

The Progress of Business Analytics and Knowledge Management for Enterprise Performance Using Artificial Intelligence and Man-Machine Coordination

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ABSTRACT

This study aims to explore the integration of human-computer interaction (HCI) technology and platform ecosystem in artificial intelligence (AI) environment, thus providing a practical basis for the intelligent development of strategic management of platform ecosystem. With clothing e-commerce as an example, first, the business model of brand clothing is simply analyzed. Then, the fashion knowledge management method is adopted to build the fashion data warehouse. The platform intelligent clothing ecosystem is innovatively put forward through the research of business analytics and management mode of clothing e-commerce industry. The optimized genetic algorithm is used to solve the objective function of the model, and a flexible production scheduling model with multiple constraints and maximum cost-saving is established. Finally, the questionnaire results of voice interaction users are analyzed by HCI customer trust model.

KEYWORDS

Artificial Intelligence, Benefit, Business Analysis, Enterprise Performance, Human-Computer Interaction, Knowledge Management, Platform Ecosystem

INTRODUCTION

The relationship among business ecosystems is similar to the interaction between biological and natural ecosystems. Enterprises should regard themselves as the constituent elements of the business ecosystem system (Rong et al., 2018). All the agents in the same business system will influence each other and form a complex and multi-faceted system through interaction. The system's main body includes enterprises, suppliers, government departments, operators, and stakeholders. Each participant has a very close relationship with the system, including its internal participants (Leminen et al., 2018; Lüftenegger et al., 2017). Small and medium-sized enterprises (SMEs) can gain benefits in the fierce market competition, suggesting that their ecological status differs from that of large enterprises. A dynamic process for enterprises to improve the niche in the business ecosystem is to compete with each other for ecological status (Banoun et al., 2016). In the same niche, two competing species

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cannot coexist for a long time. Niche is also the time and space position of all living things in the natural ecosystem, and technological niche and enterprise niche are crucial in the development of SMEs (Roundy et al., 2018).

Artificial intelligence (AI) is a technology making computers simulate human thinking processes and intelligent behavior. The principle of intelligence is realized through computers. Devices similar to human brain intelligence are obtained to enable computers to realize deeper applications (Lu et al., 2018). AI covers a wide range, including computer science, psychology, philosophy, and linguistics. It is almost all disciplines in natural science and social science, and its field has completely exceeded the scope of computer science. The relationship between AI and thinking science is the relationship between practice and theory. AI is at the technical application level of thinking science. It is to carry out logical thinking and consider image thinking and inspiration thinking so that AI can have a breakthrough development. Mathematics is also a basic science of many subjects, and it is involved in language and thinking. AI discipline also needs to use mathematical tools in the scope of standard logic and fuzzy mathematics. When mathematics enters the AI discipline, they can promote each other and develop faster (Raza & Khosravi, 2015; Zang et al., 2015). Human-computer interaction (HCI) technology in the AI field, such as interactive robots, has been applied in various fields, including medicine, military, and business. Shen et al. (2019) showed that the trend analysis of online to offline (O2O) development in different language regions was revealed through AI. HCI technology makes AI technology more humanized and improves its applicability in application fields (Rigas et al., 2014).

The development of science and technology promotes online shopping, bringing more convenience to the process of commodity exchange. More importantly, it greatly impacts consumers' shopping habits and changes people's consumption behavior (Shen et al., 2018; Ding & Lu, 2017). E-commerce can be adopted to describe a place that uses different platforms for online shopping. As the media of e-commerce, the AI interactive design of the business website is a platform for building brand image, attracting users to browse the website, and cultivating customer loyalty (Zhao et al., 2017; Jahanshahi & Brem, 2017). However, there will be multiple problems accompanied by the convenience of interactive e-commerce in the AI environment, such as security and privacy, website stability, customer experience, and platform trust (Wan et al., 2018; Freathy & Calderwood, 2016).

In this study,, the platform intelligent clothing ecosystem was proposed under the theory of platform ecosystem. The structure of the intelligent clothing ecosystem was planned, and then the production scheduling model of clothing ecosystem based on the AI algorithm was proposed innovatively. A flexible production scheduling model with multiple constraints and maximum cost efficiency was established from the two directions of constraints and objective function. Then, the human-computer interactive customer trust model was proposed to address the problem of customer trust. Customer questionnaires are conducted in the form of voice interaction, and the results were evaluated using structural equation modeling. The proposed model provides a practical basis for the efficient application of HCI technology in the strategic management of the platform ecosystem.

RELATED WORKS

Intelligent clothing customization means to combine the personal preferences and needs of customers with the production process of customized clothing design. It is a higher-level service mode, which is more diversified, personalized and intelligent. It can be said that customized clothing is a clothing product or service for a single customer, and a complete set of intelligent solutions for customers. This model is mainly established based on the needs of consumers, and it can also meet the spiritual and cultural needs of consumers. It is primarily reflected in the additional functions of clothing products: design aesthetics, comfort, social and cultural connotation, taste, and self-esteem needs.

There is less theoretical research on online intelligent clothing customization abroad, and more on the practical application of online intelligent clothing customization by clothing brand enterprises. At present, multiple foreign clothing brand enterprises have built their own online intelligent

customization system for clothing brands, such as J. Hilburn and super cloth in the United States. In China, Zhu (2015) studied and developed the O2O network customization system for clothing and designed three customization modes: online booking service, three-dimensional virtual customization, and clothing customization according to consumers' different customization needs and psychology. Tao (2019) studied the factors influencing the personalized design of wedding dresses and the basis of digital design, and designed the personalized design platform of the wedding dresses using computer technology and CAD technology. The platform allows customers to customize the design and realize the personalized customization of wedding dresses. In China, intelligent clothing customization starts late, but cloud clothing customization has emerged with the increasingly strong demand for personalized and intelligent customization of clothing. The platform can meet the personalized design needs of customers and provide one-stop solutions through cloud computing, big data, and Internet technology (Qian & Zhao, 2021). The clothing needs to be produced after customization. The efficient clothing production scheduling model can improve the operation efficiency of the clothing industry to a great extent. Akhtar et al. (2019) showed that a scheduling model with minimizing the maximum completion time as the objective function was established for the batch scheduling problem of a multi-unit flexible manufacturing system. Moreover, it can be solved by the artificial immune algorithm and simulated annealing algorithm. Chen et al. (2020) suggested that in a multi-variety and small-batch clothing environment, a bi-level discrete programming model should be established and solved by a genetic algorithm (GA) to realize clothing scheduling based on symbol coding strategy. Longo et al. (2021) studied the garment industry of mass customization through the design and optimization of the garment product platform, combined with the evolutionary decision-making assistant model, and applied it in the real industrial case study verified by pilot product release. The results showed that scale-based platform product design is effective for garment mass customization. Xu et al. (2021) estimated and studied the tag length of mass garment customization based on machine learning. Using the methods of multiple linear regression and radial basis function neural network, the tag length for various garment production modes was estimated by considering various garment sizes and different tag types. The results showed that the proposed method has good performance in estimating the tag length of different types.

However, regarding clothing categories and consumer groups, the types of customized products of cloud clothing customization are single, and the consumer groups are limited by occupation, age, and consumption level, which cannot be popularized. Meanwhile, there is also a lack of intelligent service help. Hence, the breakthrough of this exploration is how to make the clothing ecosystem intelligent, and how to use agile supply chain thinking and internet thinking to put forward a smart clothing ecosystem integrating clothing design, production and intelligent after-sales service (Deng et al., 2021; Lei et al., 2021; Yang et al., 2021; Zheng et al., 2021a; Zheng et al., 2021b; Zheng et al., 2022; Zheng et al., 2021c).

Market Survey

The clothing ecosystem is taken as a research example, and the worldwide online personalized customization of the clothing industry is investigated. The results suggest that J. Hilburn of the United States and UNIQLQ of Japan are the most representative.

J. Hilburn Market Survey

J. Hilburn has no fixed physical stores but some temporary exhibitions, and it attracts customers by mainly relying on its own online website. It has two types of clothing customization models. One is one-to-one offline customization, selecting two garment factories in Malaysia and Portugal for customization of garments. However, the selling price under this model is far lower than the two high-end clothing brands mentioned above. At present, J. Hilburn only provides customization services of online personalized shirts. This model provides a shirt generation module for consumers with various personalized choices.

Nevertheless, this model is featured by a single online personalized customization service, and the designer decides all customization options. More importantly, its online customization service only helps to complete the offline customization service mode, that is, J. Hilbum's online customization mode is only for consumers to choose the clothing style, while its clothing designers still need to provide on-site service for clothing size measurement.

Market Survey of UNIQLO in Japan

Utme is an online T-shirt customization application designed and promoted by UNIQLO, a Japanese clothing brand. All consumers who have personalized demand for T-shirts can design their own patterns through the personalized design options provided by the app, such as online graffiti, text stickers, and direct transmission of pictures. To highlight the personalized design of T-shirts, Utme provides common cutting tools and adds smartphone's mobile sensor information to the design pattern. The same design effect can be achieved through a simple operation. However, the basic T-shirt still follows the traditional size standard and cannot provide the right T-shirt products for every consumer. Moreover, its personalized design options only include the personalized design of the pattern, without the customized options of T-shirt style and fabric. Even if consumers can design patterns at will, they may not be able to obtain satisfactory T-shirt styles, so personalized customization has great limitations.

Compared with foreign countries, domestic network personalized clothing customization develops at a relatively slow pace. For example, there are multiple T-shirt online customization platforms, such as Orimuse, Tclub and Taobao. These customization platforms are similar to Utme of UNIQLO, only providing simple customization options such as pattern and color, while the basic style and fabric have already been determined.

The intelligent clothing ecosystem based on the supply chain idea is proposed to solve the shortcomings of the worldwide clothing personalized customization mode. The personalized clothing customization platform in the system is studied and combined with AI technology to realize real intelligence.

PLATFORM INTELLIGENT CLOTHING BUSINESS ECOSYSTEM

Business Model Analysis of Brand Clothing

Brand clothing should seek its own unique development positioning and value proposition in the business environment of "Internet" and "big data," and clearly convey its own value concept, which is the respective business model of the brand. The clothing e-commerce industry focuses more on model innovation with the development of the O2O business model. Various brands of clothing have transformed to O2O mode in the new business environment to meet consumers' new consumption experience. Unlike the traditional business model, O2O perfectly combines the networking of physical stores with the materialization of online stores through the Internet, and establishes a new business model. After completing the consumption payment and other processes in the online store, users can go to the offline physical store to extract goods and enjoy services with the order voucher.

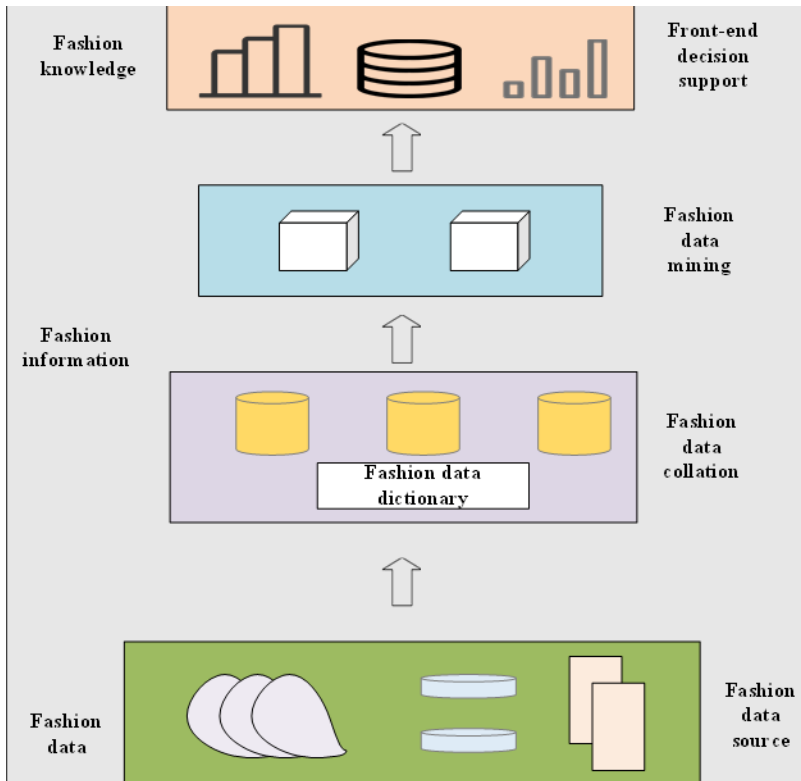
The application analysis and development advantages and disadvantages comparison of previous business models reveal that the O2O model is mainly restricted by the development of Internet technology and consumer experience demand. For example, UNIQLO started the prototype of O2O as early as 2008, and users could see UNIQLO's new products every season on their blog. In 2010, UNIQLO designed an "online queuing" game on renren.com. Users participating in the game could get coupons at random, and coupons could be used in offline stores. This combination of online and offline improves users' shopping experience and creates a new business model.

Clothing Fashion Data Warehouse Based on Fashion Knowledge Management

Knowledge management refers to the induction and management of the mastered knowledge resources in an efficient way to expand the knowledge increment and achieve the overall knowledge improvement. It includes the creation, acquisition, processing, storage, and dissemination of knowledge. In fashion design, the fashion data warehouse is built through knowledge management of fashion data collected from various channels. Standardizing data sources and converting data according to certain standards can further meet the needs of data mining and decision support. Fashion data warehouse mainly refers to the unification and integration of data obtained from different sources, and the analysis of new product design around clothing style. Besides, it also includes the storage of themes such as color, fabric, pattern, and technology of different clothing designs for long-term storage to facilitate later queries and statistics. The architecture of fashion data warehouse includes several modules, such as fashion data dictionary, fashion data source, fashion data collation, fashion data mining, and front-end decision support, as shown in Figure 1.

The fashion data dictionary is the basis of the data warehouse, which is used to standardize the expression forms and rules of fashion data in the data warehouse. Then, fashion data sources are adopted to collect fashion data from various channels in multiple directions. Next, fashion data collation is used to extract and store various fashion information and applied to format conversion. Moreover, fashion data mining is used for data mining of fashion information. Front-end decision support is used to provide HCI interface for fashion knowledge decision support.

Figure 1. Structure of fashion data warehouse based on fashion knowledge management



Theoretical Basis of Platform Intelligent Clothing Business Ecosystem

The co-evolution of the business ecosystem is studied with the relevant research of the platform. The co-evolution of the main enterprises in the business ecosystem is selected as the core research object (Gilson et al., 2016; Kim et al., 2016; Wu et al., 2021). The integration of platform and business ecosystem theory is a hot topic in the research of platform ecosystem theory. From the perspective of ecology, the platform ecosystem can be regarded as an organic ecosystem. On the internet platform of big data, highly related enterprises promote each other and share resources, fully reflecting the platform's role and making different subjects related (Lüftenegger et al., 2017; Stergiou & Psannis, 2017; Wu et al., 2018; Wu et al., 2017). Unlike the essence and characteristics of the traditional business ecosystem, the center of the platform ecosystem is the platform. The basic characteristics are as follows. The system attribute is open and inclusive, and its region can exceed the enterprise boundary or industry boundary. The system is not immutable, but has dynamic characteristics, which will change at any time, both outside and inside the system (Deng et al., 2015; Peng & Huang, 2017). It takes a long time for the formation of a platform ecosystem. A good system must include the internal structure adjustment in each development stage to produce adaptability to the external environment changes (Dong et al., 2021; Li et al., 2021; Liu et al., 2020a; Vigan et al., 2016; Xiong, et al., 2022).

The core idea of the intelligent clothing business ecosystem is to achieve a new and more advanced development form in enterprises or industries through intelligent information collection, intelligent process optimization, the extensive integration of resources, and intelligent decision-making of operation management, based on internet, Internet of things, integration technology, cloud computing, big data, and AI technology (Huang et al., 2021; Liu et al., 2020b; Sun et al., 2020; Yan et al., 2019).

Clothing Production Scheduling Model Based on AI Algorithm

Since there are different customization needs for personalized and customized clothing, a flexible production scheduling model with multiple constraints and maximum cost-saving is established from the three directions: constraints, objective function, and the model solving algorithm.

The first direction is constraints. In case of no delay in delivery, all orders must be delivered in the specified time, and the production task can be completed in advance. If there are m orders, and the completion time of final process n of each m order cannot exceed the product delivery time t , the constraint equation is:

$$Rt_{n,V_{mn}}^m \leq P_m, m = 1, 2, \dots, M \quad (1)$$

The above equation can be used to guarantee the order's delivery time, effectively improving customer satisfaction. Then, the available production capacity is strictly regulated. The number of orders arranged in each cycle should be less than the maximum available production capacity in the production cluster to make the scheduling scheme work normally. Moreover, each stage's deficiency of available production capacity should be considered. Its expression reads:

$$\sum_{m=1}^M \alpha_{n,p}^m \left(Y_{n,p_{mn}}^m - P_{n,p_{mn}}^m \right) \leq E_n, m = 1, 2, \dots, M; n = 1, 2, \dots, N \quad (2)$$

$$\sum_{m=1}^M \sum_{n=1}^N \alpha_{n,p}^m \left(Y_{n,p_{mn}}^m - P_{n,p_{mn}}^m \right) \leq \sum_{n=1}^N E_n, m = 1, 2, \dots, M; n = 1, 2, \dots, N \quad (3)$$

Equation (2) represents the maximum available capacity of each operation, that is, the total processing time of all orders if the m -th operation exceeds the maximum capacity E_n of the n -th operation. Equation (3) represents the total processing time of all orders, which should be less than the sum of the maximum capacity of all processes.

This constraint can promote the production capacity of the production cluster to a certain extent to prevent the order delay caused by insufficient capacity. Finally, the processing task arrangement is specified. From the perspective of operational research, task arrangement belongs to the scope of combinatorial optimization, which is to plan and schedule the strategy to complete the selection sequence of the production workshop, the beginning of the order process, and the technical time arrangement of an optimal process arrangement. Therefore, the order processing sequence should be specified in the planning and scheduling to prevent the contradiction between the processing time of each operation and the order allocation. This provision can be expressed as follows:

$$Pt_{n',p_{mn}}^m \geq Yt_{n,p_{mn}}^m, w_{n,n'} = 1$$

$$Pt_{n,p_{mn}}^m \geq Yt_{n,p_{mn}}^{m'} \tag{4}$$

n' is the next process of the n -th process. $Pt_{n',p_{mn}}^m$ is the start time of the m -th order on the p -th production equipment of the n' -th process. $Yt_{n,p_{mn}}^m$ is the end time of the m -th order on the p -th production equipment of the n -th process. $Pt_{n,p_{mn}}^m$ is the start time of the m -th order on the p -th production machine of the n -th process. $Yt_{n,p_{mn}}^{m'}$ is the start time of the m' -th order on the p -th production equipment of the n -th process and m' is the next order of m . $Pt_{n',p_{mn}}^m \geq Yt_{n,p_{mn}}^m, w_{n,n'} = 1$ is to specify the production time between all processes. For the same order m , the start time of the later operation n' of the n -th operation is later than the end time of the n -th operation. $Pt_{n,p_{mn}}^m \geq Yt_{n,p_{mn}}^{m'}$ can define the task allocation strategy of each workshop. For the n -th process, the start time of the next order m' is later than the end time of the m -th order.

The second direction is the objective function. The objective function of the model is obtained as follows after the analysis of cost-saving and time-saving:

$$MaxQ(b) = \eta_1 (C^0 - C^1) + \eta_2 \left(\sum_{m=1}^{M\Sigma} (K_m - Ht^{1N,P_{mn}^m}()) \right) \tag{5}$$

C^0 represents the non-cooperative feasible solution of the model, C^1 is the optimal solution of the model problem, K_m is the delivery time of the current order, and Ht^{1N,P_{mn}^m} represents the time taken by the current order to complete the last operation under the best arrangement.

The third direction is the model solving algorithm. The flexible production model is used in this system (Francesconi et al., 2017), so the system management problem is solved based on the process sequence arrangement. Moreover, the appropriate processing workshop should be specified for all processes. The optimized standard GA (Morris et al., 1998) is adopted to solve the model (based on double-layer integer coding; Yang & Liew, 2014) to solve the problem of system management. The specific steps are as follows:

Step 1: Population initialization is conducted. The relevant parameters such as population size P , maximum iteration number T , crossover probability p , mutation probability p' and generation

gap G of the algorithm are specified, and then chromosomes (P) are generated to be used as the initial population of iteration.

Step 2: It is to select individuals under the guidance of mutation probability p' , and generate new individuals by the set mutation operation.

Step 3: The individual selection is guided by the crossover probability p , and the parent chromosome crossover is performed by the set mutation operation. The two best chromosomes of the parent are selected and used as the next generation of individuals.

Step 4: Chromosome decoding is then carried out. First, the process code is decoded to obtain the scheduling sequence of the process and the corresponding equipment sequence. The end time of each order on the corresponding workshop machine of each process is calculated.

Step 5: Individual fitness value is calculated, and then the selection is completed by the roulette selection operator (Drmac & Gugercin, 2016).

Step 6: Whether there is a maximum number of iterations is analyzed. If it is generated, the optimal objective function value and the optimal scheduling strategy will be generated. If it is not generated, it will return to the second step to continue the optimization. The generation steps of the optimal scheduling strategy are as follows. First, the processing sequence is defined. Then, according to the end time of the order process, each process is inserted into the feasible machine for optimal time arrangement for processing to ensure that all processes are arranged on the optimal feasible machine. Finally, the optimal scheduling scheme is generated, and the Gantt chart can represent the output result.

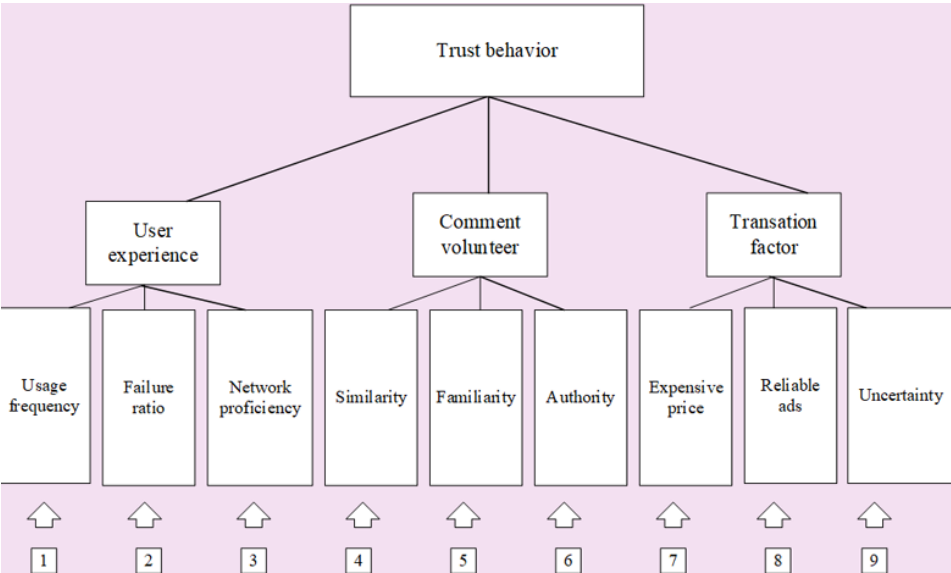
Human-Computer Interactive Customer Trust Model

The evaluation given by other customers, the past reputation of the business, and logistics services are the main factors that affect the trust of each type of customer.

An intelligent questionnaire is conducted here according to the trust factors of clothing consumers. According to the questionnaire, customers input voice interactively on mobile devices, and the system gives valid or invalid voice prompts. Then, the structural equation model is used to solve the problems in the questionnaire. Based on the identification problem of the model, the trust factor is investigated by numerical questions, and the user background is investigated through sub-type questions. The numerical questions are scored with the Likert scale (Reed et al., 2017; "1" stands for "strongly disagree", and "5" for "strongly agree"). The four factors affecting the mutual trust between customers and machines include customer experience, transaction determinants, advice providers, and website applicability. A total of 10 observation factors are extracted based on the factor analysis of the structural equation model. 10 questions are designed for these 10 factors, two questions are proposed for the background research, and a questionnaire with 12 questions is finally designed. A total of 100 online customers of a clothing company are randomly selected, and 90 valid questionnaires are collected according to the voice interaction results. The structural equation model is used for analysis based on the questionnaire results, thereby completing the design of the human-computer interactive customer trust model (Yao et al., 2016), as shown in Figure 2.

Based on the questionnaire results, structural equation model analysis technology is used to verify the model. In the first stage, AMOS (Analysis of Moment Structures) is adopted to establish the initial interactive customer trust model for later model modification. According to the index standard matching degree of the model, there are problems in the model, especially in the practical factors of the network, suggesting that the results of the sub-factor data obtained through the questionnaire survey are not perfect. One reason is that there are problems in the questionnaire design, and the other is that the derived sub-factors are not suitable for measuring website practicability. Hence, the analysis of the impact of website practicability on trust behavior is not tenable, and the model cannot accurately point out the impact of practicability on trust behavior. In the second stage, the practicability factor of the website is deleted according to the revision guidance of AMOS software, and the limitation of wrong items is released to complete the design of the interactive customer trust model.

Figure 2. Human-computer interactive customer trust model



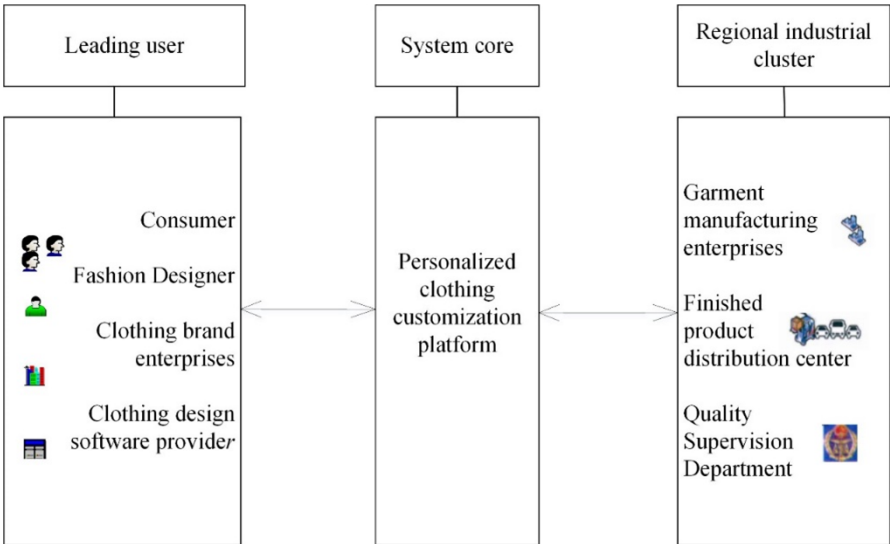
Construction of Intelligent Clothing Ecosystem

The structure of the intelligent clothing ecosystem is designed, as shown in Figure 3.

Leading Users

Leading users include consumers, clothing designers, clothing brand enterprises and enterprises supplying clothing design software. They are the core power of the intelligent clothing ecosystem.

Figure 3. Structure of intelligent clothing ecosystem



Personalized Clothing Customization Platform

The personalized clothing customization platform is the core component of the intelligent clothing ecosystem. From the supply chain perspective, the platform belongs to the core enterprise in the clothing supply chain. It communicates the demand of suppliers, and organizes and makes intelligent decisions for each participant and management activity in the intelligent clothing ecosystem, including human-computer interactive customer trust service.

Regional Industrial Cluster

There are several regional industrial clusters in the intelligent clothing ecosystem. The target of each industrial cluster is the small and medium-sized clothing production enterprise cluster. It contains several small and medium-sized clothing production enterprises, transportation centers and quality supervision departments. Small and medium-sized garment manufacturers produce the orders, and the transportation center will package, sort and transport the finished garments. The quality supervision department is responsible for the quality supervision and testing of all links within the industrial cluster, especially the small links in each production line, to ensure the quality of finished clothing products and prevent potential quality hazards. Among them, it also includes the negotiation between raw material suppliers and small and medium-sized garment manufacturers. The information-sharing mechanism can monitor the current inventory and consumption of materials in the cluster in real-time, and take centralized purchasing measures for each material supplier. Meanwhile, the purchased materials are allocated on demand.

SYSTEM ENVIRONMENT DESCRIPTION

Environment Description and Parameter Setting

It is necessary to investigate the practical basis for the intelligent development of platform business ecosystem strategic management to explore the integration results of HCI technology and platform business ecosystem in the AI environment. Besides, the performance system of the model needs to be evaluated in combination with the value of system environmental parameters. Table 1 displays the parameters and environment settings of intelligent garment ecosystem based on garment production scheduling model, human-computer interactive customer trust model and AI algorithm.

The Datasets

The datasets used include the Mixed National Institute of Standards and Technology database (MNIST) dataset and standard Chinese character set GB13000.1 and SQL server database, in which MNIST dataset contains 60000 training sets and 10000 examples. After sorting the data, origin 2018 software is used to analyze and process the statistical data.

RESULTS

Effectiveness of Optimized Standard GA for Solving Order Size

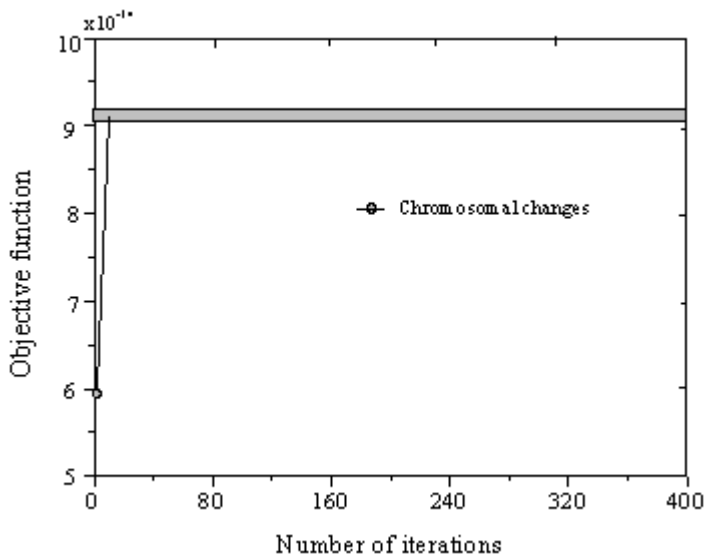
For two order sizes, the change curve of the objective function is compared based on the iteration time change of the algorithm, as shown in Figure 4a and Figure 4b. Figure 4 show results of objective function.

Figure 4(a) shows that the abscissa represents the number of iterations and the ordinate represents the objective function. The curve represents the convergence curve of GA, and the algorithm starts to converge in the 6th generation, indicating that the global optimal solution is obtained at this time. The optimal solution value is 9.21×10^{-14} , which is the maximum additional cost that can be saved in the production of 6 orders. When the order size is expanded to 40, the global optimal solution is

Table 1. Parameters and environment settings

Different Models and Systems	Main Parameters and Environment
Clothing Production Scheduling Model	Two order sizes are designed to form a contrast. The first size is: 6 orders, 6 processing procedures for all orders, 6 intelligent processing machines in 6 workshops, and 7 days of delivery time. The second size is: 40 orders, 6 processing procedures for all orders, 12 intelligent processing machines in 12 workshops, and 7 days of delivery time. Before solving, the parameters of the algorithm need to be set. If the population size is Popsiz=40, and the maximum iteration number is Maxgen=400, the generation gap is Gap=1, the crossover probability is P=0.8, and the mutation probability is P'=0.1. The MATLAB simulation tool is used to write the algorithm, and then the actual clothing experiment is solved.
Intelligent Clothing Ecosystem	CPU: I Intel(R) Core(TM) i5-4590 Memory: 8G Browser: Firefox v58.0.2
Human-Computer Interactive Customer Trust Model	Windows+SAPI, SASDK toolkit, SAPI engine, IBM SPSS Amos 21

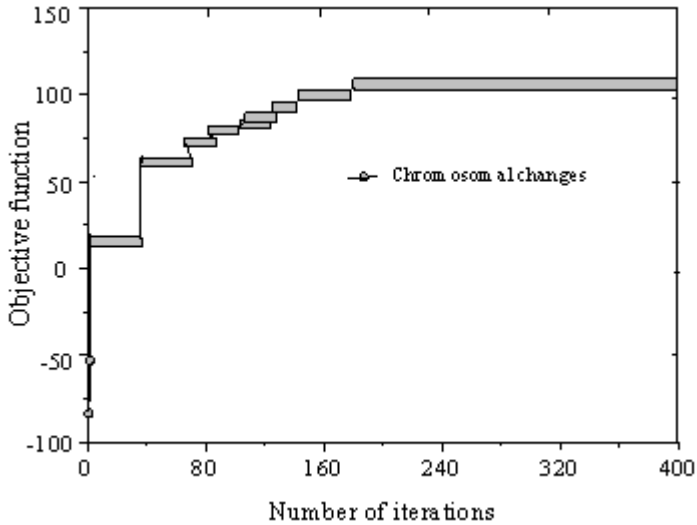
Figure 4a. Objective function curve of order 1



obtained around the 170th generation. For different order quantities, the iterative change trend of the objective function is good.

Coding is crucial for the successful implementation of GA and it is divided into two layers for the two-layer goal of processing sequence solving and machine arrangement. One layer is based on the processing sequence code to determine the order processing sequence. The other is based on the workshop machine code to determine each process's corresponding workshop processing machine. The machine code in the workshop represents the number of machines that the process can use. As a

Figure 4b. Objective function curve of order 2



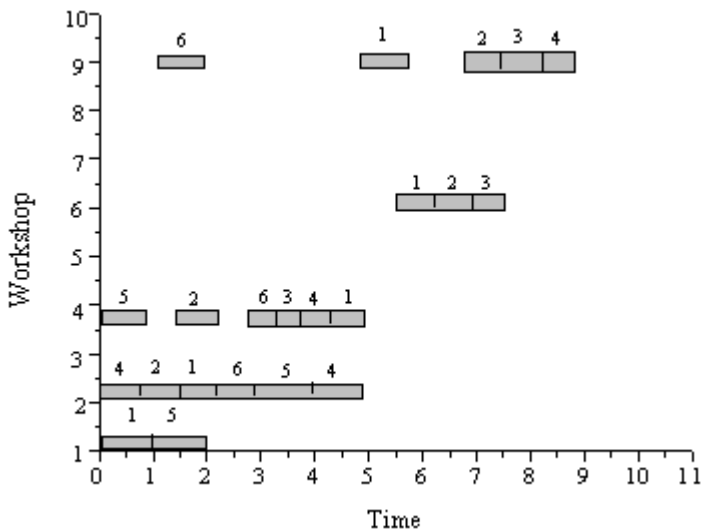
key step to improving the performance of the algorithm, it can facilitate the process of determining the processing machine in each workshop and ensure that the subsequent genetic operation can produce a feasible solution.

Optimal Order Scheduling Scheme

With the size of 6 orders as an example, the Gantt chart of production scheduling is obtained after iteration through the algorithm (i.e., the optimal scheduling scheme), as shown in Figure 5.

Figure 5 shows the equipment selection strategy, start time, and end time of each order in different workshops. The combination of each operation scheduling strategy is the production scheduling

Figure 5. Optimal scheduling scheme



scheme corresponding to the order. A total of 6 processes need to be completed. The scheduling strategies are as follows. The first process selects equipment Q_{11} , taking 1h. The second process selects equipment Q_{21} , taking 1.4h. The third process selects equipment Q_{31} , taking 1.4h. The fourth process selects equipment Q_{41} , taking 0.9h. The fifth process selects equipment Q_{51} , taking 1.8h. The third process selects equipment Q_{51} , taking 1.8h. The third process selects equipment Q_{61} , taking 1.8h. Therefore, the equipment selection sequence of this order is: $Q = \{ Q_{11}, Q_{21}, Q_{31}, Q_{41}, Q_{51}, Q_{61} \}$, with a total time of 7.3h.

The important management direction for the intelligent clothing ecosystem is clothing order production planning. It is essential to reform and optimize the previous production model of clothing production enterprises. Then, the rapid production of personalized and customized clothing with the best production cost can be realized. Under the background of industry 4.0, the production workshops of enterprises are developing towards intelligence and visualization. The proposed algorithm can improve the management and deployment efficiency of intelligent clothing ecosystem and realize the system's efficient and reasonable strategic management. Besides, business ecosystem is a material system with material circulation, energy flow and information transmission. It has the main characteristics of coevolution, key species, and complexity. Enterprise niche is the basic position of clothing enterprises in the whole business ecosystem network. Clothing enterprises must find their own order production mode according to their own advantages to find their own niche and enter the business ecosystem. In this way, they can survive and develop in the fierce market competition environment. They need to continuously optimize through cross-border, continuous innovation, ecological experience, collaborative development, and other means, give full play to their own advantages, build a strong enterprise competitiveness based on their own niche, consolidate and expand the niche, and grow into the leader of the ecosystem. The competitiveness of clothing enterprises is closely related to the business ecosystem. Clothing enterprises must establish a business ecosystem suitable for their own situation, which can meet future development needs. Only with open enough, reasonable planning and a complete business ecosystem can enterprises meet the basic needs of users, gather strength as far as possible, constantly improve themselves, give users a high-quality clothing experience, and maintain a competitive advantage in the cruel market competition. Generally, the more sound the business ecosystem is, the stronger the competitiveness of clothing enterprises is. The stable development of the business ecosystem can also improve the competitiveness of clothing enterprises.

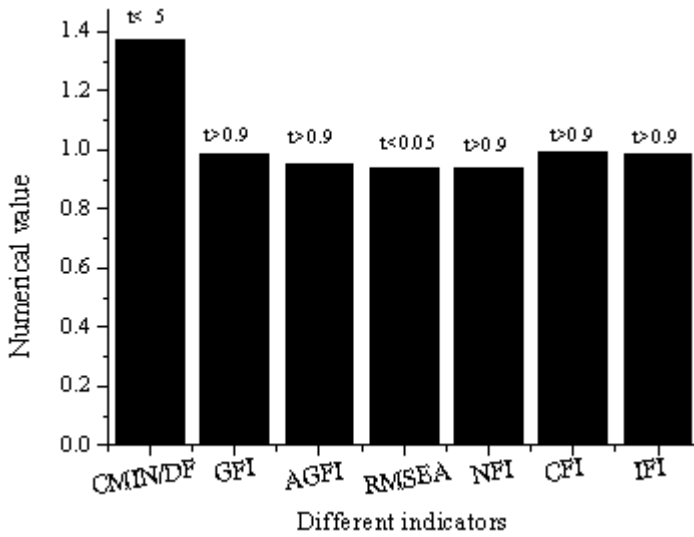
Assignment Results of Human-Computer Interactive Customer Trust Model

Figure 6 shows the output results of the human-computer interactive customer trust model.

Figure 6 reveals that the value of CMIN/DF is 1.38, GFI is 0.95, AGFI is 0.92, RMSEA is 0.9, NFI is 0.9, CFI is 0.95, and IFI is 0.94. The t values of GFI, AGFI, NFI, CFI, and IFI are all greater than 0.9, CMIN/DF is less than 5, and RMSEA is less than 0.05. In other words, the relationship among all factors is significant. Even if the price is not significant, it is close to significant. The structure and factor load can be used to complete the follow-up study, indicating that the proposed structural equation modeling is valid.

Intelligent scheduling decisions based on big data and big data analysis technologies are the most critical module in the clothing business platform. The key problem is to solve the cost and time problem of personalized clothing customization and respond to consumers' personalized needs quickly, which is also the basis of realizing small batch and multi-category personalized clothing production. The invisibility of the interaction process will make customers feel that the transaction is uncertain, and then they will lose trust in the platform. Customers will feel distrust if the seller's information is inaccurate or incomplete (Gerbing et al., 1994). The best model generally conveys a good image of e-commerce. When users can really feel the information, they will fully trust the platform. The high price is not a very important transaction factor, because few users buy high price products on the internet, and most of them will buy high price products in physical stores. These customers are not very interested in high price online goods, so they seldom buy high price products online. Some

Figure 6. Assignment results of human-computer interactive customer trust model (t: acceptable value)

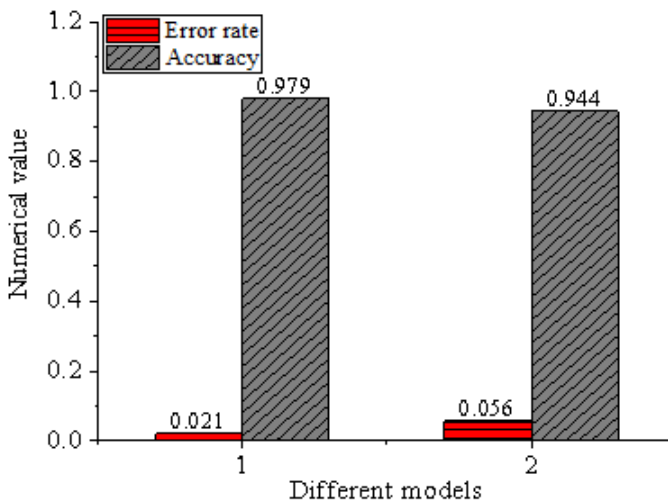


customers believe that the high price network products are not necessarily proportional to their quality (Benjamin & Lin, 2020). The platform should adjust the strategic management direction according to the actual situation. Thereby, which customers are long-term customers and which customers do not have the consumption prospect of the website brand can be judged and an effective performance evaluation can be performed.

Then, the model’s performance is compared. The performance of the human-computer interactive customer trust model and the general customer trust model is compared, as shown in Figure 7.

Figure 7 reveals that the error rate and accuracy of the proposed human-computer interactive customer trust model are 2.1% and 97.9%, respectively, while those of the general customer trust

Figure 7. Performance comparison between human-computer interactive customer trust model and general customer trust model (Note: 1 stands for the human-computer interactive customer trust model; 2 stands for the general customer trust model)



model are 5.6% and 94.4%, respectively. It indicates that the proposed human-computer interactive customer trust model has higher accuracy and a lower error rate.

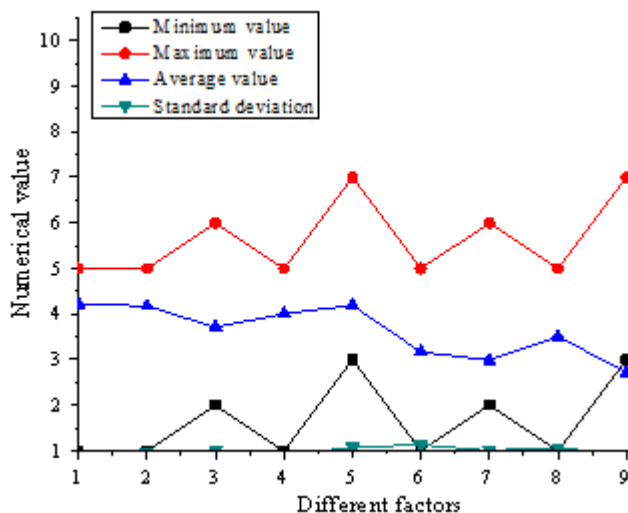
Analysis of the Effect of Human-Computer Interactive Customer Trust Factors

The effect of customer trust factors is analyzed based on the questionnaire results, as shown in Figure 8.

In Figure 8, for the factors that usage frequency is conducive to trust behavior and failure ratio is not conducive to trust behavior, the maximum, minimum, and average values are 5, 1, and 4.2, respectively; for the factor that network proficiency is conducive to trust behavior, the maximum, minimum, and average values are 6, 2, and 4.1, respectively; for the factor that similarity is conducive to trust behavior, the maximum, minimum, and average values are 5, 1, and 4.15, respectively; for the factor that familiarity is conducive to trust behavior, the maximum, minimum, and average values are 7.5, 3, and 4.23, respectively; for the factor that authority is conducive to trust behavior, the maximum, minimum, and average values are 5.1, 1, and 3.5, respectively; for the factor that expensive price is conducive to trust behavior, the maximum, minimum, and average values are 6.1, 2.2, and 3.1, respectively; for the factor that reliable advertising is conducive to trust behavior, the maximum, minimum, and average values are 5.1, 1 and 3.7, respectively; for the factor that function interest is not conducive to trust behavior, the maximum, minimum, and average values are 7.3, 3.2 and 3.3, respectively. In other words, the average score of the factor that function interest is not conducive to trust behavior is less than 3, indicating that the relationship between function interest and customer trust behavior is positive, so function interest is conducive to trust behavior. The average scores of other factors are higher than 3, suggesting that these factors positively affect customer trust behavior.

If the seller's information is inaccurate or incomplete, the customer will doubt the transaction. Reliable advertising usually is crucial in market competition strategy. However, the graphic design level of these advertisements affects the credibility of advertisements. The model shows that reliable advertising does impact trust, but the real impact is the information hidden behind the advertisement. High-quality advertising often conveys a good e-commerce image of wealth, power, high grade, noble service, and fast logistics. When users can see the information, they will trust the platform.

Figure 8. Description of results of human-computer interactive customer trust factors (1: usage frequency is conducive to trust behavior; 2: failure ratio is not conducive to trust behavior; 3: network proficiency is conducive to trust behavior; 4: similarity is conducive to trust behavior; 5: familiarity is conducive to trust behavior; 6: authority is conducive to trust behavior; 7: expensive price is conducive to trust behavior; 8: reliable advertising is conducive to trust behavior; 9: function interest is not conducive to trust behavior)



The previous customer trust model cannot measure the relationship among variables quantitatively, and it can only carry out the overall evaluation. In the interactive customer trust model proposed, the structural equation model can measure the variable relationship which is not easy to be measured, measure the micro feelings in the interaction design and user experience, and evaluate the effect in the form of specific numbers. It is incomparable with other customer trust models.

DISCUSSION

According to customers' personalized clothing orders, efficient organization and coordination of available resources in the regional industrial cluster and the establishment of a production scheduling mechanism quickly respond to customers' personalized needs and bring considerable economic benefits. It is the first problem to be solved for small and medium-sized clothing manufacturing enterprises in regional industrial clusters and even the whole clothing business ecosystem. Regarding the production and processing of personalized clothing, the production of a piece of clothing needs to go through complex production processes, such as fabric processing (pre-shrinking and cutting), sample clothing, semi-finished product processing, sewing, nailing, and ironing. Especially when consumers have more personalized demand for some production processes, a single clothing processing enterprise cannot independently complete its production tasks or it can complete the production tasks with the high cost and long production cycle. The traditional production mode of clothing production enterprises needs to be changed to quickly respond to the personalized needs of consumers and solve the problems of long production time and high processing cost for customized clothing. In this way, the production mode can complete the rapid production of personalized and customized clothing with reasonable production costs. Hence, using GA to optimize the performance of the clothing ecosystem can improve the efficiency of clothing production to the greatest extent. The results of clothing production scheduling optimization based on GA proposed are consistent with those of Lee et al. (2016), and the efficiency of clothing production has been improved to varying degrees. Compared with traditional production scheduling algorithms, the advantage of GA is not to design the problem-solving variables directly, but to design the coding of variables, thus improving the generality of the algorithm. Moreover, the search of GA starts from an initial population with multiple chromosome individuals, and has the characteristics of implicit parallel search, which can effectively avoid premature convergence of the algorithm. Liu et al. (2020a) showed that the improved GA could represent the process planning and scheduling in a separate model. For the priority constraints between operations, the specially designed operation can ensure the feasibility of the operation sequence, and the algorithm has certain advantages. Yan et al. (2022) studied the dynamic task allocation system of intelligent garment manufacturing through optimized GA. An objective function was defined to minimize the manufacturing span under conveyor belt constraints. A goal optimization method based on GA was proposed to allocate system resources. The results show that the model's effectiveness is enhanced by GA optimization.

A clothing business ecosystem is a form of cooperation among various raw material suppliers, small and medium-sized clothing production enterprises and logistics enterprises. They purchase raw materials and carry out clothing production activities. Accordingly, it is essential to focus on clothing production, develop a scientific and economic scheduling plan, and solve the following three problems. The first is the selection mechanism and scheme of production and processing machine in each production process. The second is the production time of different orders in each production process. The third is whether all production tasks in each order can be completed by its delivery date. The foundation of this module is to establish a production scheduling decision model based on data analysis. The core goal is to organize and execute various kinds of production under the guidance of lots of orders. The proposed clothing production model can reasonably allocate the clothing scale according to different orders, which is consistent with the research results of Nadarajah et al. (2017). The questionnaire is conducted by voice interaction. This is consistent with the research results of

Fomby and Sastry (2019), which shows that interactive voice response technology produces a high survey response rate.

CONCLUSION

Task interaction customer trust is a concept of customer trust of an e-commerce platform based on interaction design thinking mode, which reflects the customer's trust psychology to an e-commerce platform and services in the process of interaction with the e-commerce platform.

Due to the good interaction design and user experience of e-commerce platforms, the generation of interactive customer trust usually positively impacts customers' trust behavior on the e-commerce platform. There are many scenarios for users to use e-commerce platforms. The factor affecting customer trust is to consider the risks brought by situational factors under special circumstances. Providing corresponding services to eliminate this risk is very important to win customers' trust. First, there are network risks anyway. In the case of customer key information input, the network risk mainly comes from the public network, which cannot guarantee the user's information security and is easy to lead to information disclosure. In addition, there are privacy risks. From a certain point of view, the content of the user's touch-screen mobile phone is clear. If others are present, the interface can be improved. In addition to the user's intelligence and alertness, this kind of design can also eliminate the risk of concealment. Finally, there is a personal safety risk, that is, the risk coefficient of users when using the platform is different from that when using the platform in sports, and accidents are easy to occur in sports. If the platform does not remind users to pay attention to safety, it can easily cause accidents and tragedies.

Based on the theory of platform ecosystem, the intelligent platform clothing ecosystem is proposed here. AI algorithm is proposed to optimize the production scheduling model of the clothing ecosystem, and then the objective function of the model is calculated and solved by using the optimized GA. According to the customer questionnaire survey results and combined with the applicable structural model, the human-computer interactive customer trust model is successfully proposed under the guidance of AI technology. The results show that the platform intelligent clothing ecosystem can select the best scheme in the strategic management of production scheduling, so that the system can run efficiently and ecologically. The main research contribution is that the proposed customer trust model can fully consider customers' influencing factors and meet customers' needs through intelligent voice interaction on mobile devices. However, some research deficiencies are difficult to avoid. The main deficiency is that the order instance in the production scheduling model of the garment ecosystem is too single and does not have global representation. HCI model only involves voice interaction, not gesture interaction. In future work and research, the model's production scheduling and resource allocation need to be carried out according to the different number of clothing orders and in combination with the ecosystem to further improve the efficiency of system production scheduling through performance evaluation and strategic management.

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CONFLICTS OF INTEREST

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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