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Design and Operation of a GPT-powered Smart Manufacturing System

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Abstract

The recent surge in popularity of OpenAI's chatGPT, a Generative Pre-trained Transformer (GPT) model, has highlighted the potential of these large language models for a variety of tasks. More and more people are using chatGPT as a virtual assistant in their daily lives, from work to personal tasks, to enhance efficiency. The rise of GPT-related technology could transform the interaction between humans and machines into a collaborative team. This requires shared situational awareness, a level of understanding and agreement among team members on common aspects of the situation. Large, general-purpose multi-modal models like GPT have the potential to meet this requirement. Large global manufacturing organizations face many challenges in daily operations and management. These include the time and cost-intensive process of designing and developing new products and manufacturing processes, limited communication between factories in different countries, and the need for improved supply chain flexibility and risk management. The paper proposes a framework for a smart manufacturing system powered by a Generative Pre-trained Transformer (GPT) model. The system is designed to construct a human-AI team and aims to reduce costs and time in product and process design, enhance operational efficiency, and boost internal and external communication effectiveness.

Keywords
Artificial intelligence, smart manufacturing, system design, generative pre-trained transformer, and human-AI interaction

1. Introduction
The explosive growth of chatGPT, an AI chatbot developed by OpenAI, in the past few months, has attracted a huge amount of attention among the public to the capabilities of Generative Pre-trained Transformer (GPT) models, a family series of large language models that is suitable for general non-specific task related applications. There is already a trend showing that more and more people are starting to use chatGPT, either with base model GPT3.5 or GPT4, as a virtual assistant in day-to-day life, from work to personal life to handle things more efficiently. The newest technology release of the chatGPT also enables the model to decide when and how to use web browsing or plugins during the conversation. Being the first series of large language models that is able to solve a variety of tasks well, the GPT models attract people through the chatGPT platform to learn their potential capability (Zhou et al 2023; OpenAI 2022). Many add-ons and AI tools are developed and deployed in various applications through API integration for better user experience and further exploration.

With the rapid advancement of AI and other technology, the concept of Industry 5.0 has been proposed. Unlike Industry 4.0 where the focus is on data digitization and machine automation to reduce human involvement, Industry 5.0 aims to rebuild a human-centric environment where humans and machines work together to boost work efficiency in a smart manufacturing system (Adel 2022). With the integration of the enabling technologies of smart manufacturing, such as smart sensing, IoT, AI, big data analytics, cyber-physical system, etc., Industry 4.0 has already brought higher flexibility, production efficiency, and real-time data-driven decision-making capability to organizations. The use of artificial intelligence and machine learning in Industry 4.0 focuses more on task-specific applications. For example, predictive maintenance can be realized based on real-time data collection and analysis and model development. The use of machine learning for product inspection has also increased in manufacturing plants to effectively reduce the possibility of delivering defective final products to customers. At this level, AI is a tool that aids and assists human who acts as supervisor.

The emergence of GPT-related technology may transform the interaction between humans and autonomy to another form of Concept of Operation (COO): AI and Human acting as collaborating teammates. This form of COO requires shared situation awareness, which refers to the level of understanding and agreement among members of the team on common aspects of the situation, including relevant data, interpretation, and projections needed by both parties (Endsley et al. 2017; Endsley & Jones 2001). Unlike AI models designed for specific tasks, a large general-purpose multi-modal model has the potential to meet this high-level requirement.

For large-size global manufacturing organizations, there are many challenges existing in daily operations and management. First, the procedure of new products and manufacturing process design and development usually requires solid engineering knowledge. However, since the capability of humans largely depends on experience, it is inevitable to spend excessive money and time on experimental studies or trial-and-error during development. Second, because factories that produce similar products may spread to different countries for various purposes, such as lower operations costs and better connection with local markets, there is limited communication between these sibling factories. Lack of communication causes the automation level among those factories to be inconsistent and a factory may spend unnecessary resources to develop an automation technology that has already been deployed in other factories. Potential factors that prevent effective communication across the organization include but are not limited to cultural differences, lack of structured data or documentation, and unawareness of the adoption of certain technology within the organization. Third, after experiencing the global supply chain disruption caused by covid-19 pandemic and the Ukraine-Russia war, more and more organizations are aware of the importance of supply chain flexibility and risk management. There is a great potential for improvement throughout the supply chain, from demand forecast, supplier risk, and inventory management to downstream consumer satisfaction.

1.1 Objectives

This paper proposes a framework of a GPT-powered smart manufacturing system that incorporates the GPT model as a collaborative team member to construct a human-AI team in order to

1. reduce the cost, both time-wise and money-wise, for the design and development of new products and manufacturing processes
2. improve the operations and production efficiency of the smart manufacturing system
3. increase effectiveness and efficiency of communication within the system, as well as with stakeholders outside of the system

2. Literature Review

The Generative Pre-trained Transformer model is a derivative model from the vanilla transformer, which is the origin of the transformer-based research field. Transformer models are more flexible with the data type intrinsically than other types of deep neural networks and are able to perform multimodal generative tasks (Xu et al 2023). In March 2023, OpenAI released the newest model in the GPT family, the large-scale multimodal model GPT4, which is able to accept text and image as input and generate output in the form of text. Based on a series of academic and professional exams, the model shows human-level performance (OpenAI 2023).

Research has been done on the potential application of chatGPT/GPT in the field of biology, medicine, and healthcare (Zhang and Qian 2023; Chavez et al 2023; Korngiebel and Mooney 2021). The ability of GPT models to generate content such as innovative concept designs, stories, and translations has also been explored (Saravanan and Sudha 2022; Zhu and Luo 2022). Studies regarding the use of ChatGPT for robotics applications have been performed by researchers from Microsoft Autonomous Systems and Robotics Research and the result suggests that ChatGPT allows users to use natural language instruction to solve tasks in the robotics domain effectively (Vemprala et al 2023)

The emergence of Industry 5.0 also brings researchers to investigate potential opportunities and limitations. Similar to Industry 4.0, Industry 5.0 also has a focus on smart manufacturing, which includes elements of smart sensing, IoT, AI/ML, and more. However, the role of humans has been emphasized in Industry 5.0. Research has been done on how to construct a cyber-physical system with human in the loop and a human-AI or human-machine collaborative team to maximize efficiency (Bhattacharya et al 2023; Endsley 2022; Jiao et al 2020).

3. System Design and Analysis

Figure 1 provides a detailed illustration of the system architecture of the proposed system. The general-purpose GPT model is pre-trained with vast amounts of general public data. This step ensures the model's robustness and applicability across a wide range of open tasks. Once it is completed, the model can be fine-tuned for each user group, or organization, using internal documents on specific information (for instance, organizational structure, product details, operations, and financial status) within the organization to generate better results when performing tasks related to the specific domain. By learning massive well-structured data from the organization, the model is expected to gain a deeper and more comprehensive understanding of the organization and this level of understanding is expected to surpass the knowledge base of most of the human users within the organization. As this new AI technology advances, the demand for new jobs relevant to this technology also emerges. For example, in order to fine-tune the model with massive organizations' confidential information, it would make more sense to hire people with high levels of AI knowledge and competency skills to perform the work and maintain the model for daily operations.

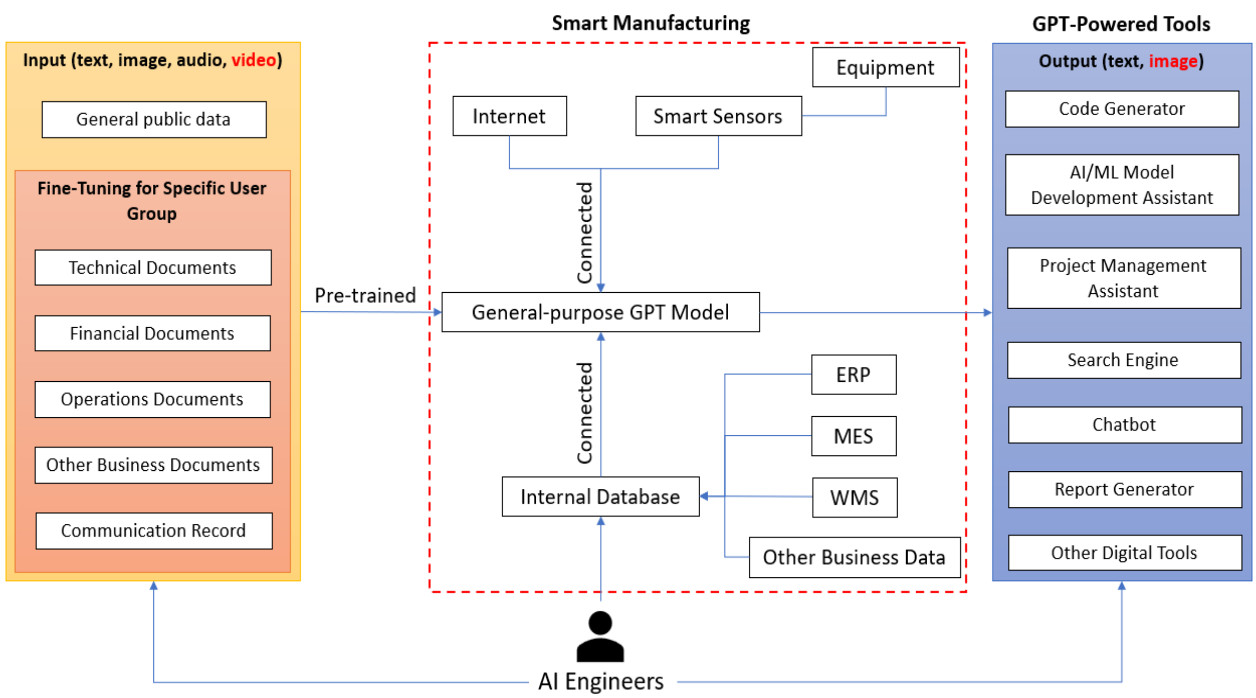

Figure 1. System architecture of the proposed GPT-powered smart manufacturing system

Over the past decade, since the introduction of the Industry 4.0 concept, the adoption of digitalization and automation in large-scale manufacturing systems has led to the implementation of various systems, including Enterprise Resource Planning (ERP), Manufacturing Execution System (MES), and Warehouse Management System (WMS). The pre-trained model is integrated into the smart manufacturing system by connecting to the organization's internal database which can be either local or on the cloud, internet, and smart sensors to get data that is most relevant, up-to-date, and accurate. Many types of AI-based tools can be derived from this general-purpose model. Chatbot-type tools without any doubt are the most successful example, as the ChatGPT platform was able to gain 1.8 billion visits up to April 2023. Other text generation-type of tools such as report/document generators and code generators have also been experimented with by many researchers (Saravanan and Sudha 2022). Although the latest GPT4 model is a multi-modality to single-modality model that can only handle input in the format of text and image and output of text, it is able to call Plugins/APIs and utilize technology from external sources to extend its functionality and practicability (https://openai.com/blog/chatgpt-plugins). Furthermore, the transformer neural network inherently can represent and model different types of data more flexibly (Xu et al 2023). The future development of the GPT-family models has the potential to become multi-modality to multi-modality that can handle more types of data.

4. Use Case Analysis

4.1 Overview

Figure 2 shows the use case diagram of the proposed GPT-powered smart manufacturing system. There are three main components in this diagram: 1. Actors, roles that users play with respect to the system, 2. Use cases, scenarios that describe the interactions between actors and the system, 3. System boundary, a rectangular frame that represents the boundary between the actors and the system. In this case, the actors are users within the organization (top management and lower-level employees), users external to the organization (suppliers and customers), as well as GPT-powered tools (both for internal and external use). GPT-powered tools act as team member collaborating with human members. Internal users collaborate with the internal GPT-powered tools which have the most comprehensive knowledge of the organization, while external users use the external GPT-powered tools as a collaborative and/or service platform. The system refers to the smart manufacturing system. The purpose of the diagram is to model the interaction between actors and the system. Details about the listed five parent use cases and their sub-use-cases are described in the following subsections.

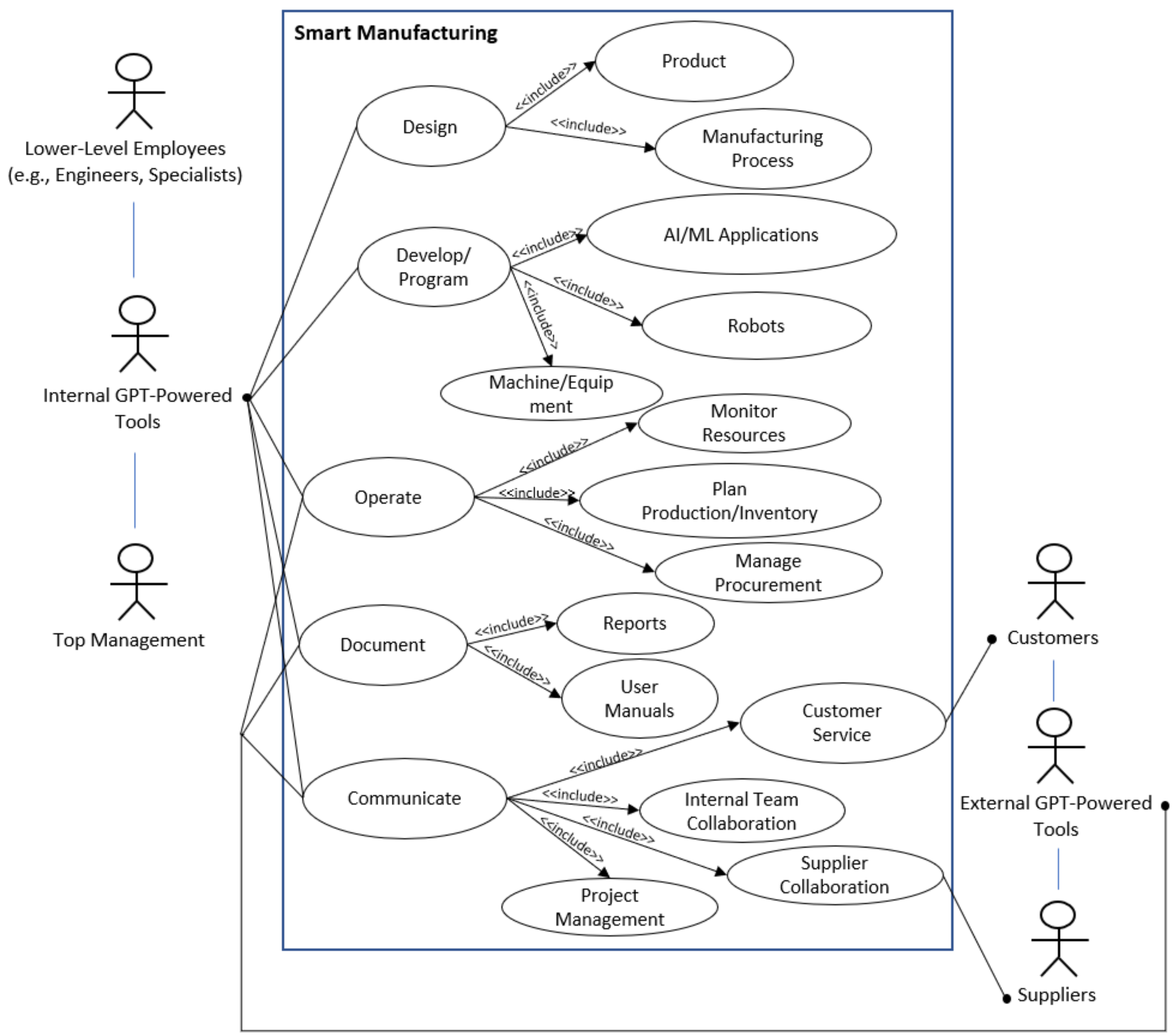

Figure 2. Use case analysis of the proposed GPT-powered smart manufacturing system

4.2 Design

Designing a new product or manufacturing process is one of the important procedures in a smart manufacturing system. The general design flow for both the product and manufacturing process is shown in Figure 3. The process starts with an understanding of customer needs and requirements, which can be obtained from market research and extensive communication with potential customers. In this case, GPT-powered tools can perform internet searches for general market trends and macroeconomic environments and perform analysis for internal communication records with existing customers. It speeds up the initial preparatory work. After all necessary needs and requirements are clearly identified based on human-made decisions, GPT-powered tools can again help with calculating the technical parameters based on the complete engineering knowledge inside the model or from the internet and generate text-description or even CAD drawings of concept designs. After the design concepts are generated, humans evaluate and make the decision to select the optimal design for the next step, testing. This is an iterative process that may involve experiments, trial & error, and back-and-forth design modification to make sure the selected design can meet the target specifications. One big advantage of having an organization-specific general-purpose GPT model is that knowledge can be shared throughout the whole organization regardless of the physical distance. In the event that the needs and requirements show similarity to existing entries within the database, reference will be made to past experience and technical details. This capability will largely reduce the time and money spent on design iteration by eliminating infeasible designs beforehand.

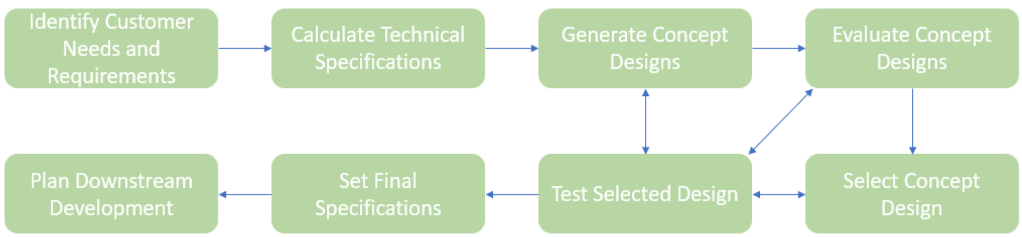

Figure 3. General design flow

4.3 Develop / Program

The development and programming in this context refer more to the manufacturing process rather than the product itself. Figure 4 presents the general workflow of deploying equipment, for instance, machines and robots, into the actual production environment. The overall process may take months or even years depending on various factors such as supply chain stability, the complexity of the system, and even internal team communication. The first step involving hardware requires a human in the loop to perform such tasks. Machines and robots are the hardware for producing or handling products and software embedded in them controls the logic of motions. The programming of software is also dependent on experience. A software program that is not well designed may cause issues such as failure to meet target specifications or increased equipment downtime which decreases production efficiency. Even an experienced engineer may consume a lot of time for debugging the program. In addition, the transition to smart machines adds more sensors and communication methods, enabling the machine to perform tasks with minimal human intervention while having better connectivity for real-time monitoring. A well-structured program also should take account of all the data connections and transfers. With the assistance of GPT-powered tools, a basic framework of the program can be established without much human effort.

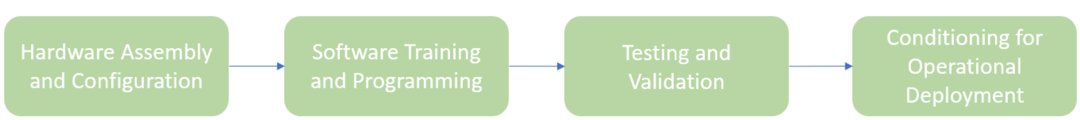

Figure 4. General flowchart for equipment deployment

Studies related to the use of ChatGPT for robotics applications show that the GPT model provides a strong foundation of logical reasoning and basic robotics knowledge, making it a good tool for developing advanced robotics abilities (Vemprala et al 2023). Not only can GPT generate Python codes for robotics applications, but it can also generate scripts in different robot languages and generate codes to set up robot simulations in RoboDK. Figures 5, 6, 7and 8 show a simplified example. The prompt is given in Figure 5, and the code generated for UR software and RoboDK software are in Figures 6 and 7, respectively. Moreover, ChatGPT is also capable of generating a diagram for the motion flow with the integration of the Show Me Plugin. The prompt and the diagram are shown in Figure 8.

> Please create a robot program for Universal Robot 5. The task to be formed is to pick up a part from a tray that is on the left of the robot base. The distance between the robot base and this tray is 50cm.. The robot then move the part in front of a camera for inspection. The camera is in right in the front of the robot and is 70cm away from the robot base. The distance between the part and the camera should be 10 cm to have a focused image. The robot will hold the part for inspection. After inspection, the robot will bring the part to a tray on the right side of the robot base. The distance between this second tray and the robot base is also 50cm. Can you write a URScript for this robot application?
>
> Can you convert this code to Python so that it can be used with the RoboDK API?

Figure 5. Prompt for a simplified example of robot application

URScript

```
def pick_and_inspect():

  # Define the waypoints
  tray1 = p[0.5, 0, 0, 0, 0, 0]  # Tray on the left, 50cm from the robot base
  camera = p[0, 0.7, 0, 0, 0, 0]  # Camera in front, 70cm from the robot base
  tray2 = p[-0.5, 0, 0, 0, 0, 0]  # Tray on the right, 50cm from the robot bas

  # Define the gripper
  gripper = rpc_factory("xmlrpc", "http://127.0.0.1:12345")

  # Move to the first tray
  movej(tray1, a=1.0, v=0.5)

  # Pick up the part
  gripper.open()
  sleep(1)
  gripper.close()
  sleep(1)

  # Move the part in front of the camera for inspection
  movej(camera, a=1.0, v=0.5)

  # Hold the part for inspection
  sleep(5)  # Adjust this time as needed for the inspection process

  # Move to the second tray
  movej(tray2, a=1.0, v=0.5)

  # Place the part in the second tray
  gripper.open()
  sleep(1)

  # Return to the home position
  movej(home, a=1.0, v=0.5)

end
```

Figure 6. UR script generated from the given prompt

python

```python
from robodk import *

# Start the RoboDK API
RDK = Robolink()

# Get the robot item
robot = RDK.Item('UR5')

# Get the targets
tray1 = RDK.Item('Tray1')
camera = RDK.Item('Camera')
tray2 = RDK.Item('Tray2')

# Get the gripper item
gripper = RDK.Item('Gripper')

# Move to the first tray
robot.MoveJ(tray1)

# Pick up the part
gripper.RunInstruction('Open', INSTRUCTION_CALL_PROGRAM)
robot.Pause(1)
gripper.RunInstruction('Close', INSTRUCTION_CALL_PROGRAM)
robot.Pause(1)

# Move the part in front of the camera for inspection
robot.MoveJ(camera)

# Hold the part for inspection
robot.Pause(5)  # Adjust this time as needed for the inspection process

# Move to the second tray
robot.MoveJ(tray2)

# Place the part in the second tray
gripper.RunInstruction('Open', INSTRUCTION_CALL_PROGRAM)
robot.Pause(1)

# Return to the home position
robot.MoveJ(tray1)
```

Figure 7. Python code generated from the given prompt

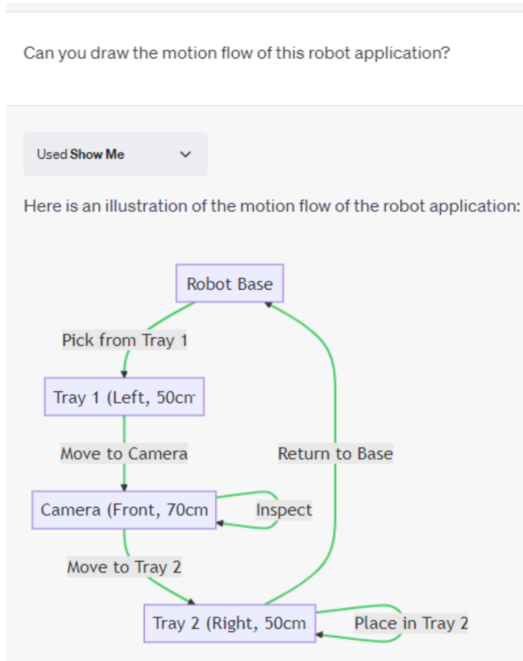

Figure 8. Prompt and response for the motion flow diagram

As the utility of such autonomous systems has been gradually seen, AI/ML deployments for specific tasks such as final product inspection have become commonplace. Large language model like GPT is invaluable in the development of AI models because they can function as assistant for coding, data labeling, feature extraction, and also data augmentation (Eloundou et al 2023). These tools leverage the GPT model's advanced language process capabilities and generate high-quality, contextually relevant code to reduce development costs.

4.4 Operate

Common tasks during daily operations include planning and scheduling for long, medium, and short term, resource monitoring, continuous production optimization, and more. The short-term planning and scheduling procedure usually involves back-and-forth discussions between people from different functional teams (such as the raw material planning team and the shop floor production team) about checking schedule feasibility, which make it challenging to automate this procedure. Among the various factors that affect the feasibility of a proposed schedule, resource availability is a key factor. In situations where the information regarding the resource availability appears to be unstructured data, for instance, two people chatting in a business messaging app, GPT-powered tools will be able to extract and analyze this information so that when it comes to planning and scheduling, it can provide accurate status of the human resources. Furthermore, for resources such as machines and tools, with the integration of smart multi-modal sensors (e.g. vision sensor and vibration sensor) into the shop floor, the real-time monitoring combined with the capability of a GPT-powered tool can enhance the level of shared context and situational awareness, making the collaboration between human and GPT-powered tools will be more unhindered (Endsley 2017; Wang et al 2021).

4.5 Document

Documentation as an inevitable part of work provides not only the material for knowledge sharing but also better communication among people. However, no matter how important documentation is, it is undeniable that this task is also time-consuming without help from other sources. Being the most prominent strength of the large language models, GPT is extremely capable of generating text-based documentation. For better utility, template documents can be fed into the model as training data during the model fine-tuning process and the additional plugins can be integrated into the general-purpose GPT model for multi-modal processing. With the assistance of GPT-powered tools, documents could be generated more efficiently and even more professionally. This, in turn, can free up valuable human resources for more critical and strategic tasks, ultimately bolstering productivity and fostering an environment of innovation within the organization.

4.6 Communicate

Effective and efficient communication boosts the productivity of organizations in a way that streamlines workflows, minimizes misunderstandings, and fosters collaboration among team members. By participating in all working scenarios along with human employees, the GPT-powered tools can analyze the progress of different projects based on content from meetings, chats, emails, etc. Since the model is connected to the internal database, project-related financial reports and planned timelines are also accessible by the tools. With all the information available, the GPT-powered tool is able to calculate the percentage of completion of the projects and predict whether the project can be finished on time and budget or has the risk of being delayed and over budget. This type of project management tool will be an integral part of organizations seeking to optimize project planning, enhance resource allocation, and improve overall project execution.

Communication with upstream suppliers and downstream targeted customers is as important as communication with organizations' internal teams. An AI-based chatbot for handling customer complaints and requests will significantly increase the response time, leading to enhanced customer satisfaction. Likewise, an AI-based supplier collaboration platform enables timely information exchange and improves visibility across the supply chain.

5. Discussion and Limitations

Although the potential opportunities of integrating a general-purpose GPT model into a smart manufacturing system are promising, limitations and challenges still exist. The first is the need for substantial computational resources for training and fine-tuning the model. Additionally, the construction, maintenance, and management of such a large-scale multimodal model also require significant technical expertise and human capital. The second challenge is the risk of data privacy and security when handling sensitive organizational information. Thirdly, the performance of the model along with the GPT-powered tools largely depends on the quality of training data, which may not always be readily available or adequately representative of a specific task. Lastly, when an AI system becomes a part of a team, the "black box" nature of complex AI models creates more challenges for human teammates to understand and trust the model's outputs, which is crucial for effective collaboration. Thus, addressing challenges of transparency, explainability, and accountability is critical to the successful integration of a generalized AI model into a smart manufacturing system.

6. Conclusion

The paper proposes a framework for a smart manufacturing system powered by a Generative Pre-trained Transformer (GPT) model. The system is designed to construct a human-AI team and aims to reduce costs and time in product and process design, enhance operational efficiency, and boost internal and external communication effectiveness. The general-purpose GPT model is pre-trained on public data and then fine-tuned with specific organizational data to better perform tasks related to the specific domain. The model is integrated into the smart manufacturing system, connecting to the organization's internal database, internet, and smart sensors to gather relevant, up-to-date, and accurate data.

The system is constructed to handle various tasks in a manufacturing setting. In the design phase, GPT-powered tools can help with market research, technical parameter calculation, and concept design generation. During the development and programming phase, these tools can assist in establishing a basic framework for the program and generate codes for robotics applications. In daily operations, the tools can extract and analyze unstructured data, enhancing shared context and situational awareness. For documentation, GPT-powered tools can generate text-based documents efficiently. In communication, these tools can analyze project progress, predict project outcomes, and handle communication with suppliers and customers. In essence, the GPT-powered smart manufacturing system is designed to act as a collaborative team member, enhancing various aspects of the manufacturing process from design to communication while supporting the adoption of new technologies.

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Biographies

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