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Constructing a knowledge graph-driven intelligent data-enabled design system for mold using deep semantic understanding and intelligent decision support

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To address the inefficiency and high error rates in traditional methods for handling complex design processes in modern mold design, this study proposes a Knowledge Graph-driven Intelligent Data-enabled Design System for molds. Initially, deep semantic understanding techniques are employed to intelligently parse a large volume of mold design documents and data. Using Bidirectional Encoder Representations from Transformers (BERT) and Random Forest (RF) algorithms, key information and knowledge points are accurately extracted from the design documents, laying a solid foundation for constructing the knowledge graph. The study collects a significant number of representative mold design documents, followed by detailed data preprocessing and cleaning. Subsequently, the BERT model is utilized for semantic analysis to precisely extract various entities (such as components, materials, and process parameters) and their complex relationships during the design process. Research findings show that the system significantly reduces the error rate in mold design processes, decreasing from 0.15 to 0.0975. Regarding design efficiency, the average completion time per design task reduces from 20 h to 12 h. Compared to traditional design methods, the system shortens the average design cycle from 30 days to 22.5 days, achieving a reduction of 0.25. Validation through examples further demonstrates that the system exhibits notable advantages in intelligence and automation during mold design processes, effectively enhancing design quality and efficiency. Additionally, it reduces related labor costs by 0.2. In summary, the proposed Knowledge Graph-based mold design system not only demonstrates significant innovation and application prospects theoretically but also shows substantial effectiveness and value in practical applications. Future research directions include further optimizing system performance, expanding application domains, and exploring integration with other intelligent manufacturing technologies to elevate the overall level of smart manufacturing.

Keywords Knowledge graph, Deep semantic understanding, Mold design, Intelligent decision support, Data-driven approach

Mold design holds a critical position in modern manufacturing, as it directly determines product quality and production efficiency, while also having a profound impact on manufacturing costs. However, traditional mold design methods typically rely on designers' experience and manual operations, which prove inadequate when faced with increasingly complex design requirements and diverse products[1]. Traditional approaches are inefficient and prone to errors when handling complex design tasks, making it difficult to meet the demands of modern manufacturing for efficient and precise designs. At the same time, with the intensification of market competition and the rapid development of manufacturing technologies, enterprises urgently need solutions that can improve design efficiency and accuracy to meet the rapidly changing market demands[2–4]. In recent years, the rapid development of artificial intelligence and big data technologies has brought new opportunities to the manufacturing industry, with smart manufacturing becoming a key component of Industry 4.0. In this context, knowledge graphs, as a powerful knowledge representation and management technology, can systematically and

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structurally represent the vast knowledge and experience accumulated during the mold design process[5]. This technology not only helps designers quickly retrieve and apply relevant knowledge but also supports intelligent analysis and decision-making for complex design tasks. Furthermore, the maturation of deep semantic understanding technologies has made it possible to extract key information and relationships from large volumes of design documents, further enhancing the value of knowledge graphs in mold design. In the field of semantic analysis, deep learning-based language models provide strong support for extracting knowledge from unstructured design documents. The Bidirectional Encoder Representations from Transformers (BERT) model can capture the complex semantic relationships within text, laying the foundation for constructing high-quality knowledge graphs. Random Forest (RF) algorithms, as efficient decision-support tools, excel at handling multi-variable decision-making issues in mold design. Combining BERT and RF technologies in mold design can significantly improve the intelligence level of the design process and the accuracy of decision-making. To address these challenges, this study proposes an intelligent, data-driven mold design system based on knowledge graphs. Unlike traditional methods, this system incorporates deep semantic understanding technologies to extract key information from vast design documents and construct structured knowledge graphs, providing systematic knowledge management and decision support. The main contributions of this study are as follows:

(1) A mold design knowledge representation framework combining the BERT model and knowledge graphs is constructed to effectively extract and manage design knowledge.
(2) The RF algorithm is used to provide intelligent support for multi-variable complex decision-making in the mold design process.
(3) Through experimental validation, the system is shown to offer significant advantages in improving design efficiency, accuracy, and stability, providing an important reference for the intelligent transformation of the mold design industry.

This study combines knowledge graphs, deep semantic understanding technologies, and RF algorithms to offer an intelligent solution for mold design, making a substantial contribution both theoretically and practically.

Literature review

"Deep semantic understanding" is a technology based on natural language processing that aims to enable computers to "understand" the deeper meanings within text, rather than just the literal interpretation. It typically involves deep learning models and language modeling techniques to analyze the context and structure of text, thereby extracting more complex semantic relationships and information. In traditional research, Lughofer and Pichler (2024) pointed out that knowledge graphs could effectively integrate and represent heterogeneous data sources in manufacturing processes, thereby achieving automation and intelligence in complex manufacturing tasks[6]. Tan et al. (2023) proposed that knowledge graph-based intelligent manufacturing systems could extract key information from extensive design documents and data using semantic analysis techniques, thereby enhancing the efficiency and accuracy of the design process[7]. Yu et al. (2023) demonstrated in the mold design field that knowledge graphs could structurally represent design experience and knowledge, facilitating knowledge accumulation, sharing, and reducing design errors[8]. Wang et al. (2024) discovered that the BERT model, as a powerful tool for deep semantic understanding, accurately extracted key entities and relationships from design documents, significantly improving information extraction accuracy[9]. Lin and Chen (2024) proposed that combining deep learning and natural language processing techniques could automatically extract and analyze design knowledge from unstructured design documents to construct high-quality knowledge graphs[10]. Fischbach et al. (2022) pointed out that the application of deep semantic understanding technology in mold design significantly improved the efficiency and accuracy of design document parsing, providing technical support for the construction of intelligent design systems[11]. Fernández-León et al. (2024) studied the efficiency and stability of the RF algorithm in handling complex decision-making problems, suggesting its application for intelligent decision support in mold design to enhance decision-making accuracy[12]. Pereira et al. (2023) proposed that the RF algorithm, in mold design optimization, could comprehensively analyze and optimize various design parameters, thereby improving design effectiveness[13].

Existing mold design systems have significant limitations. First, traditional systems heavily rely on manual operations and the experience of designers, leading to inefficiency and human errors, particularly when dealing with complex design tasks. This limitation becomes more evident in such cases. Additionally, current systems lack a deep understanding of the semantic information in design documents and are unable to extract key information and logical relationships from unstructured data, restricting the system's capabilities in knowledge mining and application. To address these limitations, this study proposes an intelligent, data-driven mold design system based on knowledge graphs, which resolves the issues through two core improvements. On the one hand, the system combines knowledge graph technology to systematically and structurally represent key entities in the design (such as parts, materials, and process parameters) and their relationships, creating a dynamically updated knowledge base. This approach not only integrates design experience but also provides robust knowledge management support. On the other hand, the system introduces deep semantic understanding technology, using the BERT model to automatically extract entities and relationships from design documents. This allows unstructured design knowledge to be effectively parsed and utilized, significantly enhancing the system's intelligence. With these improvements, the proposed system significantly reduces the error rate in the design process and enhances design efficiency and decision support capabilities, providing a practical solution for the intelligent transformation of the mold design industry.

Knowledge graph mold intelligent Data-Driven design system

Principles and applications of BERT model and RF algorithm

In the intelligent data-enabled mold design system, the BERT model and RF algorithm play pivotal roles. The BERT model, as a deep learning technology primarily used in natural language processing, and the RF algorithm, an ensemble learning method for classification and regression problems, are essential components[14–17].

The BERT model is based on the Transformer architecture and is pre-trained to capture contextual information of text through bidirectional encoding[18–21]. Unlike traditional unidirectional language models, BERT considers both forward and backward contexts during training, thereby achieving more precise semantic understanding[22]. In mold design, the BERT model is utilized for semantic parsing of mold design documents to extract key design information and knowledge points, for instance, extracting component names, materials, dimensions, and other critical information from technical specifications. Concurrently, the knowledge points extracted from documents are linked using the BERT model to construct a knowledge graph specific to mold design. This approach facilitates the creation of a structured knowledge repository for designers to query and utilize. The RF algorithm is an ensemble learning method that improves model prediction accuracy and robustness by constructing multiple decision trees and integrating their results[23]. Key technologies of BERT model and RF algorithm are outlined in Table 1:

In mold design, the RF algorithm is utilized to optimize key parameters. For instance, based on historical design data and actual application results, the RF algorithm identifies the optimal combination of material selection and process parameters to enhance mold quality and performance. Moreover, during mold production, the RF algorithm analyzes various production data, predicts possible faults, and performs diagnostics to improve production efficiency and reduce downtime.

In summary, the application of the BERT model and RF algorithm in the intelligent data-driven mold design system achieves efficient extraction and utilization of design information through deep semantic understanding and ensemble learning methods. This approach optimizes design parameters, predicts production faults, and provides robust intelligent support for mold design, thereby significantly improving design efficiency and quality in practical applications.

Knowledge Graph-Based intelligent Data-Driven mold design system

The knowledge graph-based intelligent data-driven mold design system aims to enhance design efficiency and quality by integrating and intelligently processing various data and knowledge in mold design. Leveraging knowledge graph technology, the system systematically and structurally manages every aspect and element of mold design. It integrates advanced AI algorithms to achieve intelligent and automated design processes. The algorithm proposed in this study integrates knowledge graph construction and RF technology to optimize the intelligent process of mold design. The core objective of the algorithm is to leverage semantic understanding and knowledge reasoning techniques to achieve automatic parsing of design documents, structured representation of knowledge, and intelligent decision support, thereby improving design efficiency and accuracy. The architecture of the knowledge graph-based intelligent data-driven mold design system includes several core modules, as depicted in Fig. 1:

The system architecture consists of five main modules. The first is the data input module, which receives various sources of mold design-related data, such as design documents, historical data, and process parameters, supporting multiple formats. The data processing module is responsible for semantic parsing of unstructured text data to extract design entities (such as parts and materials) and their relationships. The extracted entities and relationships are systematically stored and managed through the knowledge graph module. The decision support module utilizes the knowledge graph and RF algorithm to support key decisions in the design, such as material selection and process optimization. Finally, the user interaction module provides an intuitive visual interface to help designers quickly retrieve knowledge, validate design solutions, and manage design versions. The construction of the knowledge graph is the core component of system development, employing a method that combines domain ontology and automated entity-relationship creation. First, based on the knowledge background of mold design, a domain ontology was developed. This ontology includes key entity types (such as parts, materials, and process parameters) along with their attributes and relationships (such as assembly sequence and material compatibility). The development of the ontology follows standardized knowledge management methods, referencing international standards and industry practices in the mold design field, and is continuously refined through expert interviews and literature analysis. Based on the ontology, the system integrates deep semantic understanding technology and uses the BERT model to automatically extract entities and their relationships from unstructured text. This method understands the semantic meaning of terms through contextual analysis and automatically generates nodes and edges in the knowledge graph. For example, from a document describing mold material selection, the entity node “Steel (AISI 4140)” is extracted and linked

Algorithm model	Technology	Description
BERT model	Bidirectional encoder	Consider both the forward and backward context of words to improve the accuracy of semantic understanding
	Pre-training	Pre-train on a large corpus and then fine-tune on specific tasks
	Transformer architecture	Use the self-attention mechanism to model long-distance dependencies
RF algorithm	Decision tree ensemble	Randomly select samples and features to build multiple decision trees to improve model diversity
	Voting mechanism	Integrate the results of each decision tree through voting or averaging mechanisms to improve prediction accuracy

Table 1. Key technologies of BERT model and RF algorithm.

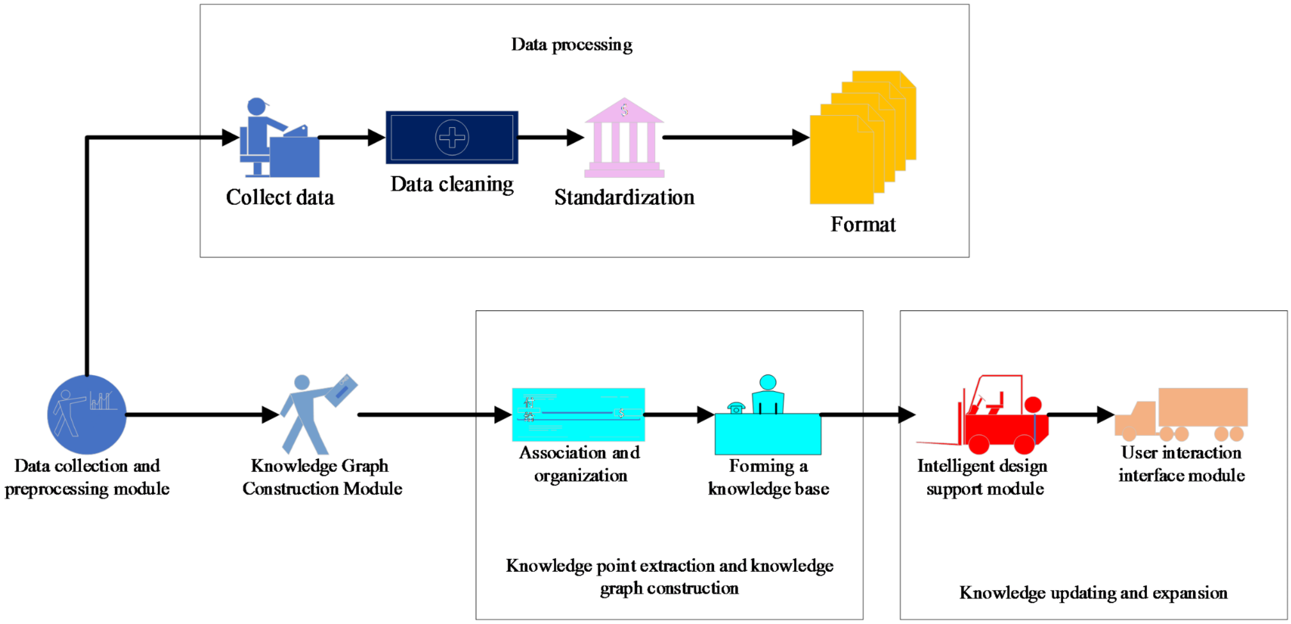


Fig. 1. Core modules in the system framework.

to the relationship "Heat Treatment." The extracted entities and relationships are represented using the Resource Description Framework (RDF) and stored in a graph database, supporting fast queries and dynamic updates.

The system presented in this study incorporates multiple key technologies to ensure efficient operation. Deep semantic understanding technology uses the BERT model to extract key entities and complex relationships from design documents. The knowledge graph is constructed using RDF and Web Ontology Language (WOL), with Semantic Protocol and Resource Description Architecture Query Language (SPARQL) employed for efficient knowledge retrieval. The decision support module utilizes the RF algorithm to model and optimize multivariable problems, providing intelligent support for complex decisions in mold design. Furthermore, the system's visualization module employs NetworkX and Matplotlib to present the knowledge graph to designers in a visually intuitive manner. During development, the system faced several challenges. First, the diversity and inconsistency of data led to complexities in data preprocessing, requiring the standardization of data from different formats. Second, the dynamic nature and scalability of the knowledge graph presented high technical demands, particularly in maintaining efficient query performance with large-scale datasets. Additionally, the precision of semantic understanding was a key issue, as proprietary terms and complex contexts within the mold design field required in-depth analysis, incorporating domain knowledge. Finally, as the knowledge graph expands, system performance may be impacted, necessitating continuous optimization of the graph database's storage and retrieval mechanisms.

In summary, the system presented in this study constructs the knowledge graph by integrating domain ontology and automated relationship creation techniques, and achieves efficient intelligent design support by combining deep learning and machine learning technologies. The development of the system provides important technical insights for the intelligent transformation of the mold design industry, while also paving the way for the integration of knowledge graph and intelligent manufacturing technologies. Future research will focus on optimizing the dynamic update capabilities of the knowledge graph and exploring its potential applications in other design and manufacturing fields.

Code availability

The custom code and mathematical algorithms used in this study have been open-sourced for reference and use by readers. The code mainly includes the following modules: data preprocessing, semantic parsing (based on the BERT model), knowledge graph construction (based on RDF and OWL), and the RF decision support module. The complete code and related instructions are provided as supplementary attachments. To ensure correct usage, the code repository contains detailed usage guides and example data. Additionally, the repository specifies the required dependencies and environment configuration instructions. Some modules rely on third-party pre-trained models (e.g., BERT), and users are required to download or configure these models according to the instructions. Moreover, since the construction of the knowledge graph involves custom development of certain domain ontologies, users wishing to extend the application to other domains can make adjustments based on the provided examples. The code is freely available for academic research and non-commercial use, with access and usage subject to the license terms included with the project.

Experimental design

The dataset selected for the experiment is the computer-Aided Design Assembly Dataset, which consists of a large number of CAD assembly drawings and related metadata. This publicly available dataset can be used for research and development of algorithms and systems related to CAD mold design. The dataset includes various components, assembly relationships, and design documents, which can be used for training and evaluating knowledge graph-based mold design systems. The dataset can be downloaded from the official website(https://www.researchgate.net/publication/222411318_Developing_an_engineering_shape_benchmark_for_CAD_models). During the model training process, to ensure that the model maintains good generalization performance on unseen data, the dataset is split into training and validation sets with an 80:20 ratio. Specifically, 80% of the data is used for training the model, while 20% is used to validate the model's performance. A random seed is used to ensure the reproducibility of the data split. The data is randomly assigned to the training and validation sets to avoid any bias in model performance caused by uneven data distribution.

The experiment is conducted in a high-performance computing environment. The processor used is the Intel(R) Xeon(R) CPU E5-2620 v4, with a clock speed of 2.10 GHz, known for its efficient multitasking capabilities to support complex computing tasks and data processing. The graphics processing unit (GPU) selected is the NVIDIA Titan Xp with 12GB of memory, providing powerful computing capabilities, especially suitable for deep learning and image processing tasks. The system is equipped with 64 GB of memory, capable of supporting the loading and processing of large-scale datasets to ensure smooth experimentation. Python 3.6 is used as the programming language due to its simplicity, extensive library support, and widespread application in scientific computing and machine learning. For the technical framework, PyTorch 1.7.0 deep learning framework is employed, known for its flexibility and dynamic computation graph, widely used in deep learning research. The combination of hardware and software provides a powerful computing capability and a flexible development environment for efficient deep learning-related research work. Part of the relevant code used in the article's calculations is shown in Fig. 2.

In order to ensure the accuracy of the data, the experiment uniformly sets the system parameters. To ensure the model's generalization ability and prevent overfitting, the experiment optimized and adjusted the model's hyperparameters. Specifically, the design accuracy was set to 0.05 mm, the mesh density was set to 50 elements/cm^2, and the model complexity was set to "Moderate." The simulation time step was chosen as 0.1 s, with the load application method set to Incremental, and the material properties were set to Standard Aluminum Alloy 4. Additionally, batch normalization was enabled to stabilize the model training process. During both model training and validation, cross-validation was used, with the dataset split into training and validation sets in an 80:20 ratio. To prevent overfitting, in addition to using batch normalization, regularization terms were added to the model. Hyperparameters such as the depth of the RF model and the number of trees were optimized through grid search and cross-validation. Through hyperparameter optimization, the experiment identified the optimal parameter combination for the model's performance.

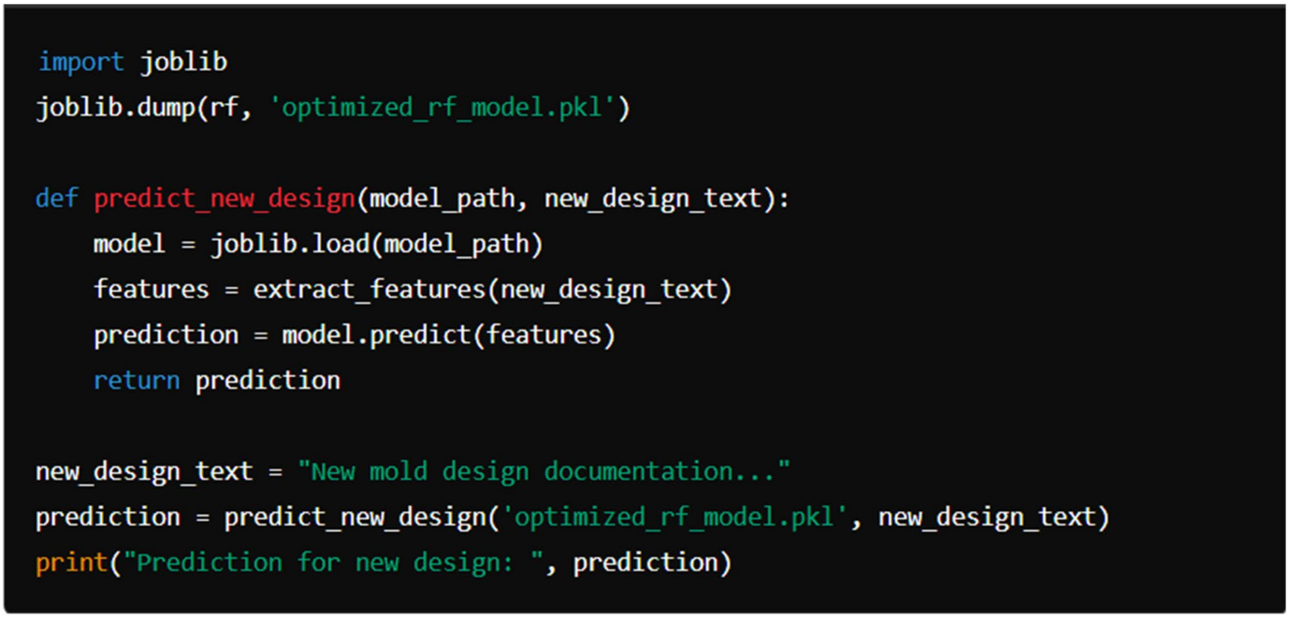
The systems selected for comparison in the experiment are shown in Table 2:

Experimental evaluation of mold intelligent data-driven design system

System performance evaluation

The performance evaluation of the system in the experiment includes error rate, design efficiency, design accuracy, and system response time. The experimental results are shown in Fig. 3.

In the comparison of error rates, with a data size of 1000, the traditional system shows an error rate of 0.17, Autodesk Fusion 360 at 0.1176, Unigraphics at 0.1172, Ptc Creo at 0.1332, and CATIA at 0.1229, while the optimized system achieves 0.105. At a data size of 2000, the traditional system decreases to 0.16, and the



```
import joblib
joblib.dump(rf, 'optimized_rf_model.pkl')

def predict_new_design(model_path, new_design_text):
    model = joblib.load(model_path)
    features = extract_features(new_design_text)
    prediction = model.predict(features)
    return prediction

new_design_text = "New mold design documentation..."
prediction = predict_new_design('optimized_rf_model.pkl', new_design_text)
print("Prediction for new design: ", prediction)
```

Fig. 2. Model running code.

Model	Reasons for selection
Traditional systems	Baseline Comparison: Traditional systems serve as a baseline comparison, highlighting improvements in design accuracy, efficiency, quality, and user satisfaction brought by new technologies such as knowledge graphs and deep semantic understanding Current Situation Reflection: The use of traditional systems remains widespread, especially in industries reliant on manual operations and accumulated experience. Through comparison, it can demonstrate the limitations of traditional methods and the superiority of new systems
Autodesk Fusion 360	Integrated Platform: Fusion 360 is a cloud-based product development platform covering the entire process from design to manufacturing Innovation: The system supports advanced features like generative design and topology optimization, demonstrating high innovation and market share Cloud Collaboration: Its cloud-based collaborative design environment enhances team collaboration efficiency, representing modern design systems
Unigraphics	Long History: Unigraphics is a historically established and powerful system widely used in industrial design and manufacturing Multidisciplinary Simulation: Supports multidisciplinary simulation and optimization, capable of handling complex design tasks, suitable for high-precision industries such as aerospace and automotive manufacturing Stability and Reliability: Known for its stability and reliability, suitable for demanding industrial design requirements
Ptc Creo	Flexibility: PTC Creo provides a comprehensive toolkit from conceptual design to manufacturing, supporting parametric design, direct modeling, and generative design Engineering Simulation: Includes various engineering simulation and optimization tools to improve design quality and efficiency Wide Application: Widely applied in consumer product design, medical equipment, and industrial manufacturing, demonstrating high practicality
Computer-aided three-dimensional interactive application (CATIA)	High-Precision Modeling: CATIA is renowned for its high-precision 3D modeling and surface design tools, extensively used in the design and engineering of complex products Systems Engineering: Supports multidisciplinary simulation and systems engineering, suitable for complex product design in aerospace and automotive manufacturing Collaborative Design: Offers powerful collaborative design and management features, enhancing team design efficiency and quality

Table 2. Comparison models.

optimized system further reduces to 0.1. With a data size of 3000, the traditional system maintains 0.15, while the optimized system achieves 0.0975. Regarding design efficiency, the optimized system excels, reducing the average completion time per design task from 20 h in the traditional system to 12 h, a reduction rate of 0.4. In comparison, Autodesk Fusion 360 completes tasks in 15 h (reduction rate of 0.25), Unigraphics in 16 h (reduction rate of 0.2), Ptc Creo in 14 h (reduction rate of 0.3), and CATIA in 13 h (reduction rate of 0.35). Additionally, the overall design cycle is reduced from 30 days to 22.5 days in the optimized system, achieving a reduction rate of 0.25. In terms of design accuracy, at a data size of 1000, the traditional system achieves 85.0%, while the optimized system achieves 90.50%. At 2000 data size, the optimized system improves to 91.00%, and at 3000 data size, it further increases to 91.25%. Regarding system response time, at a data size of 1000, the traditional system takes 30.0 s, Autodesk Fusion 360 29.77 s, Unigraphics 30.03 s, Ptc Creo 28.12 s, CATIA 24.40 s, while the optimized system responds in 20.0 s. At 2000 data size, the traditional system takes 35.0 s, Autodesk Fusion 360 29.57 s, Unigraphics 29.08 s, Ptc Creo 25.30 s, CATIA 23.26 s, and the optimized system responds in 22.5 s. At 3000 data size, the traditional system takes 40.0 s, Autodesk Fusion 360 27.32 s, Unigraphics 29.60 s, Ptc Creo 25.34 s, CATIA 24.28 s, while the optimized system responds in 25.0 s.

Example results evaluation

To further validate the effectiveness of the optimized system, instance experiments are conducted, comparing metrics such as design quality score, labor cost, user satisfaction score, and system stability, where design quality score and user satisfaction score are rated out of 10 points. The evaluation results are shown in Fig. 4.

In Fig. 4, regarding the design quality score, the optimized system in this study performs exceptionally well under various part quantity conditions. For a part quantity of 100, the scores are 6.56 for the traditional system, 8.43 for Autodesk Fusion 360, 7.73 for Unigraphics, 8.10 for Ptc Creo, 8.16 for CATIA, and the score for the optimized system in this study is highest at 9.16. With an increase in part quantity to 200, the score for the optimized system in this study rises to 9.97. At a part quantity of 300, the score remains highest for the optimized system in this study at 9.52. Regarding labor cost, for a dataset size of 100, the labor costs are 1000 for the traditional system, 893.19 for Autodesk Fusion 360, 813.95 for Unigraphics, 795.61 for Ptc Creo, 751.42 for CATIA, and the labor cost for the optimized system in this study is the lowest at 800.0. With an increase in dataset size to 200, the labor costs are 2000 for the traditional system, 1758.25 for Autodesk Fusion 360, 1658.43 for Unigraphics, 1657.04 for Ptc Creo, 1518.48 for CATIA, and the labor cost for the optimized system in this study is 1600.0. At a dataset size of 300, the labor costs are 3000 for the traditional system, 2733.56 for Autodesk Fusion 360, 2509.91 for Unigraphics, 2309.90 for Ptc Creo, 2113.94 for CATIA, and the labor cost for the optimized system in this study is 2400.0. In terms of user satisfaction, the optimized system in this study shows significant advantages under various rating conditions. Specific data shows that user satisfaction scores for the traditional system fluctuate between 6.05 and 7.25, for Autodesk Fusion 360 between 7.15 and 8.43, for Unigraphics between 7.07 and 7.97, for Ptc Creo between 7.64 and 8.45, for CATIA between 8.02 and 8.97, while the satisfaction score for the optimized system in this study is highest, fluctuating between 9.05 and 9.97. In terms of system stability, the optimized system in this study demonstrates significant advantages under various dataset conditions. For a dataset size of 1000, the stability scores are 0.87 for the traditional system, 0.90 for Autodesk Fusion 360, 0.88 for Unigraphics, 0.94 for Ptc Creo, 0.90 for CATIA, and the stability score for the optimized system in this study is highest at 0.98. With an increase in dataset size to 2000, the stability scores are 0.86 for the traditional system, 0.89 for Autodesk Fusion 360, 0.91 for Unigraphics, 0.93 for Ptc Creo, 0.94 for CATIA, and the stability score for the optimized system in this study is 0.98. At a dataset size of 3000, the stability scores are 0.89 for the traditional system, 0.91 for Autodesk Fusion 360, 0.87 for Unigraphics, 0.90 for Ptc Creo, 0.94 for CATIA, and the stability score for the optimized system in this study is 0.95.

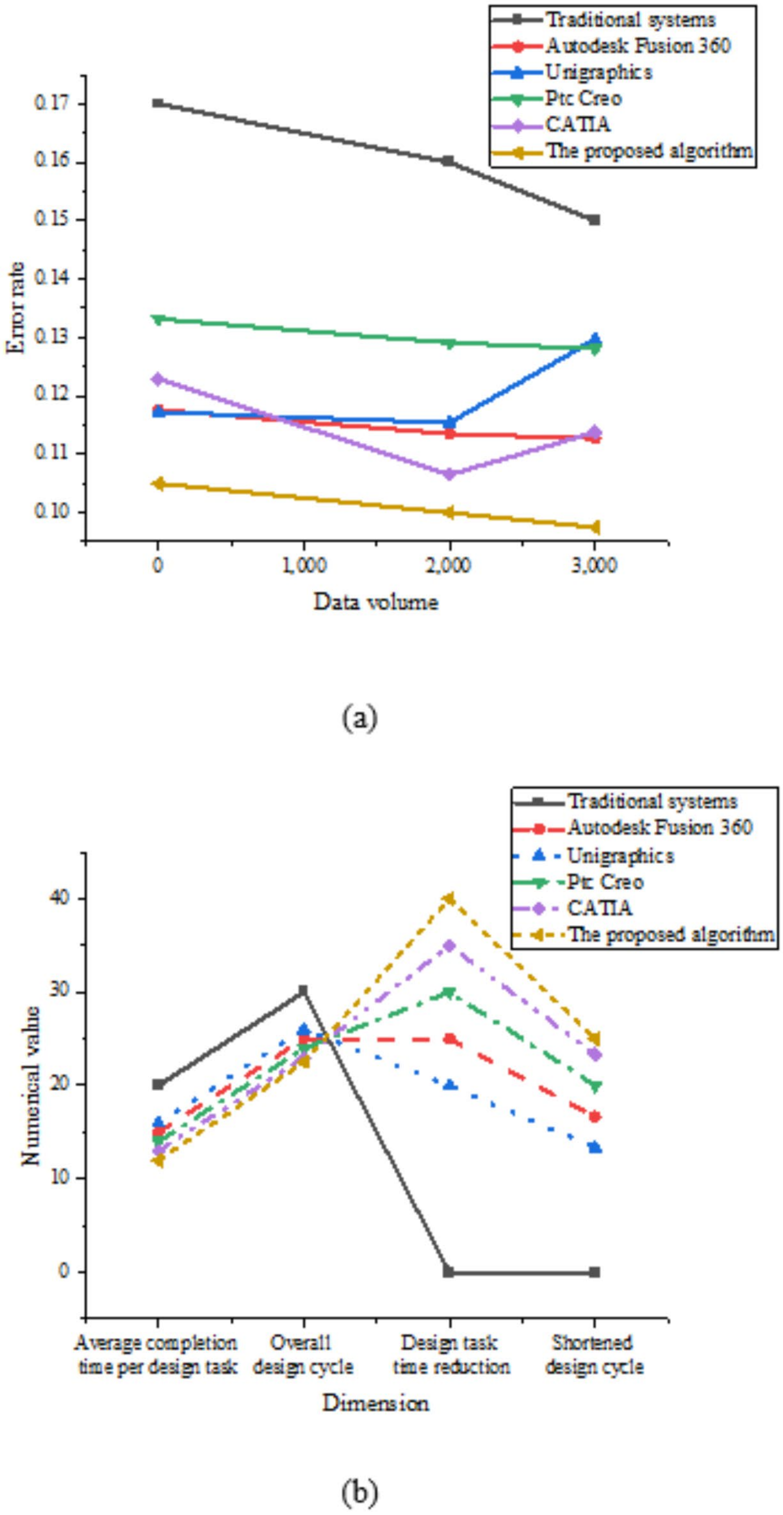
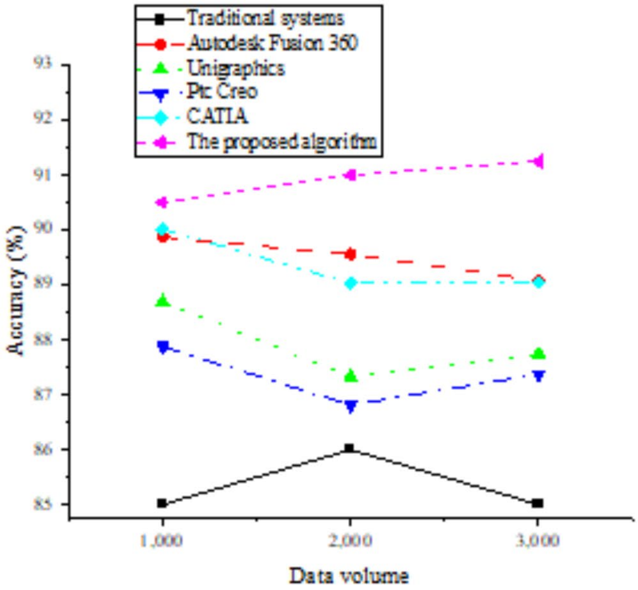


Fig. 3. Experimental results of system performance comparison (**a**) Error rate; (**b**) design efficiency; (**c**) design accuracy; (**d**) system response time.

Discussion

The optimized system in this study consistently exhibits lower error rates than other systems across different data volumes, demonstrating its significant advantage in improving design accuracy. While the error rates of traditional systems decrease somewhat with increasing data volume, they remain significantly higher than other systems. This indicates that traditional systems encounter substantial design errors when handling large volumes of data, making it difficult to meet the demands of high-precision design. In terms of design efficiency comparison,



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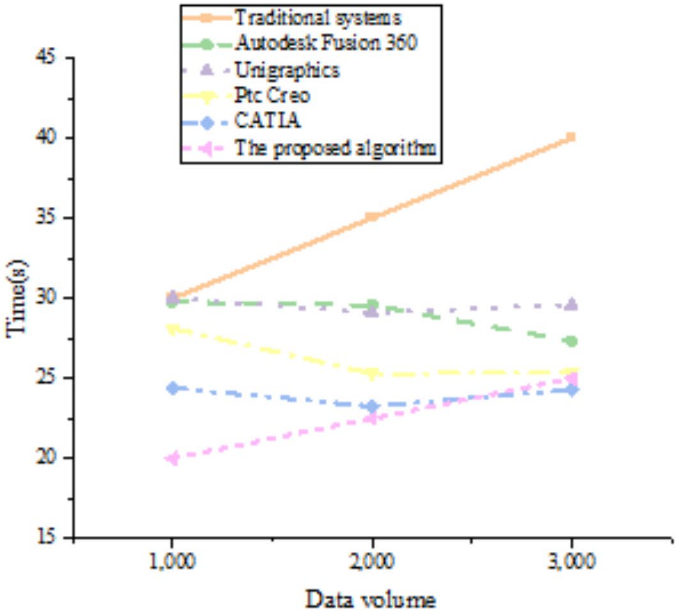
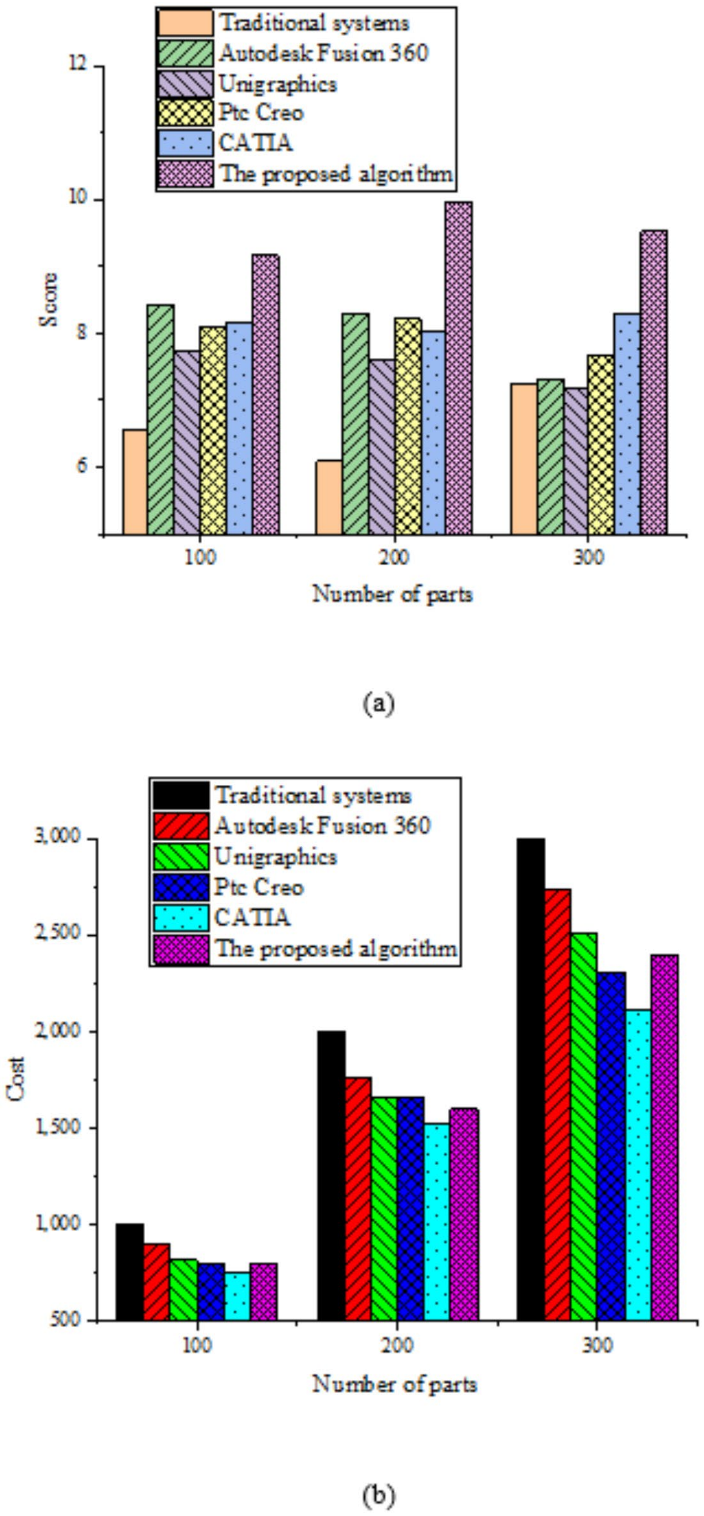


(d)

Figure 3. (continued)

traditional systems have longer design task completion times and overall design cycles primarily due to their reliance on manual operations and accumulated experience, resulting in cumbersome and time-consuming design processes. In contrast, modern design systems such as Autodesk Fusion 360, Unigraphics, Ptc Creo, and CATIA have made significant improvements in design efficiency but still fall short of the level achieved by the optimized system in this study. The optimized system in this study simplifies the design process significantly by integrating knowledge graphs, deep semantic understanding technologies, and intelligent decision support. Regarding design accuracy, modern design systems like Autodesk Fusion 360, Unigraphics, Ptc Creo, and

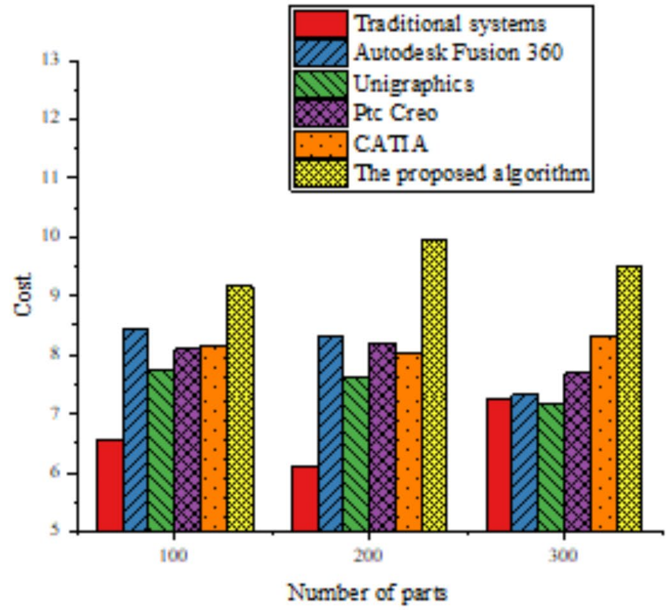


(a)

(b)

Fig. 4. Simulation experiment results (**a**) Design quality score; (**b**) Labor cost; (**c**) User satisfaction score; (**d**) System stability.

CATIA have improved design accuracy but have not yet reached the level of the optimized system in this study. The optimized system combines knowledge graphs and deep semantic understanding technologies to accurately extract key information and knowledge points from design documents, thereby significantly enhancing design accuracy. The construction and utilization of knowledge graphs enable systematic and structured representation of design knowledge, reducing information gaps and errors. In terms of response time, the optimized system in this study demonstrates significant advantages. Traditional systems have longer response times, which increase



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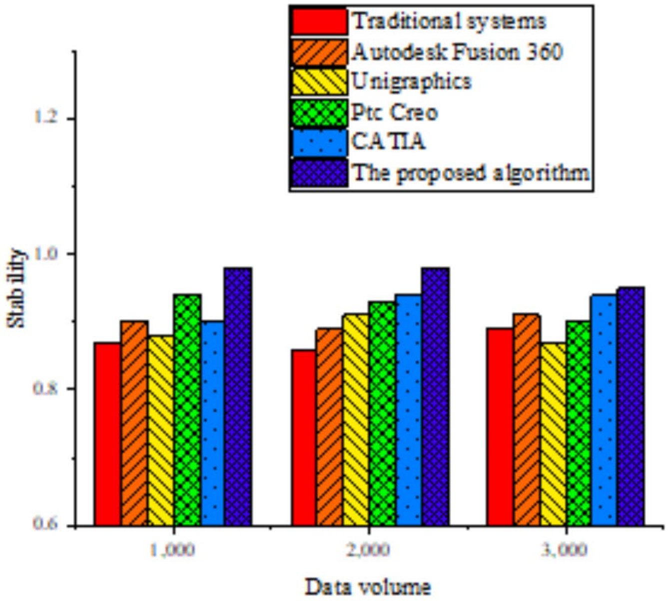

(d)

Figure 4. (continued)

significantly with data volume, indicating lower efficiency in handling large amounts of data. The combination of deep semantic understanding technology and knowledge graphs allows the system to rapidly extract and process key information from design documents, thereby improving data processing efficiency. The intelligent decision support system further reduces response times by optimizing decision-making processes using RF algorithms. In terms of design quality score, the optimized system in this study shows clear advantages. The lower scores of traditional systems suggest significant room for improvement in design quality. In comparison, other modern design systems such as Autodesk Fusion 360, Unigraphics, Ptc Creo, and CATIA perform well in design quality scores but have not yet reached the level of the optimized system in this study. The optimized system in this study significantly enhances the automation and intelligence of the design process by integrating knowledge graphs and deep semantic understanding technologies, thereby reducing manual operations and interventions, and consequently lowering labor costs. The intelligent decision support system optimizes design decisions using RF algorithms, further reducing manual involvement in the design process. In terms of user satisfaction score, the optimized system in this study demonstrates significant advantages. The lower scores of traditional systems indicate considerable room for improvement in user experience and functionality. The optimized system in this study enhances system intelligence and automation significantly by integrating knowledge graphs and deep semantic understanding technologies, thereby enhancing user experience during usage. Regarding system stability, the optimized system in this study also exhibits significant advantages. The lower stability scores of traditional systems indicate poorer performance when handling large volumes of data, potentially leading to system crashes or performance degradation. In comparison, other modern design systems such as Autodesk Fusion 360, Unigraphics, Ptc Creo, and CATIA perform well in system stability scores but have not yet reached the level of the optimized system in this study. The optimized system in this study enhances system stability and reliability significantly by integrating knowledge graphs and deep semantic understanding technologies. When processing large volumes of data, the system maintains high stability, avoiding potential performance degradation or crashes that traditional systems may experience.

Although the optimized system presented in this study demonstrates significant advantages across various key metrics, the underlying technical implementation is also worth discussing. During the construction and application of the knowledge graph, the optimized system not only addressed the problem of traditional design knowledge being fragmented and unorganized, but also incorporated a dynamic updating mechanism that allows the knowledge graph to adapt to rapidly changing design requirements. This dynamic knowledge management capability provides designers with more comprehensive and timely knowledge support, which not only improves design efficiency but also significantly reduces design errors caused by information omissions. In the application of deep semantic understanding technology, the optimized system employs the BERT model to extract key information and complex relationships from unstructured design documents, laying a solid foundation for the construction of the knowledge graph. Compared to traditional rule-based methods, the contextual semantic understanding capability of the BERT model is better suited to handle specialized terminology and polysemy issues in the field of mold design. This technological breakthrough significantly enhances the accuracy of knowledge extraction and representation, making the knowledge graph more reliable and precise when supporting intelligent decision-making. In intelligent decision support, the introduction of the RF algorithm provides an efficient analytical tool for the optimized system in multivariable design tasks. By combining the inference results from the knowledge graph, the RF algorithm is able to analyze the complex relationships between design variables more comprehensively, leading to more optimized design solutions. This knowledge- and data-driven decision support not only improves design quality but also offers greater flexibility to designers, making complex design tasks more controllable and efficient. Therefore, the optimized system, through the integration of knowledge graphs, deep semantic understanding technology, and RF algorithms, demonstrates significant advantages in improving mold design efficiency, accuracy, system stability, and user experience. This system provides strong technical support for the intelligent transformation of the mold design industry, while also offering direction and insights for further optimizing and expanding intelligent manufacturing systems in the future.

Conclusion

This study investigates a knowledge graph-based intelligent data-driven design system for molds and validates its significant advantages through experiments in multiple aspects. Firstly, the optimized system in this study consistently exhibits lower error rates than other systems across different data volumes, demonstrating outstanding performance in enhancing design accuracy. Traditional systems encounter significant design errors when handling large volumes of data, making it challenging to meet the demands of high-precision design. In contrast, the system proposed in this study integrates knowledge graphs and deep semantic understanding technologies to accurately extract key information and knowledge points from design documents. It utilizes RF algorithms for intelligent decision support, significantly reducing error rates in the design process. Secondly, in terms of design efficiency, the optimized system in this study outperforms traditional systems and other modern design systems significantly. Traditional systems rely on manual operations and accumulated experience, resulting in cumbersome and time-consuming design processes. In contrast, the system in this study simplifies the design process significantly through the integration of knowledge graphs, deep semantic understanding technologies, and intelligent decision support, thereby reducing design time and cycle time. Thirdly, the optimized system in this study also excels in design accuracy. Traditional systems are prone to human errors due to manual operations, while other modern design systems have improved design accuracy but have not yet reached the level of the system proposed in this study. The system in this study systematically and structurally represents design knowledge through the construction and utilization of knowledge graphs, reducing information gaps and errors. Additionally, the optimized system in this study demonstrates significant advantages in system response time. Traditional systems have longer response times and lower efficiency, whereas the system in this study rapidly extracts and processes key information from design documents through the combination of deep semantic understanding technology and knowledge graphs, thereby improving data processing efficiency and reducing system response time.

Although the knowledge graph-based intelligent data-driven design system proposed in this study excels in multiple aspects, there are still some limitations. The system heavily relies on existing knowledge graph and deep semantic understanding technologies, and has not fully explored and applied emerging technologies and methods such as generative adversarial networks and transfer learning. Moreover, the system may face challenges in integrating and standardizing heterogeneous data sources, affecting overall system performance and reliability. Future research will explore and introduce more emerging technologies to further enhance the system's intelligence and automation. Additionally, efforts will focus on integrating the system with other intelligent manufacturing technologies to build more comprehensive and efficient intelligent manufacturing solutions.

Data availability

All data generated or analysed during this study are included in this published article [and its supplementary information files].

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Author contributions

J.D., C.H., and J.C. contributed to conception and design of the study. B.Q. organized the database. J.W. performed the statistical analysis. Q.H. wrote the first draft of the manuscript. Y.L., J.D., C.H., and J.C. wrote sections of the manuscript. All authors contributed to manuscript revision, read, and approved the submitted version.

Declarations

Competing interests

The authors declare no competing interests.

Additional information

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