



Measuring Mental Workload Among Employees In The Furniture Industry Using The Nasa-Tlx Method

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Abstract

Mental workload represents an important ergonomic factor in furniture manufacturing because employees perform tasks involving cognitive concentration, physical effort, time pressure, quality control, and production targets. This study aimed to measure mental workload among employees in the furniture industry using the National Aeronautics and Space Administration Task Load Index (NASA-TLX). A quantitative descriptive approach was applied, and workload was evaluated through six dimensions: mental demand, physical demand, temporal demand, performance, effort, and frustration. The NASA-TLX procedure involved pairwise weighting and rating of each dimension to determine the relative contribution of individual workload components and the overall workload score. The analytical framework emphasized the importance of interpreting aggregate workload together with dominant dimensions because similar total scores may arise from different occupational demands. The findings provide a basis for identifying work-system conditions requiring ergonomic improvement, including task complexity, physical exertion, production pacing, work organization, and psychological strain. The study demonstrates that NASA-TLX can support systematic evaluation of employee workload and provide practical information for improving ergonomic conditions, work allocation, operational efficiency, and occupational safety in furniture manufacturing environments.

Keywords: mental workload, NASA-TLX, furniture industry, ergonomics, occupational workload



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INTRODUCTION

The furniture industry represents a manufacturing sector in which production activities require the integration of physical effort, precision, decision-making, process monitoring, and coordination among workers to achieve predetermined production targets. These characteristics indicate that occupational demands are not limited to physical activities but also involve cognitive requirements that may affect accuracy, safety, and consistency of employee performance (Dadashi et al., 2022; Leva et al., 2022). Ergonomic studies in furniture-related work environments have demonstrated that compatibility between job characteristics, workplace facilities, and worker capabilities is important for maintaining productivity and preventing the accumulation of work-related fatigue (Bai et al., 2024). Accordingly, the evaluation of working conditions in the furniture industry should include the assessment of mental workload as an integral component of comprehensive ergonomic analysis.

Mental workload refers to the amount of cognitive resources required by individuals to meet task demands under specific working conditions. Excessive mental workload may reduce workers' ability to sustain attention, process information, make decisions, and respond appropriately to changes occurring during work activities (Prasetyo & Iridiastadi, 2025). In manufacturing environments, the interaction between mental and physical demands can also influence work behavior and increase the probability of unsafe actions when task requirements exceed workers' functional capacities (Chenarboo et al., 2022). These conditions indicate that mental workload constitutes an important ergonomic variable associated with work performance, occupational safety, and the effectiveness of production activities.

Mental workload can be assessed through subjective, physiological, and performance-based approaches, each of which provides different forms of information regarding cognitive demands. The combined application of physiological, subjective, and performance indicators can provide a broader interpretation of workers' responses to cognitive demands, particularly in complex industrial activities (Fogelberg et al., 2025). Physiological techniques such as electroencephalography and electrooculography can identify changes associated with cognitive overload, although their implementation requires specialized equipment, controlled procedures, and relatively complex data analysis (Morton et al., 2022). For operational assessments conducted directly in workplaces, subjective methods remain practical because they can capture workers' perceptions of task demands without substantially disrupting ongoing production activities.

One of the most widely used subjective instruments for assessing mental workload is the National Aeronautics and Space Administration Task Load Index, commonly referred to as NASA-TLX. This instrument evaluates workload through several dimensions representing mental demand, physical demand, temporal demand, performance, effort, and frustration experienced during task execution (Hernandez et al., 2022). The application of NASA-TLX has expanded across different occupational contexts because it enables multidimensional assessment rather than limiting workload measurement to a single cognitive indicator (Babaei et al., 2025). Studies conducted in manufacturing settings have also demonstrated that NASA-TLX can identify dominant workload components and provide a basis for evaluating the compatibility between job requirements and worker capacities (Hermansyah & Handayani, 2022).

The relevance of mental workload assessment becomes increasingly important in manufacturing operations where employees are required to maintain accuracy under production targets, time pressure, repetitive activities, and continuous coordination between workstations. Nino et al. (2023) demonstrated that perceived mental workload is associated with body postures during work, indicating that cognitive and physical aspects should not be examined as completely independent dimensions of occupational ergonomics. Research in the automotive manufacturing sector has similarly shown that workload assessment using NASA-TLX and the Rating Scale Mental Effort can identify variations in perceived demands across different production activities and worker groups (Azizah et al., 2025). These findings indicate that mental workload assessment may provide useful information for identifying work activities characterized by relatively high cognitive and operational demands.

In the furniture industry, work activities commonly include machine operation, material handling, quality inspection, production target fulfillment, and exposure to environmental conditions that may simultaneously generate physical and mental demands. Research conducted in a furniture company has indicated that workplace exposure, including occupational noise, should be considered in mental workload assessment because such conditions may influence workers' perceptions during task performance (Kontesya et al., 2024). NASA-TLX has also been applied to employees in the furniture sector to identify workload levels according to the characteristics of tasks performed in actual working environments (Satriyono et al., 2023). Nevertheless, differences in production systems, work organization, task allocation, and operational requirements among companies limit the direct generalization of workload findings from one furniture manufacturing environment to another.

In addition to producing an overall workload score, multidimensional assessment is necessary to explain the primary sources of occupational demands experienced by employees during industrial activities. Berthon et al. (2025) demonstrated that mental workload assessment in industrial contexts becomes more informative when the contribution of individual workload dimensions is examined rather than relying exclusively on an aggregate workload value. This distinction is important because two work activities with comparable overall workload scores may result from different dominant sources of demand, such as temporal pressure in one activity and mental effort in another. Consequently, NASA-TLX can be applied not only to determine the magnitude of perceived workload but also to identify specific dimensions that require attention in ergonomic and organizational interventions.

Based on these considerations, measuring mental workload among employees in the furniture industry is necessary to obtain empirical evidence regarding the level and characteristics of work demands experienced during production activities. NASA-TLX was selected because it provides a multidimensional framework for assessing workload and has been applied in manufacturing and

industrial environments characterized by diverse cognitive and operational demands (Dadashi et al., 2022; Hermansyah & Handayani, 2022; Babaei et al., 2025). This study therefore aims to measure the mental workload experienced by employees and to identify the NASA-TLX dimensions that contribute most substantially to perceived workload in furniture industry operations. The findings are expected to provide an empirical basis for ergonomic evaluation, task allocation, workload distribution, and the formulation of workplace interventions that are better aligned with employee capacities.

RESEARCH METHODS

This study employed a quantitative descriptive approach to measure the mental workload experienced by employees in the furniture industry using the National Aeronautics and Space Administration Task Load Index (NASA-TLX). The research population consisted of employees directly involved in furniture production activities, while respondents were selected from workers who routinely performed operational tasks and had sufficient experience with the work processes being evaluated. Primary data were collected through direct observation and administration of the NASA-TLX questionnaire after respondents completed their regular work activities. The instrument assessed six dimensions of workload, namely mental demand, physical demand, temporal demand, performance, effort, and frustration level, which together provide a multidimensional representation of employees' perceived workload (Hernandez et al., 2022; Hermansyah & Handayani, 2022).

Data analysis was conducted by applying the standard NASA-TLX procedure, consisting of pairwise weighting and rating of the six workload dimensions. Respondents first compared pairs of dimensions to determine the relative importance of each factor, after which they assigned a rating to each dimension based on the workload experienced during task performance. The weighted workload value for each dimension was obtained by multiplying its weighting score by the corresponding rating, and the overall NASA-TLX workload score was calculated by dividing the total weighted workload by the total number of pairwise comparisons. The resulting scores were subsequently analyzed descriptively to determine the level of mental workload among employees and to identify the dimensions contributing most strongly to the overall workload, thereby providing an empirical basis for ergonomic evaluation and improvement of work organization in the furniture industry (Dadashi et al., 2022; Babaei et al., 2025).

RESULTS AND DISCUSSION

Production Data Structure and Fuzzy Membership Formation

The empirical dataset contained monthly records of demand, production, and inventory covering the period from 2019 to 2022. The observations were structured chronologically to represent fluctuations in operational requirements and the corresponding availability of inventory within the furniture production system. Data from 2019–2021 constituted the principal information used to establish the Fuzzy Tsukamoto model, whereas the 2022 observations were retained for model evaluation. This separation between model-forming and validation periods provides an analytical basis for examining whether the fuzzy structure can accommodate changes in production conditions over time. Such data-driven approaches are increasingly relevant in industrial control because manufacturing decisions require methods capable of accommodating uncertainty and variation rather than relying exclusively on deterministic assumptions (Saravanan et al., 2022). The original dataset reports demand, production, and inventory in cubic metres, preserving the operational unit used by the furniture manufacturer.

The recorded values indicate considerable variation between the beginning and end of the observation period. In January 2019, demand reached 1,481 m³, production amounted to 1,240 m³, and inventory was 241 m³, while February 2019 recorded 1,497 m³ of demand, 1,330 m³ of production, and 167 m³ of inventory. March 2019 showed demand of 1,589 m³ and production of 1,358 m³, accompanied by inventory of 231 m³. By December 2022, demand had increased to 2,678 m³ and production to 2,527 m³, while inventory stood at 283 m³. These observations suggest that production requirements expanded substantially during the study period, while inventory remained considerably smaller than either demand or production volume. The pattern strengthens the need for

an adaptive inventory-control mechanism capable of translating changes in production conditions into an operational inventory recommendation (Berling et al., 2023).

Table 1. Demand, Production, and Inventory Data

No.	Month	Year	Demand (m ³)	Production (m ³)	Inventory (m ³)
1	January	2019	1,481	1,240	241
2	February	2019	1,497	1,330	167
3	March	2019	1,589	1,358	231
...	...	...	...	...	...
48	December	2022	2,678	2,527	283

The relationship shown in Table 1 indicates that inventory cannot be determined effectively from production volume alone. Inventory requirements arise from the simultaneous behavior of demand and production, because changes in either variable alter the amount of stock required to maintain continuity. Contemporary inventory-control research similarly stresses that inventory decisions must account for variability in customer requirements and operating conditions rather than treating demand as a fixed quantity (Teunter & Kuipers, 2022). For the present dataset, this consideration justified the use of demand and production as input variables and inventory as the output variable. The resulting fuzzy architecture therefore corresponds directly to the structure of the historical operational data. This arrangement also permits nonlinear relationships to be represented through membership functions rather than rigid threshold values.

The demand variable was divided into two fuzzy sets, namely DECREASES and INCREASES, representing the lower and upper behavior of observed demand. Membership functions convert numerical demand values into degrees of membership ranging between zero and one, allowing an observation to possess partial membership in more than one linguistic category. This property is central to fuzzy modelling because production data rarely change according to perfectly discrete boundaries. The demand membership function retained from the original manuscript is shown in Figure 1. The graphical structure must remain unchanged because it represents the parameterization used in the original calculations. Fuzzy-control research has similarly demonstrated that membership-based representations are useful for managing gradual transitions in systems characterized by uncertain or continuous operational conditions (Dombi & Hussain, 2020).

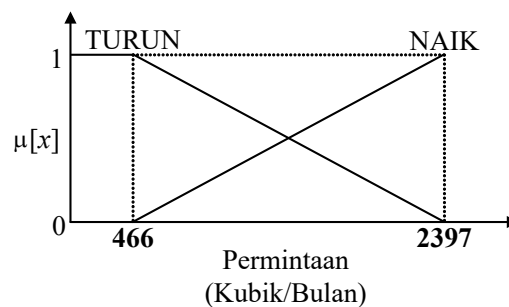


Figure 1. Membership Function Graph of the Demand Variable in the Fuzzy Tsukamoto Model

The graphical representation in Figure 1 provides the mathematical transition between decreasing and increasing demand categories. Rather than allocating a demand observation to only one categorical state, the membership function assigns proportional membership according to its position within the predefined demand interval. This approach is important for inventory modelling because a demand value located between the observed minimum and maximum cannot reasonably be interpreted as completely low or completely high. Gradual membership allows the inference process to preserve information about intermediate operating states. Luukka and Stoklasa (2024) have emphasized that fuzzy-system outputs depend strongly on the representation and subsequent transformation of fuzzy information during the inference process. The demand membership function

therefore forms the first quantitative layer through which historical production information is translated into fuzzy rules.

Production was treated as the second input variable and divided into the linguistic sets DECREASES and INCREASES. This classification reflects the operational assumption that changes in production volume alter the amount of stock that should be maintained under a given level of demand. The production membership function is retained in Figure 2 exactly as it appeared in the original manuscript. As with demand, intermediate production values can possess partial membership in both categories, which avoids abrupt classification at a single numerical threshold. Such flexibility is particularly valuable when production schedules are influenced by changing orders, capacity utilization, and manufacturing constraints. Flexible rule-based systems have been shown to provide useful decision support where supply-chain variables cannot be represented adequately by crisp categories alone (Kumar et al., 2013).

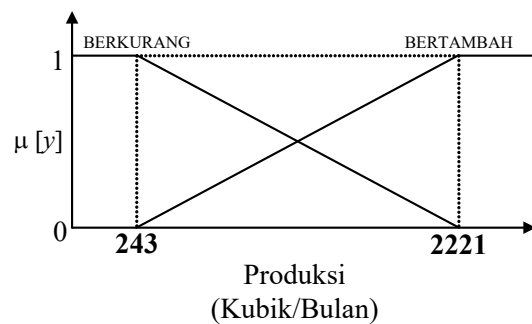


Figure 2. Membership Function Graph of the Production Variable in the Fuzzy Tsukamoto Model

Figure 2 establishes the transformation of actual production quantities into fuzzy membership values required for subsequent inference. The function provides a quantitative basis for distinguishing production states while preserving gradual movement between the lower and upper conditions. This structure is analytically important because production volume does not change independently from demand, inventory availability, or manufacturing constraints. Research on industrial inventory control has similarly demonstrated that coordination between multiple operational variables is necessary when material availability and production processes change dynamically (Yaqot et al., 2023). The production membership values are therefore interpreted jointly with demand membership rather than as an independent predictor. Their interaction becomes explicit in the fuzzy-rule evaluation stage.

Inventory was specified as the output variable and divided into the fuzzy sets LITTLE and MUCH. The distinction reflects the objective of estimating an inventory quantity that responds to concurrent changes in demand and production rather than maximizing stored material. Figure 3 presents the original membership-function graph used to define these two inventory conditions. The output membership structure is essential because the Tsukamoto procedure requires each consequent to be represented through a monotonic membership function. The method consequently produces a crisp output for each activated rule before the final defuzzification stage. Theodorou et al. (2023) similarly emphasize the value of adaptable inventory frameworks that can transform operational data into inventory decisions without relying solely on fixed-policy assumptions.

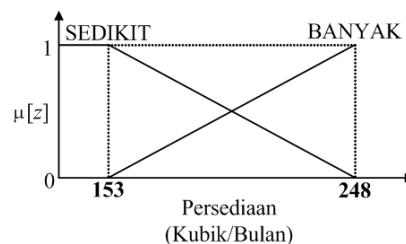


Figure 3. Membership Function Graph of the Inventory Variable in the Fuzzy Tsukamoto Model

The three membership structures collectively establish the functional relationship between demand, production, and the predicted inventory quantity. Demand and production act as antecedent variables, whereas inventory serves as the consequent variable derived through the inference mechanism. This configuration is consistent with the original data structure and permits four logical combinations of the two input conditions. Membership-based modelling has practical relevance where industrial variables show gradual transitions and where rigid classification may cause unstable decisions close to threshold values (Badola et al., 2023). The use of two membership sets for each variable also maintains computational simplicity while retaining sufficient differentiation for the observed production conditions. The subsequent fuzzy rules convert these membership relationships into operational inventory predictions.

The model consequently defined four rules: decreasing demand combined with decreasing production produces little inventory; decreasing demand combined with increasing production also produces little inventory; increasing demand combined with decreasing production produces much inventory; and increasing demand combined with increasing production produces much inventory. These rules formalize the operational relationship assumed between market requirements, production activity, and stock requirements. Their structure indicates that demand acts as the principal determinant of whether the required inventory belongs to the lower or upper output set, while production affects the firing strength of each rule. Rule-based inference provides a transparent mechanism for representing expert or operational reasoning in mathematical form and has been used across different fuzzy decision-support applications (Memmedova, 2017). The transparency of the rules is advantageous in industrial applications because each output can be traced to an identifiable combination of input conditions. This feature differentiates the model from purely opaque predictive approaches.

Membership Values and Rule Activation for the January 2022 Observation

The January 2022 observation was used in the original manuscript to demonstrate the operation of the developed fuzzy model. Demand during this period was 1,711 m³, while production reached 1,469 m³. These values were inserted into the corresponding membership functions to determine their degrees of membership in the defined fuzzy sets. The calculations produced partial membership in both decreasing and increasing categories rather than assigning either input to a single binary state. This outcome reflects the continuous structure of fuzzy inference and allows the model to accommodate intermediate production conditions. The numerical example provides a traceable sequence from observed production data to the final recommended inventory quantity.

For demand of 1,711 m³, the original calculation produced a membership value of 0.355 in the decreasing-demand set and 0.645 in the increasing-demand set. The two values sum to 1.000, indicating that the observation lies between the lower and upper demand boundaries represented in the model. Figure 4 retains the graphical depiction of this calculation from the source manuscript. The predominance of the increasing-demand membership indicates that January 2022 demand was located closer to the upper portion of the historical range. This does not imply that demand was classified exclusively as high, because 35.5% membership remained in the decreasing set. Such partial classification is one of the main analytical advantages of fuzzy systems when historical observations lie between conventional categorical thresholds (Saravanan et al., 2022).

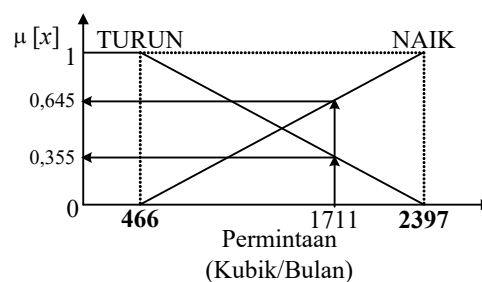


Figure 4. Demand Variable Membership Values in the Fuzzy Tsukamoto Model

The representation in Figure 4 has direct implications for rule activation because both demand categories contribute to the inference process. Rules R1 and R2 use the decreasing-demand value of 0.355, whereas R3 and R4 use the increasing-demand value of 0.645. The final output is therefore constructed from multiple simultaneously active rules rather than from a single deterministic decision path. This mechanism reduces the sensitivity of the model to marginal movements in demand near a boundary value. Fuzzy inference has long been used for this purpose because it accommodates ambiguity through graded membership rather than forcing observations into mutually exclusive states (Chattopadhyay, 2017). The resulting calculation preserves more information about the relative position of the January demand value within the historical range.

Production of 1,469 m³ produced a membership value of 0.380 in the decreasing-production set and 0.620 in the increasing-production set. The higher membership in the increasing-production set indicates that production during the test period was positioned closer to the upper production boundary, although the decreasing set retained a nonzero contribution. Figure 5 shows the original graphical representation of these membership values. Because both production memberships remain active, each of the four fuzzy rules receives a nonzero firing strength when combined with the corresponding demand membership. This characteristic allows the model to integrate both current demand pressure and the production system's response. Dynamic production environments benefit from such graded representations because operational inputs frequently occupy intermediate rather than extreme states (Marchionni et al., 2023).

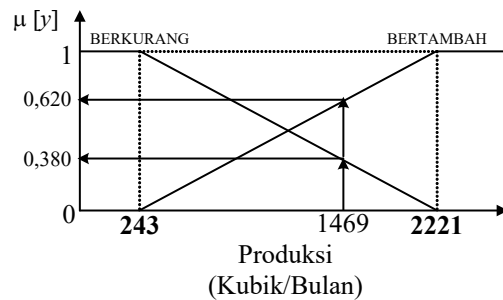


Figure 5. Production Variable Membership Values in the Fuzzy Tsukamoto Model

The combination of demand and production memberships generated the firing strengths required for the four inference rules. Using the minimum operator, R1 combined 0.355 and 0.380 to produce an α -predicate of 0.355, while R2 combined 0.355 and 0.620 and also produced 0.355. R3 combined 0.645 and 0.380, producing 0.380, whereas R4 combined 0.645 and 0.620 and produced the highest firing strength of 0.620. The relative magnitudes indicate that the rule representing increasing demand and increasing production made the strongest contribution to the January 2022 inventory prediction. This result corresponds logically to the membership profiles shown in Figures 4 and 5, in which both demand and production have greater membership in their increasing sets. The rule structure therefore retains internal consistency between the graphical membership representation and the numerical inference process.

The original model associated R1 and R2 with an inventory consequent of 153 m³, while R3 and R4 were associated with 248 m³. Multiplication of these consequent values by their respective firing strengths produced rule contributions of approximately 54.35, 54.35, 94.29, and 153.71. R4 generated the largest individual contribution because its α -predicate of 0.620 was considerably higher than the other three firing strengths. The numerical pattern confirms that conditions corresponding to increasing demand and increasing production dominate the inferred inventory requirement for the tested period. This relationship is consistent with inventory-control logic in which rising operating requirements increase the importance of maintaining an adequate stock position (Nya et al., 2022). The model nevertheless incorporates lower-state contributions rather than eliminating them, preserving the fuzzy character of the calculation.

Defuzzification and Predicted Inventory Requirement

The final inference stage converted the activated fuzzy rules into a single crisp inventory recommendation. The four rule outputs retained from the original calculation are presented in Table 2 to preserve the computational evidence underlying the model. The MIN values correspond to the α -predicates derived from the interaction between demand and production membership degrees. Each α -predicate was combined with its corresponding inventory consequent to determine the individual rule contribution. The table demonstrates that the output does not originate from a single rule but from the weighted interaction of the four fuzzy conditions. This form of aggregation is consistent with the Tsukamoto approach, in which each rule yields a crisp consequent before final weighted averaging.

Table 2. Fuzzy Tsukamoto Inventory Prediction

Rule	Demand Membership	Production Membership	MIN	Inventory Value	Prediction (Z)
R1	0.355	0.380	0.355	153.00	54.35
R2	0.355	0.620	0.355	153.00	54.35
R3	0.645	0.380	0.380	248.00	94.29
R4	0.645	0.620	0.620	248.00	153.71

Table 2 shows that the strongest contribution is generated by R4, which combines increasing demand with increasing production. Its predicted contribution of 153.71 is substantially greater than those of R1 and R2 and remains higher than the contribution generated by R3. The result indicates that the January 2022 operating condition was more strongly represented by simultaneous growth in both principal inputs than by any other combination. The distribution of rule strengths also demonstrates why a rule-based fuzzy model differs from a conventional deterministic lookup mechanism, because multiple operating states contribute concurrently to the final output. Model-independent and data-oriented inventory studies similarly emphasize the importance of allowing stock decisions to respond to changing operating patterns rather than relying on fixed inventory quantities (Theodorou et al., 2023). The inference values therefore provide an interpretable link between the observed inputs and the recommended stock quantity.

The original defuzzification calculation aggregated the four rule contributions and divided them by the sum of their firing strengths, producing a final inventory prediction of approximately 208 m³. This value was generated from January 2022 demand of 1,711 m³ and production of 1,469 m³. The predicted inventory is lower than both input volumes because it represents the quantity retained as stock rather than the volume of production or customer demand. The result also lies between the lower and upper inventory consequents embedded in the fuzzy model, which is consistent with the intermediate membership characteristics of the tested observation. Similar inventory-control approaches seek an operationally appropriate level rather than the largest possible stockholding because excessive inventories create storage and capital costs (Van Foreest & Kilic, 2023). The 208 m³ output should consequently be interpreted as the model's calculated stock requirement under the tested demand-production combination.

The final value is analytically relevant because it illustrates how relatively small changes in membership degrees can alter the contribution of individual rules without creating abrupt output discontinuities. Had the January values been interpreted through rigid categories, demand and production might have been assigned entirely to one state, potentially producing a less differentiated recommendation. The fuzzy model instead combines the extent to which each input belongs to its alternative states. This behavior corresponds to the broader use of fuzzy control in systems where continuous operational variation must be translated into actionable decisions (Dombi & Hussain, 2020). The transparency of the calculation also permits the inventory manager to identify which input combination contributed most strongly to the recommendation. Such interpretability is valuable in industrial environments where decision rules need to be understood by operational personnel.

From a production-management perspective, the predicted value should be evaluated against subsequent realized demand, actual stock consumption, service levels, and inventory costs before the system is adopted as a routine decision tool. The original manuscript demonstrates the calculation mechanism but does not report a complete error analysis across all 2022 observations. Consequently,

the January 2022 example establishes computational feasibility rather than comprehensive predictive superiority. Contemporary inventory research generally evaluates control policies across repeated observations or scenarios because performance can vary with demand volatility and operational constraints (Berling et al., 2023; Teunter & Kuipers, 2022). A stronger validation stage would compare predicted and realized inventory requirements throughout the validation period and report measures of prediction error or operational cost. This limitation should be acknowledged when interpreting the 208 m³ result.

The preserved figures and tables collectively document the complete sequence of the original Fuzzy Tsukamoto calculation, beginning with historical production data, progressing through demand and production membership functions, and ending with rule aggregation and defuzzification. Figures 1–3 define the fuzzy architecture, whereas Figures 4–5 show how the January 2022 observation is positioned within the input membership functions. Table 2 subsequently records the numerical firing strength and contribution of each rule. Together, these elements provide traceability between the raw input observations and the predicted inventory quantity. Fuzzy modelling is particularly valuable when such traceability is retained because the user can examine how a numerical recommendation emerges from individual rules rather than accepting a purely opaque output (Luukka & Stoklasa, 2024). The original graphical materials should therefore remain attached to the corresponding analytical passages in any revised version of the manuscript.

The main empirical result retained from the source manuscript is an estimated inventory requirement of 208 m³ for January 2022 under demand of 1,711 m³ and production of 1,469 m³. The result derives from the interaction of four fuzzy rules with firing strengths ranging from 0.355 to 0.620, with the increasing-demand and increasing-production rule making the largest contribution. This finding demonstrates the operational mechanism of the Fuzzy Tsukamoto model and its capacity to transform continuous production information into a single interpretable inventory recommendation. Inventory-control research has increasingly emphasized adaptive approaches that respond to variations in demand, production, and system constraints rather than relying on static inventory policies (Yaqot et al., 2023). Further validation across the remaining 2022 observations would be required to establish the reliability, stability, and practical economic value of the model. The present result nevertheless provides a reproducible illustration of the inference structure applied to the furniture-industry dataset.

CONCLUSION

The assessment of mental workload using the NASA-TLX framework provides a structured basis for understanding how employees in the furniture industry experience cognitive, physical, temporal, performance-related, effort-related, and psychological demands during work activities. The multidimensional structure of NASA-TLX is particularly relevant to furniture manufacturing because production tasks commonly combine machine operation, material handling, quality control, production targets, and continuous coordination. The findings should therefore be interpreted by considering both the overall workload score and the relative contribution of each dimension. Such an approach enables the identification of specific occupational demands that require ergonomic attention rather than treating workload as a single undifferentiated condition.

The practical implication of this study lies in the use of workload assessment as a basis for improving work-system design, task allocation, production scheduling, workplace ergonomics, and occupational safety. Interventions should be directed toward the dimensions that contribute most strongly to perceived workload, such as simplifying work instructions, improving workstation design, adjusting production pacing, strengthening operational support, and reducing sources of frustration. NASA-TLX can consequently support evidence-based decisions in furniture manufacturing when its results are interpreted alongside the actual characteristics of the production process. However, final conclusions regarding workload intensity and dominant dimensions must be based on the empirical ratings and weighting scores obtained from the participating employees.

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