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Abstract

The transition to Industry 5.0 emphasizes the need for inclusive and intelligent systems in manufacturing. Traditional text-based assembly instructions can create barriers for workers with cognitive diversity, including dyslexia, by making tasks more challenging and less accessible. This study introduces an AI-driven smart manufacturing interface designed to address these challenges through an integrated approach combining computer vision techniques and natural language processing. The system provides real-time, multimodal guidance through voice, visual, and interactive instructions tailored to individual needs, effectively reducing cognitive load and enhancing task performance. Experimental results show a 22.1% reduction in assembly time and a 57.1% decrease in error rates, demonstrating the system's effectiveness in improving operational efficiency and accuracy. By leveraging innovative information technologies, the interface aligns with the human-centric principles of Industry 5.0, supporting diverse and adaptable manufacturing environments. These findings highlight the potential of smart systems to drive inclusivity and sustainability in industrial ecosystems.

CCS Concepts

• **Accessibility technologies**; • **Computer-aided manufacturing**; • **Sensor networks**;

Keywords

Industry 5.0, inclusive manufacturing, AI-driven interfaces, human-machine interaction, cognitive diversity

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1 Introduction

Manufacturing environments have historically relied heavily on written instructions and visual cues, presenting significant challenges for operators with reading-related neurodiversity, particularly those with dyslexia [1], [2]. Recent studies highlight that up to 80% of assembly instructions in surveyed manufacturing plants are primarily text-based, potentially hindering workers with reading difficulties [3].

Information technology has emerged as a transformative force in modern manufacturing, reshaping how we approach workplace inclusivity and operational efficiency [4], [5]. The integration of AI-driven information systems is particularly crucial in creating adaptive manufacturing environments that can accommodate diverse cognitive needs. These systems leverage advanced data processing and real-time analytics to transform traditional manufacturing processes into more accessible and inclusive workflows. Recent developments in information technology have made it possible to create intelligent interfaces that can adapt to different learning styles and cognitive preferences, marking a significant step forward in making manufacturing more accessible to all workers.

Dyslexia, affecting 5-10% of the adult population worldwide, necessitates a reevaluation of traditional instruction methods in industrial manufacturing [6]. The continued reliance on text-heavy instructions not only impacts individual performance but also contradicts the principles of inclusive design in modern manufacturing environments [7]. These text-based instructions pose several challenges for dyslexic operators, including increased cognitive load, higher error rates, reduced confidence and job satisfaction, and limited career progression [2], [6]. They have broader implications for workforce diversity, productivity, and overall inclusivity in manufacturing.

The emergence of Industry 5.0 has brought a renewed focus on human-centric manufacturing, where information technology serves as a bridge between human capabilities and automated systems [8], [9]. This paradigm shift emphasizes the need for intelligent information systems that can enhance human-machine interaction while accommodating individual differences. Our research aligns closely with this vision by developing information processing solutions that support cognitive diversity in manufacturing environments. This approach not only addresses immediate operational challenges but also contributes to the broader goals of creating more adaptable and inclusive industrial workplaces.

To address these challenges, this research aims to develop and evaluate a dyslexic-friendly digital instruction system for manufacturing assembly tasks. The objectives include designing a multimodal human-machine interface, developing a real-time error detection system, leveraging large language models for personalized instructions, and evaluating the system's effectiveness in improving task performance and user satisfaction among dyslexic operators.

Based on these manufacturing challenges, this research aims to develop an intelligent information processing framework that integrates computer vision, natural language processing, and adaptive interface technologies. The primary goal is to create a system that supports cognitive diversity through real-time error detection and personalized instruction delivery. The framework combines YOLOv7-based object detection with context-aware instruction generation, focusing on operators with reading-related neurodiversity. The significance of this work is particularly relevant as manufacturing transitions to Industry 5.0, where human-centered approaches are increasingly important.

This study is targeted to contribute to inclusive manufacturing by integrating advanced technologies to address the needs of dyslexic operators. Aligning with Industry 5.0 principles of human-centric design, the findings have the potential to improve productivity, reduce errors, and create more diverse and efficient manufacturing environments, with possible applications to support various forms of neurodiversity in industrial settings.

2 LITERATURE REVIEW

Human-machine interfaces (HMIs) in manufacturing have evolved from paper-based instructions to sophisticated digital systems, incorporating interactive elements and real-time feedback [1], [10]. These advancements aim to enhance worker performance and reduce errors, even if their implementation remains inconsistent across industries [3].

Universal design principles in HMIs emphasize flexibility, simplicity, and perceptible information, improving accessibility for all workers [11]. Multimodal interfaces, combining visual, auditory, and haptic feedback, have shown effectiveness in reducing cognitive load during assembly tasks [12]. The software industry's customizable interfaces offer valuable insights for manufacturing applications, demonstrating the potential for personalized HMIs catering to diverse cognitive needs [13].

Beyond interface design considerations, the role of information technology in manufacturing has undergone significant transformation in recent years, particularly in the context of smart manufacturing environments. Recent comprehensive reviews highlight how advanced information systems are revolutionizing manufacturing processes through real-time data analytics, intelligent decision support, and adaptive control systems [14]. Recent studies of big data analytics in manufacturing demonstrate how modern information systems can systematically integrate and process multi-source data streams, serving as a foundational element for Industry 5.0's digital transformation and enabling more responsive and efficient production environments [15]. These systems are increasingly incorporating artificial intelligence to enhance their capability to adapt to different user needs and operational contexts. Recent systematic reviews of AI applications in management information systems highlight how intelligent process automation and predictive analytics are creating more responsive manufacturing environments, where information systems serve as key enablers for both automated processes and human-centric operations [16].

Artificial Intelligence (AI) could further enhance HMIs in manufacturing through increasingly sophisticated applications. Modern object detection algorithms now offer unprecedented accuracy in real-time quality control and error detection [17], while large language models demonstrate remarkable potential for generating context-aware and personalized instructions [18]. These technological advances, combined with improved information processing capabilities, present significant opportunities for creating more inclusive and efficient manufacturing environments that can adapt to diverse user needs and preferences.

The literature indicates a need for a comprehensive approach to HMI design in manufacturing, integrating accessibility principles, multimodal interaction, and AI-driven personalization. Such an approach could address the needs of neurodiverse workers while enhancing overall productivity and user satisfaction in industrial settings.

3 METHODOLOGY

This digital instruction system is designed to provide real-time, personalized support for dyslexic operators in manufacturing environments through integrated information processing and adaptive data flows. At its core, the system processes and coordinates multiple data streams, including real-time visual inputs, user interactions, and system feedback, to create a cohesive and responsive manufacturing support environment. The system architecture consists of four integrated components: (i) a User Interface, (ii) a Visual Object Detection and Error Classification System, (iii) a Personalized Instruction Generator, and (iv) a module for Dyslexic Operator Interactions, as shown in Fig.1.

The system implements an integrated information architecture that orchestrates three key data streams: real-time visual inputs from assembly operations, user interaction signals, and system feedback responses. This unified data flow enables rapid error detection while maintaining system responsiveness to operator needs. This integrated approach ensures that all system components work in harmony to provide timely and relevant support to operators.

This multimodal approach creates an inclusive learning environment while maintaining operational efficiency.

The User Interface functions as an information hub that combines visual guidance with voice instructions for assembly operations. The interface presents assembly information through three coordinated channels:

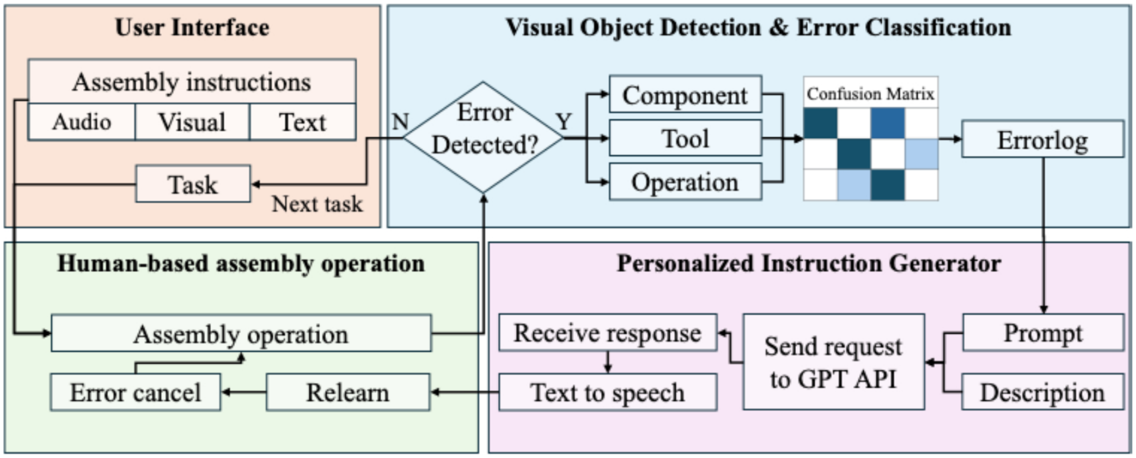

Figure 1: System architecture overview

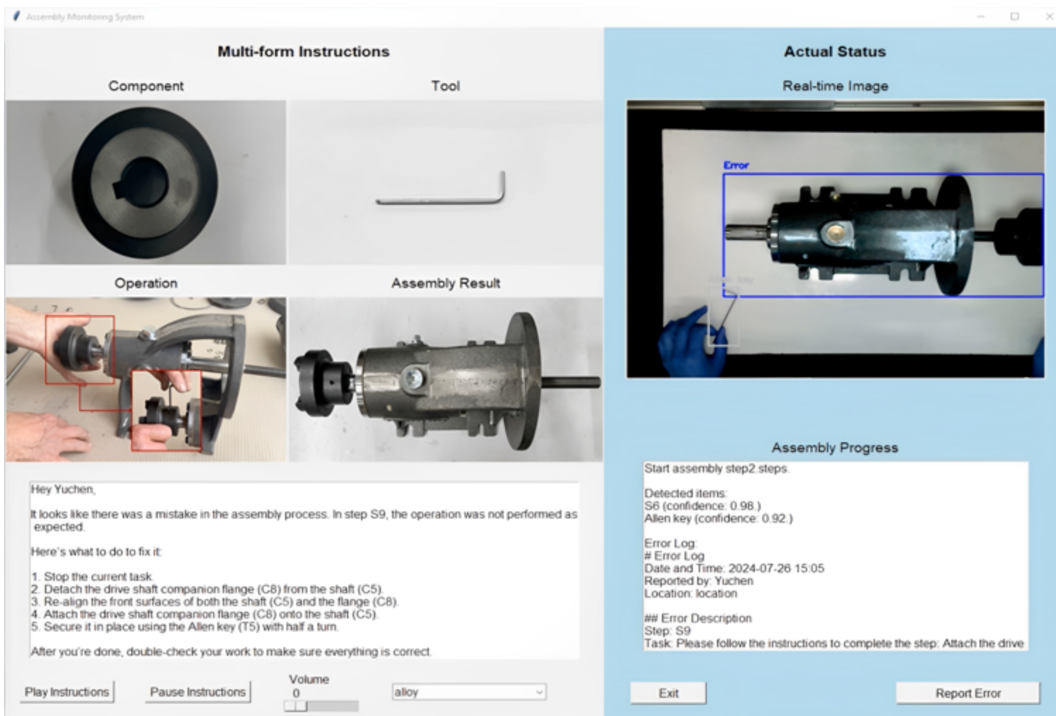

Figure 2: The User Interface

The visual component displays real-time camera feeds alongside component identification markers, with clear component outlines and tool positions highlighted for easy recognition. A dedicated section shows the current assembly step with corresponding component images and tool requirements. The voice instruction system provides step-by-step guidance through text-to-speech conversion, offering clear directives particularly beneficial for operators with reading difficulties. These elements work in concert to provide clear task guidance while accommodating different information processing preferences.

The interface incorporates adaptive layout principles that adjust to user preferences and interaction patterns, ensuring optimal information accessibility. Interactive elements are strategically positioned to create an intuitive workflow, with clear visual hierarchies guiding operators through complex assembly sequences. The system presents assembly instructions through multiple modalities - audio, visual, and textual formats - allowing operators to choose their preferred method of information intake. This multimodal approach creates a flexible and inclusive learning environment that adapts to individual cognitive preferences.

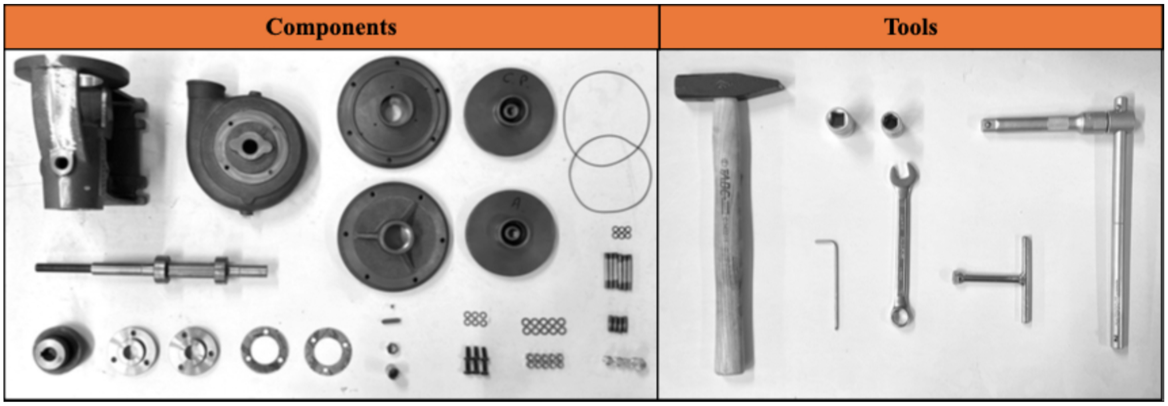

Figure 3: Horizontal bare-shaft centrifugal pump components

The Visual Object Detection and Error Classification System functions as the system's primary data acquisition and analysis engine. This module leverages advanced computer vision techniques, including YOLOv7 [19], selected for its specific advantages in manufacturing environments: (1) high inference speed (30ms per detection) essential for real-time monitoring, (2) superior accuracy in detecting small manufacturing components (mAP of 0.993 at IoU=0.5), and (3) robust performance under the varying lighting conditions common in industrial environments. These capabilities make it particularly well suited for continuous assembly monitoring compared to alternatives such as Faster R-CNN or YOLO v5. The system continuously processes visual data streams from the assembly area, identifying and tracking components and tools with high precision. When an error is detected, the system processes this information through multiple classification layers, categorizing issues into component-, tool-, or operation-related categories. This sophisticated error classification process generates detailed error logs that feed into both immediate operator feedback and long-term system optimization.

Upon error detection, the Personalized Instruction Generator activates its information synthesis processes. This component, powered by GPT-4, creates context-aware, dyslexic-friendly instructions by processing multiple data inputs: the specific error type, current assembly stage, and historical operator interaction patterns. The resulting instructions are optimized through natural language processing to ensure clarity and accessibility, featuring simplified language structures, active voice, and concrete terms that enhance comprehension for dyslexic users. The system's text-to-speech component further processes these instructions into clear audio output, providing additional accessibility options.

The Dyslexic Operator Interactions module serves as the final integration point for all system processes, enabling operators to engage with the assembled information through various interaction modes including assembly operations, error cancellation, and relearning processes. This module continuously monitors and adapts to operator preferences and interaction patterns, ensuring the system remains responsive to individual needs.

4 CASE STUDY

4.1 Assembly Tasks

For this study, the assembly of a horizontal bare-shaft centrifugal pump was selected. This choice was motivated by the pump's complexity, involving 26 distinct components and 7 different tools (as shown in Fig.3), which provided a suitably challenging task to evaluate the system. The diverse operations required in the assembly process, such as aligning, threading, and securing components, allowed for comprehensive testing of the system across various task types.

4.2 Experimental Setup

The assembly workstation consisted of a standard industrial workbench equipped with the necessary tools and components. A webcam was installed above the workstation for real-time monitoring of the assembly process. This dyslexic-friendly digital instruction system was integrated into the workstation, including: (i) a computer running the custom-trained YOLOv7 object detection model; (ii) noise-cancelling headphones for audio instructions; (iii) a large, high-contrast screen display for visual aids; (iv) a processing unit for error detection and instruction generation, as shown in Fig.4.

5 RESULTS AND DISCUSSION

This study evaluated the effectiveness of a dyslexic-friendly digital instruction system for manufacturing assembly tasks, comparing it with traditional text-based instructions. The results demonstrate significant improvements in various performance metrics, including both task completion efficiency and error reduction.

The digital instruction system significantly reduced the average assembly time for the horizontal bare-shaft centrifugal pump from 25.3 minutes (SD = 3.2) with the traditional system to 19.7 minutes (SD = 2.5), representing a 22.1% improvement. This reduction in assembly time indicates enhanced efficiency and potentially reduced cognitive load for operators with dyslexia.

A substantial decrease in the overall error rate was observed, with the traditional system resulting in an average of 2.8 errors per assembly (SD = 0.7), while the digital system reduced this to 1.2 errors per assembly (SD = 0.4), marking a 57.1% reduction.

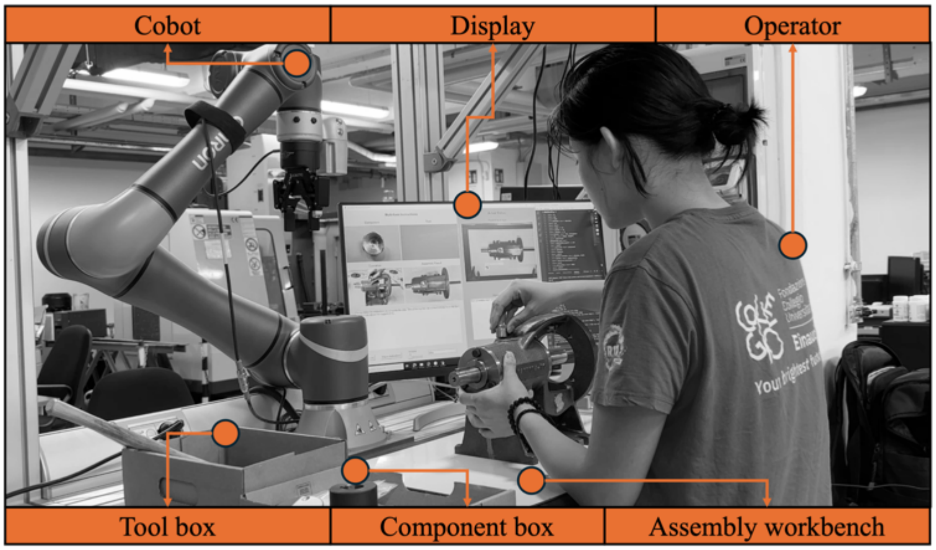

Figure 4: Experimental scenario.

Hey Yuchen,
It looks like there was a small mistake in the assembly process. In step S6, you picked up the wrong component.
Here's what to do to fix it:
1. Stop the current task.
2. Remove the 'Drive shaft companion flange' from the assembly area.
3. Find and pick up the correct component: 'Hex cap screw (big), C26'.
4. Thread the 'Hex cap screw (big), C26' by hand into the threaded hole above the support (C1).
After you're done, double-check your work to make sure that the 'Hex cap screw (big), C26' is properly installed.
If you need any more help, just let us know.

Figure 5: Digital instructions transcription example (from Error 1).

This significant improvement in accuracy suggests that the digital system not only aids in faster assembly but also in error prevention through its integrated information processing approach.

The digital instruction system demonstrated remarkable improvements in error handling times. For component-related errors (E1), the time required decreased from 94 seconds in the traditional system to 36 seconds in the digital system, a reduction of 61.7%. For tool-related errors (E2), error handling time reduced from 88 seconds to 52 seconds, representing a 40.9% improvement.

For E1, instruction input time decreased by 46.8% (from 27.8 to 14.8 seconds), error detection time saw a dramatic 95.6% reduction (from 45 to 2 seconds), and error rectification time improved by 90.9% (from 33 to 3 seconds). For E2, instruction input time reduced by 33.8% (from 14.8 to 9.8 seconds) and error detection time improved by 92.0% (from 25 to 2 seconds).

The YOLOv7 model, a key component of this digital instruction system, demonstrated high accuracy in object detection with an overall mAP@.5 of 0.993 and mAP@.5:.95 of 0.899, and precision (P) of 0.992 and recall (R) of 0.94 across all classes. These performance metrics indicate that the model is effective in identifying components and tools, contributing to the system's ability to detect errors quickly and accurately.

In addition to the quantitative improvements, the system leveraged GPT-4 to generate personalized, dyslexic-friendly instructions based on detected errors. For example, when the system detected a component-related error (E1), it generated the prompt shown in Fig.5. These results demonstrate that the dyslexic-friendly digital instruction system could significantly enhance assembly task performance for operators with reading-related neurodiversities.

6 CONCLUSION

This study demonstrates the significant potential of integrating advanced information technologies to create an inclusive digital instruction system for manufacturing environments. Through the innovative combination of computer vision, natural language processing, and adaptive interface design, our system showcases how modern IT solutions can effectively address workplace accessibility challenges. The empirical results provide compelling evidence for the value of intelligent information systems in creating more inclusive manufacturing environments.

Table 1: PERFORMANCE COMPARISON BETWEEN TRADITIONAL AND DIGITAL INSTRUCTION SYSTEMS

Metric	Traditional System	Digital System	Improvement
Average Assembly Time (minutes)	25.3 (SD = 3.2)	19.7 (SD = 2.5)	22.1% reduction
Overall Error Rate	2.8 (SD = 0.7)	1.2 (SD = 0.4)	57.1% reduction
Error E1 (Component-related) Timeline (seconds)			
Instruction Reading	27.8	15.0	46.0% reduction
Component Selection	5.0	5.0	No change
Component Movement	3.0	3.0	No change
Error Detection	45.0	2.0	95.6% reduction
Error Information	20.0	20.0	No change
Error Recovery	33.0	3.0	90.9% reduction
Component Reselection	5.0	5.0	No change
Component Movement 2	3.0	3.0	No change
Error Detection 2	10.0	2.0	80.0% reduction
Total Time for E1	151.8	58.0	61.8% reduction
Error E2 (Tool-related) Timeline (seconds)			
Instruction Reading	15.0	10.0	33.3% reduction
Tool Selection	5.0	5.0	No change
Tool Movement	3.0	3.0	No change
Error Detection	25.0	2.0	92.0% reduction
Error Information	18.0	18.0	No change
Error Recovery	3.0	3.0	No change
Tool Reselection	5.0	5.0	No change
Tool Movement 2	3.0	3.0	No change
Error Detection 2	10.0	2.0	80.0% reduction
Total Time for E2	87.0	51.0	41.4% reduction
YOLOv7 Model Performance			
mAP@.5	N/A	0.993	N/A
mAP@.5:.95	N/A	0.899	N/A
Precision (P)	N/A	0.992	N/A
Recall (R)	N/A	0.94	N/A

The integration of YOLOv7 for real-time object detection and GPT-4 for context-aware instruction generation represents a novel application of cutting-edge information technologies in manufacturing. This approach not only improved operational efficiency but also demonstrated how sophisticated IT systems can be leveraged to support workforce diversity. The significant reductions in assembly time (22.1%) and error rates (57.1%) highlight the practical benefits of implementing intelligent information processing solutions in industrial settings.

While this study demonstrates promising results, several areas warrant further investigation. The current implementation primarily focuses on visual and auditory information processing, which could be expanded to incorporate more diverse data streams and interaction modalities. Future research directions should address both technical advancement and system scalability:

- System Interoperability: Develop standardized protocols for integrating the digital instruction system with existing manufacturing execution systems (MES) and enterprise resource planning (ERP) platforms. This would enable seamless data exchange and broader system adoption across different manufacturing environments.
- Scalable Information Architecture: Design flexible data structures and processing pipelines that can accommodate varying levels of manufacturing complexity and different types of assembly operations. This includes developing modular system components that can be easily adapted to different production contexts.
- Cognitive Load Assessment: Integrate real-time cognitive load monitoring using physiological sensors, with adaptive information delivery mechanisms that automatically adjust instruction complexity based on operator response patterns.
- Collaborative Robotics: Investigate the integration of collaborative robots with this system to provide physical assistance and real-time guidance, enhancing workplace inclusivity and enabling more complex assembly tasks.

As manufacturing environments continue to evolve toward Industry 5.0, the development of intelligent and inclusive information systems becomes increasingly critical. Our approach demonstrates how thoughtfully designed IT solutions can enhance both productivity and workplace inclusivity. By leveraging advanced information processing capabilities while maintaining a human-centric focus, such systems can contribute significantly to creating more efficient, adaptable, and inclusive manufacturing environments.

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