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An Integrated Fuzzy Delphi and Fuzzy AHP Model for Evaluating Factors Affecting Human Errors in Manual Assembly Processes

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Abstract: Human errors (HEs) are prevalent issues in manual assembly, leading to product defects and increased costs. Understanding and knowing the factors influencing human errors in manual assembly processes is essential for improving product quality and efficiency. This study aims to determine and rank factors influencing HEs in manual assembly processes based on expert judgments. To achieve this objective, an integrated model was developed using two multi-criteria decision-making (MCDM) techniques—specifically, the fuzzy Delphi Method (FDM) and the fuzzy Analytic Hierarchy Process (FAHP). Firstly, two rounds of the FDM were conducted to identify and categorize the primary factors contributing to HEs in manual assembly. Expert consensus with at least 75% agreement determined that 27 factors with influence scores of 0.7 or higher significantly impact HEs in these processes. After that, the priorities of the 27 influencing factors in assembly HEs were determined using a third round of the FAHP method. Data analysis was performed using SPSS 22.0 to evaluate the reliability and normality of the survey responses. This study has divided the affecting factors on assembly HEs into two levels: level 1, called main factors, and level 2, called sub-factors. Based on the final measured weights for level 1, the proposed model estimation results revealed that the most influential factors on HEs in a manual assembly are the individual factor, followed by the tool factor and the task factor. For level 2, the model results showed a lack of experience, poor instructions and procedures, and misunderstanding as the most critical factors influencing manual assembly errors. Sensitivity analysis was performed to determine how changes in model inputs or parameters affect final decisions to ensure reliable and practical results. The findings of this study provide valuable insights to help organizations develop effective strategies for reducing worker errors in manual assembly. Identifying the key and root factors contributing to assembly errors, this research offers a solid foundation for enhancing the overall quality of final products.

Keywords: integrated model; human errors; manual assembly; fuzzy Delphi; fuzzy AHP

1. Introduction

Manual assembly is a human-centric process where skilled workers use their hands and cognitive abilities to combine components into finished products [1]. This task necessitates spatial problem-solving, requiring workers to mentally visualize and interact with the assembly process [2]. Work instructions are crucial in this context, as their clarity and effectiveness greatly influence the performance of assemblers and thus reduce their errors [3–6]. Optimal work instructions should be easily understandable, outlining component usage and assembly procedures to minimize cognitive load that leads to human errors (HEs) [5]. The universal accessibility of work instructions is a widely accepted principle [7]. Traditionally, digital work instructions combining text and visuals have been the norm [3–6]. However, Mattsson et al. [8] advocate for highly perceptual instructions, suggesting richer sensory inputs. Three-dimensional models incorporated into work instructions (MBIs)

enhance realism, precision, and clarity in representing the assembly process [9,10]. These models can provide multiple perspectives and essential assembly guidance.

The assembly process is a critical stage in manufacturing, directly influencing the final product's quality. Engineers meticulously select assembly systems based on factors such as flexibility, product variety, production volume, and productivity [7,11]. While manual assembly systems offer greater flexibility and product variety, they typically exhibit lower productivity and production volume than automated systems. Worker productivity, a measure of output per worker or group, is a key consideration. Despite the advancements in automation, including the significant contributions of industrial robots, product complexity, and diversity remain challenges hindering the complete replacement of manual labor in assembly [7,12]. As a result, manual assembly plays a critical role in numerous industries, including engines, different-size electronics, telecommunications, aviation, automotive, and machinery manufacturing [13,14]. This process is vital for ensuring precision and quality in the construction of complex products, allowing for the meticulous attention to detail that is often necessary in these high-stakes fields.

Successful manual assembly requires implementing several steps to ensure the product meets quality standards. Human errors (HEs), as Torabi et al. [15] noted, can arise in different phases such as design, product assembly processes, manufacturing processes, maintenance strategies, industrial operations, and software development. To tackle assembly mistakes, Park et al. [16] created a software tool called Foolproof Joint, which streamlines the assembly process of 3D models. Moreover, Gursel et al. [17] introduced an intelligent detection method that utilizes artificial intelligence to pinpoint human errors in the maintenance and assembly of nuclear power plants. Additionally, Wang et al. [18] established a connection between assembly errors and vibration problems in spindle systems.

Assembly errors in supporting components, such as bearings, can significantly influence bearing performance and spindle vibration characteristics [19,20]. Human error (HE) is a prevalent cause of accidents across various industries, contributing to between 30% and 90% of all accidents despite rigorous safety measures [21]. Many HEs can occur through assembly processes such as incorrect installation, missing parts, or improper fastening [22,23]. Moreover, poor cognitive and physical ergonomics have been associated with lower quality of the produced part and higher error rates [12,24].

Human errors are deviations from intended actions made by individuals during task execution [1]. These errors can arise from various factors, including inadequate training, fatigue, and unclear work instructions. Recognizing that these errors can be interconnected and affect each other is crucial, resulting in more severe assembly process problems. Therefore, early identification of these errors and their underlying causes is essential for preventing more significant issues.

Although previous efforts have been made to classify the potential causes of human errors in assembly, a comprehensive understanding of the most critical factors remains elusive due to the inherent complexities of the research process. While past studies have laid a foundation, further investigation is needed to prioritize and quantify the relative importance of these factors in the context of assembly processes. Therefore, the primary goal of this study is to identify the key factors affecting human errors in manual assembly tasks by employing two multi-criteria decision-making (MCDM) techniques: the fuzzy Delphi method (FDM) and the fuzzy analytic hierarchy process (FAHP). These techniques have prioritized and ranked the significance of various factors influencing human error occurrence.

1.1. The Need and Motivation for the Research

The need and motivation of this study is to address the critical issue of human error reduction in assembly processes by identifying the main factors that contribute to assembly errors. Hence, this research has implications for a variety of stakeholders, including:

(1) Organizations and Employers: This research can benefit organizations that deal with manufacturing and assembly processes. By identifying the root causes of worker errors, organizations can implement targeted strategies to minimize errors, boost

productivity, and enhance product quality. This can result in significant cost savings, increased customer satisfaction, and a stronger competitive edge in the marketplace.

(2) Workers: The benefits of this study are directly reflected in workers by improving their working conditions and reducing the chances of errors to support them in performing their tasks. Factors contributing to assembly errors can be reduced by implementing some measures, such as improving training programs, improving the equipment and tools used, improving the work environment, and enhancing safety measures, in order to increase job satisfaction among workers and improve their well-being.

(3) Consumers: Reducing product assembly errors increases product quality and reliability. This enhances consumer satisfaction and meets their expectations.

(4) Researchers and academics: This study encourages researchers interested in conducting more research and knowledge and developing new theories and methodologies to reduce errors in various industries.

Hence, the main motivation of this research was to enhance productivity, product quality, and worker well-being through minimizing assembly errors. This would ultimately lead to increased efficiency, cost savings, and a stronger competitive advantage while creating a safer and more fulfilling work environment.

1.2. Research Contributions

This research significantly advances the existing literature through several contributions, including the following:

(1) To our knowledge, this study is among the first to identify factors influencing human errors in manual assembly using the combination of FDM and FAHP techniques simultaneously, expanding the current understanding of error causes.

(2) This study ranks factors contributing to human errors in manual assembly processes and investigates their underlying causes.

(3) The proposed methodology helps managers and experts understand why assembly errors occur on manual assembly lines, enabling them to prioritize corrective actions and reduce errors.

(4) The combination of FDM and FAHP offers a synergistic approach to MCDM. FDM provides a structured framework for identifying and refining critical criteria, while FAHP enables the quantification of their relative importance. By addressing both the qualitative and quantitative aspects of decision-making, this integrated methodology can enhance the accuracy and reliability of decision outcomes.

The structure of this study is organized as follows: Section 2 describes the literature review, and Section 3 explains the research approach. The FDM and FAHP models are detailed in Section 4. The results and discussion are presented in Section 5. Finally, Section 6 summarizes the key findings, offers conclusions, and suggests some future directions.

2. Literature Review

Several studies have explored the contributing factors to human errors (HEs) in various industries. Lopez et al. [25] categorized these factors into personal and organizational influences. Iraj et al. [26] expanded this analysis to include task-related, organizational, and environmental factors in the mining process. Through inspection and maintenance actions in the conical lighting pole industry, Noman et al. [27] found many factors contributing to inspection errors, such as unclear instructions, stress, and some environmental conditions. Moreover, Yaniel et al. [28] conducted a comprehensive study on a complex assembly line, identifying more than thirty contributing factors related to assembly errors. These studies highlight a common theme: HEs are often influenced by a combination of factors, including individual characteristics, task demands, organizational practices, and some environmental factors [1]. Identifying the factors that cause assembly errors in various industries is crucial to developing effective strategies to reduce these errors in the future.

The existing literature was reviewed to identify potential factors contributing to assembly errors. Then, the experts were emailed a fuzzy Delphi questionnaire, which asked

them to identify and classify the most significant of those factors. Additionally, experts were encouraged to review and revise the list of factors, adding any missing elements deemed crucial. Based on the literature and experts, Table 1 provides a comprehensive overview of the various factors that can contribute to assembly errors. These factors are categorized into five main groups: individual factors (IFs), tool factors (TFs), task factors (TsFs), organizational factors (OFs), and environmental factors (EFs).

- Individual Factors (IFs)
    - Psychological factors: depression, disappointment, fatigue, fear of failure, financial problems, lack of motivation, lack of trust, and psychological stress can significantly impact performance.
    - Cognitive factors: lack of experience, knowledge deficiency, low intelligence, misunderstanding, poor perception, and poor memory can lead to errors.

    Physical factors: age, body physique, poor health, sleep deprivation, and risk-taking can influence assembly performance.

- Tool Factors (TFs)
    - Equipment issues: Shortages and using incorrect equipment can contribute to errors.
- Task Factors (TFs)
    - Workload and time pressure: Multitasking, repetitive tasks, task complexity, and time pressure can increase the likelihood of errors.
    - Instructional issues: Poor instructions and procedures can lead to misunderstandings and mistakes.
- Organizational Factors (OFs)
    - Management and culture: Poor management, communication, planning, and organizational culture can create an environment that is conducive to errors.
    - Resource allocation: Inadequate training, resources, and supervision can contribute to errors.
- Environmental Factors (EFs)
    - Workplace conditions: Factors such as temperature, humidity, lighting, noise, ergonomics, air quality, and layout can affect worker performance and increase the risk of errors.

Table 1. Classifying factors affecting assembly errors based on the literature.

Main Factors	Sub-Factors
Ifs	Age [29], body physique [30], depression [26], disappointment [26], fatigue [26], fear of failure [31], financial problems [26,32], gender [29], haste in doing work [33], job dissatisfaction [33], lack of experience [34], knowledge deficiency [35–39], lack of motivation [26], lack of trust in performance [26], low intelligence coefficient [26,32], misunderstanding [33], personal issues [40], personality type [26], poor perception [26], poor health [40], poor memory [40], risk-taking [41], sleep deprivation/disorder [7,28,42], psychological stress [3], Unknown roles and responsibilities [26,32], and unintentional errors [33].
TFs	Equipment shortages and using wrong equipment [33,40].
TsFs	Multitasking [43–46], poor instructions and procedures [47], repetitive tasks [30,48], task complexity [49], time pressure [29], and workload [3].
OFs	Failure to address the error-causing problem [33], improper quality control [33], lack of training [26], poor communication [33,40], poor management type [26], poor organization culture [26], poor planning [33], poor resource allocation [26,33], and poor supervision [26,33].
EFs	Accessibility problems [26], improper temperature and humidity [50,51], inappropriate lighting [50,51], noise [50,51], poor ergonomics design of the workplace [29], poor indoor air quality [26], and poor workplace layout [26].

HE remains a significant challenge in manual assembly, impacting product quality, efficiency, and worker safety [1]. To effectively address this issue, it is crucial to determine the primary factors related to the assembly errors. Therefore, our study employs multi-criteria decision-making (MCDM) techniques—specifically, the fuzzy Delphi method and the fuzzy AHP—to systematically analyze and prioritize these factors based on expert knowledge. MCDM offers a structured approach to handling complex multi-criteria decision-making problems simultaneously. Applying FDM and AHP methods, this research aims to provide valuable insights for developing targeted strategies to prevent human errors and enhance overall assembly performance.

Researchers and decision-makers have used many MCDM techniques in the literature. Selecting a suitable MCDM technique hinges on carefully considering various factors inherent to the decision-making problem. These include the problem's specific characteristics, the nature and availability of data, the decision-maker's preferences, and the overall goals of the decision-making process. Among the MCDM techniques, the fuzzy Delphi and the fuzzy AHP methods have emerged as powerful tools for handling the inherent uncertainties and complexities often associated with decision-making processes.

In 1993, Ishikawa et al. [52] proposed the FDM, which was derived from the traditional Delphi (TDM) method and the fuzzy set theory (FST). FDM is a powerful tool for researchers to achieve consensus among experts within a specific domain [53]. Recognized as a reliable and widely used approach for gathering expert opinions and conducting surveys [54,55], the FDM is adept at addressing a broad spectrum of group decision-making challenges, including factor selection, ranking, questionnaire development, and index calculation [56]. Building upon the TDM, the FDM incorporates fuzzy set theory to enhance its robustness [26]. Key advantages of the FDM include its capacity to aggregate expert perspectives into a consensus, reduced time and costs compared to the TDM, and fewer rounds of expert opinion collection [1]. Moreover, the key features of FDM include its reliance on unexplored and unidentified initial responses, its sequential statistical processing based on conditional phases, and its iterative, controllable, and manageable nature, guided by a feedback loop focused on outcome improvement [1]. The method produces consistent, updated, and collective statistical outputs. Additionally, the FDM excels at handling qualitative complexities through multiple survey rounds, fostering consensus building, and facilitating efficient decision-making. As a result, it has been widely adopted across various fields to gather coherent and evolving expert insights through successive survey iterations [54–56]. Recently, in the context of determining the factors affecting HEs, the FDM has emerged as a valuable tool for identifying factors contributing to HEs. For instance, Iraj et al. [26] employed the FDM to pinpoint the factors influencing HEs within mining process design. Similarly, Adel et al. [40] utilized the FDM to uncover the root causes of HE-related accidents in industrial park construction projects, revealing a significant impact on accident occurrence. Daniel et al. [33] also applied the FDM to the construction industry, identifying numerous factors with moderate to strong influence on HEs. In the healthcare domain, Cheryl et al. [57] successfully employed a two-round FDM to identify human factors contributing to nursing errors.

FAHP is a decision-making method that combines the traditional analytic hierarchy process (TAHP) with fuzzy set theory (FST). Introduced by Laarhoven and Pedrycz in 1983 [58] and further developed by Saaty in 1990 [59], FAHP addresses the limitations of AHP by incorporating fuzzy logic to handle uncertainty and subjectivity in decision-making. By representing expert judgments as triangular fuzzy numbers instead of crisp values, FAHP better aligns with human reasoning and enables more accurate evaluations. Key advantages of the FAHP include its simplicity and ability to process diverse data types making it a versatile tool. FAHP is grounded on three fundamental principles: hierarchical problem structuring, pairwise comparisons of alternatives and criteria, and synthesis of priorities [60]. In addition, the FAHP method has been extensively applied to determine the factors affecting HEs in various industries and domains. Recent studies have demonstrated the effectiveness of FAHP in this context, as it allows for handling uncertainty

and subjective judgments in the decision-making process. FAHP has been used to identify and prioritize key human error factors in healthcare [61], high-speed train operations [62], construction [63], civil aviation [64], nuclear plants [65], and public transportation [66].

FDM and FAHP techniques are complementary methods for decision-making under uncertainty. FDM is primarily a consensus-building technique that utilizes fuzzy logic to manage imprecise expert judgments. It iteratively gathers expert opinions to reach a shared understanding of complex issues. On the other hand, FAHP is a multi-criteria decision-making method that employs fuzzy set theory to handle subjective judgments and prioritize alternatives based on various criteria. While FDM focuses on qualitative aspects and consensus formation, FAHP concentrates on quantitative evaluation and ranking. Often, these methods are combined to leverage their strengths, with FDM used to identify key criteria and FAHP to weight and evaluate alternatives [67–69]. The literature reveals a dearth of studies that delve into the factors influencing assembly errors, particularly those employing the combined FDM and FAHP techniques. Previous studies have concentrated on identifying the variables impacting HEs in healthcare [57,61], construction [33,40,63,70], public transportation [66], and mining process design [26]. Therefore, this study aims to expand the body of knowledge and fill existing gaps relative to human error in manual assembly processes by identifying key influencing factors using FDM and FAHP methods from the perspective of multiple factors.

(1)	Conduct a literature review to identify and categorize factors that contribute to human error in manual assembly processes;
(2)	Determine the critical factors impacting assembly errors using the FDM method;
(3)	Prioritize the identified factors contributing to human errors using the FAHP method.

3. Research Methodology

The research methodology and its implementation steps are illustrated in Figure 1.

The following sections detail the steps taken to implement the proposed methodology.

Step 1: Reviewing the Literature and Identifying Variables: The existing literature was reviewed to identify potential factors contributing to assembly errors.

Step 2: Developing a Fuzzy Delphi Questionnaire: In the first round of the fuzzy Delphi process, an initial questionnaire was created to identify and prioritize factors influencing manual assembly HEs. The fuzzy Delphi questionnaire is shown in Appendix A.

Step 3: Selecting Expert Panel: The study of John Baker et al. [71] recommended that researchers ensure accuracy in selecting experts for the fuzzy research by choosing experts with a minimum of ten years' experience, based on their academic experience or level of knowledge in the same field. Therefore, experts with at least ten years of experience in the field of assembly processes were selected based on their academic credentials and knowledge in this study. The demographic details of the experts are provided in Table 2.

Step 4: Sending the Questionnaire to the Experts: The experts were emailed the questionnaire, which asked them to classify and rank the most significant factors under individual, tool, task, organizational, and environmental categories. Additionally, experts were encouraged to review and revise the list of factors, adding any missing elements deemed crucial.

Step 5: Developing a Revised Fuzzy Delphi Questionnaire: Some factors did not reach the expert consensus in the first round of the fuzzy Delphi study. Those factors were eliminated from the Delphi questionnaire, then a second revised questionnaire was developed and sent to the experts in the second round of the fuzzy Delphi process. Hence, 27 factors that obtained expert consensus in the second round of the Delphi study were analyzed and considered the most important factors affecting human errors in the manual assembly processes. The same panel of thirty-two experts, consisting of individuals with academic expertise and knowledge in the field, participated in both rounds of the Delphi study.

Step 6: Data Collection and Examination: The reliability and normality tests are crucial in data analysis. Reliability ensures consistent and accurate measurement, while normality allows for the use of various statistical tests. In addition, this study used these tests to

determine whether the number of experts was sufficient by ensuring the reliability and normality of the data collected from them.

The reliability of the survey data was assessed using Cronbach's alpha coefficients, as shown in Table 3. Results indicated strong internal consistency for both individual factors (all $\alpha > 0.70$) and the overall questionnaire ($\alpha = 0.91$), suggesting the data are suitable for further analysis [16]. In addition, to assess whether the survey data adhered to a normal distribution, we employed the Shapiro–Wilk test. Given the sample size of less than 50, this test is particularly suitable for detecting deviations from normality [33]. The Shapiro–Wilk test compares the observed data to a theoretical normal distribution, yielding a *p*-value indicating the likelihood of such deviations occurring by chance if the data were normally distributed. We applied this test to all survey variables, including those related to IFs, TFs, TsFs, OFs, and EFs. The results, summarized in Table 4, show a non-significant *p*-value (greater than 0.05) for all factors examined. Consequently, we concluded that the data followed a normal distribution at a 95% confidence level.
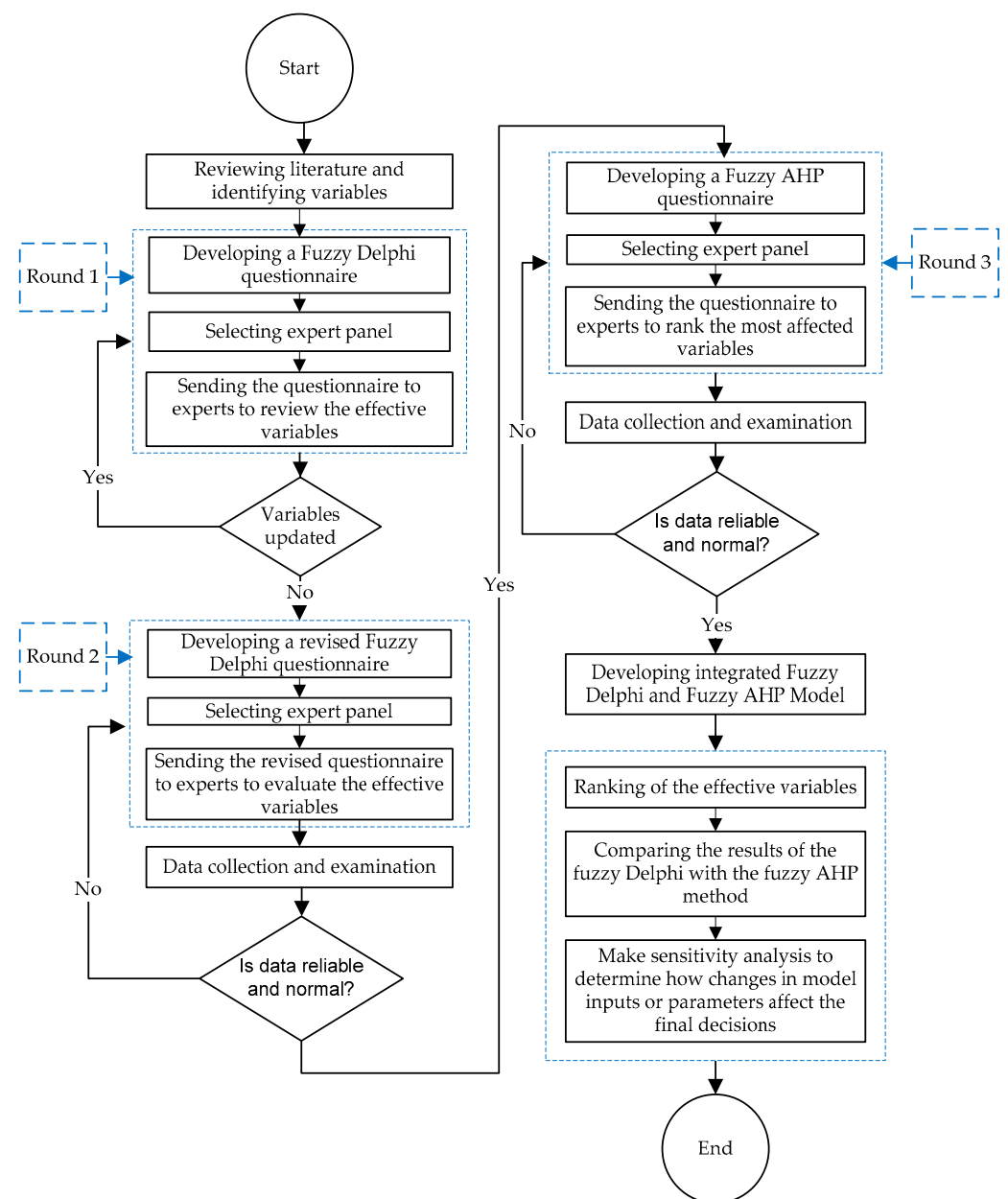

Figure 1. Research methodology.

Table 2. Participant demographic information.

Category	Item	Frequency	Percentage (%)
Participant gender	Male	25	78.1
	Female	7	21.9
Participant age	Less than 35 years	6	18.7
	36–50 years	23	71.9
	More than 50 years	3	9.4
Education	Bachelor's degree	14	43.8
	MSC	9	28.1
	PhD	9	28.1
Experience in manual assembly	10–15 years	24	75
	16–20 years	3	9.4
	21–25 years	2	6.2
	More than 25 years	3	9.4
Relevant experience	Academic	16	50.0
	Assembly worker	13	40.6
	Production manager, safety manager, and supervisor.	3	9.4

Table 3. Survey reliability analysis.

Main Factors	Items	Cronbach's α for Each Factor	Cronbach's α for Overall Questionnaire
IF	26	0.91	
TF	2	0.79	
TsF	6	0.71	0.91
OF	9	0.86	
EF	8	0.83	

Table 4. Survey normality analysis using the Shapiro–Wilk test.

Main Factors	Using Shapiro–Wilk Test		α	Is the Data Normally Distributed?
	Sig.	Statistics		
IF	0.085	0.942		Yes
TF	0.120	0.996		Yes
TsF	0.110	0.992	0.05	Yes
OF	0.100	0.980		Yes
EF	0.380	0.961		Yes

Step 7: Developing a fuzzy AHP Questionnaire: This step is called round 3. In this step, the most significant factors identified in the fuzzy Delphi process were used to create a fuzzy AHP questionnaire (Appendix B).

Step 8: Selecting Expert Panel: The same panel of experts who participated in the previous rounds of the Delphi study was selected to answer the FAHP questionnaire. The participants were carefully selected according to their academic and knowledge experience in the field of manual assembly processes, so they were chosen to perform both the fuzzy Delphi and fuzzy AHP questionnaires.

Step 9: Sending the Questionnaire to the Experts: The experts were emailed the questionnaire, which asked them to rank the identified factors based on their perceived importance in influencing HEs in manual assembly processes.

Step 10: Developing Integrated Fuzzy Delphi and Fuzzy AHP Model.

Step 11: Ranking the Factors Influencing HEs in Manual Assembly Processes: A fuzzy Delphi model was constructed to integrate expert opinions and identify significant factors affecting HEs in the manual assembly processes. Factors with a rating below 70% were

eliminated [26,56]. After that, the expert opinions gathered in the Delphi process were analyzed to identify the most significant factors influencing manual assembly HEs. A consensus agreement rate of 75% or higher was used as the threshold for determining the importance of each factor [26,56]. By examining each expert's individual agreement ratings, a collective consensus for each factor was established. This analysis allowed for selecting the most critical factors based on the shared expert opinions. Then, a fuzzy AHP model was constructed to determine the priorities of the most influencing factors in assembly HEs based on their weights.

Step 12: Comparing the results of the fuzzy Delphi with the fuzzy AHP method.

Step 13: Make a sensitivity analysis to determine how changes in model inputs or parameters affect the final decisions.

This multi-step approach combined expert knowledge and quantitative analysis to identify and prioritize key factors contributing to HEs in manual assembly processes.

4. Integrated Model Based on Fuzzy Delphi and AHP Methods

4.1. Fuzzy Delphi-Based Model

This study employs fuzzy logic, a methodology introduced by Lotfi A. Zadeh in 1955 for managing uncertainty and ambiguity in decision-making. The model utilizes Trigonometric Fuzzy Numbers (TFNs) to quantify expert opinions from linguistic assessments. These fuzzy numbers represent expert judgments as triangular distributions with three values: minimum possible (a), most likely (b), and maximum possible (c), as detailed in Table 5.

Table 5. Fuzzy Delphi linguistic terms and corresponding fuzzy numbers [26,40,72].

Code	Description	Fuzzy Numbers (*a,b,c*)
NI	Negligible influence	(0, 0, 0.25)
LI	Low influence	(0, 0.25, 0.5)
MI	Moderate influence	(0.25, 0.5, 0.75)
HI	High influence	(0.5, 0.75, 1)
OI	Overwhelming influence	(0.75, 1, 1)

The fuzzy Delphi model is a multi-stage decision-making process that combines expert opinion with fuzzy logic to achieve consensus on complex issues. In this study, to implement the fuzzy Delphi technique, several steps were established as follows:

4.1.1. Determining Factor's Average Fuzzy Rating Score

Firstly, each influencing factor's average fuzzy rating weights were determined during this step. The importance estimation for factor *j*, as provided by expert *i* among *n* experts, is assumed to be calculated using Equation (1).

$$\widetilde{w}_{ij} = \left(a_{ij}.b_{ij}.c_{ij}\right), for\ i = 1, 2, \ldots n,\ and\ j = 1, 2, \ldots m. \tag{1}$$

After that, the mean of the fuzzy weights $\left(\widetilde{w}_j\right)$, which were determined in the first step for each factor, can be calculated as Equation (2):

$$\widetilde{w}_j = \left(\alpha_j \cdot \beta_j \cdot c_j\right) = \left(\frac{1}{n}\sum_{i=1}^{n}a_{ij} \cdot \frac{1}{n}\sum_{i=1}^{n}b_{ij} \cdot \frac{1}{n}\sum_{i=1}^{n}c_{ij}\right), for\ j = 1, 2, \ldots m. \tag{2}$$

4.1.2. Ranking of Factors Influencing Errors

In this step, the mean of the fuzzy weights for each factor was transformed into aggregated fuzzy weights $\left(W_j \right)$ called crisp values as Equation (3) [26]:

$$W_j = \frac{a_j + b_j + c_j}{3}, j = 1, 2, \ldots m.$$ (3)

After that, the aggregated fuzzy weights W_j are used to rank the rating weights to show the importance of each factor. Based on expert judgments, factors with a score of 0.7 or higher were considered significant contributors to human errors and included in this study. Factors with scores below 0.7 were excluded [26].

4.1.3. Assessing the Validity of the Estimation Domain

To assess the validity of the estimation domain, the following steps were organized. Firstly, calculate the difference values (D_{ij}) for each expert as Equation (4):

$$D_{ij} = \sqrt{\frac{1}{3}\left[\left(a_j - a_{ij} \right)^2 + \left(b - b_{ij} \right)^2 + \left(c_j - c_{ij} \right)^2 \right]}.$$ (4)

After that, calculate the threshold value (*d*) for each factor as Equation (5):

$$d = \frac{1}{n}\sum_{i=1}^{n} D_{ij}.$$ (5)

Then, check the threshold value (Th_d) for each estimation domain as Equation (6):

$$Th_d = \frac{1}{n}\sum_{i=1}^{m} d_j.$$ (6)

The assessing the validity of the estimation domain was determined by the threshold value (Th_d). A domain was considered acceptable if Th_d was less than or equal to 0.2.

Finally, determine the expert's group consensus on each factor as Equation (7) and (EA_j) [56]:

$$EA_j = \frac{E_j}{n}\%$$ (7)

A consensus was considered achieved if EA_j was greater than or equal to 75%. Factors with EA_j below 75% were excluded from further analysis [56].

4.2. Fuzzy AHP-Based Model

Fuzzy Analytic Hierarchy Process (FAHP), an extension of Saaty's Analytic Hierarchy Process (AHP) [59], is a multi-criteria decision-making (MCDM) technique for prioritizing attributes. It accommodates human judgment uncertainties by employing fuzzy numbers in comparison matrices. To derive weights from these matrices, various algorithms exist, including logarithmic least squares, fuzzy extent analysis, and geometric mean [73]. This study adopts Buckley's geometric mean method [74], known for its efficiency with smaller datasets. The subsequent sections provide an overview of fuzzy set theory and the detailed steps of Buckley's FAHP.

Zadeh introduced fuzzy set theory in 1965 [75] to model vagueness inherent in decision-making parameters. A fuzzy set $\widetilde{A}$ is characterized by a membership function $\mu_{\widetilde{A}}(X)$ that assigns a degree of membership to each element within the set as given in

Equation (8). This study employs triangular fuzzy numbers (TFNs) $\widetilde{A}$ to represent fuzzy sets, defined by a triplet of values (a, b, c) as shown in Table 4.

$$\mu_{\widetilde{A}}(x) = \begin{cases} \frac{x-a}{b-a}, & a \leq x \leq b \\ \frac{c-x}{c-b}, & b \leq x \leq c \\ 0 & otherwise \end{cases} \tag{8}$$

Common arithmetic operations applicable to the following TFNs include addition, multiplication, scalar multiplication, and inversion: $\widetilde{A}_1 = (a_1 + b_1 + c_1)$; and $\widetilde{A}_2 = (a_2 + b_2 + c_2)$ are shown in Equations (9) to (12), respectively.

$$\widetilde{A}_1 \oplus \widetilde{A}_2 = (a_1 + a_2, b_1 + b_2, c_1 + c_2) \tag{9}$$

$$\widetilde{A}_1 \otimes \widetilde{A}_2 = (a_1 a_2, b_1 b_2, c_1 c_2) \tag{10}$$

$$k \otimes \widetilde{A}_1 = (ka_1, kb_1, kc_1) \tag{11}$$

$$\widetilde{A}_1^{-1} = \left(\frac{1}{c_1}, \frac{1}{b_1}, \frac{1}{a_1} \right) \tag{12}$$

To build the fuzzy AHP model, several steps should be implemented as the following:

4.2.1. Establishing the Hierarchy Structure for the Goal

The application of fuzzy AHP necessitates the a priori establishment of a well-defined objective (goal). Subsequently, the relevant domains and their constituent factors influencing the attainment of this objective are identified. This process necessitates the integration of theoretical frameworks and expert elicitation.

4.2.2. Designing the Pairwise Comparison Matrix

The pairwise comparison matrix $(\widetilde{M}^k)$ is obtained using the fuzzy number scale (Table 6). If a k decision-maker (DM) considers the first attribute to be very strong over the second then the first gets $(6, 7, 8)$ and the second will get $(1/8, 1/7, 1/6)$. This results in a pairwise comparison matrix as shown in Equation (13).

$$\widetilde{M}^k = \begin{bmatrix} \widetilde{a}_{11}^k & \cdots & \widetilde{a}_{1n}^k \\ \vdots & \ddots & \vdots \\ \widetilde{a}_{n1}^k & \cdots & \widetilde{a}_{nn}^k \end{bmatrix} \tag{13}$$

where $\widetilde{a}_{ij}^k$ represents rating of kth DM for i^{th} attribute over j^{th} attribute.

Table 6. Fuzzy AHP linguistic terms and corresponding fuzzy numbers [76].

Importance Degree	Linguistic Terms	Fuzzy Numbers (a,b,c)
1	Equally influential	(1, 1, 1)
3	Weakly influential	(2, 3, 4)
5	Strongly influential	(4, 5, 6)
7	Very strongly influential	(6, 7, 8)
9	Extremely influential	(9, 9, 9)
2, 4, 6, 8	Intermediate levels	(1, 2, 3), (3, 4, 5), (5, 6, 7), (7, 8, 9)

After that, the total pairwise comparison matrix $(\widetilde{M})$ that averages the ratings of k DMs, was computed as shown in Equation (14).

$$\widetilde{M} = \begin{bmatrix} \widetilde{a}_{11} & \cdots & \widetilde{a}_{1n} \\ \vdots & \ddots & \vdots \\ \widetilde{a}_{n1} & \cdots & \widetilde{a}_{nn} \end{bmatrix} \tag{14}$$

where $\widetilde{a}_{ij}$ represents average rating of all DMs for i^{th} attribute over j^{th} attribute, and it can be calculated as Equation (15).

$$\widetilde{a}_{ij} = \frac{\sum_{k=1}^{K} \widetilde{a}_{ij}^{k}}{K} \tag{15}$$

4.2.3. Analyzing the Consistency of Pairwise Comparison Matrix

Saaty et al. [59] proposed a method to assess how consistent decision-maker (DM) judgments are in a comparison matrix. This method uses a Consistency Index (*CI*) as the following.

1. First, the TFNs in the comparison matrix should be converted from fuzzy numbers into crisp numbers to make a crisp comparison matrix (M_{crisp}) as shown in Equation (16).

$$M_{crisp} = \frac{a + 4b + c}{6} \tag{16}$$

2. Then, a priority vector (*PV*), which shows the weights for each criterion (*i*) is calculated by averaging each column of the comparison matrix $(\widetilde{M})$ after normalizing it as shown in Equation (17).

$$PV_i = \frac{\sum_{j=i}^{n} \frac{a_{ij}}{\sum_{x=1}^{n} a_{xi}}}{n} \tag{17}$$

3. Next, a weighted sum matrix (*WSM*) is from multiplication of crisp comparison matrix (M_{crisp}) by the priority vector (*PV*) as shown in Equation (18)

$$WSM = [M_{crisp}] \times [PV] \tag{18}$$

4. The largest eigenvalue (λ_{max}) of a specific matrix equation is then computed using Equation (19).

$$\lambda_{max} = \frac{\sum_{i=i}^{n} \frac{WSM_i}{PV_i}}{n} \tag{19}$$

5. Finally, the *CI* and Consistency Ratio (*CR*) are obtained using formulas that involve λ_{max} and the matrix size as shown in Equations (20) and (21), respectively.

$$CI = \frac{\lambda_{\max} - n}{n - 1} \tag{20}$$

$$CR = \frac{CI}{RI(n)} \tag{21}$$

Figure 2 provides a reference value (Random Consistency Index or *RI*) for different matrix sizes (*n*). To ensure acceptable consistency in DMs' judgments, the *CR* value should be less than 0.10.
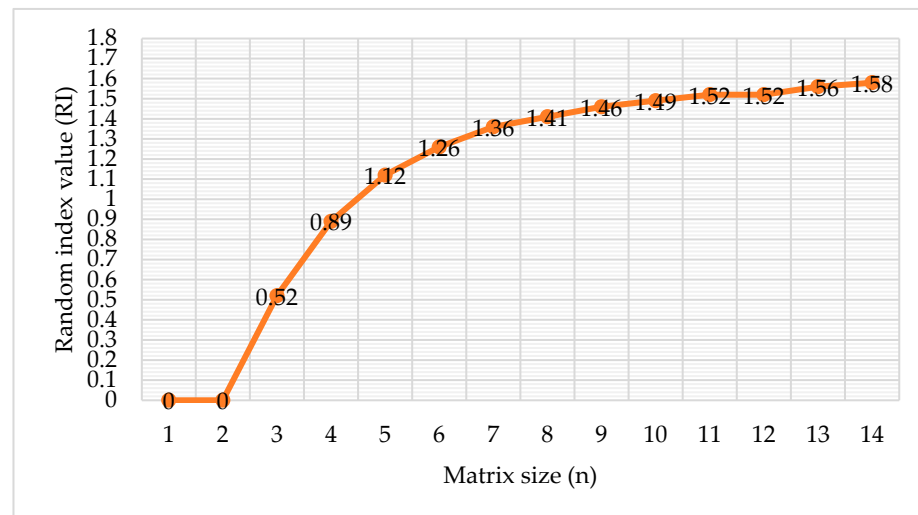
Figure 2. Randomness measure for consistency.

4.2.4. Determining Attribute Weights with Fuzzy Logic

1. Construct a Fuzzy Geometric Mean Matrix: A special matrix is created that captures the relative importance of different attributes using fuzzy numbers, as shown in Equation (22).

$$\widetilde{g}_i = \left(\prod_{j=1}^{n} \widetilde{a}_{ij} \right)^{\frac{1}{n}}, i = 1, 2, \ldots, n \tag{22}$$

2. Calculate Fuzzy Weights: Weights are assigned to each attribute based on the fuzzy geometric mean matrix. These weights represent their significance in the overall evaluation and incorporate a degree of uncertainty using fuzzy logic, as shown in Equation (23).

$$\widetilde{w}_i = \widetilde{g}_i \otimes \left[\widetilde{g}_1 \oplus \widetilde{g}_2 \oplus \ldots \oplus \widetilde{g}_n \right]^{-1} = (lw_i, mw_i, uw_i) \tag{23}$$

where $lw_i, mw_i,$ and uw_i are a lower, middle, and upper value of the fuzzy weight of w_i.

4.2.5. Determining Normalized Values and Ranking of Attributes

The de-fuzzy number for FTNs (D_i) is calculated using the center-of-area method as shown in Equation (24) and normalized (N_i) using as shown in Equation (25).

$$(D_i) = \frac{lw_i, mw_i, uw_i}{3} \tag{24}$$

$$(N_i) = \frac{D_i}{\sum_{i=1}^{n} D_i} \tag{25}$$

5. Results and Discussion

A thorough examination of existing research in the literature was undertaken to pinpoint the primary factors that lead to human errors in manual assembly tasks. Then, these factors were subsequently categorized based on the literature and experts into five main factors: individual-related factors, tool-related factors, task-related factors, organizational-related factors, and environmental-related factors. A novel model combining fuzzy Delphi and fuzzy AHP methods was developed to prioritize these factors and accurately assess their impact on human error occurrence. Detailed findings and interpretations of the model's results are presented in the following sections.

5.1. Ranking Main and Sub-Factors of Assembly Errors Using FDM

Using the fuzzy Delphi method, the most significant factors influencing assembly errors were determined and listed in Table 7. The defuzzified evaluation rating scores (W_j) for each factor were computed using Equations (3). If a factor's W_j score was 0.7 or higher, as per expert opinions, it was considered a significant factor affecting human errors. Factors with scores below this threshold were excluded from further analysis [26]. Additionally, the consensus among experts for each factor was assessed using the expert agreement metric (EA_j), with a threshold of 75% or higher required for a factor to be retained, as determined by Equation (7).

Table 7. Ranking the main and sub-factors of HEs in manual assembly tasks based on FDM.

Main Factors	EA_j	Normal Weight	Ranking	Sub-Factors	W_j	EA_j	Normal Weight	Ranking
IF	91%	0.2093	1	Inexperience (F1)	0.875	100%	0.0847	1
				Misunderstanding (F2)	0.8281	100%	0.0802	2
				Knowledge deficiency (F3)	0.8229	94%	0.0797	3
				Poor perception (F4)	0.8177	100%	0.0792	4
				Risk-taking behavior (F5)	0.8151	91%	0.0789	5
				Memory issues (F6)	0.8099	91%	0.0784	6
				Physical or mental fatigue (F7)	0.7813	94%	0.0756	7
				Psychological stress (F8)	0.776	88%	0.0751	8
				Unknown roles and responsibilities (F9)	0.776	94%	0.0751	9
				Unintentional errors (F10)	0.776	88%	0.0751	10
				Rushed work (F11)	0.7578	84%	0.0734	11
				Health problems (F12)	0.75	81%	0.0726	12
				Intelligence quotient (F13)	0.7448	81%	0.0721	13
TF	88%	0.1972	3	Using the wrong equipment (F14)	0.7604	94%	0.5034	1
				Equipment shortages (F15)	0.75	81%	0.4966	2
TsF	91%	0.2071	2	Poor instructions and procedures (F16)	0.8464	97%	0.2147	1
				Task complexity (F17)	0.8229	94%	0.2087	2
				Time pressure (F18)	0.8099	97%	0.2054	3
				Workload (F19)	0.75	88%	0.1902	4
				Multitasking (F20)	0.7135	78%	0.1810	5
OF	89%	0.1970	4	No training (F21)	0.8229	100%	0.3628	1
				Lack of supervision (F22)	0.7448	88%	0.3284	2
				Problem to address error (F23)	0.7005	78%	0.3088	3
EF	80%	0.1894	5	Inappropriate lighting (F24)	0.75	88%	0.2567	1
				Noise (F25)	0.7266	75%	0.2487	2
				Ergonomics problems (F26)	0.724	78%	0.2478	3
				Poor layout (F27)	0.7214	78%	0.2469	4

According to the results shown in Table 7, the main factors affecting HEs in the manual assembly processes are individual factor (IF), task factor (TsF), tool factor (TF), organizational factor (OF), and environmental factor (EF) with weights of 0.2093, 0.2071, 0.1972, 0.1970, and 0.1894, respectively. Based on the local ranking, the findings indicated that IF significantly impacts human error in manual assembly processes, with a lack of experience, misunderstanding, and fatigue being particularly influential. TF, including the absence of necessary tools and the use of inappropriate tools, had the most substantial effect on human errors. Among the TsF, poor instructions and procedures, task complexity, and time pressure were identified as strongly influencing assembly errors. OF, such as inadequate training, failure to address error-causing issues, and poor supervision, were shown to have the most significant impact on human errors. Lastly, the EF, including noise, inadequate lighting, and poor ergonomic design in the workplace, were found to be the most influential factors affecting human assembly errors.

5.2. Ranking Main and Sub-Factors of Assembly Errors Using FAHP

Using the fuzzy AHP method, the most significant factors influencing assembly errors were determined and listed in Table 8. According to the results shown in Table 8, the main factors affecting HEs in the manual assembly processes are IFs, TsFs, TFs, EFs, and OFs with weights of 0.2115, 0.2031, 0.1989, 0.1940, and 0.1925, respectively. At the sub-factor level, specific elements within each main factor are identified and ranked. For instance, under individual factors, lack of experience is deemed the most significant contributor, followed by misunderstanding and lack of knowledge. Similarly, using inappropriate tools is considered the primary factor within task factors, followed by a lack of necessary tools. These rankings highlight the areas that require the most attention to reduce human error rates in manual assembly operations.

Table 8. Ranking the main and sub-factors of HEs in manual assembly tasks based on FAHP.

Main Factors	Test Value	Normal Weight	Ranking	Sub-Factors	Test Value	Normal Weight	Ranking
IF	CI = 0.031 CR = 0.028	0.2115	1	F1	CI = 0.137 CR = 0.088	0.0979	1
				F2		0.0881	2
				F3		0.0835	3
				F4		0.0827	4
				F5		0.0813	5
				F6		0.0802	6
				F7		0.0725	7
				F8		0.0701	8
				F9		0.0692	9
				F10		0.0691	10
				F11		0.0690	11
				F12		0.0683	12
				F13		0.0682	13
TF		0.1989	3	F14	CI = 0.092 CR < 0.10	0.5064	1
				F15		0.4936	2

Table 8. *Cont.*

Main Factors	Test Value	Normal Weight	Ranking	Sub-Factors	Test Value	Normal Weight	Ranking
TsF		0.2031	2	F16	CI = 0.079 CR = 0.071	0.2403	1
				F17		0.2263	2
				F18		0.2093	3
				F19		0.1718	4
				F20		0.1523	5
OF	CI = 0.031 CR = 0.028	0.1925	5	F21	CI = 0.035 CR = 0.068	0.4127	1
				F22		0.3150	2
				F23		0.2724	3
EF		0.1940	4	F24	CI = 0.080 CR = 0.090	0.2689	1
				F25		0.2478	2
				F26		0.2435	3
				F27		0.2398	4

5.3. Ranking the Factors Influencing HEs Based on the Integrated FDM and FAHP Model

Table 9 compares the performance of 27 factors (F1 to F27) using two different methods (fuzzy Delphi and fuzzy AHP). Each factor is assigned a global weight using both fuzzy Delphi and fuzzy AHP methods. The global weight indicates the relative importance of a factor. A higher weight suggests a more important factor. The overall ranking shows the order of the factors based on their global weights, with rank one being the most important factor. For example, inexperience or the lack of experience (F1) has the highest fuzzy Delphi global weight (0.0419) and fuzzy AHP global weight (0.0488), indicating it is the most important factor that influences human errors in manual assembly processes according to both methods. The second important factor is the poor instructions and procedures (F16), with global weights of 0.0404 and 0.0442 using fuzzy Delphi and fuzzy AHP methods, respectively. The misunderstanding factor (F2) comes in third place as the most influential factor in human error. In addition, other factors significantly impact assembly errors, such as the lack of knowledge (F3) and task complexity (F17). Moreover, Figure 3 compares the overall ranking of all the important factors affecting human assembly errors using fuzzy Delphi and fuzzy AHP.
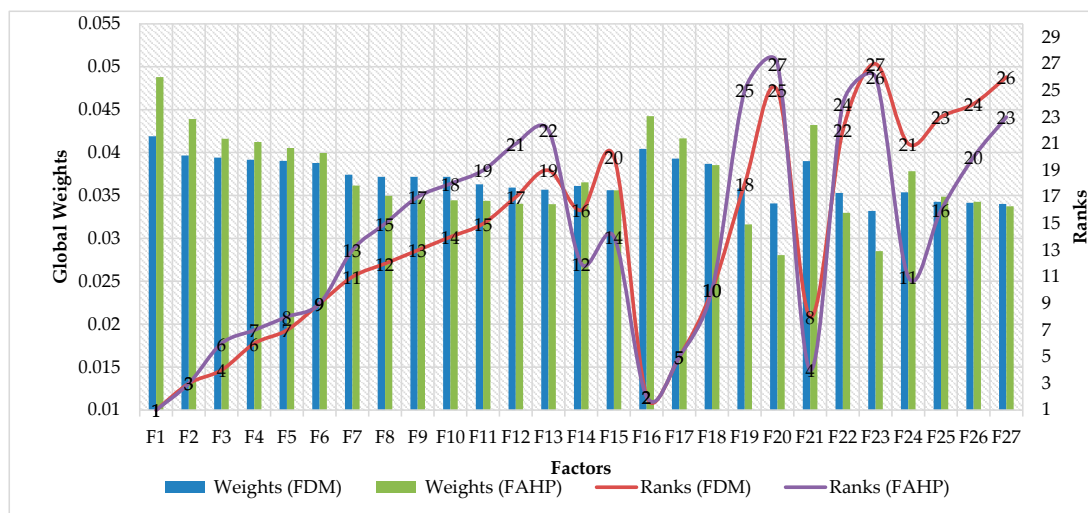

Figure 3. Overall weights and ranks using fuzzy Delphi and fuzzy AHP.

Table 9. Ranking the affecting factors according to FDM and FAHP methods.

Index	Fuzzy Delphi		Fuzzy AHP	
	Global Weight	Overall Ranking	Global Weight	Overall Ranking
F1	0.0419	1	0.0488	1
F2	0.0397	3	0.0439	3
F3	0.0394	4	0.0416	6
F4	0.0392	6	0.0412	7
F5	0.0390	7	0.0405	8
F6	0.0388	9	0.0400	9
F7	0.0374	11	0.0361	13
F8	0.0372	12	0.0350	15
F9	0.0372	13	0.0345	17
F10	0.0372	14	0.0344	18
F11	0.0363	15	0.0344	19
F12	0.0359	17	0.0340	21
F13	0.0357	19	0.0340	22
F14	0.0361	16	0.0365	12
F15	0.0356	20	0.0356	14
F16	0.0404	2	0.0442	2
F17	0.0393	5	0.0417	5
F18	0.0387	10	0.0385	10
F19	0.0358	18	0.0316	25
F20	0.0341	25	0.0280	27
F21	0.0390	8	0.0432	4
F22	0.0353	22	0.0330	24
F23	0.0332	27	0.0285	26
F24	0.0354	21	0.0378	11
F25	0.0343	23	0.0349	16
F26	0.0341	24	0.0343	20
F27	0.0340	26	0.0337	23

5.4. Paired Samples t-Test

In this study, the paired samples t-test was used to compare the global weights of the factors resulting from the fuzzy Delphi and fuzzy AHP methods. This statistical test is used to determine if there is a significant difference between the means of two related samples [77]. In this case, the *p*-value is 0.990, much greater than the testing alpha level of 0.05 as shown in Table 10. This means no statistically significant difference exists between the FDM and FAHP methods. The small mean difference of 0.0000074 and the wide confidence interval (-0.0011825 to 0.0011973) further support the conclusion that there is no meaningful difference between the two methods. Therefore, based on the paired *t*-test, no evidence suggests that the FDM and FAHP methods produce significantly different results.

Table 10. Paired samples test for FDM and FAHP methods.

Paired *t*-Test		Paired Differences					T	df	Sig. (2-Tailed)
		Mean	Std. Dev.	Std. Error Mean	95% Confidence Interval of the Difference		T	df	Sig. (2-Tailed)
					Lower	Upper			
Pair 1	fuzzy Delphi and fuzzy_AHP	0.0000074	0.0030080	0.0005789	−0.0011825	0.0011973	0.013	26	0.990

5.5. Sensitivity Analysis

Sensitivity analysis is a crucial step in model development using decision-making methods [78]. It helps to determine how changes in model inputs or parameters affect the final decisions [79]. This analysis ensures that the outcomes are reliable and practical. Therefore, we can make more accurate forecasts and develop more effective future plans.

In this study, the sensitivity analysis was performed according to the study of Moslem et al. [78], as shown in Figure 4 as follows: At the first level, the weight of the "individual" factor was adjusted from 0.2093 to 0.2111 in the fuzzy Delphi and from 0.2115 to 0.2129 in the fuzzy AHP according to the maximum range value of the weight of the individual factor with no change in the ranking of the other factors at the second level. The slight change in the weight of the individual factor in both methods is to detect the stability of the weights of the other factors, which is the goal of conducting the sensitivity analysis.
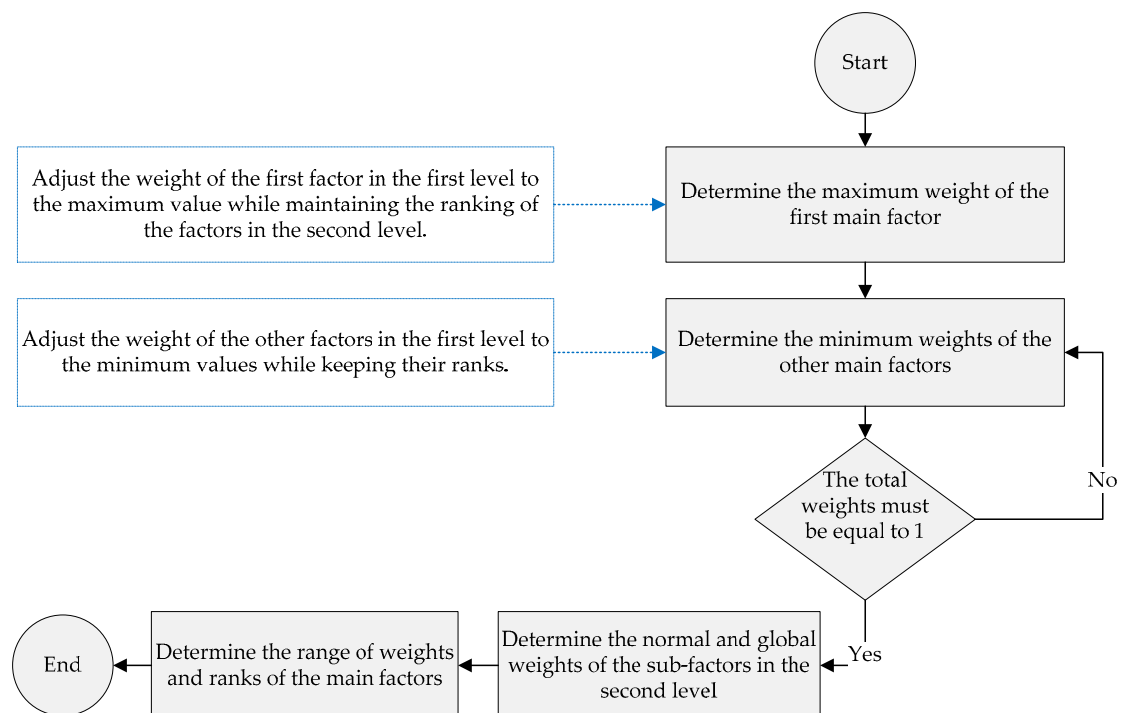

Figure 4. Methodology of the sensitivity analysis.

The weight scores of the other factors (TsF, TF, OF, and EF) at this level were adjusted according to the minimum range to maintain a single score for the total calculation of the weight scores while keeping their ranks. Therefore, the minimum range weights for the factors (TsF, TF, OF, and EF), which keep their ranks, are 0.1967, 0.2066, 0.1966, and 0.1890 for the fuzzy Delphi method, and 0.1986, 0.2030, 0.1920, and 0.1935 for the fuzzy AHP method, as shown in Table 11.

Table 11. Range of weights and ranks for the main factors after the sensitivity analysis.

Main Factors	Fuzzy Delphi		Fuzzy AHP	
	Range of Weights	Rank	Range of Weights	Rank
IF	0.2093–0.2111	1	0.2115–0.2129	1
TF	0.1967–0.1972	3	0.1986–0.1989	3
TsF	0.2066–0.2071	2	0.2030–0.2031	2
OF	0.1966–0.1970	4	0.1920–0.1925	5
EF	0.1890–0.1894	5	0.1935–0.1940	4

Accordingly, the scores of the lower-level factors were changed while maintaining the first-order level. This suggestion may cause the importance of the evaluators to be modified. However, the overall ranking of the main factors remains relatively consistent between the two methods before and after the sensitivity analysis. This indicates that the results are reasonably robust to changes in the input data or parameters, a desirable property for any decision-making model.

The sensitivity analysis conducted on the sub-factors, as shown in Figure 5, has revealed minor changes in the rankings obtained using both the fuzzy Delphi and fuzzy AHP methods. This indicates that the initial rankings were relatively robust and not significantly influenced by the sensitivity analysis.
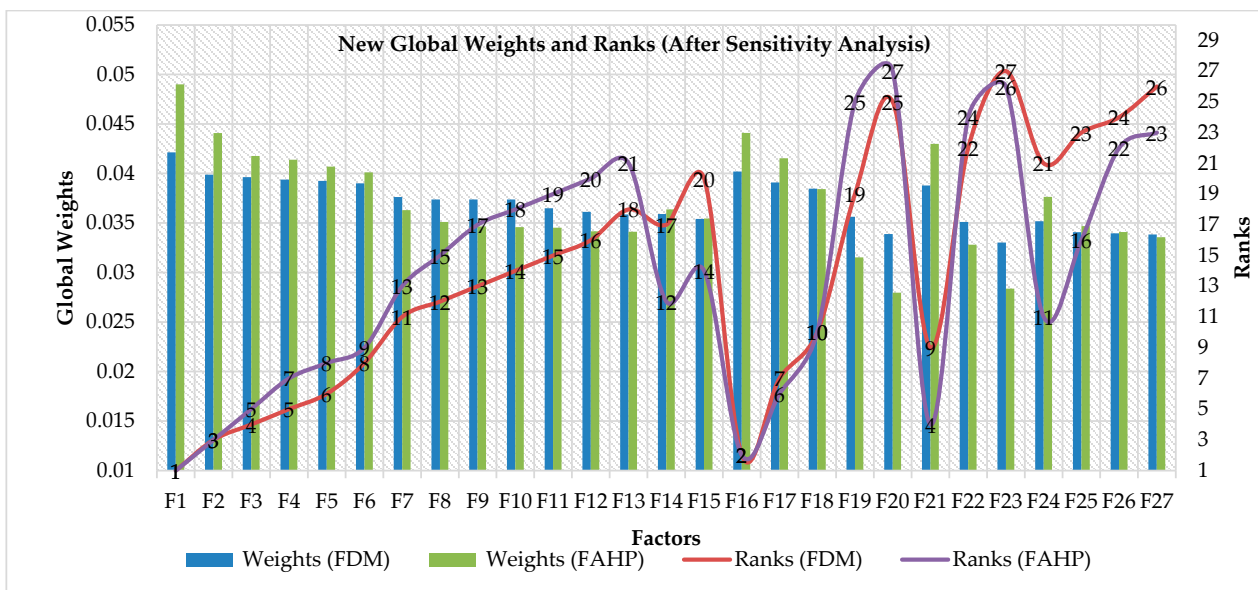

Figure 5. Overall weights and ranks after sensitivity analysis.

Several sub-factors maintained their positions in the rankings regardless of the method or the sensitivity analysis. These included lack of experience (F1), misunderstanding (F2), fatigue (F7), stress (F8), non-understanding roles and responsibilities (F9), unintentional unsafe acts (F10), haste in doing work (F11), lack of necessary tools (F15), poor instructions and procedures (F16), time pressure (F18), multitasking (F20), poor supervision (F22), failure to address the error-causing problem (F23), inappropriate lighting (F24), noise (F25), and poor workplace layout (F27). The consistent ranking of these factors suggests that they are consistently perceived as critical contributors to human error. However, some sub-factors experienced slight shifts in their rankings after the sensitivity analysis. For instance, "lack of knowledge" (F3) moved down one rank in the fuzzy AHP method but remained unchanged in the fuzzy Delphi method. Similarly, "poor health" (F12) and "low intelligence coefficient" (F13) experienced minor rank changes in both methods. These

shifts, while present, were relatively small and did not alter the overall ranking of the main factors.

Overall, the sensitivity analysis demonstrated that the initial rankings of the sub-factors were generally stable and not highly sensitive to changes in the input data or the methods used. This suggests that the identified factors are indeed significant contributors to human error and that the rankings obtained are reliable and can be used to inform interventions and prevention strategies.

The decision-making techniques offer significant advantages in decision-making processes within complex domains. This study developed an integrated model using two multi-criteria decision-making (MCDM) techniques: the fuzzy Delphi and the fuzzy AHP methods for determining and ranking the factors affecting human errors in manual assembly processes. These techniques effectively address the inherent uncertainties and complexities associated with expert judgments. Through its iterative process of expert consultation and feedback, the fuzzy Delphi method helps to refine and converge opinions on the factors influencing human errors. Meanwhile, the fuzzy AHP method provides a structured framework for ranking the identified factors based on their relative importance. Incorporating fuzzy logic, both techniques allow for considering linguistic variables and subjective judgments, which are often prevalent in human-centric decision-making. The combined application of these methods can lead to more robust and reliable insights into the critical factors contributing to human errors in manual assembly, facilitating the development of effective mitigation strategies.

Previous studies have identified multiple root causes of human errors in various industries, highlighting personal, organizational, task-related, and environmental factors, which include negative behaviors, inadequate training, poor management, and unfavorable working conditions [25,26,28]. Recently, some studies have consistently identified several key factors contributing to manual assembly errors. The studies of Noman et al. [27] and Fahad et al. [1] emphasized the significant roles of lack of experience, insufficient procedures and instructions, stress, inadequate training, task complexity, and environmental factors such as noise and workplace design. These findings align with our study, further solidifying the importance of addressing these issues to enhance assembly accuracy. Additionally, our research aligns with Torres and Landau's study [7], which demonstrated the effectiveness of attention-grabbing assembly instructions in reducing errors and improving performance. This suggests that clear and engaging communication can significantly impact worker efficiency and product quality. Furthermore, Alogla and Mansoor's research [80] highlighted the criticality of understanding human errors in manufacturing settings. By identifying and addressing these errors, organizations can prevent quality problems, reduce rework, and optimize labor input, ultimately improving overall productivity.

The findings of this study align with previous research that highlights key factors contributing to human errors in various industries. For example, Azhdari et al. [81] emphasized that enhancing employee training and closely monitoring performance are vital in reducing human errors. Similarly, Morais et al. [82] identified causes such as insufficient skills, lack of information, poor quality control, inadequate communication, limited working hours, design flaws, and management problems. Amiri et al. [83] noted that burnout and heat significantly contribute to accidents. Xu et al. [84] pointed out that education is crucial in minimizing human error risks, with age, experience, and workplace conditions also playing important roles. Dhalmahapatra et al. [85] emphasized the negative impact of inadequate interaction between humans and technology on error-related accidents. The study of Cheng et al. [86] analyzed human errors in remotely operated autonomous ships and found that available time, task complexity, and pre-warning significantly influence performance. At the same time, boredom and experience had limited impact. Finally, Rafieyan et al. [40] identified nine categories of these factors, including incorrect actions, misinterpretations, planning issues, equipment problems, organizational shortcomings, individual behaviors, environmental conditions, emergency responses, and technology. Among these, mismanagement, inadequate supervision, and

insufficient financial resources were highlighted as primary contributors to errors. Despite significant efforts to reduce human errors in various industries, many challenges and uncertainties persist. Previous research and the findings of this study highlighted the ongoing struggle to fully address this issue.

The objectivity of the proposed model was supported through sensitivity analyses that tested a range of weight values and their corresponding alternative scenarios. The fuzzy method applies to all decision support areas where layman evaluators assess decision system elements, particularly techniques using pairwise comparisons. Additionally, the proposed model familiarizes experts with the entire assessment process, as confirmed by survey data in this study. The integrated method assists decision-makers in focusing on the most critical factors affecting assembly errors. In summary, our study reinforces previous research findings, confirming the prevalence of specific factors contributing to manual assembly errors. Organizations can enhance assembly accuracy, reduce costs, and improve overall product quality by addressing these factors and implementing strategies such as enhanced training, clearer instructions, and optimized work environments.

6. Conclusions and Future Research

This study developed an integrated model to determine the factors influencing human errors (HEs) in the manual assembly processes and rank them using two MCDM techniques. The first technique used to build the developed model is the fuzzy Delphi, which conducted two rounds of the survey to identify the primary factors contributing to HEs in manual assembly. After expert consensus, 27 factors were determined to have a significant impact on HEs, with influence scores of 0.7 or higher. The second technique is the fuzzy AHP, which used a third round of surveys to determine the priorities of the 27 influencing factors in assembly HEs based on their weights.

The results of this analysis revealed that a lack of experience, inadequate instructions and procedures, and misunderstandings constitute the most critical contributors to errors in manual assembly. These findings offer valuable insights for organizations seeking to mitigate human errors and enhance the overall quality of their products. To ensure reliable and practical results of the developed model, sensitivity analysis was conducted on model inputs and parameters that affect final decisions.

While this study provides a comprehensive overview of factors contributing to human errors in manual assembly, certain limitations warrant consideration for future research. The current analysis primarily focuses on identifying individual factors without delving into their intricate interrelationships. Future investigations should employ methodologies capable of exploring these complex interactions. Furthermore, empirical studies are encouraged to examine the mental and physical workloads experienced by workers during manual assembly tasks. Such research would provide deeper insights into the underlying causes of human errors, potentially leading to strategies that enhance both worker efficiency and comfort in the workplace.

Appendix A. The Fuzzy Delphi Questionnaire

Study Title: Evaluating the Most Important Factors Affecting Human Errors in Manual Assembly Processes Using Fuzzy Delphi Method

Thank you for taking the time to help us. Please read this questionnaire and determine if the main factors and variables affect human errors in the manual assembly process or not. In addition, you can add any important factor or variable missing in the questionnaire. The outputs of this questionnaire will be for academic research and will be published in scientific journals while keeping your personal information.

I. Demographic information

Please indicate to the answer by placing X or check mark.

1. Gender: ☐male ☐female

2. Age: ☐35 years old (inclusive) under; ☐36 to 40 years old; ☐41 to 45 years old; ☐46 to 50 years old; ☐51 years old (inclusive) or older.

3. Education level: ☐Bachelor; ☐Master; ☐Doctoral; ☐Other: _____

4. Experience in industry/academia: ☐10 to 15 years; ☐16 to 20; ☐21 to 25; ☐More than 25 years.

5. Service sector (Industry): _____

6. Job title: _____

II. Pairwise assessment criteria

Judgment scale

Code	Description	Fuzzy Numbers (a, b, c)
NI	Negligible influence	(0, 0, 0.25)
LI	Low influence	(0, 0.25, 0.5)
MI	Moderate influence	(0.25, 0.5, 0.75)
HI	High influence	(0.5, 0.75, 1)
OI	Overwhelming influence	(0.75, 1, 1)

Please assess criteria based on the judgment scale and place only one check mark for each row during assessment criteria.

Determine the impact of the main factors concerning manual assembly errors.

Main Factors	Does a factor influence human error in the manual assembly process? (Yes or No)	If Yes, how much does the factor influence human error in the manual assembly process?				
		NL	LI	MI	HI	OI
Individual Factors		☐	☐	☐	☐	☐
Tool Factors		☐	☐	☐	☐	☐
Task Factors		☐	☐	☐	☐	☐
Organizational Factors		☐	☐	☐	☐	☐
Work environment Factors		☐	☐	☐	☐	☐

Determine the impact of the individual factors concerning manual assembly errors.

Individual Factors	Does a variable influence human error in the manual assembly process? (Yes or No)	If Yes, how much does the variable influence human error in the manual assembly process?				
		NL	LI	MI	HI	OI
Lack of experience		☐	☐	☐	☐	☐
Misunderstanding		☐	☐	☐	☐	☐
Lack of knowledge		☐	☐	☐	☐	☐
Poor perception		☐	☐	☐	☐	☐
Risk-taking behavior		☐	☐	☐	☐	☐
Memory issues		☐	☐	☐	☐	☐
Fatigue		☐	☐	☐	☐	☐
Stress		☐	☐	☐	☐	☐
Unknown roles and responsibilities		☐	☐	☐	☐	☐
Unintentional errors		☐	☐	☐	☐	☐
Rushed work		☐	☐	☐	☐	☐
Health problems		☐	☐	☐	☐	☐
Intelligence quotient		☐	☐	☐	☐	☐

Determine the impact of the tool factors concerning manual assembly errors.

Tool Factors	Does a variable influence human error in the manual assembly process? (Yes or No)	If Yes, how much does the variable influence human error in the manual assembly process?				
		NL	LI	MI	HI	OI
Using the wrong equipment		☐	☐	☐	☐	☐
Equipment shortages		☐	☐	☐	☐	☐

Determine the impact of the task factors concerning manual assembly errors.

Task Factors	Does a variable influence human error in the manual assembly process? (Yes or No)	If Yes, how much does the variable influence human error in the manual assembly process?				
		NL	LI	MI	HI	OI
Poor instructions and procedures		☐	☐	☐	☐	☐
Task complexity		☐	☐	☐	☐	☐
Time pressure		☐	☐	☐	☐	☐
Workload		☐	☐	☐	☐	☐
Multitasking		☐	☐	☐	☐	☐

Determine the impact of the organizational factors concerning manual assembly errors.

Organizational Factors	Does a variable influence human error in the manual assembly process? (Yes or No)	If Yes, how much does the variable influence human error in the manual assembly process?				
		NL	LI	MI	HI	OI
Poor training		☐	☐	☐	☐	☐
Lack of supervision		☐	☐	☐	☐	☐
Problem to address error		☐	☐	☐	☐	☐

Determine the impact of the environmental factors concerning manual assembly errors.

Environmental Factors	Does a variable influence human error in the manual assembly process? (Yes or No)	If Yes, how much does the variable influence human error in the manual assembly process?				
		NL	LI	MI	HI	OI
Inappropriate lighting		☐	☐	☐	☐	☐
Noise		☐	☐	☐	☐	☐
Ergonomics problems		☐	☐	☐	☐	☐
Poor layout		☐	☐	☐	☐	☐

Appendix B. The Fuzzy AHP Questionnaire

Study Title: Evaluating the Most Important Factors Affecting Human Errors in Manual Assembly Processes Using Fuzzy AHP Method

Thank you for taking the time to help us. Your feedback will help us to evaluate the most important factors which affect human errors in manual assembly processes. The outputs of this questionnaire will be for academic research and will be published in scientific journals while keeping your personal information.

I. Demographic information

Please indicate to the answer by placing X or check mark.

1. Gender: ☐male ☐female

2. Age: ☐35 years old (inclusive) under; ☐36 to 40 years old; ☐41 to 45 years old; ☐46 to 50 years old; ☐51 years old (inclusive) or older.

3. Education level: ☐Bachelor; ☐Master; ☐Doctoral; ☐Other: _____

4. Experience in industry/academia: ☐10 to15 years; ☐16 to20; ☐21 to25; ☐More than 25 years.

5. Service sector (Industry): _____

6. Job title: _____

II. Pairwise comparisons scenarios

Judgment scale

Importance Degree	Linguistic Terms	Fuzzy Numbers (a, b, c)
1	Equally influential	(1, 1, 1)
3	Weakly influential	(2, 3, 4)
5	Strongly influential	(4, 5, 6)
7	Very strongly influential	(6, 7, 8)
9	Extremely influential	(9, 9, 9)
2, 4, 6, 8	Intermediate levels	(1, 2, 3), (3, 4, 5), (5, 6, 7), (7, 8, 9)

Please compare criteria based on judgment scale and place only one circle or check mark for each row during comparing criteria.

Compare the importance of the main factors concerning manual assembly errors.

Main Factors	Individual Factors	Tool Factors	Task Factors	Organizational Factors	Environment Factors
Individual Factors	(1, 1, 1)				
Tool Factors		(1, 1, 1)			
Task Factors			(1, 1, 1)		
Organizational Factors				(1, 1, 1)	
Environment Factors					(1, 1, 1)

Compare the importance of the individual factors concerning manual assembly errors.

Individual Factors	Lack of experience	Misunderstanding	Lack of knowledge	Poor perception	Risk-taking behavior	Memory issues	Fatigue	Stress	Unknown roles and responsibilities	Unintentional errors	Rushed work	Health problems	Intelligence quotient
Lack of experience	(1, 1, 1)												
Misunderstanding		(1, 1, 1)											
Lack of knowledge			(1, 1, 1)										
Poor perception				(1, 1, 1)									
Risk-taking behavior					(1, 1, 1)								
Memory issues						(1, 1, 1)							
Fatigue							(1, 1, 1)						
Stress								(1, 1, 1)					
Unknown roles and responsibilities									(1, 1, 1)				
Unintentional errors										(1, 1, 1)			
Rushed work											(1, 1, 1)		
Health problems												(1, 1, 1)	
Intelligence quotient													(1, 1, 1)

Compare the importance of the tool factors concerning manual assembly errors.

Tool Factors	Using the wrong equipment	Equipment shortages
Using the wrong equipment	(1, 1, 1)	
Equipment shortages		(1, 1, 1)

Compare the importance of the task factors concerning manual assembly errors.

Task Factors	Poor instructions and procedures	Task complexity	Time pressure	Workload	Multitasking
Poor instructions and procedures	(1, 1, 1)				
Task complexity		(1, 1, 1)			
Time pressure			(1, 1, 1)		
Workload				(1, 1, 1)	
Multitasking					(1, 1, 1)

Compare the importance of the organizational factors concerning manual assembly errors.

Organizational Factors	Poor training	Lack of supervision	Problem to address error
Poor training	(1, 1, 1)		
Lack of supervision		(1, 1, 1)	
Problem to address error			(1, 1, 1)

Compare the importance of the environmental factors concerning manual assembly errors.

Environmental Factors	Inappropriate lighting	Noise	Ergonomics problems	Poor layout
Inappropriate lighting	(1, 1, 1)			
Noise		(1, 1, 1)		
Ergonomics problems			(1, 1, 1)	
Poor layout				(1, 1, 1)

References

1. Alqahtani, F.M.; Noman, M.A.; Alabdulkarim, S.A.; Alharkan, I.; Alhaag, M.H.; Alessa, F.M. A New Model for Determining Factors Affecting Human Errors in Manual Assembly Processes Using Fuzzy Delphi and DEMATEL Methods. *Symmetry* **2023**, *15*, 1967. [CrossRef]
2. Richardson, M.; Jones, G.; Torrance, M.; Baguley, T. Identifying the task variables that predict object assembly difficulty. *Hum. Factors* **2006**, *48*, 511–525. [CrossRef] [PubMed]
3. Brolin, A.; Thorvald, P.; Case, K. Experimental study of cognitive aspects affecting human performance in manual assembly. *Prod. Manuf. Res.* **2017**, *5*, 141–163. [CrossRef]
4. Bavafa, A.; Mahdiyar, A.; Marsono, A.K. Identifying and assessing the critical factors for effective implementation of safety programs in construction projects. *Saf. Sci.* **2018**, *106*, 47–56. [CrossRef]
5. Li, D.; Mattsson, S.; Salunkhe, O.; Fast-Berglund, Å.; Skoogh, A.; Broberg, J. Effects of information content in work instructions for operator performance. *Procedia Manuf.* **2018**, *25*, 628–635. [CrossRef]
6. Bäckstrand, G.; Thorvald, P.; De Vin, L.J.; Högberg, D.; Case, K. The impact of information presentation on work environment and product quality: A case study. In Proceedings of the 40th Annual Conference of the Nordic Ergonomics Society, Reykjavík, Iceland, 11–13 August 2008.
7. Torres, Y.; Nadeau, S.; Landau, K. Classification and quantification of human error in manufacturing: A case study in complex manual assembly. *Appl. Sci.* **2021**, *11*, 749. [CrossRef]
8. Mattsson, S.; Fast-Berglund, Å.; Li, D. Evaluation of guidelines for assembly instructions. *IFAC-PapersOnLine* **2016**, *49*, 209–214. [CrossRef]
9. Lichtner, D.; Senesac, C.J.; Hagan, R.J.; Gandhi, F. Three-dimensional model based manufacturing work instructions. In Proceedings of the 65th Annual Forum Proceedings-AHS International, Grapevine, TX, USA, 27–29 May 2009; pp. 2115–2120.
10. Geng, J.; Zhang, S.; Yang, B. A publishing method of lightweight three-dimensional assembly instruction for complex products. *J. Comput. Inf. Sci. Eng.* **2015**, *15*, 031004. [CrossRef]
11. Lotter, B.; Wiendahl, H.-P. Changeable and reconfigurable assembly systems. In *Changeable and Reconfigurable Manufacturing Systems*; Springer: Berlin/Heidelberg, Germany, 2009; pp. 127–142.

12. Dinlersoz, E.; Wolf, Z. Automation, labor share, and productivity: Plant-level evidence from US Manufacturing. *Econ. Innov. New Technol.* **2018**, *33*, 604–626. [CrossRef]

13. BEUß, F.; Sender, J.; Flügge, W. Ergonomics simulation in aircraft manufacturing–methods and potentials. *Procedia CIRP* **2019**, *81*, 742–746. [CrossRef]

14. Judt, D.; Lawson, C.; Lockett, H. Experimental investigation into aircraft system manual assembly performance under varying structural component orientations. *Proc. Inst. Mech. Eng. Part B J. Eng. Manuf.* **2020**, *234*, 840–855. [CrossRef]

15. Torabi, N.; Gunay, H.B.; O'Brien, W.; Barton, T. Common human errors in design, installation, and operation of VAV AHU control systems–A review and a practitioner interview. *Build. Environ.* **2022**, *221*, 109333. [CrossRef]

16. Park, K.; Lempert, C.; Abdullah, M.; Katakura, S.; Shigeyama, J.; Roumen, T.; Baudisch, P. FoolProofJoint: Reducing Assembly Errors of Laser Cut 3D Models by Means of Custom Joint Patterns. In Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems, New Orleans, LA, USA, 29 April–5 May 2022; pp. 1–12.

17. Gursel, E.; Reddy, B.; Khojandi, A.; Madadi, M.; Coble, J.B.; Agarwal, V.; Yadav, V.; Boring, R.L. Using artificial intelligence to detect human errors in nuclear power plants: A case in operation and maintenance. *Nucl. Eng. Technol.* **2023**, *55*, 603–622. [CrossRef]

18. Wang, P.; Yang, Y.; Wen, B.; Ma, H.; Han, Q.; Luo, Z.; Li, X.; Wen, B. Numerical and experimental analysis of vibration characteristics of spindle system under bearing assembly errors. *Mech. Based Des. Struct. Mach.* **2024**, *52*, 4811–4838. [CrossRef]

19. Miao, H.; Wang, C.; Li, C.; Yao, G.; Zhang, X.; Liu, Z.; Xu, M. Dynamic modeling and nonlinear vibration analysis of spindle system during ball end milling process. *Int. J. Adv. Manuf. Technol.* **2022**, *121*, 7867–7889. [CrossRef]

20. Xu, H.; Wang, P.; Ma, H.; Yang, Y.; Li, X.; Luo, Z.; Han, Q.; Wen, B. Dynamic behaviors and contact characteristics of ball bearings in a multi-supported rotor system under the effects of 3D clearance fit. *Mech. Syst. Signal Process.* **2023**, *196*, 110334. [CrossRef]

21. Farhadi, S.; Mohammadfam, I.; Kalatpour, O.; Ghasemi, F. Determining performance shaping factors to assess human error in the emergency response team in chemical process industries: A case study. *Int. J. Occup. Saf. Ergon.* **2023**, *29*, 294–305. [CrossRef]

22. Wong, Y.C.; Wong, K.Y.; Ali, A. Key practice areas of lean manufacturing. In Proceedings of the 2009 International Association of Computer Science and Information Technology-Spring Conference, Singapore, 17–20 April 2009; pp. 267–271.

23. Weyer, S.; Schmitt, M.; Ohmer, M.; Gorecky, D. Towards Industry 4.0—Standardization as the crucial challenge for highly modular, multi-vendor production systems. *IFAC-PapersOnLine* **2015**, *48*, 579–584. [CrossRef]

24. Thoben, K.-D.; Wiesner, S.; Wuest, T. "Industrie 4.0" and smart manufacturing—A review of research issues and application examples. *Int. J. Autom. Technol.* **2017**, *11*, 4–16. [CrossRef]

25. Lopez, R.; Love, P.E.; Edwards, D.J.; Davis, P.R. Design error classification, causation, and prevention in construction engineering. *J. Perform. Constr. Facil.* **2010**, *24*, 399–408. [CrossRef]

26. Mohammadfam, I.; Khajevandi, A.A.; Dehghani, H.; Babamiri, M.; Farhadian, M. Analysis of factors affecting human reliability in the mining process design using Fuzzy Delphi and DEMATEL methods. *Sustainability* **2022**, *14*, 8168. [CrossRef]

27. Noman, M.A.; Alqahtani, F.M.; Al-Harkan, I.; Alabdulkarim, S.A.; Alasim, F. A new integrated risk-assessment model for minimizing human-machine error consequences in a preventive maintenance system. *IEEE Access* **2023**, *11*, 25253–25265. [CrossRef]

28. Torres, Y.; Nadeau, S.; Landau, K. Applying AcciMap and STAMP to the analysis of human error in complex manual assembly. *Hum. Factors Ergon. Manuf. Serv. Ind.* **2022**, *32*, 462–481. [CrossRef]

29. Saptari, A.; Leau, J.X.; Mohamad, N.A. The effect of time pressure, working position, component bin position and gender on human error in manual assembly line. In Proceedings of the 2015 International Conference on Industrial Engineering and Operations Management (IEOM), Dubai, United Arab Emirates, 3–5 March 2015; pp. 1–6.

30. Morais, C.; Estrada-Lugo, H.D.; Tolo, S.; Jacques, T.; Moura, R.; Beer, M.; Patelli, E. Robust data-driven human reliability analysis using credal networks. *Reliab. Eng. Syst. Saf.* **2022**, *218*, 107990. [CrossRef]

31. Dhanalakshmi, C.S.; Madhu, P.; Hemachandran, M.N.; Muthukumar, M.V.; Arvinth, L.H. Design and Fabrication of Robotic Arm for the assembly of Phase Selector Switch. *IOP Conf. Ser. Mater. Sci. Eng.* **2021**, *1059*, 012032. [CrossRef]

32. Mohammadfam, I.; Aliabadi, M.M.; Soltanian, A.R.; Tabibzadeh, M.; Mahdinia, M. Investigating interactions among vital variables affecting situation awareness based on Fuzzy DEMATEL method. *Int. J. Ind. Ergon.* **2019**, *74*, 102842. [CrossRef]

33. Chan, D.W.; Baghbaderani, A.B.; Sarvari, H. An empirical study of the human error-related factors leading to site accidents in the Iranian urban construction industry. *Buildings* **2022**, *12*, 1858. [CrossRef]

34. Nordqvist, M.; Lindblom, J. Operators' Experience of Trust in Manual Assembly with a Collaborative Robot. In Proceedings of the 6th International Conference on Human-Agent Interaction, Southampton, UK, 15–18 December 2018; pp. 341–343.

35. Müller, B.C.; Reise, C.; Duc, B.M.; Seliger, G. Simulation-games for learning conducive workplaces: A case study for manual assembly. *Procedia CIRP* **2016**, *40*, 353–358. [CrossRef]

36. Lavric, T.; Bricard, E.; Preda, M.; Zaharia, T. Exploring low-cost visual assets for conveying assembly instructions in AR. In Proceedings of the 2021 International Conference on INnovations in Intelligent SysTems and Applications (INISTA), Kocaeli, Turkey, 25–27 August 2021; pp. 1–6.

37. Lavric, T. *Methodologies and Tools for Expert Knowledge Sharing in Manual Assembly Industries by Using Augmented Reality*; Institut Polytechnique de Paris: Palaiseau, France, 2022.

38. Miqueo, A.; Torralba, M.; Yagüe-Fabra, J.A. Lean manual assembly 4.0: A systematic review. *Appl. Sci.* **2020**, *10*, 8555. [CrossRef]

39. Krugh, M.; Garimella, R.S.; Baburaj, A.; Wescoat, E.; Mears, L. Closed loop feedback mechanism effect pilot investigation on manual assembly time and process variation. *Procedia Manuf.* **2020**, *48*, 95–104. [CrossRef]
40. Rafieyan, A.; Sarvari, H.; Beer, M.; Chan, D.W. Determining the effective factors leading to incidence of human error accidents in industrial parks construction projects: Results of a fuzzy Delphi survey. *Int. J. Constr. Manag.* **2024**, *24*, 748–760. [CrossRef]
41. Winkelhake, U. Challenges in the digital transformation of the automotive industry. *ATZ Worldw.* **2019**, *121*, 36–43. [CrossRef]
42. Liu, L.; Liu, Y.; Zhang, J. Learning-based hand motion capture and understanding in assembly process. *IEEE Trans. Ind. Electron.* **2018**, *66*, 9703–9712. [CrossRef]
43. Pankok, C., Jr.; Zahabi, M.; Zhang, W.; Choi, I.; Liao, Y.-F.; Nam, C.S.; Kaber, D. The effects of interruption similarity and complexity on performance in a simulated visual-manual assembly operation. *Appl. Ergon.* **2017**, *59*, 94–103. [CrossRef]
44. Turk, M.; Pipan, M.; Šimic, M.; Herakovič, N. Simulation-based time evaluation of basic manual assembly tasks. *Adv. Prod. Eng. Manag.* **2020**, *15*, 331–344. [CrossRef]
45. Kolbeinsson, A.; Thorvald, P.; Lindblom, J. Coordinating the interruption of assembly workers in manufacturing. *Appl. Ergon.* **2017**, *58*, 361–371. [CrossRef]
46. Ribbe, M.W.; Górecki, K.; Grosch, M.; Solomon, J.B.; Quechol, R.; Liu, Y.A.; Lee, C.C.; Hu, Y. Nitrogenase Fe protein: A multi-tasking player in substrate reduction and metallocluster assembly. *Molecules* **2022**, *27*, 6743. [CrossRef]
47. Wang, Z.; Bai, X.; Zhang, S.; Billinghurst, M.; He, W.; Wang, P.; Lan, W.; Min, H.; Chen, Y. A comprehensive review of augmented reality-based instruction in manual assembly, training and repair. *Robot. Comput.-Integr. Manuf.* **2022**, *78*, 102407. [CrossRef]
48. Fruggiero, F.; Fera, M.; Iannone, R.; Lambiase, A. Revealing a frame to incorporate safe human behaviour in assembly processes. *IFAC-PapersOnLine* **2018**, *51*, 661–668. [CrossRef]
49. Bläsing, D.; Bornewasser, M. Influence of increasing task complexity and use of informational assistance systems on mental workload. *Brain Sci.* **2021**, *11*, 102. [CrossRef]
50. Bläsing, D.; Bornewasser, M. Influence of complexity and noise on mental workload during a manual assembly task. In Proceedings of the Human Mental Workload: Models and Applications: 4th International Symposium, H-WORKLOAD 2020, Granada, Spain, 3–5 December 2020; Proceedings 4. 2020; pp. 147–174.
51. Anghel, D.-C.; Nițu, E.-L.; Rizea, A.-D.; Gavriluță, A.; Gavriluță, A.; Belu, N. Ergonomics study on an assembly line used in the automotive industry. *MATEC Web Conf.* **2019**, *290*, 12001. [CrossRef]
52. Ishikawa, A.; Amagasa, M.; Shiga, T.; Tomizawa, G.; Tatsuta, R.; Mieno, H. The max-min Delphi method and fuzzy Delphi method via fuzzy integration. *Fuzzy Sets Syst.* **1993**, *55*, 241–253. [CrossRef]
53. Häder, M.; Häder, S. Delphi und kognitionspsychologie: Ein zugang zur theoretischen fundierung der Delphi-Methode. *ZUMA Nachrichten* **1995**, *19*, 8–34.
54. Skulmoski, G.J.; Hartman, F.T.; Krahn, J. The Delphi method for graduate research. *J. Inf. Technol. Educ. Res.* **2007**, *6*, 1–21. [CrossRef] [PubMed]
55. Boulkedid, R.; Abdoul, H.; Loustau, M.; Sibony, O.; Alberti, C. Using and reporting the Delphi method for selecting healthcare quality indicators: A systematic review. *PLoS ONE* **2011**, *6*, e20476. [CrossRef]
56. Alghawli, A.S.A.; Al-khulaidi, A.A.; Nasser, A.A.; AL-Khulaidi, N.A.; Abass, F.A. Application of the Fuzzy Delphi Method to Identify and Prioritize the Social-Health Family Disintegration Indicators in Yemen. *Int. J. Adv. Comput. Sci. Appl.* **2022**, *13*, 680–691. [CrossRef]
57. Roth, C.; Brewer, M.; Wieck, K.L. Using a Delphi method to identify human factors contributing to nursing errors. *Nurs. Forum* **2017**, *52*, 173–179. [CrossRef]
58. Van Laarhoven, P.J.; Pedrycz, W. A fuzzy extension of Saaty's priority theory. *Fuzzy Sets Syst.* **1983**, *11*, 229–241. [CrossRef]
59. Saaty, T.L. The analytic hierarchy process (AHP). *J. Oper. Res. Soc.* **1980**, *41*, 1073–1076.
60. Dağdeviren, M.; Yavuz, S.; Kılınç, N. Weapon selection using the AHP and TOPSIS methods under fuzzy environment. *Expert Syst. Appl.* **2009**, *36*, 8143–8151. [CrossRef]
61. Marznaki, Z.H.; Khanjankhani, K.; Salisu, W.J.; Hajihosseini, F.; Barzegari, S. Identifying and ranking the factors affecting the choice of nursing discipline among nursing students in Iran: A fuzzy hierarchical analysis. *J. Nurs. Res.* **2021**, *29*, e171. [CrossRef]
62. Ping, D.Y.; Limin, J.; Fang, C.; Zhenhua, Z.; Yong, Q. Fuzzy analytic hierarchy process for high-speed rail train plan evaluation on special operation conditions. *JCIT J. Converg. Inf. Technol.* **2011**, *6*, 237–244.
63. Zhou, C.; Kou, X.-j. Method of estimating human error probabilities in construction for structural reliability analysis based on analytic hierarchy process and failure likelihood index method. *J. Shanghai Jiaotong Univ.* **2010**, *15*, 291–296. [CrossRef]
64. Chai, Y.; Wang, Y.; Wang, Y.; Peng, L.; Hou, L. Safety evaluation of human-caused errors in civil aviation based on analytic hierarchy process and fuzzy comprehensive evaluation method. *Aircr. Eng. Aerosp. Technol.* **2024**, *96*, 826–837. [CrossRef]
65. Karthick, M.; Robert, T.P.; Kumar, C.S. HFACS-based FAHP implementation to identify critical factors influencing human error occurrence in nuclear plant control room. *Soft Comput.* **2020**, *24*, 16577–16591. [CrossRef]
66. Sarsangi, V.; Karimi, A.; Hadavandi, E.; Hokmabadi, R. Prioritizing risk factors of hazardous material road transportation accidents using the fuzzy AHP method. *Work* **2023**, *75*, 275–286. [CrossRef]
67. Tsai, H.-C.; Lee, A.-S.; Lee, H.-N.; Chen, C.-N.; Liu, Y.-C. An application of the fuzzy Delphi method and fuzzy AHP on the discussion of training indicators for the regional competition, Taiwan national skills competition, in the trade of joinery. *Sustainability* **2020**, *12*, 4290. [CrossRef]

68. Kabir, G.; Sumi, R.S. Integrating fuzzy delphi with fuzzy analytic hierarchy process for multiple criteria inventory classification. *J. Eng. Proj. Prod. Manag.* **2013**, *3*, 22–34. [CrossRef]
69. Mousavi, S.M.; Yazdanirad, S.; Althubiti, S.; Majdabadi, M.A.; Najarian, F.; Sepehr, P. Determination and prioritization of factors affecting the occurrence of needle stick injuries among healthcare workers using techniques of Delphi and fuzzy analytical hierarchy process (FAHP). *BMC Public Health* **2023**, *23*, 2009. [CrossRef]
70. Rafieyan, A.; Sarvari, H.; Chan, D.W. Identifying and evaluating the essential factors affecting the incidence of site accidents caused by human errors in industrial parks construction projects. *Int. J. Environ. Res. Public Health* **2022**, *19*, 10209. [CrossRef]
71. Baker, J.; Lovell, K.; Harris, N. How expert are the experts? An exploration of the concept of 'expert'within Delphi panel techniques. *Nurse Res.* **2006**, *14*, 59–70. [CrossRef]
72. Mabrouk, N. Green supplier selection using fuzzy Delphi method for developing sustainable supply chain. *Decis. Sci. Lett.* **2021**, *10*, 63–70. [CrossRef]
73. Ahmed, F.; Kilic, K. Fuzzy Analytic Hierarchy Process: A performance analysis of various algorithms. *Fuzzy Sets Syst.* **2019**, *362*, 110–128. [CrossRef]
74. Buckley, J.J. Fuzzy hierarchical analysis. *Fuzzy Sets Syst.* **1985**, *17*, 233–247. [CrossRef]
75. Zadeh, L.A. Fuzzy sets. *Inf. Control* **1965**, *8*, 338–353. [CrossRef]
76. Saaty, T.L. Decision making, scaling, and number crunching. *Decis. Sci.* **1989**, *20*, 404–409. [CrossRef]
77. Manfei, X.; Fralick, D.; Zheng, J.Z.; Wang, B.; Changyong, F. The differences and similarities between two-sample t-test and paired t-test. *Shanghai Arch. Psychiatry* **2017**, *29*, 184.
78. Moslem, S.; Farooq, D.; Jamal, A.; Almarhabi, Y.; Almoshaogeh, M.; Butt, F.M.; Tufail, R.F. An integrated fuzzy analytic hierarchy process (AHP) model for studying significant factors associated with frequent lane changing. *Entropy* **2022**, *24*, 367. [CrossRef]
79. Ravalico, J.K.; Maier, H.R.; Dandy, G.C. Sensitivity analysis for decision-making using the MORE method—A Pareto approach. *Reliab. Eng. Syst. Saf.* **2009**, *94*, 1229–1237. [CrossRef]
80. Alogla, A.A.; Alruqi, M. Aircraft assembly snags: Human errors or lack of production design? *Aerospace* **2021**, *8*, 391. [CrossRef]
81. Azhdari, M.; Monazami Tehrani, G.; Alibabaei, A. Investigating the causes of human error-induced incidents in the maintenance operations of petrochemical industry by using HFACS. *J. Occup. Hyg. Eng.* **2017**, *3*, 22–30. [CrossRef]
82. Morais, C.; Moura, R.; Beer, M.; Patelli, E. Human reliability analysis—Accounting for human actions and external factors through the project life cycle. In *Safety and Reliability–Safe Societies in a Changing World*; CRC Press: Boca Raton, FL, USA, 2018; pp. 329–338.
83. Amiri, M.; Ardeshir, A.; Zarandi, M.H.F. Risk-based analysis of construction accidents in Iran during 2007–2011-meta analyze study. *Iran. J. Public Health* **2014**, *43*, 507. [PubMed]
84. Xu, S.; Zhang, M.; Hou, L. Formulating a learner model for evaluating construction workers' learning ability during safety training. *Saf. Sci.* **2019**, *116*, 97–107. [CrossRef]
85. Dhalmahapatra, K.; Singh, K.; Jain, Y.; Maiti, J. Exploring causes of crane accidents from incident reports using decision tree. In Proceedings of the Information and Communication Technology for Intelligent Systems: Proceedings of ICTIS 2018, Ahmedabad, India, 6–7 April 2018; Springer: Singapore, 2019; Volume 1, pp. 175–183.
86. Cheng, T.; Veitch, E.A.; Utne, I.B.; Ramos, M.A.; Mosleh, A.; Alsos, O.A.; Wu, B. Analysis of human errors in human-autonomy collaboration in autonomous ships operations through shore control experimental data. *Reliab. Eng. Syst. Saf.* **2024**, *246*, 110080. [CrossRef]