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Performance Fuzzy Decision Model for Evaluating Employees' Work-from-Home Performance

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Abstract

This study aims to identify key workplace environmental parameters and develop a Decision Support Model (DSM) to evaluate the performance of work-from-home (WFH). The methods utilized include Tsukamoto Fuzzy Logic and conventional techniques. Key parameters incorporated into the DSM-WFHP model include room temperature, internet speed, number of children, virtual office setup, and physical activity (sport). The research culminates in the DSM-WFHP model, which provides accurate assessments of WFH employee performance. Findings indicate that variations in these parameters significantly impact performance, with specific quantitative results demonstrating that optimal room temperature, high internet speed, fewer children present, an effective virtual office setup, and regular physical activity correlate with higher performance scores. Thus, this research concludes that the DSM-WFHP model effectively offers precise performance evaluation guidance for remote employees, making a valuable contribution to remote work management. With regards to the novelty of this study, this is the first time that the synergetic effect of multiple environmental factors has been incorporated into a comprehensive DSM.

Keywords: Work from Home, Decision Support Model, Fuzzy Logic, Employee Performance

1. Introduction

In recent years, rapid advances in information technology [1] and a shift toward flexible work arrangements have transformed work environments. Technologies such as video conferencing tools, cloud-based platforms, and high-speed internet have facilitated the adoption of WFH [2], a trend accelerated by the COVID-19 pandemic to ensure business continuity and employee safety [3]. With the rise of WFH practices, IT managers play a crucial role in maintaining the technological infrastructure, ensuring data security, providing technical support, and monitoring remote worker performance [4]. Their performance is essential for the efficiency of an organization's remote work initiatives and includes selecting appropriate technologies, allocating resources effectively, and evaluating remote worker performance. However, WFH introduces challenges such as feelings of isolation, loneliness, and anxiety, which impact employee performance [5]. Additionally, the lack of direct supervision makes it difficult to assess performance objectively [6]. IT managers need comprehensive data-driven insights to make decisions regarding technology, resource allocation, and employee performance evaluation [7]. To make these decisions effectively, they require comprehensive data-driven insights. To address this need, a system that can assess employee performance accurately, objectively, and efficiently is essential. This system can assist managers in making decisions regarding whether employees are suitable for WFH, when to issue warnings, provide training, and predict the suitability of new employees for WFH.

This is where DSM becomes a crucial system for use in the current situation. A DSM is a systematic approach that combines data analysis, machine learning, and domain-specific knowledge to aid IT managers in making decisions about remote worker performance. IT managers can directly utilize the model in several specific tasks. The model offers a detailed analysis of employee performance by considering various environmental and personal factors. IT managers can use this model to identify employees who are excelling in the WFH setup and those who may need additional support or resources to improve their performance. The model's ability to handle both fuzzy and non-fuzzy parameters ensures that all relevant factors are accounted for, providing a holistic view of employee performance.

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The insights generated by the model can guide IT managers in allocating technological resources more effectively. For instance, if the model indicates that internet speed is a significant factor affecting performance for certain employees, IT managers can prioritize improving internet connectivity for these individuals. Similarly, the model can help identify employees who would benefit from enhanced virtual office setups or other technical support. The model can assist IT managers in making informed decisions about the suitability of employees for WFH. By analyzing performance data, the model can predict whether an employee is likely to perform well in a remote setting or if a hybrid approach might be more appropriate. This predictive capability is particularly useful for onboarding new employees, as it helps in assessing their potential effectiveness in a WFH environment.

Based on the performance assessments provided by the model, IT managers can identify specific areas where employees might need additional training or development. This targeted approach ensures that training resources are used efficiently and effectively, addressing the actual needs of the workforce. By continuously monitoring and assessing the performance of remote workers, IT managers can proactively address challenges such as isolation and anxiety. The model can highlight when employees are struggling, allowing managers to intervene with appropriate support measures, such as mental health resources or team-building activities. This model considers various factors, including network performance, social isolation, room temperature, family background, and overall job satisfaction, to provide recommendations and predictions that optimize the WFH method [8]. To ensure precise and accurate assessments, the researcher also applies fuzzy logic methods within the model. The application of this method serves to obtain precise values from the parameters used in the evaluation.

The selection of parameters for the DSM is grounded in empirical research and practical considerations. Room temperature is a key factor, as thermal comfort has been shown to significantly impact productivity and cognitive function. Studies indicate that maintaining an optimal room temperature enhances focus and efficiency, while variations can lead to discomfort and reduced performance [9]. Internet speed is another critical parameter, ensuring smooth communication, quick access to online resources, and efficient workflow management. Research has demonstrated that poor internet connectivity leads to frustration, delays, and decreased productivity [10]. The number of children present in the home environment can influence an employee’s ability to concentrate and maintain a consistent work schedule. Findings have highlighted that employee with caregiving responsibilities experience more interruptions and stress, negatively impacting their work performance [11]. The concept of a virtual office, which involves staying connected through platforms like Teams or Zoom, is essential for maintaining communication, collaboration, and a sense of team cohesion. Effective use of these tools mitigates isolation and communication barriers, leading to higher job satisfaction and productivity [12]. Lastly, physical activity plays a significant role in remote work scenarios. Regular engagement in sports or exercise is associated with improved mental health, reduced stress levels, and enhanced cognitive function, which collectively contribute to better overall performance [13].

Several research studies have explored innovative approaches to decision support and performance assessment in different contexts. In the first study [14], researchers developed a DSM that optimized the Fuzzy method for appraising Human Resources based on individual performance. This model combined fuzzy logic principles and Hill Climbing, resulting in a more time-efficient appraisal model with improved decision outcomes, reducing the required time by up to 47.5%. In the second study [15], a DSS was introduced to provide objective employee appraisals using a fuzzy model approach. Questionnaires based on management principles were employed, leading to a fuzzy-based appraisal system that demonstrated 75% accuracy compared to conventional methods. In the third study [16], a Decision Support System for student evaluation was created using fuzzy logic methods. The system encompassed group assessment, personal assessment, and peer assessment, leading to a more effective and reliable decision-making process. The fourth study [17] adopted the Analytical Hierarchy Process (AHP) Model to evaluate employee performance for appraisal. The research identified consistency in five criteria but found that Research was considered less valid as a reference for appraisal. Finally, [18] the fifth study applied the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) method within a Decision Support System to determine the best employees in an organization. The results provided a foundational basis for top management decision support in recognizing outstanding employees. These studies collectively highlight diverse approaches to enhance decision support and performance assessment processes in HR, education, and organizational contexts.

From the research that has been conducted, all of it can contribute to creating a model that supports top management decisions with objective, efficient, and accurate data. Improvements are clear when compared directly with the previous systems used in each study. However, there is no specific research on measuring employee performance during the WFH method. As previously discussed, working from home significantly impacts one's mental condition. This is why research needs to be carried out and further examined so that the evaluation of employee performance during WFH can provide results that are truly objective and accurate, even though the level of supervision is limited and minimal due to differences in work locations. Therefore, the author concludes that the problem statement is as follows: (1) What environmental parameters influence the performance of employees working from home and can be used to assess their performance? (2) How to construct a DSM for evaluating WFH performance and providing appropriate decision outcomes? After identifying the research questions above, the study aims to determine the parameters to be used and to design a DSM for measuring and evaluating the performance of employees working from home. This study also benefits both academic and practical stakeholders. Academics will obtain references for conducting further research to develop the models they desire. Meanwhile, practical parties will gain knowledge and references regarding the accurate assessment of WFH performance, particularly when there are parameters with potentially biased values used in the evaluation categories.

2. Method

Specifically, the research stages will be classified into five phases as depicted in the figure 1 below using DSM Wheel process [22]. These phases include a structured procedure that makes certain all-round development of the model and validation. In this section, each and every research stage starting from the first stage up to the final stage of model development will be discussed. By elaborating on each phase, this section aims to provide a clear and detailed roadmap of the research process, ensuring a thorough understanding of the methodology employed in developing the DSM-WFHP model.

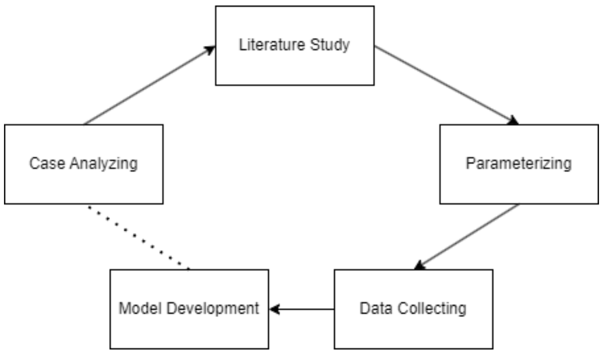

Figure 1. DSM-WFHP as proposed methods

2.1. Case Analyzing

To ensure the success of model development, researchers must adopt a comprehensive approach to understanding the WFH context. This involves examining various factors that influence employee productivity and well-being, including technical, managerial, and social aspects. Direct observation, through interviews with HR and IT managers, provides valuable insights into the organization's internal dynamics and the challenges of implementing WFH policies. These interviews highlight best practices and policies that have successfully facilitated remote work models.

Preparation for these interviews includes thorough research into WFH, remote working, and related environmental factors. By using diverse sources of information such as articles, reports, and online videos, researchers can gain a well-rounded understanding of the issues at hand. This comprehensive data collection approach, incorporating multiple perspectives, helps validate findings and enrich the analysis. The gathered data forms a robust foundation for developing a relevant and comprehensive employee performance evaluation model tailored to the evolving dynamics of remote work.

2.2. Literature Study

In this section, a thorough literature review is conducted to explore previous research studies and to identify their limitations and gaps. By comparing past research methods with the current study, we aim to highlight the improvements and innovations made in our approach to assessing WFH performance. Several research studies have explored innovative approaches to decision support and performance assessment in various contexts. For instance, [14] developed a DSM that optimized the Fuzzy method for appraising Human Resources based on individual performance. This model combined fuzzy logic principles and Hill Climbing, resulting in a more time-efficient appraisal model with improved decision outcomes, reducing the required time by up to 47.5%. However, this study primarily focused on traditional office settings and did not address the unique challenges and variables associated with WFH environments.

Another study [15] introduced a DSS to provide objective employee appraisals using a fuzzy model approach. Questionnaires based on management principles were employed, leading to a fuzzy-based appraisal system that demonstrated 75% accuracy compared to conventional methods. While this study highlighted the benefits of fuzzy logic in employee appraisal, it did not consider the specific environmental factors impacting WFH performance, such as room temperature, internet speed, and the presence of children. In a different context, [16] created a decision support system for student evaluation using fuzzy logic methods. This system encompassed group assessment, personal assessment, and peer assessment, leading to a more effective and reliable decision-making process. Despite its success in the educational sector, the study did not address workplace performance assessment, particularly in a remote work setting.

The study by [17] adopted the AHP Model to evaluate employee performance for appraisal, focusing on clear criteria. While AHP provided a structured approach to performance evaluation, it lacked the flexibility to handle fuzzy parameters and the inherent uncertainties of the WFH environment. This limitation underscores the need for integrating fuzzy logic to capture the nuances of WFH performance assessment. Furthermore, [18] applied the technique for order of preference by TOPSIS method within a decision support system to determine the best employees in an organization. The results provided a foundational basis for top management decision support in recognizing outstanding employees. However, similar to previous studies, this research did not consider the specific parameters influencing WFH performance, thereby limiting its applicability in remote work settings.

In comparison, our study addresses the gaps identified in previous research by developing a comprehensive DSM for WFH performance assessment. We incorporate both fuzzy and conventional methods to evaluate key parameters such as room temperature, internet speed, number of children, virtual office setup, and physical activity. By using the FIS Tsukamoto method for fuzzy parameters and conventional methods for non-fuzzy parameters, our model captures the complexities and uncertainties of the WFH environment, which were not adequately addressed in prior studies.

Additionally, the novelty of our research lies in its specific focus on WFH performance, a topic that has become increasingly relevant in the current global work landscape but has not been extensively explored in the literature. This focus allows us to provide actionable insights and data-driven outcomes tailored to the unique challenges of remote work. In summary, while previous studies have made significant contributions to decision support and performance assessment, they have primarily focused on traditional work environments and did not fully address the specific factors influencing WFH performance. Our research builds on these foundations by introducing a hybrid model that integrates fuzzy and conventional methods, providing a more nuanced and comprehensive assessment of WFH performance. This approach not only fills the gaps identified in the literature but also offers a valuable tool for organizations to optimize remote work policies and improve employee productivity in a remote work setting.

2.3. Parameterizing

The selection of the FIS Tsukamoto method as the approach for building the WFH performance assessment model compared to other methods such as AHP or TOPSIS can be influenced by several factors.

First, the FIS Tsukamoto method allows for the representation of uncertain or ambiguous variables and values in the model, in line with the complex and difficult-to-predict nature of the WFH environment. The fuzzy logic approach enables handling this uncertainty more flexibly than crisp methods. Second, the ability to address uncertainty and ambiguity strengthens the position of FIS Tsukamoto. With membership functions, the model can handle uncertainty and ambiguity better than crisp approaches like AHP or TOPSIS. Third, the representation capability of membership levels in FIS Tsukamoto allows the model to capture nuances in WFH performance assessment that are difficult to express accurately using crisp methods. Finally, the ease of implementation and interpretation of FIS Tsukamoto are important considerations. It's simple inferencing logic structure facilitates implementation and interpretation by users who may not have a strong mathematical background. Applying the Tsukamoto method involves several steps, beginning with fuzzification, where crisp input values are transformed into fuzzy values using membership functions. For instance, a room temperature of 25°C might be classified as 0.7 "medium" and 0.3 "high." Next, the rule evaluation step applies fuzzy rules to the fuzzified inputs. An example rule might state, "IF temperature is medium AND internet speed is high THEN performance is good," and the degree to which this rule is satisfied is calculated. Following this, aggregation combines the outputs of all the rules to produce a single fuzzy output value, calculating the degree of truth for each rule and aggregating these values. The final step is defuzzification, which converts the fuzzy output value back into a crisp value. The Tsukamoto method typically uses the weighted average method for defuzzification, where the output is a weighted average of all the rule outputs. Considering these factors, FIS Tsukamoto is deemed more suitable for building the WFH performance assessment model due to its ability to handle uncertainty, represent membership levels, and ease of implementation and interpretation. This makes it particularly advantageous for assessing performance in environments characterized by ambiguity and variability, such as remote work settings.

Furthermore, the parameter weighting stage is conducted to determine the appropriate weight values for each parameter. Direct interviews with the Head of HR serve as the key in determining these parameter weights, while also considering information and research from literature studies as in the previous method. The weights assigned by the expert refer to the impact of each parameter on WFH employee performance, which has also been analyzed and studied through relevant literature reviews. Additionally, by incorporating conventional assessment concepts currently used in the company, the weights are also easier to determine. Thus, the process of collecting and arranging these parameters becomes an important initial step in building a comprehensive and effective employee performance evaluation model in the WFH context.

2.4. Data Collecting

Data collection in this research is a crucial stage to obtain the necessary information for developing a quality WFH performance assessment model. The findings of this study are based on a sample size of 24 employees, which, while sufficient for our specific analysis, raises considerations regarding the generalizability of the results. A larger sample size could provide more comprehensive insights into the broader population of remote workers. However, despite the small sample size, 24 samples are sufficient to simulate the model, as this model was not only built through data-oriented or data-driven approaches but also focused more on the analysis of phenomena with efforts made to ensure diversity in participant demographics and organizational roles, thereby enhancing the representativeness within our study cohort. This diversity helps to capture a variety of experiences and conditions in the remote work environment, providing a robust basis for our conclusions. Additionally, the simulation capabilities of our model allow for the exploration of different WFH scenarios, offering valuable insights and practical applications even with a smaller sample size.

The method used is direct field studies, where every employee involved in the research (a total of 24 employees) will work under predetermined conditions, including variables such as the home working environment, disturbance levels, network connection, and other relevant aspects. The researcher visited the homes of 5 out of 24 respondents directly to gain a real insight into the field conditions. However, due to time constraints, only 5 respondents were willing to be visited directly, while the rest were conducted through brief surveys and interviews. These direct observations allow the researcher to gain deep insights into the daily experiences of employees while working from home and to collect firsthand data about their working conditions.

In addition to employing field study methods, data will also be collected from the company's Helpdesk Ticketing System. This system records the total number of tickets handled by employees on specific workdays, offering insights into their productivity and performance while working from home. However, it's important to acknowledge potential biases introduced through this method of data collection. The Helpdesk Ticketing System primarily captures task-related activities and may not fully encompass other critical aspects of remote work performance, such as collaboration, creativity, or overall job satisfaction. To mitigate these biases, rigorous measures have been implemented.

Firstly, the study incorporates qualitative insights gathered from field studies, including interviews and observations. These qualitative methods aim to provide a comprehensive understanding of employee experiences and performance factors beyond the metrics captured by the Helpdesk System. Secondly, all data obtained from the IT helpdesk system undergoes thorough verification. This process involves cross-checking against data collected through field studies to ensure consistency and accuracy. Any discrepancies identified during this verification process are addressed promptly to uphold the reliability of the data used for further analysis.

By integrating these strategies, the study aims to minimize biases associated with data collected via the company's IT helpdesk system. This approach ensures that the developed WFH performance assessment model is based on robust and representative data, contributing to the reliability of the study's conclusions. Subsequently, both data obtained through these methods will undergo verification to strengthen the validity of the data to be used in the research. This is done by cross-checking the data obtained from field studies with data from the company's information systems. This ensures that the data used in further analysis can be relied upon and is representative for building an accurate WFH performance assessment model. After using these methods, all data to be used will undergo a data pre-processing stage before becoming the final dataset to be used. By carefully pre-processing the data before analysis, the researcher can ensure that the dataset used in the research is of good quality, consistent, and aligned with the intended analysis objectives. This helps improve the accuracy, reliability, and validity of the analysis results generated from the research.

To perform data pre-processing, the first step is to handle missing or incomplete values in the dataset. Identify missing values and determine strategies for handling them, such as deleting rows or columns with missing values, or replacing missing values with the mean, median, or mode of the corresponding column. The second step is to remove duplicate data in the dataset to prevent its influence on data analysis and interpretation. After that, the next step is to perform data transformation, such as normalization or standardization, to ensure uniformity and consistency in the dataset. This involves converting values in the dataset into a more uniform range or distribution more suitable for specific statistical analyses.

2.5. Model Development

In the model development stage, we begin by setting the weighting parameters to measure each parameter's influence on WFH performance assessment. The FIS Tsukamoto method is used to handle fuzzy parameters (ax), which include room temperature, internet speed, and having children. These parameters are processed through three main stages: fuzzification (converting crisp values into fuzzy values), inference (applying fuzzy rules), and defuzzification (converting fuzzy values back into crisp values). For non-fuzzy parameters (bx), which include virtual office setup and physical activity, conventional methods are used for straightforward calculations. The final step involves combining the results from both fuzzy and non-fuzzy parameters to determine the overall WFH performance assessment, or Decision Value. This model, implemented using Python, helps decide if an employee is suitable for WFH, if a hybrid approach is feasible, and predicts WFH efficiency for new recruits. The model can be continuously updated based on new data and evolving case studies to improve accuracy. The overview of the model development process can be further shown in figure 2.

3. Results and Discussion

3.1. Parameters

The following section describes the strategy used to identify the parameters incorporated in the development of the model. The approach to collecting these parameters integrates two complementary methods: a comprehensive analysis of the data available in the preceding academic research and some no less productive and compelling interviews with one of the heads of HRD. Therefore, through the use of these two strategies, it is considerably effective in achieving parameter understanding and subsequent selection. The specified literature review, taken from [19], provided a conceptual background for the choice of parameters and provided analysis of beneficial trends. However, it can be noted that the expert interviews provided the practical insight into the matter that enriched the validity of the opinions regarding the parameters' importance and further specified the range of parameters. Furthermore, the identified parameters are then weighted using the same dual methodology, The literature review and the experts' input are also employed in this process. This merged strategy not only improves the parameter selection but also increases the general improvement and usability of the said model.

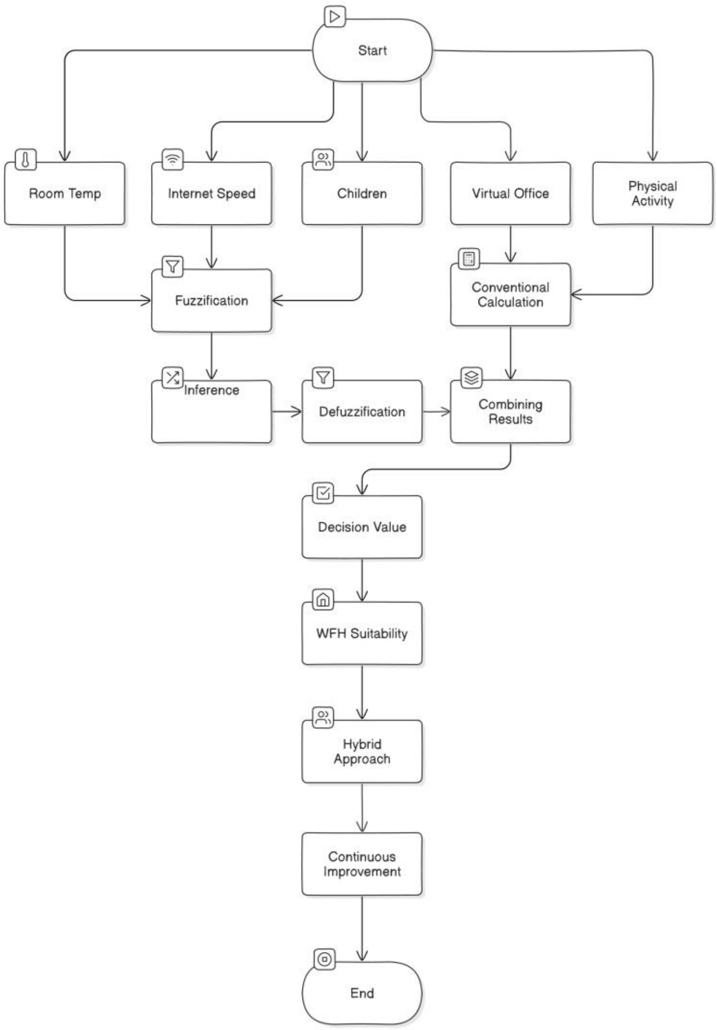

Figure 2. DSM-WFHP Model Development Process

3.2. Parameter Grouping

In this section, we categorize the parameters used in the model into two distinct groups: fuzzy parameters (ax) and non-fuzzy parameters (bx), also known as conventional parameters. This classification is essential for understanding the inherent uncertainty or precision associated with each parameter. Fuzzy parameters (ax) encompass elements within our dataset that exhibit uncertainty or imprecision and are characterized by linguistic variables such as high, medium/moderate, and low. These parameters include room temperature, internet speed, and number of children. For instance, room temperature can vary and be subjectively perceived as high, medium, or low based on individual comfort levels. Similarly, internet speed and the number of children can fluctuate and impact performance in subjective ways.

Non-fuzzy parameters (bx), on the other hand, are characterized by well-defined, precise values without inherent uncertainty. These parameters typically have binary outcomes where 0 represents "not met" or "false," and 1 represents "met" or "true." In our model, non-fuzzy parameters include virtual office setup and physical activity (sport). Virtual office setup is assessed based on whether it is implemented (1) or not (0), while physical activity is categorized as either engaged (1) or not engaged (0).

The distinction between ax and bx parameters is critical for constructing our decision support model effectively. By categorizing parameters based on their degree of uncertainty, we tailor our approach to handle both qualitative linguistic variables and binary data appropriately. This approach ensures that our model accommodates the complexities of real-world scenarios where precise measurements may be challenging to ascertain. In summary, ax parameters reflect uncertainty and variability, requiring fuzzy logic methods to process and analyze data effectively. In contrast, bx parameters are characterized by their straightforward, deterministic nature, allowing for simpler calculation and interpretation within our model framework.

3.3. Dataset Resource

The dataset operated in this research was collected through two methods: (1) By conducting direct observations and extracting data through the company's IT helpdesk system to obtain employee job data over a specific time period. The data will then be sorted and selected only when employees are working from home. (2) By distributing an online questionnaire using the Google Forms platform to obtain a complete profile of employees. The collected data includes all employees working in the IT SAP department, with a total of 24 employees, each having various parameter conditions. The collected data is presented in table 1.

Table 1. Collected Dataset

No	P1	P2	P3	P4	P5
1.	26	5	1	Y	Y
2.	28	35	1	N	N
…	…	…	…	…	…
23.	33	30	2	Y	Y
24.	27	1	0	N	N

3.4. Variable Analysis

One of the tools for representing a decision model graphically is by using an influence diagram. This is necessary to assist in the design, understanding, and future development of the model. In building the model, the researcher uses an influence diagram to represent the graphical form of the model itself as shown in figure 3.

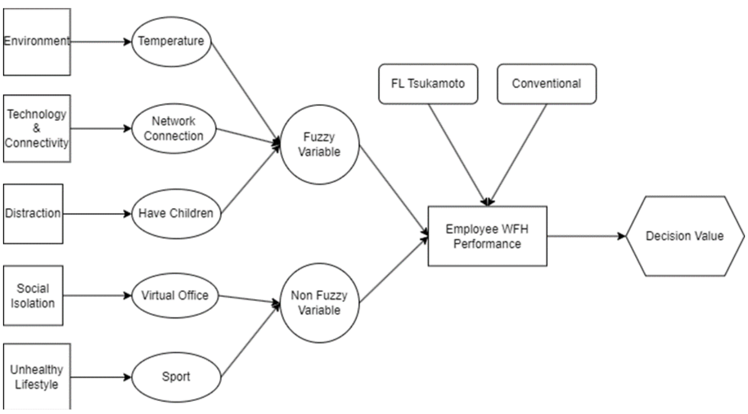

Figure 3. Influence diagram of DSM-WFHP

From the influence diagram, the output of this research is to determine a decision in the form of the final assessment result (decision value) of the performance of employees WFH within a specified period. This output is also the expected outcome of the problem statement within the model. The model is constructed using a combination of two methods, namely Fuzzy Logic (FL) Tsukamoto and conventional methods [23]. The FL Tsukamoto method is used for assessing fuzzy parameters (ax), while the conventional method is used for grouping non-fuzzy parameters (bx). In the (ax) group, three fuzzy parameters are considered: temperature, network connection, and having children. These parameters are assessed using fuzzy logic due to their inherent uncertainty and variability. For instance, temperature can range from low to high, impacting comfort and productivity. Network connection quality can fluctuate, affecting communication and workflow efficiency. The presence of children can vary, influencing distraction levels and available work time.

In the (bx) group, two non-fuzzy parameters are evaluated: virtual office setup and sports (physical activity). These parameters are assessed using conventional methods because they are binary and straightforward. The virtual office setup is evaluated based on its presence or absence, which directly influences the ability to collaborate and access necessary resources. Participation in sports is considered a yes/no variable, impacting physical health and overall well-being. The influence diagram illustrates how each parameter, both fuzzy and non-fuzzy, contributes to the overall performance evaluation of employees working from home. The fuzzy parameters are processed through the FL Tsukamoto method to account for their variability, while the non-fuzzy parameters are analyzed using conventional methods. The combination of these assessments results in a comprehensive Decision Value, reflecting the final evaluation of WFH performance.

3.5. Constructed Model

After the variable analysis is conducted, and the identified issues have been formulated in the previous chapter, the next step involves constructing a model named DSM-WFHP (Decision Support Model – Work from Home Performance). In the development of the model to be implemented in the assessment of WFH, the initial step taken is the preparation of parameters required to build the model. The collection of these parameters is carried out by combining two methods, namely through literature review and further discussions with the head of the HR department, resulting in a total of 5 parameters as shown in table 2.

Table 2. WFH Assessment Parameter

Var	Parameter	Attribute	Reference
P1	Temperature	High Comfortable Low	Seppanen et al. [9]
P2	Network Connection	High Moderate Low	Gibbs et al. [10]
P3	Have Children	Many Moderate Few	Galanti et al. [11]
P4	Virtual Office	Yes No	Weinert et al. [12]
P5	Sport	Yes No	Griep et al. [13]

Attribute values for each of these five parameters are defined based on empirical field data, with the aim of ensuring that the developed model can closely approximate the true values in the context of the issue at hand. A total of 5 parameters have been successfully identified, as recorded in table 2. Subsequently, a grouping of all parameters is carried out, resulting in two groups, namely (ax) and (bx), where (ax) represents fuzzy parameters, while (bx) is for non-fuzzy categories. Details of the parameter grouping can be found in table 3.

Table 3. Parameter Grouping

Group	Parameter
(ax)	Temperature (P1) Network Connection (P2) Have Children (P3)
(bx)	Virtual Office (P4) Sport (P5)

After the grouping stage is successfully completed, the process continues with the weighting process to generate weight values (W) for each parameter used. This weighting is applied to all parameters with the aim of determining the significant weight held by each group, represented by (∑Wf) reflecting the total influence of the fuzzy group, and (∑Wk) reflecting the total influence of the conventional group in producing the final WFH assessment. The parameter weight data is arranged in descending order from highest to lowest values for each parameter group, and the results are presented in table 4.

Table 4. Parameter Weighting

No	(ax)	W	(bx)	W
1	P2	0.33981	P4	0.20311
2	P3	0.26975	P5	0.06285
3	P1	0.12448		
	∑Wf	**0.73404**	**∑Wk**	**0.26596**

3.5.1. Class Diagram

The entity model is used to provide an overview of the relationships between the classes within this research, with the class diagram (CD) serving as a reference. The CD can provide a detailed explanation of the collection of classes, interfaces, relations, and collaborations. In this research, the CD as shown on figure 4 can be read as follows: Each individual employee has one WFH performance value, where this value is obtained from the number of FL values. The FL value, in turn, is generated from the quantity of the fuzzy rule base and membership functions.

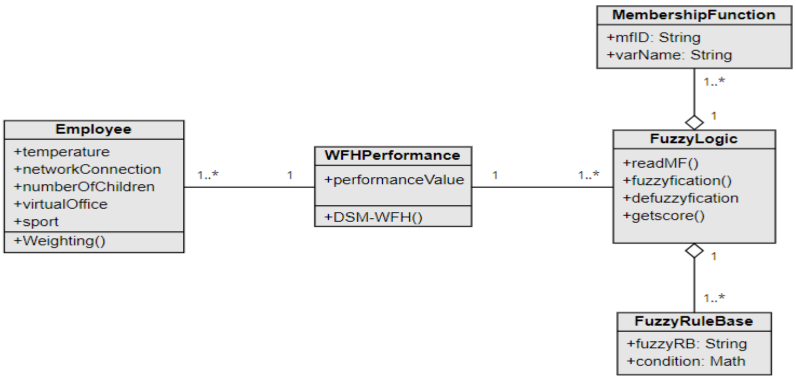

Figure 4. Class Diagram of DSM-WFHP

3.5.2. Model Algorithm

The entire algorithm process of the model to be constructed can be depicted using an activity diagram in figure 5. The first step is to define and analyze the parameters that affect WFH performance. After that, data collection is performed by direct observation and data extraction from the Helpdesk Ticketing system. The weighting of parameters is then carried out using the AHP method, so that, in the end, the priority weight (PW) can be determined. Afterward, the parameters that have obtained PW are grouped into two categories: fuzzy parameters (ax) and non-fuzzy parameters (bx). For the parameters (bx), it is necessary to define them again or provide numerical values. This is followed by a simple mathematical calculation, which involves the summation of the products of each parameter (bx) with the PW (ax), resulting in the final value of the (bx) parameters. For fuzzy parameters, their membership degrees (membership functions) will be determined first. After that, the FL Tsukamoto method is applied [20] through the process of fuzzification using equation (1), (2), and (3), inferencing by reading the rule based using equation (4), (5), and (6), last step defuzzification using (7). The results will be multiplied by importance weights, resulting in the final values for the fuzzy parameters. The ultimate outcome of the model is the decision value (DV), which serves as the final assessment value for WFH.

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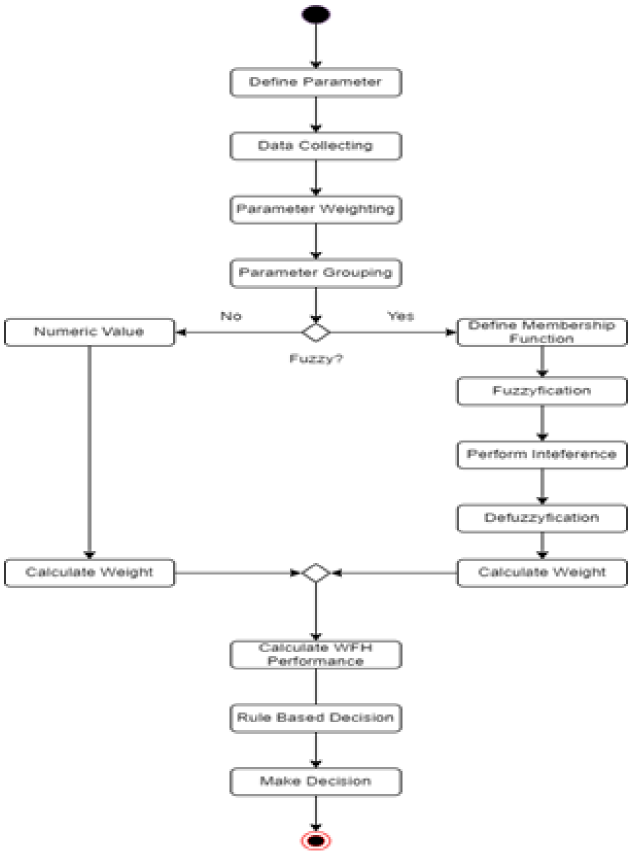

Figure 5. DSM-WFHP Activity Diagram

$$\mu MF_{Low}(x) = \begin{cases} 0, & x \geq c \\ \dfrac{c-x}{c-b}, & b \leq x \leq c \\ 1, & x \leq b \end{cases} \tag{1}$$

Here, x represents the value being evaluated, b is the lower bound where the membership is fully 1, and c is the upper bound where the membership decreases linearly to 0.

$$\mu MF_{Mid}(x) = \begin{cases} 0, & x \leq 0 \; or \; x \geq d \\ \dfrac{x-a}{b-a}, & a \leq x \leq b \\ 1, & b \leq x \leq c \\ \dfrac{d-x}{d-c}, & c \leq x \leq d \end{cases} \tag{2}$$

Here, x is the value being evaluated, a and d are the bounds where the membership is 0, b is where the membership rises to 1, and c is where it starts to decrease from 1.

$$\mu MF_{Up}(x) = \begin{cases} 0, & x \leq a \\ \dfrac{x-a}{b-a}, & a \leq x \leq b \\ 1, & x \geq b \end{cases} \tag{3}$$

Here, x represents the value being evaluated, a is the lower bound where the membership starts to increase, and b is the point where the membership reaches 1.

$$\alpha\_pred_i = \mu MF_{Low}(x) \cup \mu MF_{Up}(x) \tag{4}$$

This formula is defined as the union of the membership functions for the low and upper fuzzy sets, where x is the value being evaluated. This represents the combined membership degree of x in both the low and upper fuzzy sets.

$$z = zmax - a\_pred(zmax - zmin) \tag{5}$$

zmax is the maximum value, $zmin$ is the minimum value, and αpred is the combined membership degree from the fuzzy sets. This formula adjusts z proportionally between $zmax$ and $zmin$ based on αpred.

$$z = zmin - a\_pred(zmin - zmax) \tag{6}$$

zmin is the minimum value, $zmax$ is the maximum value, and αpred is the combined membership degree from the fuzzy sets. This formula adjusts z proportionally between $zmin$ and $zmax$ based on αpred.

$$Z^* = \frac{\sum_1^n \alpha\_pred_i * Z_i}{\sum_1^n \alpha\_pred_i} \tag{7}$$

αpred$i$ represents the combined membership degree from the fuzzy sets for the i-th term, and Zi is the corresponding value. This weighted average formula computes $Z*$ by taking the sum of the products of αpred$i$ and Zi, divided by the sum of all αpred$i$

$$\sum(bx) = (P4 + P5) * \sum Wk \tag{8}$$

P4 and P5 are coefficients or parameters, and $\sum Wk$ represents the sum of weights Wk. This formula computes $\sum(bx)$ by multiplying the sum of weights $\sum Wk$ by the sum of P4 and P5.

3.5.3. Conventional Methods

The concept for (bx) involves assigning Boolean values (0 and 1) to each attribute parameter, as seen in table 5, making calculations in the model more straightforward. Each attribute with a value of 0 indicates no positive impact on performance outcomes, while a value of 1 represents the opposite. Referring to the activity diagram model path on figure 5, the conventional method is implemented by using equation (8). Each input value corresponding to the parameters (bx) refers to the information listed in Table 3. The values of each parameter are summed and multiplied by the weight of the bx parameters (∑Wk). For example, if the total value of the (bx) parameters is 2, and it is multiplied by the weight value (∑Wk) of 0.26596, the final result for the conventional method is obtained as (∑(bx)) equal to 0.53. The results of the process in the conventional method are displayed in table 6.

Table 5. Boolean Values for (bx)

(bx)	Criteria	Attribute Value	Boolean Value
P4	Virtual Office	Yes	1
		No	0
P5	Sport	Yes	1
		No	0

Table 6. Calculation Result from (bx)

(bx)		∑Wk	∑(bx)
P4	P5		
1	1	0,26596	0,5319

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3.5.4. Fuzzy Inference Systems Tsukamoto

The process starts by defining a MF, which essentially connects a range of values to a LV. This LV serves to express how true a parameter value is on a scale from 0 to 1. In this research, four different MFs were employed, including room temperature, internet speed, number of children, and Decision Value. The utilized MF in this research is trapezoidal, and it is based on the range domain edge. Figure 6 displays the Room Temperature MF, which comprises three trapezoidal MFs, each associated with a linguistic variable (LV) - LOW, COMFORTABLE, and HIGH. The universe for these LVs is (10,36), and their respective domains are (10, 21), (18, 27), and (24, 36). Moving on to figure 7, we can observe the Internet Speed MF, which is also characterized by three LVs - LOW, MODERATE, and HIGH - with a universe spanning (0, 51). The domains for these LVs are (0,15), (10,40), and (35,50). Figure 8 illustrates the mapping of MFs on the Number of Children, with three corresponding LVs - FEW, MODERATE, and MANY. The domains for these LVs are (0,2), (1,4), and (3,5), respectively. The universe for these LVs is (0,5). Also, figure 9 show the decision value (DV) MFs, represented by Score with the universe (0,100). Score has three LVs, NOT POSSIBLE with the domain (0,40), HYBRID with the domain (25,75), and POSSIBLE with the domain (60,100). These DV MFs were employed to establish the output variable level by considering the input values.

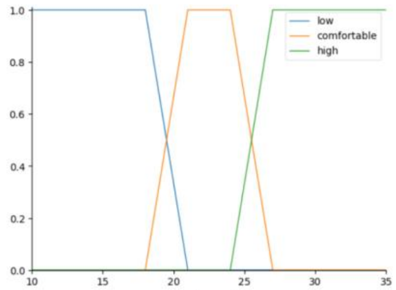

Figure 6. Room Temperature MF

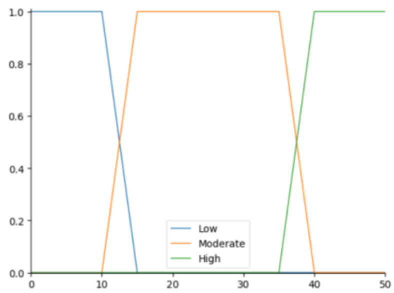

Figure 7. Internet Speed MF

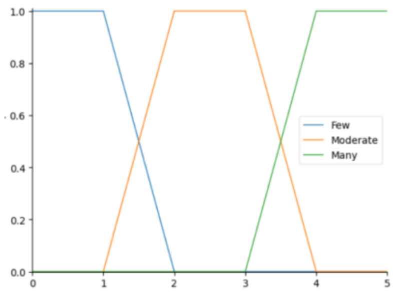

Figure 8. Number of Children MF

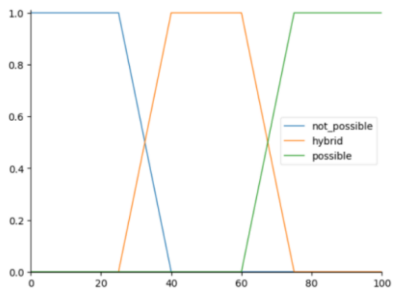

Figure 9. Score MF

Referring to the information in table 1, the input values corresponding to the parameter (ax) are processed using the FL Tsukamoto method in the fuzzy process. Detailed results of the fuzzy process can be observed in table 7. After the parameters (ax) have been successfully processed, their final values will be input back into the inference process using a set and correlation of rules. Rules are determined based on discussions with experts and findings from journal studies, taking into account reasoning and common logic. A total of 27 rules are utilized in this model, comprising 8 possible, 11 not possible, and 8 hybrid scenarios. The list of these rules can be found in table 8.

Table 6. Fuzzy Result

P1	**P2**	**P3**
26	5	1
µ*high*	µ*low*	µ*few*
0.6667	1.0000	1,0000

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Table 7. Fuzzy Rules

Rules	Condition
R1	IF P2 is low, AND P3 is few, AND P1 is comfortable THEN the score is possible
R2	IF P2 is low, AND P3 is few, AND P1 is low THEN the score is not possible
…	…
R26	IF P2 is high, AND P3 is many, AND P1 is low THEN the score is not possible
R27	IF P2 is high, AND P3 is many, AND P1 is high THEN the score is not possible

Subsequently, the result of this inference process is to find the value of z, which will be used as the final result of the defuzzification score. Equation (5) is used to calculate the not_possible score, while equation (6) is used to compute the hybrid and possible scores. Using the same example data, the inference process for R1 is calculated using Equation (6), giving a result of 46.668. Next is the final stage of the FL method, which is the defuzzification process carried out continuously until R27. By using Equation (7), the calculation results are 47,7783. To obtain the final value of the model (DV), a simple mathematical calculation is performed by adding the two parameters (ax) and (bx), where the value of each parameter is the result of multiplying by their respective weights. So, for the first dataset, Employee 1, where the subject works under the conditions of parameters (ax) and (bx) as specified in their respective tables table 6 and table 7, it results in a final value of 35.3370, which falls into the not_possible category. Thus, it can be interpreted that Employee 1 is not feasible to work remotely based on their working environment conditions. The result of defuzzifying process is shown in table 9.

3.5.5. Model Verification

$$\mathbf{Ve} = \frac{\sum_{\mathbf{i=1}}^{\mathbf{n}} \mathbf{VeTi}}{\mathbf{n}} \tag{9}$$

VeTi represents individual values of $VeTi$ from i=1 to n, and n denotes the total number of values. This formula calculates Ve by taking the average of $VeTi$ across n values.

Table 9. Calculation Result from Model

Employee	DV	Decission
1	83.46	Possible
2	50.01	Hybrid
…	…	…
23	90.32	Possible
24	35.14	Not Possible

Verification, in plain language, is the process of assessing the degree of truth of the developed model against the theoretical concept used. Model verification is an essential step aimed at confirming the accuracy of the model through an examination of its underlying formula, calculations, procedures, and adherence to the relevant theoretical framework. In the assessment of the DSM-WFHP, verification tests were employed as documented in references [21]. The verification model test was executed to gauge the precision of the constructed model and the application of the theoretical concept. This procedure entailed four fundamental elements: the formula, variables, procedures, and result. Each of these elements received a VeTi score of 1.0 when they matched both in the model and the reference. As presented in table 10. By utilizing equation (9), the Ve result was found to be 1.0, affirming the robustness and accuracy of the DSM-WFHP.

Table 8. Result of Model Verification

Sub-Model	Element	Model	Ref.	Ve-Ti
ax	Formula	7	7	1.00
	Variable	3	3	1.00
	Procedure	3	3	1.00
	Result	35,1429 – 83,4615	35,1429 – 83,4615	1.00
Bx	Formula	1	1	1
	Variable	5	5	1
	Procedure	1	1	1
	Result	0,0000 - 0,5319	0,0000 - 0,5319	1
	Ve	1.00		

3.5.6. Model Validation

Model validation, on the other hand, involved a comparison of the data within the model to real-world data. All data values fell within the range described in table 11. Model validation is performed by comparing the results of the model with real-world conditions. The company has its own calculation method that has become the standard scoring calculation. As seen in table 11, the table shows six elements consisting of all parameters and DV. All these elements have been validated and obtained an average score (Va) of 0.83. This validation result did not achieve a perfect score of 1 due to a difference in the DV element between the model calculation and the conventional calculation. The DSM-WFHP model produces a value of 35.3370, while the conventional method yields 41, resulting in an error ratio of 0.14. However, after confirmation by experts, this discrepancy is attributed to the model's more detailed calculation

Table 9. Model Validation

Element	Model	Real	VaTi
P1	$18 \leq x \leq 36$	≥ 16	1.00
P2	$1 \leq x \leq 50$	$0 \leq x \leq 1000$	1.00
P3	$0 \leq x \leq 3$	≥ 0	1.00
P4	Y / N	Y / N	1.00
P5	Y / N	Y / N	1.00
DV	35.3370	41	0.00
		Va	0.83

Compared to the existing conventional method. Therefore, the experts agree with the values generated by the model, and these results can serve as a new reference for the company in the future. Based on the Va result, it indicates that there is no significant difference between the model and the real-world conditions. Therefore, it can be interpreted that the DSM-WFHP has been constructed with accurate data values.

3.5.7. Discussion of Results

The results of this study highlight several key parameters influencing employee performance in a WFH context, namely room temperature, internet speed, the presence of children, virtual office setup, and physical activity. By integrating Fuzzy Logic Tsukamoto for fuzzy parameters and conventional methods for non-fuzzy parameters, our DSM provides a comprehensive assessment of WFH performance. The implications of our findings can be compared with existing literature. Previous research has utilized fuzzy logic to handle variables with inherent uncertainty. For instance, a study by [14] used a fuzzy method to appraise human resources, optimizing the appraisal process through a combination of fuzzy logic and Hill Climbing, reducing time by up to 47.5%. Our findings align with this approach by demonstrating that fuzzy logic effectively captures the nuances of WFH parameters like room temperature, internet speed, and the presence of children, which can fluctuate and are subject to subjective assessment. Additionally, our model improves on previous research by specifically addressing the unique challenges of the WFH environment, which had not been the focus in earlier studies.

Conventional methods have been applied to well-defined parameters in various studies. For example, [17] used the AHP to evaluate employee performance, focusing on clear criteria. Similarly, our study uses conventional methods to assess virtual office setup and physical activity, providing a straightforward evaluation of these binary parameters. This aligns with findings from [15], where a DSS using a fuzzy model showed 75% accuracy in objective employee appraisals, indicating that a mix of fuzzy and conventional approaches can enhance assessment accuracy. Our model further enhances these methodologies by integrating both fuzzy and conventional methods, allowing for a more comprehensive and precise assessment of WFH performance, a context that had not been thoroughly explored in prior research.

The integration of fuzzy and conventional methods in our DSM model reflects a hybrid approach seen in previous research. For example, [16] developed a DSS for student evaluation using fuzzy logic, improving decision-making reliability. Our model's hybrid approach allows for a nuanced assessment of WFH performance, accommodating both subjective and objective parameters. This approach is similar to [18], where TOPSIS was used within a DSS to recognize outstanding employees, providing a foundation for informed decision-making. Our model's hybrid approach not only mirrors these methods but also enhances them by tailoring the assessment specifically to the WFH context, thereby addressing a gap in the existing literature.

4. Conclusion

The research conducted has effectively identified and assessed five key parameters influencing the workplace environment in a WFH context: room temperature, internet speed, number of children, virtual office setup, and physical activity (sports). These parameters were previously managed using conventional methods that did not comprehensively cover workplace environmental aspects. Our study has introduced a process of grouping and weighting these parameters, resulting in two specific categories: "ax" for fuzzy value parameters and "bx" for Boolean value parameters. This research successfully developed the DSM-WFHP (Decision Support Model for Work from Home Performance), utilizing the FIS Tsukamoto Fuzzy to address biased values and conventional methods for Boolean values. By integrating both methods, the DSM-WFHP model provides a nuanced assessment of employee performance while working from home, helping organizations determine if employees can work remotely, need a hybrid approach, or require additional support.

The DSM-WFHP model offers organizations actionable insights and data-driven outcomes regarding WFH performance. This enables informed decision-making to optimize remote work policies, provide additional support and resources to employees, and identify areas for improvement. The DSM serves as a valuable tool to enhance the productivity and effectiveness of remote work arrangements.

While the research provides valuable insights and a practical DSM for assessing and improving WFH performance, several limitations must be addressed. The current study is limited to a single company, so future research should expand to include more extensive datasets, potentially encompassing a global perspective to enhance the model's generalizability. Additionally, the parameters used in this study are confined to the working environment, so future studies should incorporate internal factors such as personal skills, discipline level, and personality traits, providing a more holistic evaluation of WFH performance. Furthermore, the values for each linguistic variable in this study are based solely on expert judgment. Combining expert judgment with comprehensive literature reviews and empirical data could improve the accuracy and reliability of these values.

By addressing these limitations, future research can further refine and enhance the DSM-WFHP model, ensuring its applicability across diverse organizational contexts and improving its robustness. As remote work continues to play a prominent role in modern workplaces, the insights and tools presented in this study will be instrumental in helping organizations adapt and thrive in a changing work landscape. In summary, this research provides a comprehensive framework for understanding the parameters influencing WFH performance and offers a practical DSM for assessing and improving remote work arrangements. The findings and suggestions for future research underscore the importance of adaptable and resilient decision support systems in contemporary workforce management.

5. Declarations

5.1. Author Contributions

Conceptualization: C.I. and D.N.U.; Methodology: D.N.U.; Software: C.I.; Validation: C.I. and D.N.U.; Formal Analysis: C.I. and D.N.U.; Investigation: C.I.; Resources: D.N.U.; Data Curation: D.N.U.; Writing Original Draft Preparation: C.I. and D.N.U.; Writing Review and Editing: D.N.U. and C.I.; Visualization: C.I.; All authors have read and agreed to the published version of the manuscript.

5.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

5.3. Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

5.4. Institutional Review Board Statement

Not applicable.

5.5. Informed Consent Statement

Not applicable.

5.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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