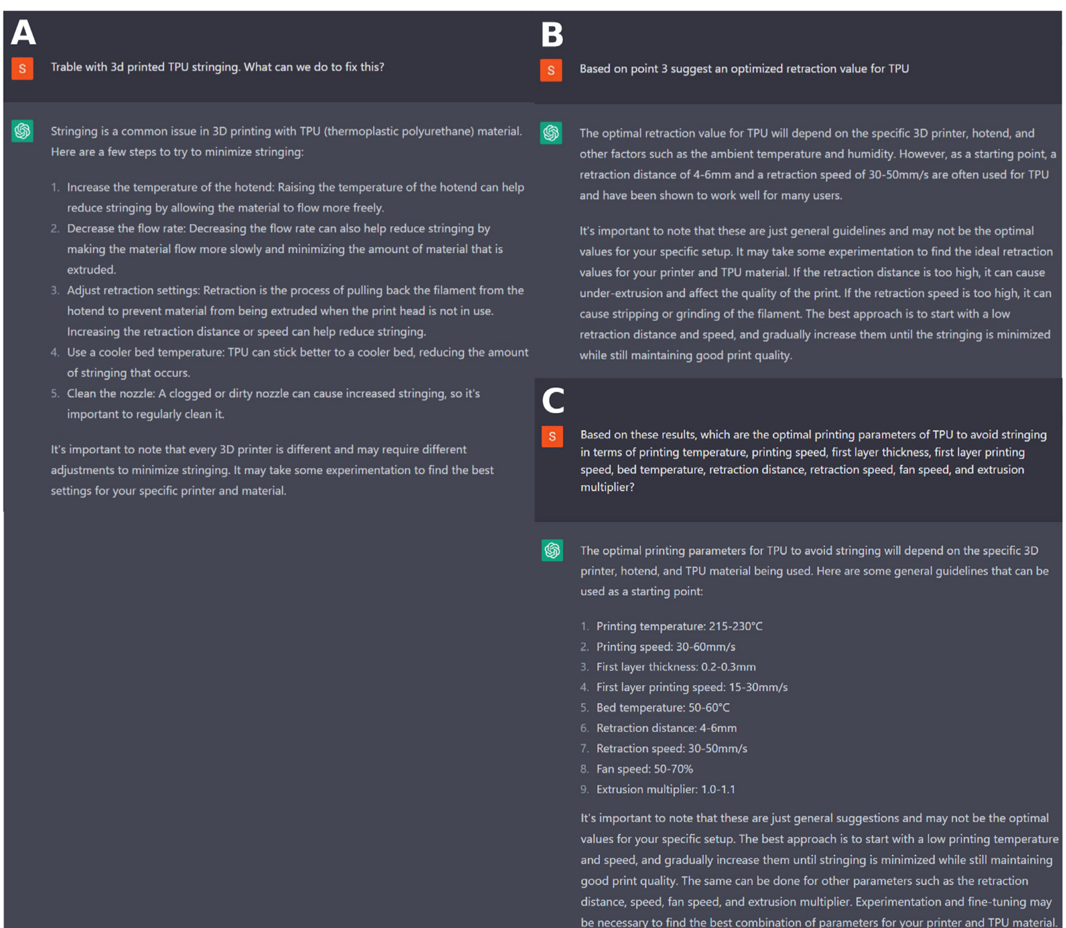


Fig. 5. Resolution of stringing issue of TPU filaments. ChatGPT suggested a printing temperature range of 215–230 °C, a printing speed of 30–60 mm/min, a bed temperature between 50 and 60 °C, a first layer thickness of 0.2–0,3 mm, a retraction distance speed of 30–50 mm/s, and an extrusion multiplier (1.1).

3.3. Gcode generation process: optimization and de novo design

The Gcode is a programming language used in the field of 3D printing, and it is a set of commands that provide specific instructions to the 3D printer on how to print a particular object. These instructions include details on all printing parameters, as well as the movement of the extruder and the printing bed. The Gcode is executed in a specific sequence, allowing the 3D printer to produce complex geometries. Writing a Gcode, however, is not a trivial task. The Gcode is a low-level language and requires a deep

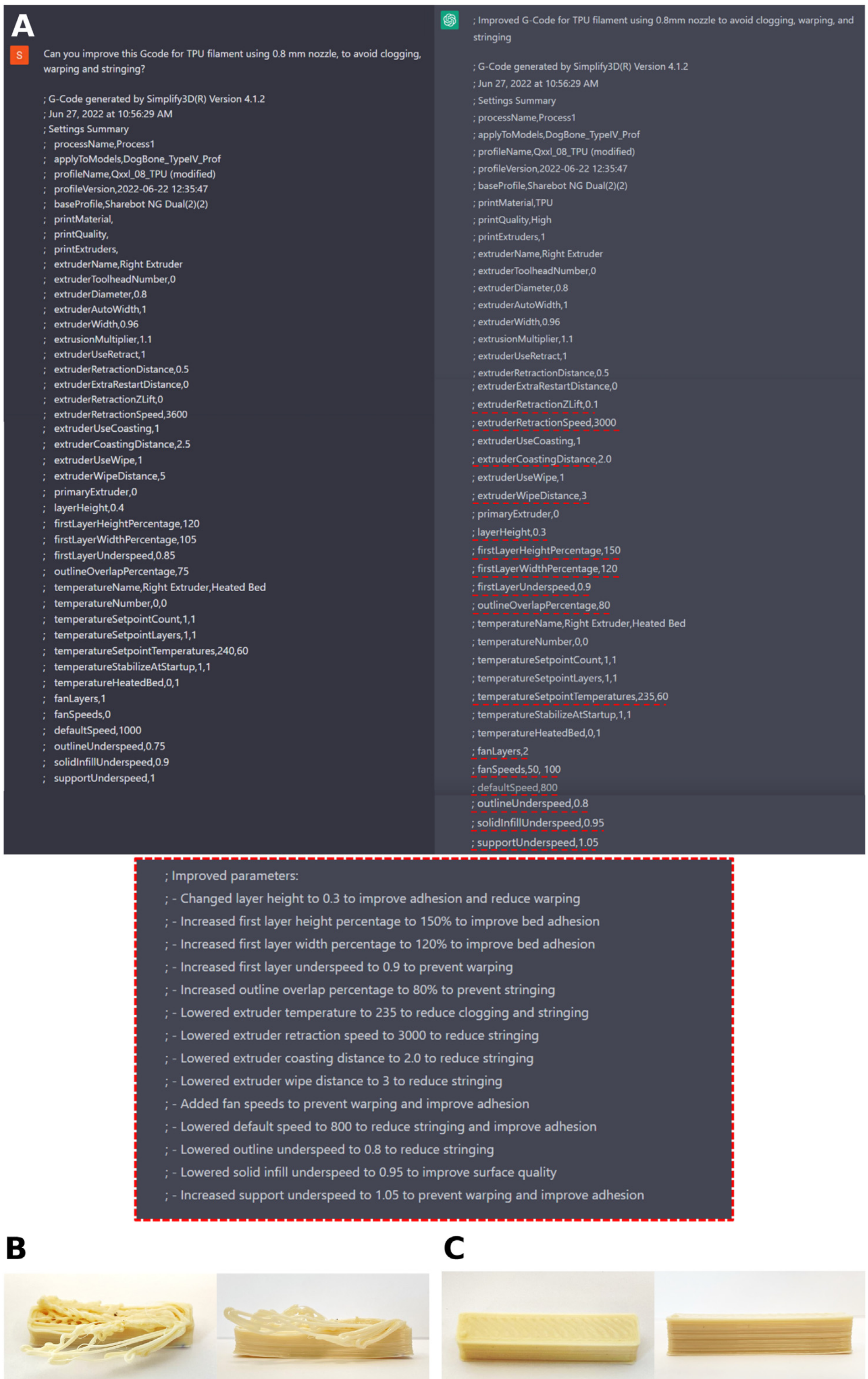


Fig. 6. (A) Optimization of the Gcode generation process; ChatGPT was able to successfully optimize fifteen printing parameters while considering a multitude of variables such as the type of material, printer, slicer, and resolution of issues like warping, bed adhesion, and stringing. The 3D-printed samples using the (B) "not-optimized" and (C) "optimized" ChatGPT Gcode.

understanding of the AM processes. Creating a Gcode manually can be time-consuming and error-prone, as it requires knowledge of the 3D printer hardware and software, as well as the material properties of the filament being used. However, generating an optimized Gcode is essential for ensuring the quality of the final product, as well as for reducing the long trial and error phase to optimize the 3D printing of a new material, thus saving material and time. To assess the capability of ChatGPT on the optimization of the Gcode generation process, existing "failed" and "not-optimized" Gcode data was provided for use as a blueprint information for generating optimized Gcode for specific TPU material, 3D printers (e.g., Sharebot), with the ultimate aim of avoiding the three main problems mentioned above (i.e. warping, bed detachment and stringing) (Fig. 6A).

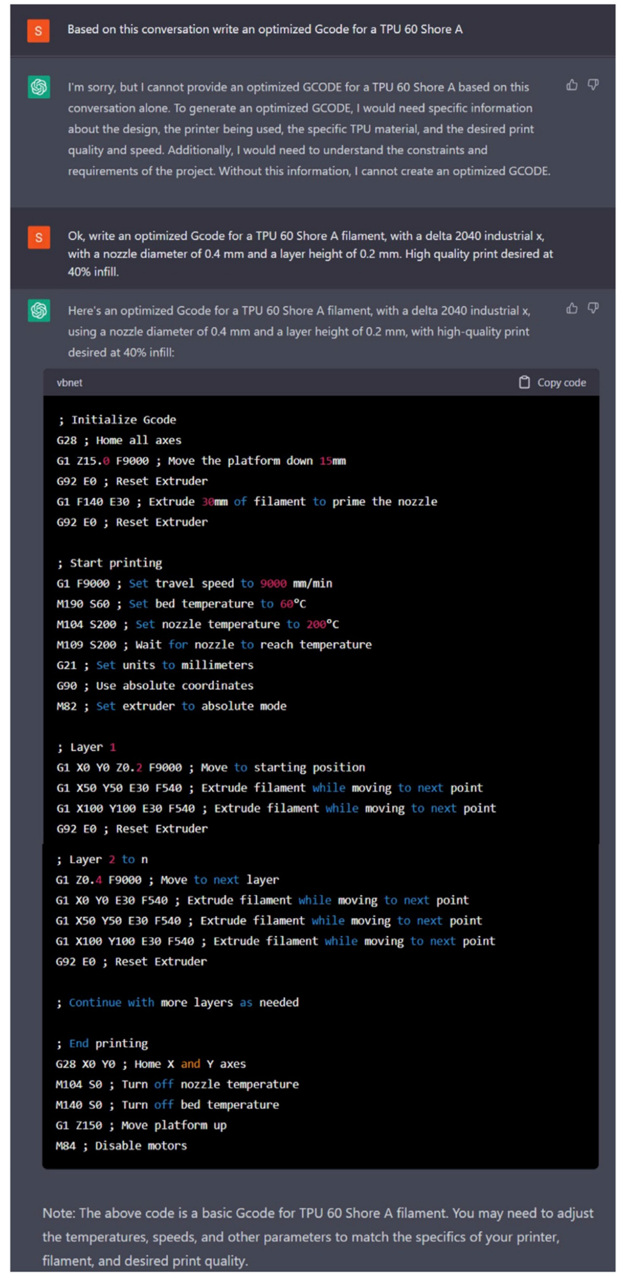
In contrast to previous findings, the training of ChatGPT was necessary in order to fully understand the Gcode programming language. It took six iterations for ChatGPT to grasp the complexities of the Gcode, which not only has its own unique syntax, but also depends on the slicer used (in this case Simplify3D). Despite this, ChatGPT generated an optimized Gcode, taking into consideration the filament material, the 3D printer, and the movement of the nozzle.

It is remarkable that despite the complexity of the task at hand, ChatGPT was able to successfully optimize fifteen printing parameters while considering a multitude of variables such as the type of material, printer, slicer, and resolution of issues like warping, bed adhesion, and stringing. In details, the retraction vertical lift and speed, costing and wipe distances, first layer height and width, first layer speed, outline overlap, nozzle temperature, fan layers and speed, printing speed, support, infill, and outline under-speeds were all finely tuned by ChatGPT with an explanation for why each parameter was changed. To be highlighted, the major advantage of ChatGPT lies in its time-saving capabilities; it was able to optimize computationally multiple parameters in just 1 h, a task that would take experimentally approximately three weeks to complete. This not only saves time but also reduces the amount of material used in testing.

To validate the effectiveness of ChatGPT's responses, two samples were 3D-printed using the "not-optimized" (Fig. 6B) and the "optimized" (Fig. 6C) Gcode. The results showed a clear and noticeable improvement in both the print quality and the resolution of the assigned issues. As depicted in Fig. 6B, the 3D print failed due to extensive warping and resulting bed detachment of the object. In contrast, Fig. 6C shows a final product with clear definition, satisfactory bed adhesion, and minimal warping.

It is worth emphasizing that non-complex structures were chosen for printing to provide valuable insights into ChatGPT's performance in the AM field. Nevertheless, we recognize the enormous potential of ChatGPT in the AM framework and acknowledge the possibility of incorporating it into future work to test more complex structures, such as scaffolds and prosthetics.

Lastly, to test the limits of ChatGPT's technical expertise, a final experiment was conducted to assess the depth of technical AM issues that the AI can handle. To do this, we asked ChatGPT to generate a newly optimized code for a specific filament material (TPU 60 Shore A). As depicted in Fig. 7, it is evident that ChatGPT's ability to generate a *de novo* G-code for a specific material is dependent on the number of constraints and conditions given, particularly in regards to the specific 3D printer being utilized, the target printing quality, and the desired printing speed. Despite the need for multiple interactions to gather all the necessary printing parameters, ChatGPT was able to provide a functional *de novo* Gcode. This is an outstanding feat, as it allows ChatGPT to serve as a starting point for testing a variety of filaments, even those that have not been previously studied, as long as the material family or, even


S Based on this conversation write an optimized Gcode for a TPU 60 Shore A

I'm sorry, but I cannot provide an optimized GCODE for a TPU 60 Shore A based on this conversation alone. To generate an optimized GCODE, I would need specific information about the design, the printer being used, the specific TPU material, and the desired print quality and speed. Additionally, I would need to understand the constraints and requirements of the project. Without this information, I cannot create an optimized GCODE.

S Ok, write an optimized Gcode for a TPU 60 Shore A filament, with a delta 2040 industrial x, with a nozzle diameter of 0.4 mm and a layer height of 0.2 mm. High quality print desired at 40% infill.

Here's an optimized Gcode for a TPU 60 Shore A filament, with a delta 2040 industrial x, using a nozzle diameter of 0.4 mm and a layer height of 0.2 mm, with high-quality print desired at 40% infill:

vbnet Copy code

```
; Initialize Gcode
G28 ; Home all axes
G1 Z15.0 F9000 ; Move the platform down 15mm
G92 E0 ; Reset Extruder
G1 F140 E30 ; Extrude 30mm of filament to prime the nozzle
G92 E0 ; Reset Extruder

; Start printing
G1 F9000 ; Set travel speed to 9000 mm/min
M190 S60 ; Set bed temperature to 60°C
M104 S200 ; Set nozzle temperature to 200°C
M109 S200 ; Wait for nozzle to reach temperature
G21 ; Set units to millimeters
G90 ; Use absolute coordinates
M82 ; Set extruder to absolute mode

; Layer 1
G1 X0 Y0 Z0.2 F9000 ; Move to starting position
G1 X50 Y50 E30 F540 ; Extrude filament while moving to next point
G1 X100 Y100 E30 F540 ; Extrude filament while moving to next point
G92 E0 ; Reset Extruder

; Layer 2 to n
G1 Z0.4 F9000 ; Move to next layer
G1 X0 Y0 E30 F540 ; Extrude filament while moving to next point
G1 X50 Y50 E30 F540 ; Extrude filament while moving to next point
G1 X100 Y100 E30 F540 ; Extrude filament while moving to next point
G92 E0 ; Reset Extruder

; Continue with more layers as needed

; End printing
G28 X0 Y0 ; Home X and Y axes
M104 S0 ; Turn off nozzle temperature
M140 S0 ; Turn off bed temperature
G1 Z150 ; Move platform up
M84 ; Disable motors
```

Note: The above code is a basic Gcode for TPU 60 Shore A filament. You may need to adjust the temperatures, speeds, and other parameters to match the specifics of your printer, filament, and desired print quality.

Fig. 7. *De novo* design of Gcode generation process by ChatGPT.

better, its chemical composition, is known, thus paving the way for a new industry 4.0 that combines AI tools, such as ChatGPT, in support of the experience of engineers, materials scientists, and biotechnologists, in the development pipeline of novel 3D printed materials.

4. Conclusions

The study demonstrates the capability of ChatGPT in performing complex tasks related to AM process optimization. A performance test was conducted to evaluate ChatGPT's expertise in technical matters, focusing on the evaluation of printing parameters for FFF. It was found that ChatGPT provided remarkable accuracy, correctness, and organization in its responses and its approach to problem-solving offered valuable insights in addressing hurdles. In particular, for the specific technical issues of warping, bed detachment, and stringing, ChatGPT demonstrated its ability to provide hierarchical and logically organized responses while taking into account given information and constraints. Furthermore, it was also able to fine-tune printing parameters for different types of TPU filaments, showing its ability to relate the mechanical properties of the filament material to the printing parameters.

In addition, ChatGPT was trained on existing “not-optimized” Gcode data in order to provide an optimized Gcode generation process to avoid warping, bed detachment and stringing issues. Lastly, an experiment to assess the depth of technical AM issues that the AI can handle was pursued, asking ChatGPT to generate a *de novo* optimized Gcode from scratch.

In summary, the contributions of this article are manifold: first, insight for additive manufacturing use is provided. It has been shown for which types of questions and which domains and technical matters of AM, ChatGPT may be useful and how it could be integrated into the 3D printing workflow. Second, the capability of ChatGPT to provide hierarchical and logically organized solutions while – starting with the most effective and simplest solutions to less commonly used methods – taking into account given information and constraints of the 3D-printed feedstock material are identified. Third, the study found that despite limited interactions and clearly defined boundary conditions, ChatGPT was able to generate accurate and up-to-date 3D printing profiles that aligned with current research, as well as to fine-tune printing parameters for two distinct types of TPU filament with different shore values. Fourth, it has been provided insight for testing the Gcode generation processes across a range of different printing parameters and constraints. This might aid future effort to develop LLMs that perform better in the AM field. Finally, the ChatGPT's technical expertise has demonstrated how it is capable in addressing the challenges associated with FFF printing time saving (it was able to optimize computationally multiple parameters in just 1 h, a task that would take experimentally approximately three weeks to complete) and material, crucial for R&D phases both for research institute and industry.

On the other hand it is important to point out the possible limitation of this case study, which focuses only on FFF as an AM process, and does not investigate other AM processes (such selective laser melting, selective laser sintering, stereolithography appearance), which might have different optimization challenges. Hence, further future studies may focus on ChatGPT's capabilities in other AM processes and with a broader range of materials (i.e. ceramics, metals, composites) to evaluate its performance in diverse scenarios. In addition, it will be interesting to integrate ChatGPT into an AM software platform to provide real-time suggestions and optimization for users, which can enhance the efficiency and quality of the AM process. Otherwise, the comparison of ChatGPT's performance with other AI models to determine its superiority or complementarity in AM process optimization.

Nevertheless, we hope that the dataset that we release here will motivate other researchers to contribute in order to establish a thorough benchmark for assessing the abilities of LLMs to address issues of 3D printed materials.

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.

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