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The Development Trends of Computer Numerical Control (CNC) Machine Tool Technology

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Abstract: In the industrial era, production equipment serves as an essential mother machine. In the global manufacturing industry, components such as laptop computers, mobile phones, and automotive parts all strive for aesthetic appearance. Taiwan's machine tool industry plays a significant role globally. Faced with the constantly changing market environment, the development and competitive advantage of CNC machines are crucial topics for manufacturers. Domestic manufacturers of computer numerical control machines should move towards the integration of automated equipment to accommodate various advanced parts processing procedures. Smart manufacturing will become the trend of the industry in the future. This study invited experts from academia, industry, and research institutions to conduct expert interviews. Their opinions were compiled and analyzed, supplemented by fuzzy Delphi analysis to establish the development trends of various modules. The feasibility and demand of the product's functional technology for industrial development were analyzed under three research dimensions and eight technical items. A total of 26 key sub-technical items were identified, achieving an expert consensus level of over 80. Furthermore, the importance ranking was analyzed using the fuzzy analytic hierarchy process, and the consistency tests were passed with C.I. < 0.1 and C.R. < 0.1. Finally, the obtained importance ranking of the hierarchical structure was used to predict the future development of computer numerical control machines through a technology roadmap, helping manufacturers use it as a reference model for future development trends to enhance market competitiveness.

Keywords: CNC machine tool; technology roadmap; technology forecasting; fuzzy Delphi method; fuzzy analytic hierarchy process

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1. Introduction

The first Industrial Revolution started in the late 18th century, with machinery playing a crucial role. With the evolution of time from the traditional industrial era to the electronic technology era of the 20th century, people have constantly pursued high-precision, high-tech products. Whether they are dealing in consumer goods, automotive components, computers, mobile phones, or other products, manufacturers strive for faster and more precise product quality, and the production equipment for these product parts depends on machine tools.

From traditional machining equipment such as lathes, milling machines, planers, grinders, drills, borers, etc., to the birth of controllers in the Industrial 3.0 automation control era, with the transmission of electronic messages, the machine tool has evolved towards automated mechanical industry. The concept of "Industry 4.0" was introduced by Germany at the Hanover Industrial Fair in 2011. The central concept involves the integration of intelligence manufacturing systems, including automation, robotics technology, big data analysis, intelligent systems, virtualization, artificial intelligence, machine learning, and

Internet of Things systems to network the service chain of the production manufacturing industry [1]. Through the Industrial Internet of Things (IIoT), intelligent manufacturing, and big data, data can be collected in real-time and analyzed using algorithms to obtain real-time information [2]. By leveraging cloud big data to build intelligent manufacturing factories, industrial artificial intelligence conducts analysis, decision making, and control adjustments to develop intelligent production, meet customer demands, produce high-quality customized products, and achieve the goal of intelligent production manufacturing and factory intelligence [3,4]. The development of artificial intelligence (AI) will undoubtedly become more widespread in future control system research and the application of machine tool equipment. Sensors may be utilized to monitor production processes and real-time optimization control, from optimizing machine equipment to human–machine collaboration [5]. Intelligent machine tools are currently a focal point in industrial development. Accurately predicting the key technologies of intelligent machine tools is a crucial issue. However, the analysis of data from the literature lacks the demands of real industrial development [6]. In the context of Industry 4.0, to determine the development sequence of the manufacturing industry, multi-criteria decision-making methods such as the Analytic Hierarchy Process (AHP) and the Analytic Network Process (ANP) can be used for analysis and validation to obtain the order of priorities [7,8]. Alternatively, the more accurate fuzzy analytic hierarchy process (FAHP) [9] can be employed to calculate weights [10], construct an importance ranking, determine the priority of each indicator, and make decisions based on the order [11].

Computer Numerical Control (CNC) machine tools, also referred to as integrated machining centers, merge functions like milling, planing, boring, and drilling into a versatile machine tool. Through the use of computer programming and code conversion by the controller, the machine operates to process materials to the specified dimensions and precision.

Laptops, mobile phones, automotive parts, and other components all strive for a sleek appearance and exquisite quality. Most of these parts need to be machined to the required shape and size using computer numerical control (CNC) machine tools. Therefore, the advancement of computer numerical control (CNC) machine tools is moving towards Industry 5.0's human–machine collaboration, which will facilitate the development of more complex-shaped products in the future. This research will focus on the development of relevant module analysis and technical maps, which are crucial from both a technical and industrial perspective.

In summary, the development of CNC machine tools will inevitably continue to optimize various modules to meet industrial advancements. Therefore, the ultimate goal of this study is to establish a technical roadmap for the modules of CNC machine tools, serving as a reference model for future development trends for manufacturers. To achieve this goal, this study consolidates technical items and other elements through expert interviews. The results obtained from the expert questionnaires using the fuzzy Delphi method are analyzed for expert consensus to establish a hierarchical structure. Subsequently, a second phase of expert questionnaires using the fuzzy analytic hierarchy process is conducted, and the results are analyzed to determine the weight values and consistency tests of the dimensions, technical items, and sub-technical items [12]. Finally, the importance ranking of the overall hierarchical structure is obtained, identifying the key technologies for the development of each module and drawing a technical roadmap for the development of CNC machine tools, providing a reference for CNC machine tool manufacturers.

2. Literature Review

According to the International Manufacturing Technology Show (IMTS), the definition of machine tools is as follows: "A machine driven by power and not capable of being carried by manpower, utilizing a combination of cutting, impacting, and other physical, chemical, or other methods to achieve the purpose of processing objects can be referred to as a machine tool". Machine tools are commonly used for shaping, cutting, and connecting other tools. Machine tools hold a significant position in the mechanical industry, particularly in the current global emphasis on energy conservation, carbon reduction, and environmental protection. The development of industries like automotive and aerospace enhances technological advancements, strengthens corporate capabilities, and improves future industry trends. In the 1950s, the first Numerical Control (NC) machine tool was developed by the Massachusetts Institute of Technology (MIT) in the United States, replacing traditional machine tools and enhancing production techniques [13].

The servo motor feed system in computer numerical control (CNC) machine tools is the part that has the most significant impact on the performance of the machine tool, thus necessitating the use of servo control technology to improve machining accuracy [14]. There are three types of motors: stepper motors, DC servo motors, and AC servo motors, with AC servo motors being the most widely used at present.

Sensors are essential measuring components in CNC machine tools, primarily used to detect the operational status of the machine and provide real-time feedback to enhance machining accuracy, efficiency, and safety in the processing environment. The servo control simulation system of CNC machine tools effectively controls the machining status of the machine, providing higher stability and durability to the CNC machine [15]. Automatic setup technology is a crucial factor in improving machine performance, enhancing the dynamic response of machine tools and achieving high-efficiency processing [16].

The Numerical Control System (Controller) is the central component of Computer Numerical Control (CNC) machine tools. Currently, there are numerous CAD/CAM software programs available. By utilizing drafting concepts, products are drawn to the required dimensions. Subsequently, tool arrangements for cutting and milling processes are made, considering different material properties. Planning includes feed rates, tool speeds, cutting amounts, tool paths, and simulating cutting trajectories for optimization. After post-processing, the NC code is generated, input into the controller for processing, and finally outputs signals to various servo motors for machining [17]. The Motion Control Command Library (MCCL) and the EtherCAT Motion Control Platform (EMP) are used to create a human–machine interface for CNC machine tools, which includes parameter setting mode, coordinate setting mode, program editing mode, tool setting mode, and program execution mode [18]. The spindle is the heart of a computer numerical control (CNC) machine tool, utilizing motor power to drive it. Through spindle servo drive and feed drive devices, the spindle performs cutting and machining operations. Therefore, the power and torque of a high-performance spindle are essential considerations for product processing [19]. When the spindle is in operation, friction and power consumption generate heat in the spindle and bearings, leading to spindle temperature rise, structural expansion, increased thermal errors, and affecting machining accuracy. A multi-objective cooling system adjusts the amount of spindle coolant to reduce spindle temperature and enhance spindle precision [20]. The dual simulation system analyzes factors affecting the machining process, including cutting forces, resonance effects, and other physical factors. By comparing simulation and actual results, with an error margin within 3%, it indicates that the spindle's machining performance can be optimized through the simulation system, thereby enhancing production efficiency [21]. Displacement sensors detect the radial rotational motion of the spindle, monitoring spindle speed to detect temperature changes that affect spindle stiffness. Using these data, the feed rate and cutting depth are adjusted to control the spindle's strength from being compromised by high temperatures [22]. A method for real-time measurement of temperature-sensitive points on machine tools is employed, incorporating deep learning technology to utilize Long Short-Term Memory (LSTM) networks for establishing and predicting a thermal displacement compensation model [23]. The spindle is prone to vibration at high speeds due to speed fluctuations, leading to potential damage to the bearings. Timely prediction of the motion state of the spindle and bearings can mitigate machine malfunctions, underscoring the significance of bearing monitoring [24].

CNC machine tools are characterized by high precision and productivity, serving as indispensable high-end equipment in the intelligent manufacturing industry. Preventing machine failures and downtime to improve production efficiency poses a significant challenge for the CNC machine tool industry. Currently, domestic CNC machine tool fault diagnosis mainly relies on manual observation of experienced operators to assess the machine's sounds and error messages generated by the control system, leading to imprecise determination of the root cause of the faults. Therefore, by deploying temperature sensors and vibration sensors on the machine tool and collecting relevant data using acquisition equipment, along with data collection through the network involving communication layer, data processing layer, web service layer, and mobile app, intelligent fault diagnosis and early warning for machine tools can be achieved, enhancing the real-time and accurate diagnosis and warning of machine tool faults [25]. Intelligent manufacturing depends on real-time data collection and analysis to monitor equipment operation, key component wear, oil consumption, and bearing conditions. This enables the prediction of equipment failures and timely maintenance, facilitating rapid repairs [26]. Through advanced smart sensors, data are collected and transmitted to cloud monitoring and data analysis, then transferred to the control system for machine utilization, monitoring, scheduling, time adjustments, idling, and response to potential faults [27]. Real-time analysis of data collected in the cloud enables intelligent design and optimization of manufacturing processes, which are then transmitted to users or service providers. The development of FOCAS data extraction methods for intelligent manufacturing CNC machine data acquisition monitoring systems aims to prevent machine tool failures and tackle data collection and monitoring issues in enterprise manufacturing CNC machine tools [28].

Reasonable Fault Diagnosis Process (RFDP) is used for remote fault detection and diagnosis of CNC machine tools. Intelligent manufacturing utilizes Internet communication and monitoring technologies to detect, diagnose, and monitor industrial machinery for faults. Remote monitoring and fault detection can predict issues without manual intervention, enabling real-time problem resolution to reduce machine downtime. However, the maturity of using CNC machine tools for remote fault detection and troubleshooting is not yet established. Research is being conducted using transfer learning methods to identify the state of previous faults, train fault troubleshooting, follow a reasonable diagnostic process, monitor different operational parts of the machine, and extract relevant data to verify its performance, aiming to enhance the accuracy of detection and diagnosis and reduce downtime [29]. For the transition of machine tools towards intelligent monitoring, a hierarchical structure is proposed for data and monitoring systems. It starts from the connection of network devices to the machine tools, the operation data collection system for analysis of operational, and fault data, leading to key technologies including CNC machine data collection technology, data communication technology, database technology, processing task modeling technology, CNC program analysis, task processing time prediction, etc. These are all crucial analysis data for machine monitoring systems. Based on the above system architecture and functions, an intelligent manufacturing system for data collection and monitoring systems is developed, establishing big data and cloud analytics systems [28]. Remote monitoring of the health status of CNC machine tools allows for the prediction of errors and timely decision making based on data collection to ensure continuous machine operation and troubleshoot equipment failures [30].

2.1. Artificial Intelligence

Artificial intelligence is an essential technology for the future development of computer numerical control (CNC) machine tools. Intelligent sensors offer advantages such as optimization, learning, error compensation, vibration monitoring, wear monitoring, condition monitoring, and preventative maintenance [31]. Monitoring tool wear, establishing cutting parameters, and improving part tolerances and geometrical dimensions are also benefits [32]. However, there are many challenges to overcome in applying these technologies to machine tools. Research has shown that understanding this field's experts is crucial for leveraging artificial intelligence in intelligence manufacturing [33]. Artificial intelligence, when applied to machine learning, can optimize machining time based on feedback from the production process, CNC codes, and sensor data [34]. The Adaptive-Dhouib-Matrix-3 (A-DM3), an improvement over Dhouib-Matrix-3 (DM3), significantly shortens machining paths and saves energy consumption [35]. Additionally, the Dhouib-Matrix-4 (DM4) metaheuristic optimizes tool paths to enhance production efficiency [36]. Integrating various artificial intelligence systems into CNC machine tools would greatly benefit equipment manufacturers.

2.2. Fuzzy Delphi Method (FDM)

The Delphi method is a widely used analytical forecasting tool that gathers relevant experts and scholars to conduct surveys on issues with unknown outcomes. Through multiple rounds of expert surveys, the predictions are eventually aligned. However, this method requires a longer time and significant costs. When the differences in problem indicators are not significant, there may be a risk of misunderstanding the experts' intentions. Therefore, Ishikawa proposed the theory of the fuzzy Delphi method [37].

The fuzzy Delphi method can reduce the number of expert questionnaires or meetings. Typically, through a single expert questionnaire survey, the opinions of experts are consolidated. With the fuzzy Delphi method, the issue can converge towards expert consensus on the importance of higher-rated evaluation indicators, aligning with the problem predictions proposed by the experts. The fuzzy Delphi method combines fuzzy theory with the Delphi method to improve the shortcomings of the traditional Delphi method, which requires significant resources. It aims to enhance the overall evaluation by considering the experts' intended indicators, which may be helpful but could be overlooked and lead to missed opportunities. By using the fuzzy Delphi method for analysis, we can obtain the degree items of consensus among experts on the importance of the indicator [38]. Use the conservative triangular fuzzy number and optimistic triangular fuzzy number as illustrated in Figure 1. Employ the "gray zone test method" in the overlapping area to verify if expert cognition has reached a consensus, enhancing the alignment of the fuzzy Delphi method analysis results with expert opinions [39,40].

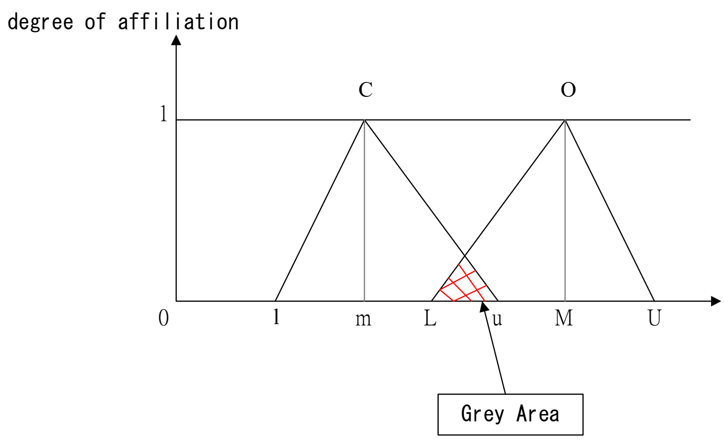

Figure 1. Double triangular fuzzy function diagram.

2.3. Fuzzy Analytic Hierarchy Process (FAHP)

T.L. Saaty developed the Analytic Hierarchy Process (AHP) during his tenure at the Wharton School of the University of Pennsylvania from 1971 to 1975. The Analytic Hierarchy Process (AHP) is extensively applied in multicriteria decision making, planning, resource allocation, and conflict resolution. It simplifies complex problems by hierarchically listing elements and criteria. Criteria are quantitatively assessed through pairwise comparisons to determine their importance. Consistency assessment is then conducted to aid decision-makers in choosing appropriate solutions [41,42]. However, the traditional Analytic Hierarchy Process is widely used in various decision-making scenarios. In multi-level decision-making problems, discrepancies in semantic interpretation of the importance between expert decision criteria may arise. Additionally, experts' subjective, fuzzy, and uncertain views on decision issues can lead to biased evaluation efficiency. As a result, many scholars have combined fuzzy theory with the Analytic Hierarchy Process method [43]. In 1985, Buckley introduced the theory of fuzzy analytic hierarchy process, which involves finding methods for fuzzy weights in fuzzy hierarchical analysis [44]. It is employed to solve the subjective, fuzzy, and uncertain issues in multicriteria decision analysis [45]. The FAHP integrates the concepts of fuzzy data and fuzzy sets into the hierarchical structure to improve the treatment of uncertainty between expert opinions and criteria [46]. This method can be used to assess the relative importance between different criteria and obtain the final decision sequence. Propose concrete project enhancements through interviews and utilize fuzzy hierarchical analysis to establish the priority order of importance. Subsequently, confirm the findings using the fuzzy analytic hierarchy process to prioritize similarity and the Fuzzy Grey Relational Analysis method, listing six improvement strategies [47]. Using the fuzzy analytic hierarchy technique to obtain a ranking of priority order, the ranking of these factors may be helpful for policymakers in formulating future strategies [48].

2.4. Technology Roadmap (TRM)

A technology roadmap, also called technology resource planning, is a predictive technique and communication channel that aids in technology management and organizational planning. Technology roadmaps primarily support enterprises in predicting future market trends, product development, technological breakthroughs, and resource integration. By hierarchically forecasting product development trends from the past, present, and future through a technology roadmap, it assists in the development of product technology for businesses. Motorola was one of the first companies to utilize a technology roadmap in the late 1970s for the development of car radio transistors, integrating product and technology modules. Former Chairman Robert Galvin was an advocate for technology roadmaps. The definition of a technology roadmap is given as follows [49]: "Technology roadmap is a synthesis of industry knowledge and imagination about the future development of the selected research field, gathered by the key proponents in the industry, to drive the positive advancement of technology". In the face of numerous competitive challenges, using a technology roadmap as a technical plan for product development helps in an increasingly competitive environment; moreover, a technology roadmap should be considered as an effective tool for technical planning and coordination, suitable for a wider range of planning activities. The main benefit of a technology roadmap is its ability to identify key technologies and technological gaps, as well as determining the method for utilizing research and development investments [50]. A generic technology roadmap typically includes the evolution of time on the horizontal axis (past, present, and future) and multiple aspects on the vertical axis, often including market, product, and technology. Products are positioned between the market and technology, achieving supply–demand balance through communication facilitated via the use of a technology roadmap [51]. Technology roadmaps can enhance the foresight and innovation of enterprises, integrating the improvement process of new product development into technology modules mapped out as a technology roadmap [52]. The application of technology roadmaps has emerged as a crucial tool for forecasting future market directions and technological advancements, serving as the basis for strategic decision making, particularly in key technology domains. The process of technology roadmaps should evolve with the changes in R&D generations (or characteristics) because technology and R&D planning, as well as strategic planning, are key areas of technology roadmaps [53]. The method of collecting data from the literature has been used to study and analyze case studies of technology roadmaps [54,55]. The TRM Kaizen method for technology roadmaps can serve as a methodology to upgrade the process and outputs of technology roadmaps from the perspective of achieving industrial technology policy goals [56]. A valuable technology roadmap can be created through multiple rounds of questionnaire interviews with participants including scholars, consultants, and professionals. The primary suggestion is to consider customer viewpoints in developing technology roadmaps to increase its reference value [57]. Technology roadmaps can be used to analyze the trends of Industry 4.0, as well as to understand the future development of industries. Through the identification of literature texts, analyzing data related to Industry 4.0, it is anticipated that by 2030, industries will move towards artificial intelligence, automation, and digitization [58]. Semantics are used for big data search analysis to identify key data, integrating them with technology roadmaps. This process is carried out by organizing and summarizing, inviting experts to evaluate the importance of assessment indicators, and creating a technology roadmap that can be used for monitoring market demand, product development, and technology development trends [59,60].

3. Methods

3.1. Research Scope and Constraints

The development of computer numerical control machine tools has been ongoing for decades, with advanced countries worldwide continuously investing in research and development efforts to strive for excellence. This aims to meet the evolving needs of customers, based on predicting the development trends of computer numerical control machine tools. This study aims to assist manufacturers in aligning towards Industry 4.0 and progressing towards Industry 5.0. In the short-term research, a cautious approach will be taken to analyze future trends. Due to limited time and data availability, this study will focus on the development of the vertical machining center (CNC) VPM-23 produced by Taiwan's FAIR FRIEND GROUP as an example. Experts from academia and industry will be invited to analyze the feasibility and demand of the product's technical features for industry development. The study will utilize technology roadmapping to predict the future development of computer numerical control machine tools.

3.2. Methodology

We employed a qualitative research methodology with in-depth interviews, engaging in one-on-one, face-to-face discussions to facilitate comprehensive expression of opinions by interviewed experts. This approach allows for a thorough examination of experts' viewpoints on computer numerical control machine tools and their perspectives on future development. The data gathered from the interviews were synthesized for analysis. We used the fuzzy Delphi method to conduct expert questionnaires, obtaining preliminary data for integration, quantitatively analyzing the questionnaire data, and then using the double triangular fuzzy number to determine the consensus importance values of experts. This iterative process continued until converging results were achieved. We used the fuzzy analytic hierarchy process (FAHP) to complement the technology items with expert consensus, determining the importance ranking of the overall hierarchical structure. Ultimately, a predictive technology roadmap was created.

This study utilizes semi-structured interviews [61,62] to invite 16 expert scholars for in-depth interviews, selecting experts with extensive experience in the field of computer numerical control machine tools. The interviewees include industry experts, research institution experts, and academic scholars, allowing for diverse perspectives and experiences on the development trends of computer numerical control machine tools. Through the insights and experiences shared by experts from different backgrounds and roles during the interview process, this study aims to gain a better understanding of the future technological development trends in the CNC machine tool industry and market demands. The interview records will be compiled to create an evaluation framework, as shown in Figure 2.

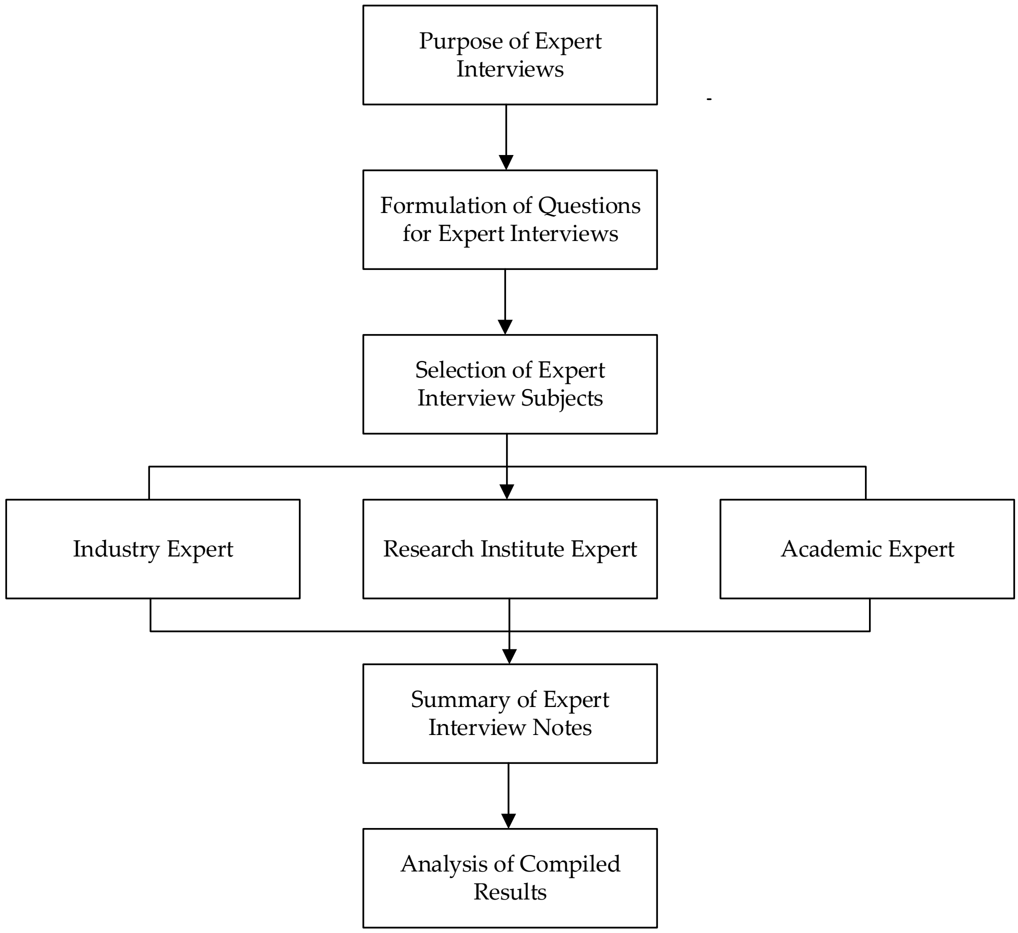

Figure 2. Process diagram for planning expert interviews.

3.3. The Research Process of the Fuzzy Delphi Method

The flowchart in Figure 3 outlines the research process of the fuzzy Delphi method, based on the evaluation framework synthesized from expert interviews. Following the expert interviews, expert questionnaires will be conducted to confirm the semantic understanding of the aggregated technical items. Subsequently, the fuzzy Delphi method will be employed to design fuzzy expert questionnaires, with input from 16 expert scholars participating in the survey. The experts' assessments of the importance of each indicator will be compiled and the most conservative and optimistic values statistically determined for each indicator. After eliminating extreme values beyond 2 standard deviations, the triangular fuzzy numbers representing the most optimistic and conservative values of each indicator will be created as evaluated by the experts. Lastly, convergence will be verified using the grey zone test method to examine whether consensus has been reached among the academic scholars and experts.

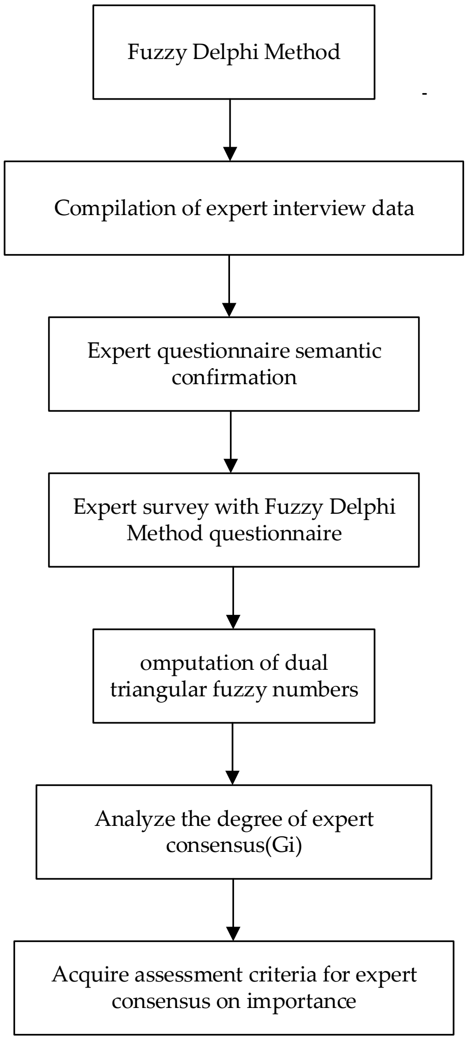

Figure 3. Research flow chart of the fuzzy Delphi method.

3.4. Research Process of the Fuzzy Analytic Hierarchy Process

This study will utilize the fuzzy Delphi method to establish expert consensus on the importance of criteria assessment for evaluating the development trends of CNC machine tools, leading to the identification of key development technology criteria. Subsequently, the fuzzy analytic hierarchy process will be applied to derive the weights of evaluation criteria, technical items, and sub-technical items associated with the development trends of CNC machine tools, enabling the determination of an essential ranking for technical development and the creation of a technology roadmap. The flowchart is shown in Figure 4.

The improved fuzzy analytic hierarchy process, based on Buckley's modification [44], combines fuzzy theory and analytic hierarchy to address issues encountered by experts when assessing the importance between two factors. The implementation steps are referenced from Chen-Shu Wang's fuzzy analytic hierarchy process [63], with the following application steps:

1. Construct the hierarchical structure for evaluating the development trends of computer numerical control machine tools based on the important development technology items obtained from the expert consensus on the importance assessment through the fuzzy Delphi method questionnaire, as shown in Figure 5.
2. Scale for criteria evaluation: After establishing the evaluation hierarchical structure, conduct pairwise comparison scale importance assessments between two criteria for each technical item at each level. Saaty [42] divides the pairwise comparison scale in the Analytic Hierarchy Process into 1 to 9 levels, representing equally important,

slightly important, fairly important, very important, absolutely important, and the adjacent values between each scale, as shown in Table 1. The semantic scale rating questionnaire for assessing relative importance is classified into five categories: equally important, slightly important, fairly important, very important, and absolutely important. The quantification of the semantic evaluation scale is arranged as 1, 3, 5, 7, and 9 based on the expert questionnaire results. Additionally, the adjacent values between the five scales of relative importance semantic scales are 2, 4, 6, and 8.

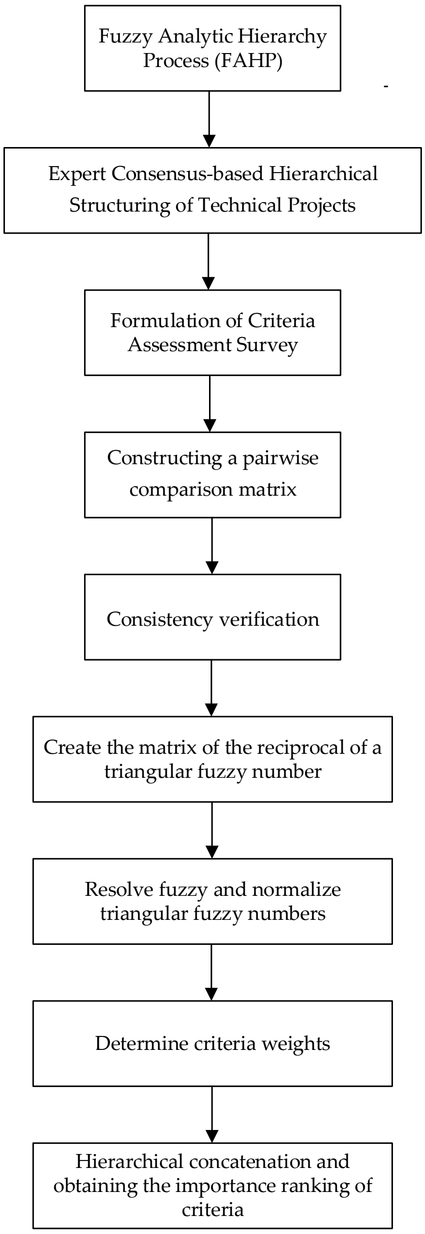

Figure 4. Process diagram for fuzzy AHP research.

3. Constructing a pairwise comparison matrix: Following the fuzzy analytic hierarchy process questionnaire survey, create pairwise comparison matrices by considering each expert's relative importance assessments of the criteria for each technical item at each level. This process generates $(n(n-1))/2$ results from pairwise comparisons of the n technical items under a specific technical item at the higher level. The quantified semantic evaluation scale results of each expert are utilized to construct a pairwise comparison matrix. The diagonal elements indicate comparisons within the same technical item, with a value of 1 representing equal importance. The upper triangular

part of the pairwise comparison matrix reflects the ratios obtained from pairwise comparisons of the n technical items, while the lower triangular part comprises the reciprocals of the values in the upper triangular part, where $a_{ij} = \frac{1}{a_{ij}}$. Thus, the pairwise comparison matrix is also known as a positive reciprocal matrix. The formula for the pairwise comparison matrix is shown as Equation (1):

$$A^k = \left[a_{ij}\right]^k = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{bmatrix}^k \tag{1}$$

- A^{k}: Pairwise comparison matrix for the k-th expert;
- aij: The ratio of the importance level between the i-th evaluation element and the j-th evaluation element;
- When a_{ij} = 1, then i = j;
- When $a_{ij} = \frac{1}{a_{ij}}$, then i, j = 1, 2, 3, 4, . . ., n.

4. Computing the largest eigenvalue (λmax) and eigenvector: Determine the maximum eigenvalue λmax and eigenvector by processing the pairwise comparison matrices provided by each expert, and derive the corresponding weight values.
5. Consistency verification: Achieving transitivity in pairwise comparisons of importance is quite difficult for experts, but in order to obtain objective and accurate evaluations of each technical item, consistency verification is necessary. This involves calculating the Consistency Index (C.I.) and Consistency Ratio (C.R.) at each level to check whether the experts' assessments of importance are consistent. The Consistency Index (C.I.) and Consistency Ratio (C.R.) are used to assess the consistency of weights. According to Saaty's research recommendations, it is suggested that the values of C.I. and C.R. should ideally be less than or equal to 0.1 to be considered an acceptable range for passing the consistency verification. Otherwise, it indicates issues among the criteria at the level, requiring further analysis of all criteria items. The calculation formulas for the Consistency Index (C.I.) and Consistency Ratio (C.R.) are as shown below:
   - Consistency Index (C.I.)
     Calculating the Consistency Index involves first determining the maximum eigenvalue, with the formula shown below:

$$\sum_{j=1}^{n} a_{ij} w_j = \lambda_{max} w_i \tag{2}$$

     Following that, the Consistency Index (C.I.) is determined by the calculation involving the maximum eigenvalue (λmax), with the formula provided as follows:

$$C.I. = \frac{\lambda_{max} - n}{n - 1} \tag{3}$$

   - Consistency Ratio (C.R.)
     The Consistency Ratio is defined as the quotient of the C.I. value and the R.I. value. With an increasing number of comparison questions, the hierarchy of pairwise comparison matrices expands, making consistency assessment more complex. Saaty [33] introduced different C.I. values corresponding to different levels of pairwise comparison matrices, referred to as the random index (R.I.), as shown in Table 2. The C.R. value is the ratio of the C.I. value to the R.I. value.

$$C.R. = \frac{C.I.}{R.I.} \tag{4}$$

According to Saaty's recommendation, the C.R. value is preferably less than or equal to 0.1, signifying a high level of consistency.

6. Determining the triangular fuzzy numbers for technical items at each level: Following the AHP consistency verification, the relative weights of each assessment criterion in each expert's questionnaire can be determined. Then, use fuzzy theory to build triangular fuzzy numbers for each evaluation criterion, establish a fuzzy reciprocal matrix, and set the minimum value (Li), middle value (Mi), and maximum value (Ri) of each criterion as the triangular fuzzy numbers for that evaluation element. The calculation formulas are shown as Equations (5)–(7), where h represents the h-th expert, i represents the i-th evaluation criterion element, and n represents the total number of experts:

$$L_i = min_h\left\{L_i^h, h = 1, 2, \ldots, n\right\} \tag{5}$$

$$M_i = \Pi_{h=1}^{n}\left\{M_i^h, h = 1, 2, \ldots, n\right\}^{\frac{1}{n}} \tag{6}$$

$$R_i = max_h\left\{R_i^h, h = 1, 2, \ldots, n\right\} \tag{7}$$

7. Normalizing triangular fuzzy numbers: Using geometric means to calculate the triangular fuzzy technique for each fuzzy matrix, and normalizing it to (nLi, nMi, nRi), as shown in Equations (8)–(10).

$$\mathrm{n}L_i = \frac{L_j}{\left\{\left[\sum_i^k R_i\right] \times \left[\sum_i^k L_i\right]\right\}^{\frac{1}{2}}} \tag{8}$$

$$\mathrm{n}M_i = \frac{M_i}{\left[\sum_i^k M_i\right]} \tag{9}$$

$$\mathrm{n}R_i = \frac{R_j}{\left\{\left[\sum_i^k R_i\right] \times \left[\sum_i^k L_i\right]\right\}^{\frac{1}{2}}} \tag{10}$$

8. Resolve fuzzy numbers and determine criteria weights: Following the normalization of the triangular fuzzy numbers, proceed with defuzzification. Transform the obtained triangular fuzzy numbers into a real number value, DFi, and ensure that the sum of DFi values obtained for each level criterion is 1, followed by another round of normalization to determine the final weight values DF_i^'. Formulas are as shown in Equations (11) and (12).

$$\mathrm{DF}_i = \frac{\{(nR_i - nL_i) + (nM_i - nL_i)\}}{3} + nL_i \tag{11}$$

$$\mathrm{DF}_i = \frac{\{(nR_i - nL_i) + (nM_i - nL_i)\}}{3} + nL_i \tag{12}$$

9. Hierarchical concatenation and obtaining the importance ranking of criteria: In a multi-level criteria framework, through hierarchical chaining, the global weight values of each sub-criterion to the overall level structure can be determined, leading to the ranking of the importance of each sub-criterion. Hierarchical concatenation involves the weights NWi of the i-th aspect in the first layer under the target layer, the weights NWij of the j-th criterion in the second layer under the i-th aspect in the first layer, and the weights NWijk of the k-th sub-criterion in the third layer under the j-th aspect in the second layer. In order to determine the weight NWk of the k-th sub-criterion in the

third layer under the target layer, hierarchical concatenation is necessary. Formulas are as shown in Equation (13).

$$NW\_k = NW\_i \times NW\_ij \times NW\_ijk \quad (13)$$

Dimension	Technical Project	Sub-Technical Item
A-1 Body structure of the numerical control machine tool	B-1 Body structure	Machine tool main body structure (including machine base, column, bed, spindle head), if a structural model can be established, using topological optimization design to achieve optimal structural rigidity and material lightweighting.
		Set up position sensors, visually compare the overlap of data workpieces and tool paths to ensure correctness, and prevent overcutting and spindle collisions.
	B-2 Spindle and bearing system	Enhancing the assembly precision of the spindle and bearing system, appropriate tolerances can prevent unnecessary deformation and temperature rise during bearing operation.
		Add sensors to the spindle and bearing system to detect the temperature generated during high-speed rotation of the spindle, facilitating feedback to the cooling system for timely temperature adjustment.
		Precision machining of high-precision product components, matching the spindle with cutting conditions based on material properties and tooling, high spindle speed and torque effectively enhance production efficiency.
		Enhance spindle dynamic balance, incorporate structural design to avoid resonance points, reducing resonance during machine operation.
A-2 Control system	B-3 Feed mechanism and servo motor	Utilizing servo intelligent tuning technology in conjunction with overall machine rigidity to swiftly adjust axial dynamic errors, thereby improving the dynamic response characteristics and part accuracy of CNC machine tools.
		Optimizing the micro displacement of the feed mechanism and servo motor will help improve product processing accuracy.
	B-4 Controller	The controller serves as the brain of the numerical control machine tool, responsible for coordinating information management and compensatory actions, enhancing its user-friendly interface, and contributing to the transition towards Industry 5.0.
		Constructing an auxiliary module in the controller—developing intelligent machining setup software to enable operators to quickly complete machining settings.
		Enhancing the controller compensation system to enable timely compensation for errors resulting from structural displacement during machine operation, achieving intelligent control.
		Enhancing the controller compensation system to promptly compensate for processing errors caused by tool wear, while also incorporating tool life and precision management functions to achieve intelligent control.
		Enhancing the controller compensation system to promptly compensate for feed mechanism movement errors, achieving intelligent control.
		Connecting sensors and measurement equipment to communicate, utilizing data collection to provide feedback to the controller system, improving machine processing speed (cost) and precision (quality).

Figure 5. *Cont.*

A-3 Intelligent manufacturing	B-5 Fault diagnosis	Set up remote connection services to handle machine shutdowns due to controller problems, enabling prompt resolution of system malfunctions remotely to minimize machine downtime and production capacity impact.
		Set up remote connection services to handle machine stoppages due to driver problems, allowing for prompt resolution of system faults remotely to reduce machine downtime and minimize the impact on production capacity.
		Remote monitoring and fault detection can predict and resolve issues without the need for manual intervention, minimizing machine downtime.
	B-6 Intelligent monitoring	Intelligent manufacturing utilizes Internet communication and monitoring technologies to conduct fault detection, diagnosis, and monitoring for CNC machine tools.
		Visual monitoring of CNC machine tools enables real-time monitoring of machining conditions, along with sensor data feedback, to prevent errors, promptly address faults, and maintain stable machine operation.
	B-7 Cloud database and data acquisition	Setting up a cloud database enables quick cross-matching for debugging and offers the best machining parameters, leading to a comprehensive processing environment.
		Connecting network devices to machine tools for CNC program analysis enables feedback for optimizing tool paths in subsequent processing, making it vital analytical data for machine monitoring systems.
		Creating a data collection system for analyzing CNC machine data collection technology facilitates swift adjustment of processing conditions (such as feed rate and speed).
		Creating a data collection system for analyzing tool wear measurement data allows for instant feedback for tool wear compensation, enhancing the smart tool life management system.
	B-8 Intelligent Manufacturing	With experienced masters able to communicate, we can move towards the goal of human–machine collaboration in Industry 5.0.
		Connecting and communicating automated equipment (such as robotic arms) is a step towards the goal of human–machine collaboration in Industry 5.0.
		Combining intelligent handling (AGV) with robotic arms is a step towards transitioning from Industry 4.0 to Industry 5.0.

Figure 5. The Hierarchical Structure for Evaluating the Development Trends of CNC Machine Tools.

Table 1. Comparison table of fuzzy scales for semantic variables.

Semantic	Degree of Importance	The Triangular Fuzzy Numbers	Degree of Importance	The Triangular fuzzy Numbers
Equal Importance	1	(1, 1, 3)	1	(1, 1, 3)
Weak Importance	3	(1, 3, 5)	$\frac{1}{3}$	$\frac{1}{5}, \frac{1}{3}, 1$
Essential Importance	5	(3, 5, 7)	$\frac{1}{5}$	$\frac{1}{7}, \frac{1}{5}, \frac{1}{3}$
Very Strong Importance	7	(5, 7, 9)	$\frac{1}{7}$	$\frac{1}{9}, \frac{1}{7}, \frac{1}{5}$
Absolute Importance	9	(7, 9, 9)	$\frac{1}{9}$	$\frac{1}{9}, \frac{1}{9}, \frac{1}{7}$

Source: Compiled by this study.

Table 2. Correspondence table of random indices at each hierarchy.

n	1	2	3	4	5	6	7	8	9	10
Random index (R.I.)	0.00	0.00	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49

Source: R. W. SAATY [42].

3.5. Drawing of a Technology Roadmap

The fuzzy Delphi method with double triangular fuzzy numbers was used to derive the evaluation results of various aspect indicators reaching a consensus convergence level with a degree value of 80 points or above, as a basis for constructing a technology map for the development trend of Computer Numerical Control (CNC) machine tools.

4. Results

4.1. Composition of Expert Panel and Establishment of Evaluation Items

This study invited experts with relevant backgrounds in the field of CNC machine tools to conduct interviews and surveys, including 4 experts from the industry sector, 10 from research institutions, and 2 from the academic sector, totaling 16 experts, as shown in Table 3.

Table 3. Expert background information.

Expert	Education	Domain of Service Unit Location	Position Title	Years of Work Experience
Expert1	Bachelor	Industrial Sector	Section Chief	20~30 years
Expert2	Master	Industrial Sector	Manager	20~30 years
Expert3	Master	Research Institution	Manager	Under 10 years
Expert4	Ph.D.	Industrial Sector	CEO	10~20 years
Expert5	Ph.D.	Research Institution	Deputy Director of Department	Under 10 years
Expert6	Ph.D.	Academic Sector	Professor	Under 10 years
Expert7	Master	Research Institution	Deputy Director of Department	10~20 years
Expert8	Master	Research Institution	Engineer	10~20 years
Expert9	Master	Industrial Sector	Engineer	Under 10 years
Expert10	Master	Research Institution	Engineer	10~20 years
Expert11	Master	Research Institution	Engineer	20~30 years
Expert12	Master	Research Institution	Deputy Manager	Under 10 years
Expert13	Master	Research Institution	Assistant Manager	20~30 years
Expert14	Master	Research Institution	Manager	10~20 years
Expert15	Ph.D.	Academic Sector	Professor	20~30 years
Expert16	Ph.D.	Research Institution	Deputy Manager	20~30 years

Semi-structured interviews were carried out inviting SIX experts and scholars for in-depth interviews, including industry experts, research institution experts, and academic scholars, through experts and scholars with different backgrounds and roles. The experiences provided by the following experts were consolidated in the semi-structured in-depth interviews on the perception and experience of the development trends of computer numerical control machine tools.

Expert1: Factors influencing the improvement of feed precision in computer numerical control machine tools are as follows: rigidity of the feed system, rigidity of the guide (track) system, rigidity of the main structure, matching of the inertia ratio between the servo motor and the feed system, matching of the servo control, accuracy of the ball screw, accuracy of the guide (track) system, accuracy of the bearings in the feed system (supporting the ball screw). Regardless of how the main body structure is designed, there must be its "system natural frequency", so the accuracy of the dynamic balance of the spindle can be corrected according to the detection technology of the dynamic balancing equipment to set the standard for dynamic balance correction.

Expert2: The controller is the heart of the computer numerical control machine tool. In equipment production, the controller is required to achieve precise machining purposes for the entire machine, enhance the user-friendly operation interface, accelerate operators' mastery of various interface settings, and improve production efficiency. Intelligent control can be achieved by constructing more auxiliary modules and improving compensation systems in the controller.

Expert6, Expert9: The construction aspect of the main structure of computer numerical control machine tools can be divided into the main structure and the spindle and bearing system. With the development of numerical control machine tools being ready for many years, further development will focus on improving the spindle and bearing system, enhancing the structural rigidity, reducing the weight of the machine, and lowering production costs, which are essential considerations for the next stage of manufacturing production.

Expert15: The feed mechanism and the servo motor are interrelated, and through the transmission of information from the servo motor, the feed mechanism is moved. The tuning technology of the servo can quickly adjust the axial dynamic error, enhancing the dynamic performance and part accuracy of the CNC machine tool.

Expert16: Intelligent manufacturing is the challenge that manufacturers will face in the future. If intelligent handling (AGV) can be introduced without increasing production costs and combined with robotic arms, it will provide significant assistance in addressing labor shortages and experience transfer, moving towards the goal of Industry 5.0 human–machine collaboration.

Following the confirmation of research aspects and technical projects, the next step involves drafting the sub-technical projects of the technical projects. Throughout the interview process, experts and scholars drew on their experiences in production and research of computer numerical control machine tools to discuss the current development status and future directions of the eight technical projects listed in Figure 6. After consolidation by this study, a total of 34 sub-technical projects were identified. Consulting with 16 experts and scholars to avoid differences in language interpretation with experts and scholars, this study adopts a more cautious attitude and seeks advice from experts and scholars to revise the sub-technical projects of "B-1 Body Structure", "B-2 Spindle and Bearing System", "B-3 Feed Mechanism and Servo Motor", "B-4 Controller", "B-7 Cloud Database and Data acquisition", and "B-8 Intelligent Manufacturing". The revised sub-technical projects are numbered 1, 2, 3, 4, 6, 8, 9, 10, 12, 31, and 32, as shown in Table 4.

Table 4. Fuzzy Delphi method analysis table.

Technical Project	No.	Sub-Technical Item		MIN	MAX	Geometric Avg.	(Ci-Zi)	Gi
B-1 Body structure	1	Machine tool main body structure (including machine base, column, bed, spindle head), if a structural model can be established, using topological optimization design to achieve optimal structural rigidity and material lightweighting.	C	70	90	82.23	1.2532	86.3434
			O	80	100	93.48		
	2	Machine tool main body structure (including machine base, column, bed, spindle head), if a structural model can be established, using topological optimization design to achieve optimal structural rigidity and material lightweighting.	C	60	90	78.66	2.1749	84.8883
			O	80	100	90.84		
B-2 Spindle and bearing system	3	A good cooling system can maintain the original rigidity of the high-speed spindle.	C	30	90	70.69	−37.4540	−1.0000
			O	40	100	83.24		
	4	Enhancing the assembly precision of the spindle and bearing system, appropriate tolerances can prevent unnecessary deformation and temperature rise during bearing operation.	C	60	90	81.10	2.2412	85.9964
			O	80	100	93.34		
	5	Add sensors to the spindle and bearing system to detect the temperature generated during high-speed rotation of the spindle, facilitating feedback to the cooling system for timely temperature adjustment.	C	60	90	80.32	3.0188	85.7939
			O	80	100	93.34		
	6	Precision machining of high-precision product components, matching the spindle with cutting conditions based on material properties and tooling, high spindle speed and torque effectively enhance production efficiency.	C	60	90	80.58	2.8293	85.8737
			O	80	100	93.41		
	7	Enhancing the precision of bearings and aligning with the spindle can decrease noise generated during operation and enhance feed accuracy.	C	50	90	76.73	−17.6524	−1.0000
			O	60	100	89.08		
	8	Enhance spindle dynamic balance, incorporate structural design to avoid resonance points, reducing resonance during machine operation.	C	60	90	81.18	2.8510	86.1382
			O	80	100	94.03		

Table 4. *Cont.*

Technical Project	No.	Sub-Technical Item		MIN	MAX	Geometric Avg.	(Ci-Zi)	Gi
B-3 Feed mechanism and servo motor	9	Utilizing servo intelligent tuning technology in conjunction with overall machine rigidity to swiftly adjust axial dynamic errors, thereby improving the dynamic response characteristics and part accuracy of CNC machine tools.	C	70	90	81.63	1.2427	86.0577
			O	80	100	92.87		
	10	Optimizing the micro displacement of the feed mechanism and servo motor will help improve product processing accuracy.	C	70	90	82.94	2.1028	86.8066
			O	80	100	95.04		
B-4 Controller	11	By using sensor components to provide feedback when the spindle generates resonance at a certain speed during rotation, the controller can perform calculations to avoid parameters that cause resonance.	C	70	90	80.99	−10.9074	−1.0000
			O	70	100	90.08		
	12	The controller serves as the brain of the numerical control machine tool, responsible for coordinating information management and compensatory actions, enhancing its user-friendly interface, and contributing to the transition towards Industry 5.0.	C	60	90	78.50	6.2976	85.6259
			O	80	100	94.79		
	13	Constructing more (interactive) troubleshooting guides in the controller to enable operators to promptly resolve minor issues, enhancing production efficiency.	C	70	90	84.05	−10.7300	−1.0000
			O	70	100	93.32		
	14	Constructing an auxiliary module in the controller—developing intelligent machining setup software to enable operators to quickly complete machining settings.	C	70	90	82.38	1.3393	86.4288
			O	80	100	93.72		
	15	Constructing an auxiliary module in the controller—developing intelligent machining setup software, utilizing computer-aided manufacturing system software to enable the machine to process the required product shape in one go.	C	60	90	79.50	−6.0749	−1.0000
			O	70	100	93.43		
	16	Enhancing the controller compensation system to enable timely compensation for errors resulting from structural displacement during machine operation, achieving intelligent control.	C	70	90	82.23	1.2532	86.3434
			O	80	100	93.48		
	17	Enhancing the controller compensation system to promptly compensate for processing errors caused by tool wear, while also incorporating tool life and precision management functions to achieve intelligent control.	C	70	90	82.29	0.4312	86.2278
			O	80	100	92.72		
	18	Enhancing the controller compensation system to promptly compensate for feed mechanism movement errors, achieving intelligent control.	C	70	90	82.84	1.2632	86.6309
			O	80	100	94.10		
	19	Connecting sensors and measurement equipment to communicate, utilizing data collection to provide feedback to the controller system, improving machine processing speed (cost) and precision (quality).	C	70	90	82.38	0.4168	86.2675
			O	80	100	92.80		
B-5 Fault diagnosis	20	Set up remote connection services to handle machine shutdowns due to controller problems, enabling prompt resolution of system malfunctions remotely to minimize machine downtime and production capacity impact.	C	70	90	81.55	1.9366	86.1458
			O	80	100	93.48		
	21	Set up remote connection services to handle machine stoppages due to driver problems, allowing for prompt resolution of system faults remotely to reduce machine downtime and minimize the impact on production capacity.	C	60	90	79.43	2.0845	85.2123
			O	80	100	91.51		
	22	Remote monitoring and fault detection can predict and resolve issues without the need for manual intervention, minimizing machine downtime.	C	60	90	78.66	2.2454	84.9046
			O	80	100	90.91		

Table 4. *Cont.*

Technical Project	No.	Sub-Technical Item		MIN	MAX	Geometric Avg.	(Ci-Zi)	Gi
B-6Intelligent monitoring	23	Intelligent manufacturing utilizes Internet communication and monitoring technologies to conduct fault detection, diagnosis, and monitoring for CNC machine tools.	C	70	90	82.15	0.04	86.08
			O	80	100	92.19		
	24	Visual monitoring of CNC machine tools enables real-time monitoring of machining conditions, along with sensor data feedback, to prevent errors, promptly address faults, and maintain stable machine operation.	C	70	90	80.27	0.04	85.15
			O	80	100	90.31		
B-7 Cloud database and data acquisition	25	Setting up a cloud database enables quick cross-matching for debugging and offers the best machining parameters, leading to a comprehensive processing environment.	C	60	90	80.09	2.7040	85.6361
			O	80	100	92.80		
	26	The connection of network devices to machine tools for task processing time prediction, facilitating production management, is crucial data for machine monitoring systems.	C	60	90	78.56	−9.2461	−1.0000
			O	70	100	89.32		
	27	The connection of network devices to machine tools for task processing time prediction, facilitating production management, is crucial data for machine monitoring systems.	C	60	90	78.56	−9.3154	−1.0000
			O	70	100	89.25		
	28	Connecting network devices to machine tools for CNC program analysis enables feedback for optimizing tool paths in subsequent processing, making it vital analytical data for machine monitoring systems.	C	60	90	80.09	1.4188	85.3742
			O	80	100	91.51		
	29	Creating a data collection system for analyzing technical data in processing task modeling enables swift setup of workpiece machining.	C	60	90	78.56	−8.5674	−1.0000
			O	70	100	90.00		
	30	Creating a data collection system for analyzing CNC machine data collection technology facilitates swift adjustment of processing conditions (such as feed rate and speed).	C	60	90	79.43	2.6891	85.3398
			O	80	100	92.12		
	31	Creating a data collection system for analyzing tool wear measurement data allows for instant feedback for tool wear compensation, enhancing the smart tool life management system.	C	70	90	82.23	1.2532	86.3434
			O	80	100	93.48		
B-8Intelligent Manufacturing	32	With experienced masters able to communicate, we can move towards the goal of human–machine collaboration in Industry 5.0.	C	70	90	83.34	1.4410	86.8953
			O	80	100	94.78		
	33	Connecting and communicating automated equipment (such as robotic arms) is a step towards the goal of human–machine collaboration in Industry 5.0.	C	60	90	80.76	2.0328	85.8078
			O	80	100	92.80		
	34	Combining intelligent handling (AGV) with robotic arms is a step towards transitioning from Industry 4.0 to Industry 5.0.	C	60	90	80.09	0.8182	85.2408
			O	80	100	90.91		

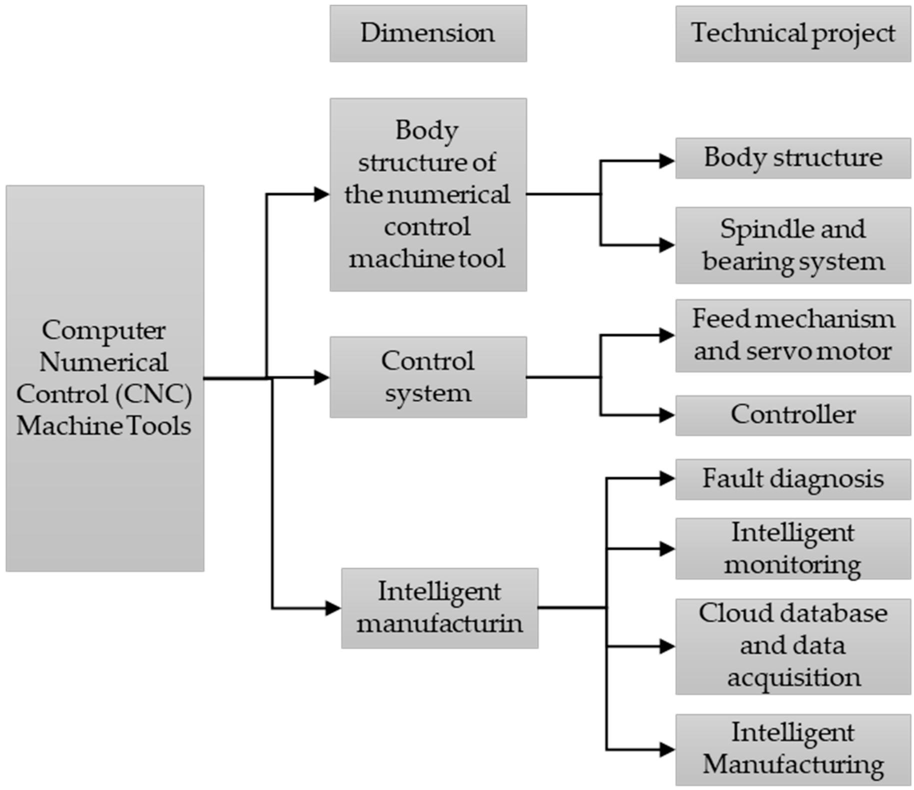

Figure 6. Diagram of research dimension structure.

4.2. Analysis of Results from the Expert Questionnaire Survey Using the Fuzzy Delphi Method

A fuzzy Delphi method expert questionnaire survey on the research aspects, technical projects, and sub-technical projects of computer numerical control machine development trends compiled after expert interviews was conducted. The perceived importance was analyzed by 16 experts and scholars based on the questionnaire results, establishing dual triangular fuzzy numbers after statistical analysis of the most optimistic and most conservative cognitive scores acceptable in experts' semantic thinking, eliminating extreme values by two standard deviations, calculating the geometric mean of the minimum and maximum values acceptable to experts, conducting a grey zone test to determine if the experts' cognition has converged, and deriving the consensus degree values (Gi) of experts on each sub-technical project, as shown in Table 5. All 34 sub-technical projects exhibit the phenomenon of dual triangular overlap, with 26 projects reaching a consensus degree value of 80 or above at the threshold of importance consensus, indicating that experts and scholars consider this indicator to be extremely important. The test values of the other eight sub-technical projects are negative, indicating significant disagreement among experts and failure to converge; thus, they are removed.

Table 5. Analysis result statistical table of FAHP—dimension.

	Dimension	Weight	Rank
A-1	Body structure of the numerical control machine tool	0.0667	3
A-2	Control system	0.5662	1
A-3	Intelligent manufacturing	0.3671	2

λ_{max} = 3.1175, C.I. = 0.0587, C.R. = 0.1013.

Experts and scholars believe that optimizing the rigidity of the numerical control machine tool main body structure in aspect "A-1 Numerical Control Machine Tool Main Body Structure" and technical item "B-1 Main Body Structure" can reduce production costs by lightweighting the overall structure. Verifying the correctness of sensor placement through visual comparison and data matching of workpiece and tool path overlap is crucial to avoid overcutting and spindle collisions. Experts and scholars in the aspect "A-1 Numerical Control Machine Tool Main Body Structure" and technical item "B-2 Spindle and Bearing System" believe that improving the assembly precision of the spindle and bearings, along with the addition of sensor components, can detect the temperature generated by the spindle during high-speed operation. This facilitates timely feedback for temperature adjustment of the cooling system. In terms of rotational speed, high spindle speed and torque effectively enhance production efficiency. High spindle dynamic balance standards, combined with the design of the main body structure to avoid resonance points, help reduce resonance during machine operation.

Experts and scholars in the aspect "A-2 Control System" and technical item "B-3 Feed Mechanism and Servo Motor" believe that intelligent servo tuning technology, combined with overall machine rigidity, allows for rapid adjustment of axial dynamic errors. The slight movements of the feed mechanism and servo motor contribute to improved processing accuracy. Experts and scholars in the aspect "A-2 Control System" and technical item "B-4 Controller" believe that constructing auxiliary modules can enable operators to quickly master the machine and enhance system compensation. This includes addressing errors caused by structural displacement, tool wear leading to processing errors, and feed mechanism movement errors, achieving intelligent control.

Experts and scholars in the aspect "A-3 Intelligent Manufacturing" and technical item "B-5 Troubleshooting" believe that establishing remote connection services to address issues with controllers and drivers that cause machine downtime is crucial. Remote connection allows for timely troubleshooting of system-generated faults, reducing machine downtime and minimizing the impact on production capacity. Experts and scholars in the aspect "A-3 Intelligent Manufacturing" and technical item "B-6 Intelligent Monitoring" believe that utilizing internet communication and (visual) monitoring technology is beneficial for fault detection, diagnosis, and monitoring of CNC machine tools. Experts and scholars in the aspect "A-3 Intelligent Manufacturing" and technical item "B-7 Cloud Database and Data Collection" believe that collecting and analyzing processing parameters, setting processing conditions, and measuring tool wear data can lead to a comprehensive processing environment through the establishment of a cloud database.

4.3. Analysis of Expert Questionnaire Survey Results Using Fuzzy Analytic Hierarchy Process (FAHP)

This study investigates the development trends of CNC machine tools. In the previous section, after analysis using the fuzzy Delphi method by experts and scholars, 26 important consensus indicators for technical items were obtained. In this section, further analysis explores three aspects, eight technical items, and the 26 sub-technical items in the hierarchical structure. Experts and scholars conduct pairwise comparisons of indicators and their importance, determine the consistency index (C.I.) and consistency ratio (C.R.) through pairwise comparisons of indicators, and establish triangular fuzzy numbers to evaluate the indicators. The weight values of technical item indicators in the overall hierarchical structure are calculated, and the importance levels are ranked.

The three main dimensions of the development trend of CNC machine tools, "Body structure of the numerical control machine tool", "Control System", and "Intelligent Manufacturing", are displayed in Table 5 with the weight values and importance ranking in the hierarchical structure. From Table 5, it is observed that the Consistency Index (C.I.) is 0.0587, below 0.1, and the Consistency Ratio (C.R.) is 0.1013, also below 0.1, passing the consistency test. The importance level of the evaluated indicators by experts and scholars is consistent. Experts and scholars consider the "A-2 Control System" dimension to be the most important, followed by the "A-3 Intelligent Manufacturing" dimension, and finally the "A-1 Body structure of the numerical control machine tool" dimension. This indicates that experts and scholars believe that the "A-2 Control System" dimension is the future important development trend for computer numerical control machines. Subsequently, combining with the "A-3 Intelligent Manufacturing" dimension, aiming to move towards Industry 5.0.

The eight technical items under the three main dimensions are categorized as "B-1 Body Structure", "B-2 Spindle and Bearing System", "B-3 Feed Mechanism and Servo Motor", "B-4 Controller", "B-5 Fault diagnosis", "B-6 Intelligent Monitoring", "B-7 Cloud Database and Data acquisition", and "B-8 Intelligent Manufacturing". Their weight values and importance levels in the hierarchical structure are presented in Table 6. According to Table 6, the Consistency Index (C.I.) for the technical items is 0.0671, which is less than 0.1, and the Consistency Ratio (C.R.) is 0.0476, also less than 0.1, passing the consistency test. The importance level of the evaluated indicators by experts and scholars is consistent. Experts and scholars consider the development sequence of the technical items, with the "B-3 Feed Mechanism and Servo Motor" technical item being the most important, followed in sequence by "B-4 Controller", "B-6 Intelligent Monitoring", "B-2 Spindle and Bearing System", "B-5 Fault diagnosis", "B-8 Intelligent Manufacturing", "B-7 Cloud Database and Data acquisition " technical items, and lastly the "B-1 Machine Structure" technical item.

Table 6. Analysis result statistical table of FAHP—technical project.

	Technical Item	**Weight**	**Rank**
B-1	Body structure	0.0257	8
B-2	Spindle and bearing system	0.1330	4
B-3	Feed mechanism and servo motor	0.1885	1
B-4	Controller	0.1440	2
B-5	Fault diagnosis	0.1257	5
B-6	Intelligent monitoring	0.1365	3
B-7	Cloud database and data acquisition	0.1225	7
B-8	Intelligent manufacturing	0.1241	6

λ_{max} = 8.4698, C.I. = 0.0671, C.R. = 0.0476.

In the hierarchy structure, the weight values and importance levels of the sub-technical items under "B-1 Body Structure", such as " B-1-1 Machine tool main body structure (including machine base, column, bed, spindle head), if a structural model can be established, using topological optimization design to achieve optimal structural rigidity and material lightweighting" and "B-1-2 Set up position sensors, visually compare the overlap of data workpieces and tool paths to ensure correctness, and prevent overcutting and spindle collisions" are ranked as shown in Table 7. Table 7 reveals that experts and scholars view the development sequence of the sub-technical items, ranking the "B-1-1 Machine tool main body structure (including machine base, column, bed, spindle head), if a structural model can be established, using topological optimization design to achieve optimal structural rigidity and material lightweighting", as the most important, followed by "B-1-2 Set up position sensors, visually compare the overlap of data workpieces and tool paths to ensure correctness, and prevent overcutting and spindle collisions".

Table 7. Analysis result statistical table of FAHP—body structure.

	Sub-Technical Item	**Weight**	**Rank**
B-1-1	Machine tool main body structure (including machine base, column, bed, spindle head), if a structural model can be established, using topological optimization design to achieve optimal structural rigidity and material lightweighting.	0.6880	1
B-1-2	Set up position sensors, visually compare the overlap of data workpieces and tool paths to ensure correctness, and prevent overcutting and spindle collisions.	0.3120	2

λ_{max} = 2, C.I. = 0.

In the hierarchical structure, the weight values and importance levels of the sub-technical items under "B-2 Spindle and Bearing System", such as "B-2-1 Enhancing the assembly precision of the spindle and bearing system, appropriate tolerances can prevent unnecessary deformation and temperature rise during bearing operation" "B-2-2 Add sensors to the spindle and bearing system to detect the temperature generated during high-speed rotation of the spindle, facilitating feedback to the cooling system for timely temperature adjustment", "B-2-3 Precision machining of high-precision product components, matching the spindle with cutting conditions based on material properties and tooling, high spindle speed and torque effectively enhance production efficiency" and "B-2-4 Enhance spindle dynamic balance, incorporate structural design to avoid resonance points, reducing resonance during machine operation" are ranked in terms of importance as shown in Table 8. According to Table 8, the Consistency Index (C.I.) for the technical items is 0.0285, which is less than 0.1, and the Consistency Ratio (C.R.) is 0.0317, also less than 0.1, passing the consistency test. The importance level of the evaluated indicators by experts and scholars is consistent. Experts and scholars consider the development sequence of the sub-technical items, ranking "B-2-1 Enhancing the assembly precision of the spindle and bearing system, appropriate tolerances can prevent unnecessary deformation and temperature rise during bearing operation" as the most important, followed by "B-2-4 Enhance spindle dynamic balance, incorporate structural design to avoid resonance points, reducing resonance during machine operation", "B-2-2 Add sensors to the spindle and bearing system to detect the temperature generated during high-speed rotation of the spindle, facilitating feedback to the cooling system for timely temperature adjustment", and lastly "B-2-3 Precision machining of high-precision product components, matching the spindle with cutting conditions based on material properties and tooling, high spindle speed and torque effectively enhance production efficiency".

Table 8. Analysis result statistical table of FAHP—spindle and bearing system.

	Sub-Technical Item	**Weight**	**Rank**
B-2-1	Enhancing the assembly precision of the spindle and bearing system, appropriate tolerances can prevent unnecessary deformation and temperature rise during bearing operation.	0.3917	1
B-2-2	Add sensors to the spindle and bearing system to detect the temperature generated during high-speed rotation of the spindle, facilitating feedback to the cooling system for timely temperature adjustment.	0.1890	3
B-2-3	Precision machining of high-precision product components, matching the spindle with cutting conditions based on material properties and tooling, high spindle speed and torque effectively enhance production efficiency.	0.1456	4
B-2-4	Enhance spindle dynamic balance, incorporate structural design to avoid resonance points, reducing resonance during machine operation.	0.2737	2

λ_{max} = 4.0855, C.I. = 0.0285, C.R. = 0.0317.

Concerning the sub-technical items of 'B-3 Feed Mechanism and Servo Motor', "B-3-1 Utilizing servo intelligent tuning technology in conjunction with overall machine rigidity to swiftly adjust axial dynamic errors, thereby improving the dynamic response characteristics and part accuracy of CNC machine tools", and "B-3-2 Optimizing the micro displacement of the feed mechanism and servo motor will help improve product processing accuracy", the weight values and levels of importance within the hierarchical structure are as indicated in Table 9. According to Table 9, experts believe that among the sub-technical projects, "B-3-1 Utilizing servo intelligent tuning technology in conjunction with overall machine rigidity to swiftly adjust axial dynamic errors, thereby improving the dynamic response characteristics and part accuracy of CNC machine tools" is of utmost importance, followed by "B-3-2 Optimizing the micro displacement of the feed mechanism and servo motor will help improve product processing accuracy" of products.

Table 9. Analysis result statistical table of FAHP—feed mechanism and servo motor.

	Sub-Technical Item	Weight	Rank
B-3-1	Utilizing servo intelligent tuning technology in conjunction with overall machine rigidity to swiftly adjust axial dynamic errors, thereby improving the dynamic response characteristics and part accuracy of CNC machine tools.	0.6080	1
B-3-2	Optimizing the micro displacement of the feed mechanism and servo motor will help improve product processing accuracy.	0.3920	2

λ_{max} = 2, C.I. = 0.

The sub-technical items of 'B-4 Controller', 'B-4-1 The controller serves as the brain of the numerical control machine tool, responsible for coordinating information management and compensatory actions, enhancing its user-friendly interface, and contributing to the transition towards Industry 5.0', 'B-4-2 Constructing an auxiliary module in the controller—developing intelligent machining setup software to enable operators to quickly complete machining settings', 'B-4-3 Enhancing the controller's compensation system, allowing for real-time compensation for errors caused by structural displacement during operation, achieving intelligent control', 'B-4-4 Enhancing the controller compensation system to promptly compensate for processing errors caused by tool wear, while also incorporating tool life and precision management functions to achieve intelligent control', 'B-4-5 Enhancing the controller compensation system to promptly compensate for feed mechanism movement errors, achieving intelligent control', and 'B-4-6 Connecting sensors and measurement equipment to communicate, utilizing data collection to provide feedback to the controller system, improving machine processing speed (cost) and precision (quality)', are ranked by their weight values and levels of importance in the hierarchical structure as shown in Table 10". According to Table 10, the consistency test analysis of the technical projects shows a Consistency Index (C.I.) of 0.0085, which is less than 0.1, and a Consistency Ratio (C.R.) of 0.0068, also less than 0.1, indicating that the consistency test has been passed. The importance level of the evaluated indicators by experts and scholars is consistent. Experts and scholars consider the development sequence of sub-technical projects, with 'B-4-4 Enhancing the controller compensation system to promptly compensate for processing errors caused by tool wear, while also incorporating tool life and precision management functions to achieve intelligent control' as the most critical, having a weight of 0.2167. This indicates that experts prioritize the perfection of the controller compensation system in the development of Computer Numerical Control (CNC) machine tools, significantly benefiting the machining of parts. This is followed by 'B-4-3 Perfecting the controller compensation system to compensate for errors due to structural displacement during operation, achieving intelligent control', 'B-4-1 The controller serves as the brain of the numerical control machine tool, responsible for coordinating information management and compensatory actions, enhancing its user-friendly interface, and contributing to the transition towards Industry 5.0.', 'B-4-5 Enhancing the controller compensation system to promptly compensate for feed mechanism movement errors, achieving intelligent control', 'B-4-6 Connecting sensors and measurement equipment to communicate, utilizing data collection to provide feedback to the controller system, improving machine processing speed (cost) and precision (quality)', and finally 'B-4-2 Constructing an auxiliary module in the controller—developing intelligent machining setup software to enable operators to quickly complete machining settings'.

Table 10. Analysis result statistical table of FAHP—controller.

	Sub-Technical Item	Weight	Rank
B-4-1	The controller serves as the brain of the numerical control machine tool, responsible for coordinating information management and compensatory actions, enhancing its user-friendly interface, and contributing to the transition towards Industry 5.0.	0.1826	3
B-4-2	Constructing an auxiliary module in the controller—developing intelligent machining setup software to enable operators to quickly complete machining settings.	0.1090	6
B-4-3	Enhancing the controller compensation system to enable timely compensation for errors resulting from structural displacement during machine operation, achieving intelligent control.	0.1829	2
B-4-4	Enhancing the controller compensation system to promptly compensate for processing errors caused by tool wear, while also incorporating tool life and precision management functions to achieve intelligent control.	0.2167	1
B-4-5	Enhancing the controller compensation system to promptly compensate for feed mechanism movement errors, achieving intelligent control.	0.1712	4
B-4-6	Connecting sensors and measurement equipment to communicate, utilizing data collection to provide feedback to the controller system, improving machine processing speed (cost) and precision (quality).	0.1376	5

λ_{max} = 6.0423, C.I. = 0.0085, C.R. = 0.0068.

The sub-technical items of ‘B-5 Troubleshooting’, ‘B-5-1 Set up remote connection services to handle machine shutdowns due to controller problems, enabling prompt resolution of system malfunctions remotely to minimize machine downtime and production capacity impact’, ‘B-5-2 Set up remote connection services to handle machine stoppages due to driver problems, allowing for prompt resolution of system faults remotely to reduce machine downtime and minimize the impact on production capacity’, and ‘B-5-3 Remote monitoring and fault detection do not require manual intervention, capable of predicting and immediately rectifying problems, thus decreasing machine downtime’, are ranked in terms of weight values and importance levels in the hierarchical structure as shown in Table 11. Table 11 reveals that the consistency test analysis of the technical items shows a Consistency Index (C.I.) of 0.038, which is below 0.1, and a Consistency Ratio (C.R.) of 0.0066, also below 0.1, indicating that the consistency test has been passed. The importance level of the evaluated indicators by experts and scholars is consistent. Experts and scholars believe that in the sequence of development for sub-technical projects, ‘B-5-1 Set up remote connection services to handle machine shutdowns due to controller problems, enabling prompt resolution of system malfunctions remotely to minimize machine downtime and production capacity impact’ is of utmost importance. This is followed by ‘B-5-3 Remote monitoring and fault detection that do not require manual intervention, capable of predicting and immediately resolving issues to minimize machine downtime’, and lastly, ‘B-5-2 Set up remote connection services to handle machine stoppages due to driver problems, allowing for prompt resolution of system faults remotely to reduce machine downtime and minimize the impact on production capacity’.

Table 11. Analysis result statistical table of FAHP—fault diagnosis.

	Sub-Technical Item	Weight	Rank
B-5-1	Set up remote connection services to handle machine shutdowns due to controller problems, enabling prompt resolution of system malfunctions remotely to minimize machine downtime and production capacity impact.	0.3772	1
B-5-2	Set up remote connection services to handle machine stoppages due to driver problems, allowing for prompt resolution of system faults remotely to reduce machine downtime and minimize the impact on production capacity.	0.2637	3
B-5-3	Remote monitoring and fault detection can predict and resolve issues without the need for manual intervention, minimizing machine downtime.	0.3591	2

λ_{max} = 3.077, C.I. = 0.038, C.R. = 0.0066.

In the sub-technical items of 'B-6 Intelligent Monitoring', 'B-6-1 Intelligent manufacturing utilizes Internet communication and monitoring technologies to conduct fault detection, diagnosis, and monitoring for CNC machine tools', and 'B-6-2 Visual monitoring of CNC machines in real-time processing conditions, with sensor data feedback, can prevent errors, promptly eliminate faults, and ensure stable machine operation'. The weight values and importance levels are ranked in the hierarchical structure as shown in Table 12. Table 12 indicates that experts and scholars consider the development sequence of sub-technical projects to prioritize 'B-6-1 Intelligent manufacturing utilizes Internet communication and monitoring technologies to conduct fault detection, diagnosis, and monitoring for CNC machine tools' as the most important. This is followed by 'B-6-2 Real-time visual monitoring of CNC machines, along with feedback from sensing components, which can prevent errors, promptly resolve faults, and ensure stable machine operation'.

Table 12. Analysis result statistical table of FAHP—intelligent monitoring.

	Sub-Technical Item	Weight	Rank
B-6-1	Intelligent manufacturing utilizes Internet communication and monitoring technologies to conduct fault detection, diagnosis, and monitoring for CNC machine tools.	0.5450	1
B-6-2	Visual monitoring of CNC machine tools enables real-time monitoring of machining conditions, along with sensor data feedback, to prevent errors, promptly address faults, and maintain stable machine operation.	0.4550	2

λ_{max} = 2, C.I. = 0.

In the sub-technical items of 'B-7 Cloud Database and Data acquisition', 'B-7-1 Setting up a cloud database enables quick cross-matching for debugging and offers the best machining parameters, leading to a comprehensive processing environment', 'B-7-2 Connecting network devices to machine tools for CNC program analysis enables feedback for optimizing tool paths in subsequent processing, making it vital analytical data for machine monitoring systems', 'B-7-3 Creating a data collection system for analyzing CNC machine data collection technology facilitates swift adjustment of processing conditions (such as feed rate and speed)', and 'B-7-4 Creating a data collection system for analyzing tool wear measurement data allows for instant feedback for tool wear compensation, enhancing the smart tool life management system', the weight values and importance levels are ranked in the hierarchical structure as shown in Table 13. Table 13 reveals that the consistency test analysis of the technical project shows a Consistency Index (C.I.) of 0.0285 and a Consistency Ratio (C.R.) of 0.0317, both below 0.1, indicating the test has passed the consistency examination. The importance level of the evaluated indicators by experts and scholars is consistent. The consensus among experts and scholars indicates that the importance levels of the evaluation indicators align. They consider 'B-7-4 Creating a data collection system for analyzing tool wear measurement data allows for instant feedback for tool wear compensation, enhancing the smart tool life management system' as the most critical. This is followed by 'B-7-2 Connecting network devices to machine tools for CNC program analysis enables feedback for optimizing tool paths in subsequent processing, making it vital analytical data for machine monitoring systems', then 'B-7-3 Creating a data collection system for analyzing CNC machine data collection technology facilitates swift adjustment of processing conditions (such as feed rate and speed)', and finally 'B-7-1 Setting up a cloud database enables quick cross-matching for debugging and offers the best machining parameters, leading to a comprehensive processing environment'.

Table 13. Analysis result statistical table of FAHP—cloud database and data acquisition.

	Sub-Technical Item	**Weight**	**Rank**
B-7-1	Setting up a cloud database enables quick cross-matching for debugging and offers the best machining parameters, leading to a comprehensive processing environment.	0.2205	4
B-7-2	Connecting network devices to machine tools for CNC program analysis enables feedback for optimizing tool paths in subsequent processing, making it vital analytical data for machine monitoring systems.	0.2456	2
B-7-3	Creating a data collection system for analyzing CNC machine data collection technology facilitates swift adjustment of processing conditions (such as feed rate and speed).	0.2315	3
B-7-4	Creating a data collection system for analyzing tool wear measurement data allows for instant feedback for tool wear compensation, enhancing the smart tool life management system.	0.3025	1

λ_{max} = 4.0855, C.I. = 0.0285, C.R. = 0.0317.

In the sub-technical items of 'B-8 Intelligent Manufacturing', 'B-8-1 With experienced masters able to communicate, we can move towards the goal of human–machine collaboration in Industry 5.0', 'B-8-2 Connecting and communicating automated equipment (such as robotic arms) is a step towards the goal of human–machine collaboration in Industry 5.0', and 'B-8-3 Combining intelligent handling (AGV) with robotic arms is a step towards transitioning from Industry 4.0 to Industry 5.0', the ranking of weight values and importance levels in the hierarchical structure is shown in Table 14. Table 14 reveals that the consistency test analysis of the technical project shows a Consistency Index (C.I.) of 0.0001 and a Consistency Ratio (C.R.) of 0.0002, both below 0.1, thereby passing the consistency examination. The importance level of the evaluated indicators by experts and scholars is consistent. Experts and scholars believe that in the sequence of development for the sub-technical project, 'B-8-3 Combining intelligent handling (AGV) with robotic arms is a step towards transitioning from Industry 4.0 to Industry 5.0' is of paramount importance, with a weight value of 0.4831. This indicates that the integration of smart transport and robotic arms is seen as the future production trend for manufacturers; thus, incorporating these devices into CNC machine tools will further advance towards Industry 5.0. Following this, 'B-8-2 Connecting and communicating automated equipment (such as robotic arms) is a step towards the goal of human–machine collaboration in Industry 5.0', and finally

'B-8-1 With experienced masters able to communicate, we can move towards the goal of human–machine collaboration in Industry 5.0'.

Table 14. Analysis result statistical table of FAHP—intelligent manufacturing.

	Sub-Technical Item	Weight	Rank
B-8-1	With experienced masters able to communicate, we can move towards the goal of human–machine collaboration in Industry 5.0.	0.2180	3
B-8-2	Connecting and communicating automated equipment (such as robotic arms) is a step towards the goal of human–machine collaboration in Industry 5.0.	0.2989	2
B-8-3	Combining intelligent handling (AGV) with robotic arms is a step towards transitioning from Industry 4.0 to Industry 5.0.	0.4831	1

λ_{max} = 3.0002, C.I. = 0.0001, C.R. = 0.0002.

In the fuzzy hierarchical analysis method, from the aforementioned results of the analysis, the weights and importance rankings of each level are obtained and have passed the consistency index test, indicating that the dimensions, technical projects, and sub-technical projects all meet the standards of consistency. To determine the overall hierarchical structure constructed in this study, the proportion of sub-technical projects in the total weight must be calculated through hierarchical linkage to obtain their global weight values and importance rankings. Table 15 is a statistical table of hierarchical linkage analysis results, intended to serve as a reference for future development trends for CNC machine tool manufacturers.

Table 15. Results table for hierarchical connection analysis via fuzzy hierarchical analysis technique.

Dimension	Technical Project		Sub-Technical Item	G.W.	Rank
A-1 Body structure of the numerical control machine tool	B-1 Body structure	B-1-1	Machine tool main body structure (including machine base, column, bed, spindle head), if a structural model can be established, using topological optimization design to achieve optimal structural rigidity and material lightweighting.	0.0012	25
		B-1-2	Set up position sensors, visually compare the overlap of data workpieces and tool paths to ensure correctness, and prevent overcutting and spindle collisions.	0.0005	26
	B-2 Spindle and bearing system	B-2-1	Enhancing the assembly precision of the spindle and bearing system, appropriate tolerances can prevent unnecessary deformation and temperature rise during bearing operation.	0.0035	21
		B-2-2	Add sensors to the spindle and bearing system to detect the temperature generated during high-speed rotation of the spindle, facilitating feedback to the cooling system for timely temperature adjustment.	0.0017	23
		B-2-3	Precision machining of high-precision product components, matching the spindle with cutting conditions based on material properties and tooling, high spindle speed and torque effectively enhance production efficiency.	0.0013	24
		B-2-4	Enhance spindle dynamic balance, incorporate structural design to avoid resonance points, reducing resonance during machine operation.	0.0024	22

Table 15. *Cont.*

Dimension	Technical Project		Sub-Technical Item	G.W.	Rank
A-2 Control system	B-3 Feed mechanism and servo motor	B-3-1	Utilizing servo intelligent tuning technology in conjunction with overall machine rigidity to swiftly adjust axial dynamic errors, thereby improving the dynamic response characteristics and part accuracy of CNC machine tools.	0.0649	1
		B-3-2	Optimizing the micro displacement of the feed mechanism and servo motor will help improve product processing accuracy.	0.0418	2
	B-4 Controller	B-4-1	The controller serves as the brain of the numerical control machine tool, responsible for coordinating information management and compensatory actions, enhancing its user-friendly interface, and contributing to the transition towards Industry 5.0.	0.0149	10
		B-4-2	Constructing an auxiliary module in the controller—developing intelligent machining setup software to enable operators to quickly complete machining settings.	0.0089	20
		B-4-3	Enhancing the controller compensation system to enable timely compensation for errors resulting from structural displacement during machine operation, achieving intelligent control.	0.0149	9
		B-4-4	Enhancing the controller compensation system to promptly compensate for processing errors caused by tool wear, while also incorporating tool life and precision management functions to achieve intelligent control.	0.0177	6
		B-4-5	Enhancing the controller compensation system to promptly compensate for feed mechanism movement errors, achieving intelligent control.	0.0140	11
		B-4-6	Connecting sensors and measurement equipment to communicate, utilizing data collection to provide feedback to the controller system, improving machine processing speed (cost) and precision (quality).	0.0112	15
A-3 Intelligent manufacturing	B-5 Fault diagnosis	B-5-1	Set up remote connection services to handle machine shutdowns due to controller problems, enabling prompt resolution of system malfunctions remotely to minimize machine downtime and production capacity impact.	0.0174	7
		B-5-2	Set up remote connection services to handle machine stoppages due to driver problems, allowing for prompt resolution of system faults remotely to reduce machine downtime and minimize the impact on production capacity.	0.0122	14
		B-5-3	Remote monitoring and fault detection can predict and resolve issues without the need for manual intervention, minimizing machine downtime.	0.0166	8
	B-6 Intelligent monitoring	B-6-1	Intelligent manufacturing utilizes Internet communication and monitoring technologies to conduct fault detection, diagnosis, and monitoring for CNC machine tools.	0.0273	3
		B-6-2	Visual monitoring of CNC machine tools enables real-time monitoring of machining conditions, along with sensor data feedback, to prevent errors, promptly address faults, and maintain stable machine operation.	0.0228	4

Table 15. *Cont.*

Dimension	Technical Project	Sub-Technical Item		G.W.	Rank
A-3 Intelligent manufacturing	B-7 Cloud database and data acquisition	B-7-1	Setting up a cloud database enables quick cross-matching for debugging and offers the best machining parameters, leading to a comprehensive processing environment.	0.0099	19
		B-7-2	Connecting network devices to machine tools for CNC program analysis enables feedback for optimizing tool paths in subsequent processing, making it vital analytical data for machine monitoring systems.	0.0110	16
		B-7-3	Creating a data collection system for analyzing CNC machine data collection technology facilitates swift adjustment of processing conditions (such as feed rate and speed).	0.0104	17
		B-7-4	Creating a data collection system for analyzing tool wear measurement data allows for instant feedback for tool wear compensation, enhancing the smart tool life management system.	0.0136	13
	B-8 Intelligent Manufacturing	B-8-1	With experienced masters able to communicate, we can move towards the goal of human–machine collaboration in Industry 5.0.	0.0099	18
		B-8-2	Connecting and communicating automated equipment (such as robotic arms) is a step towards the goal of human–machine collaboration in Industry 5.0.	0.0136	12
		B-8-3	Combining intelligent handling (AGV) with robotic arms is a step towards transitioning from Industry 4.0 to Industry 5.0.	0.0220	5

4.4. Drawing of Technology Roadmaps

Through expert interviews, the fuzzy Delphi method, and fuzzy hierarchical analysis, this study consolidates the above analyses to ascertain the pivotal technologies and their ranked importance for CNC machine tools' development trends. A technology map representing these trends in CNC machine tools is illustrated in Figure 7.

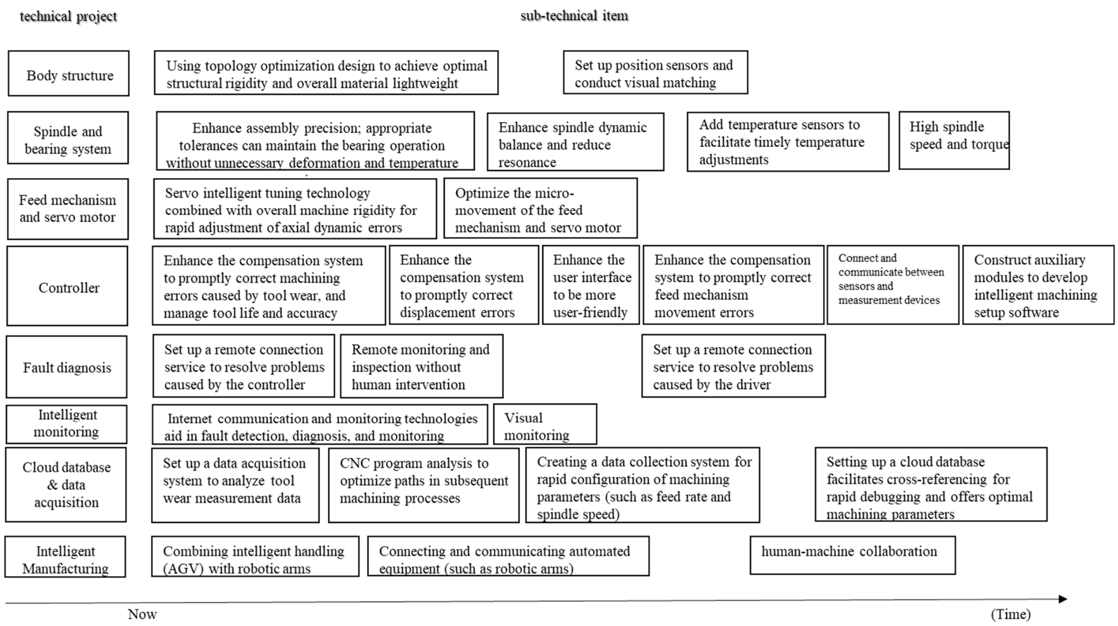

Figure 7. Technological roadmap of development trends in computer numerical control (CNC) machine tools.

5. Conclusions

This study assembled an expert panel of 16 members with extensive experience in CNC machine tools, spanning industrial, research institution, and academic fields. Through interviews with experts from industry, government, and academia, preliminary development aspects and technical projects regarding the trends of CNC machine tools were identified. After compiling and re-confirming the text with the experts, three main aspects, eight technical projects, and thirty-four sub-technical projects were established.

After the analysis performed using the FDM, among the thirty-four sub-technical projects under the eight main technical projects, twenty-six sub-technical projects achieved a consensus importance score of over 80 following a survey among expert scholars.

To ascertain the significant development order of the development trends of CNC machine tools according to expert scholars, analysis was performed through the fuzzy hierarchical analysis method. Subsequent to the experts' pairwise comparisons among indicators, all evaluations complied with the consistency index and consistency ratio checks.

After the hierarchical structure passed the consistency index, triangular fuzzy numbers for evaluation indicators were established. By calculating the weight values of technical project indicators within the overall hierarchy and ranking their importance, a technology map was drawn. This serves as a reference model for CNC machine tool manufacturers for future development trends.

Based on the results of this study, the first development from the seven technical items illustrated in the technology roadmap is as follows:

- Feed mechanism and servo motor: Utilizing servo intelligent tuning technology in conjunction with overall machine rigidity to swiftly adjust axial dynamic errors, thereby improving the dynamic response characteristics and part accuracy of CNC machine tools. (G.W. 0.0649)
- Intelligent manufacturing: Combining intelligent handling (AGV) with robotic arms is a step towards transitioning from Industry 4.0 to Industry 5.0. (G.W. 0.022)
- Controller: Enhancing the controller compensation system to promptly compensate for processing errors caused by tool wear, while also incorporating tool life and precision management functions to achieve intelligent control. (G.W. 0.0177)
- Fault diagnosis: Set up remote connection services to handle machine shutdowns due to controller problems, enabling prompt resolution of system malfunctions remotely to minimize machine downtime and production capacity impact. (G.W. 0.0174)
- Cloud database and data acquisition: Creating a data collection system for analyzing tool wear measurement data allows for instant feedback for tool wear compensation, enhancing the smart tool life management system. (G.W. 0.0136)
- Spindle and bearing system: Enhancing the assembly precision of the spindle and bearing system, appropriate tolerances can prevent unnecessary deformation and temperature rise during bearing operation. (G.W. 0.0035)
- Body structure: Machine tool main body structure (including machine base, column, bed, spindle head), if a structural model can be established, using topological optimization design to achieve optimal structural rigidity and material lightweighting. (G.W. 0.0012)

This study aims to present a technological roadmap for the development of computer numerical control (CNC) machine tools. The research analysis results indicate that the critical keys to technological development include servo intelligent tuning technology and AI-based intelligent monitoring. These technologies are crucial for prioritized development and will aid in the future collaboration between machine tools and robots, advancing towards Industry 5.0.

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