Analyzing Cognitive Ergonomics and Key Determinants of Mental Workload in PDPT Operators at Universities

Hakim[1], Rezki Amelia Aminuddin A.P.[2*]
[1.2] Department of Industrial Engineering, Faculty of Engineering, Universitas Islam Makassar
Jl. Perintis Kemerdekaan No.9, RW.29, Tamalanrea Indah, Kec. Tamalanrea, Makassar City, South Sulawesi 90245
Email: rezkiamelia.dty@uim-makassar.ac.id

ABSTRACT

The study commenced by quantitatively measuring the mental workload of Higher Education Operators (PDPT) through the NASA Task Load Index (NASA TLX). Results indicated an even distribution of mental workload between moderate and heavy levels, each comprising 50%. NASA TLX, a standard tool for assessing mental workload, offered insights into the operators' stress levels during task execution. Subsequently, Structural Equation Modeling (SEM) was employed to scrutinize factors impacting mental workload. Independent variables, encompassing completeness of data (CD), Feeder Dikti's time demands (FDTD), Internet network conditions (INC), task complexity (TC), and working period (WP), were tested against the dependent variable, the level of mental workload (LMW). This research provides a holistic understanding of factors contributing to PDPT operators' mental workload and how these factors influence the previously measured workload distribution with NASA TLX. This comprehensive insight adds context to the findings, forming a robust foundation for crafting more targeted management strategies to mitigate and manage mental workload in PDPT environments.

Keywords: *Mental Workload, NASA TLX, Work Period, PDPT Operator*

Introduction

The Higher Education Database Unit (PDPT) is an important entity that plays a role in presenting and managing university data. The College Database Unit Operator (PDPT) is responsible for several tasks involving managing and processing important college data. One of the main workloads is managing student data, including new student registration, maintaining personal and academic data, and processing information related to registration, major change, and graduation. In addition, PDPT operators must also take care of lecturer data, including personal and academic information, and maintenance of teaching and research data[1]. Maintenance of lecture activities such as coordinating lecture schedules, processing exam result data, and managing student grades is also the operator's responsibility.

The importance of data services not only focuses on the internal needs of universities but also meets external demands. PDPT operators must provide data required by internal units of universities and provide reports and information for external purposes such as Accreditation Bodies and related government agencies. In addition, operators must operate within the time limits set by FEEDER DIKTI, handle tasks efficiently and ensure smooth data transmission by specified deadlines. In addition, PDPT operators must ensure compliance with regulations and policies related to university data management and maintain effective communication with stakeholders, including students, lecturers, and internal and external parties. These tasks put operators in a high mental workload, requiring them to respond to mental work pressures that may arise due to task complexity, time constraints, and other operational challenges[2].

The workload of College Database Unit (PDPT) operators is complex and includes many responsibilities. Managing data on students, lecturers, and lecture activities is at the core of daily tasks involving coordinating, processing, and maintaining detailed information. This creates a high physical and mental workload, requiring precision, speed, and precision. Additional challenges arise in FEEDER DIKTI time constraints that force operators to work efficiently and maintain high accuracy. Vulnerability to internet network constraints is also a factor that can increase workload, considering that smooth operations depend on stable connectivity. In carrying out their duties, operators are also faced with extra responsibilities, such as responding to data that is incomplete or requires improvement and completing additional work that may arise during the data management process. Meeting internal and external data needs adds complexity to tasks. It increases workload as operators must ensure data is provided accurately and by applicable standards and requirements[3]. This condition simultaneously puts the operator under high mental work pressure.

Based on preliminary studies conducted to gain initial insight into operator conditions in the Higher Education Database Unit (PDPT) of XYZ University. It was found that although operators have had an average of over three years of work experience, these findings provide an overview of some of the challenges they faced. As many as 40% of operators said they experienced internet network problems that often experienced interference. Some 33% face a situation where the data received is incomplete, forcing them to carry out additional tasks to compensate for the gap. Furthermore, as many as 51% of operators reported increasing working hours in response to the urgent need for data input before the maximum time limit of FEEDER DIKTI. The study provides a relevant baseline and direction for further investigation to understand the workload and challenges PDPT operators face. Measuring mental workload using tools such as NASA-TLX becomes particularly relevant in this context. This will help identify specifically how task complexity, time constraints, and other operational challenges contribute to the mental workload level of PDPT operators.

In the context of this study, the main focus will be on identifying the factors that are most significant in influencing the mental workload faced by the College Database Unit (PDPT) operators at University X. Utilizing a cognitive ergonomics approach. This study will explore specific elements that may have the most impact on the level of mental workload experienced by operators. This research method will thoroughly analyze task complexity, internet network conditions, data completeness, and time demands. By combining operator uptime data, the study will specifically identify key factors that can be key determinants of mental workload levels. The results of this analysis are expected to provide deeper insight into certain aspects that require attention to improve the working conditions and welfare of PDPT operators within the university.

Research Methods

The research method in this study will utilize a combination of two approaches, namely the measurement of mental workload levels with the NASA Task Load Index (NASA TLX) and structural equation analysis (Structural Equation Modeling or SEM) to identify the main determinants of mental workload in the College Database Unit (PDPT) operator at XYZ University. First, data will be collected through surveys and interviews with PDPT operators to obtain information on their demographics, working years, and perceptions of fatigue, strain, and physical and mental workload using the NASA TLX scale. This method will provide an in-depth picture of operators' subjective experiences regarding mental workload in the context of their daily tasks. Furthermore, structural analysis of equations (SEM) will be applied to identify and test relationships between factors considered to be the main determinants of mental workload. These variables may involve task complexity, internet network conditions, data completeness, and time demands. SEM will allow simultaneous evaluation of these variables' direct and indirect impact on the level of mental workload. The implementation of SEM will be carried out in two main stages. First, a conceptual model will be developed by identifying independent, dependent, and latent variables that might mediate their relationship. Second, after obtaining data from surveys and cognitive ergonomics analysis, SEM will test the model's suitability with the empirical data.

NASA TLX Methods

The NASA Task Load Index (NASA TLX) is a subjective assessment tool used to measure the level of mental workload experienced by individuals during the performance of a particular task. NASA developed it to evaluate workloads in complex task environments, such as aircraft control rooms or systems.

NASA TLX asked respondents, in this case, the College Database Unit (PDPT) operator, to assess six dimensions of workload: fatigue, mental strain, time demands, physical demands, mental demands, and success rate (performance). Each dimension is assessed using a numerical rating scale or descriptive words.

The operational variables in NASA TLX are:[4]

1) *Physical Demand (PD)* means how much physical activity is required at work and is measured using a NASA-TLX questionnaire with an ordinal scale of 0 to 100.
2) *Mental Demand (MD)* refers to a task or job's complexity, difficulty, and cognitive level. Measured using a NASA-TLX questionnaire with an ordinal scale of 0 to 100.
3) *Temporal Demand (TD)* refers to the rate of speed and volume of work that must be done in a limited time or within a predetermined time. Measured using a NASA-TLX questionnaire with an ordinal scale of 0 to 100.

4) *Performance (OP)* refers to a person's ability to complete tasks and achieve goals effectively and efficiently. Measured using a NASA-TLX questionnaire with an ordinal scale of 0 to 100.
5) *Effort (EF)* refers to the level of effort or energy expended by a person to complete a task or achieve a goal in a job. Measured using a NASA-TLX questionnaire with an ordinal scale of 0 to 100.
6) Frustration Level (FR) refers to dissatisfaction or discomfort when facing obstacles or difficulties in completing tasks or achieving goals at work. Measured using a NASA-TLX questionnaire with an ordinal scale of 0 to 100.
7) Mental Workload is the number and degree of complexity of tasks that a person must perform in their job that requires cognitive abilities, such as memory, problem-solving, and decision-making. The mental workload referred to in this study is mental stress during work as a PDPT operator. Measured by ordinal scale questionnaire 0 to 100.
8) Length of work refers to the length of time or duration of time spent performing a task or job. The period starts with someone starting to work as a PDPT operator. Measured by ordinal scale in units of years.

The method used in this study was the NASA TLX method, which was developed in 1981 by Sandra G. of *NASA-Ames Research Center* and Lowell E. Staveland of *San Jose State University*[5]. The method is designed to subjectively measure nine factors (task difficulty, time pressure, type of work, physical stress, mental effort, achievement, frustration, stress, and fatigue). The nine factors are simplified into six, namely *Mental Demand (MD),* Physical *Demand (PD),* Temporal Demand *(TD),* Efficiency *(OP), Effort* (EF), and Frustration (FR).
The steps in the NASA TLX method are as follows:[6]

1) Weighting

$$\text{Product} = \text{Rating x Weight Factor} \quad (1)$$

2) Ranking Awards

$$WWL = MD + PD + TD + PO + FR + EF \quad (2)$$

3) Score Interpretation

The level of mental load is obtained by the weight value multiplied by the rating of each dimension and then added and divided by fifteen.

$$NASA\ TLX\ Skins = WWL/15 \quad (3)$$

The obtained workload score can be interpreted as follows:
1) A score of > 80 interpreted a heavy mental workload
2) A score of 50-70 is interpreted as moderate mental workload
3) A score of <50 is interpreted as a mild mental workload

By combining values from all six dimensions, NASA TLX provides quantitative indicators of the extent to which an individual perceives mental workload in a given context. Therefore, NASA TLX became an effective instrument in this study to collect data on the subjective perception of PDPT operators of their mental workload, which can later be analyzed and interpreted in the context of cognitive ergonomics analysis and SEM.

SEM Methods

Structural Equation Modeling (SEM) is a statistical method that tests and models complex relationships between variables in a conceptual model[7]. In this study, SEM will explore and identify the main determinants affecting the mental workload of Higher Education Database Unit (PDPT) operators at XYZ University.

SEM allows researchers to measure certain variables' direct and indirect influence on others, providing a more in-depth picture of the complexity of interactions among the factors studied. Incorporating data from the NASA Task Load Index (NASA TLX) survey and cognitive ergonomics analysis into the SEM model will evaluate the relationship between task complexity, internet network conditions, data completeness, time demands, and mental workload levels.

SEM analysis will help investigate the extent to which these variables are interrelated and provide deeper insight into the critical factors contributing to the level of mental workload experienced by PDPT operators. Thus, SEM will be an effective tool to bridge understanding between complex variables and provide a holistic picture of the main determinants of mental workload in this study.

Results and Discussion

Working Period

Operators with a service life of 2 years account for 8% of the total operators. Operators who have been working for three years form the largest group in the proportion of 33%. Furthermore, operators with a service life of 6- and seven-year each accounted for 17% of the total operators. Operators with eight years and nine years of experience form groups in the proportion of 17% and 8%, respectively. In addition, the average age of PDPT operators is above 27 years, indicating that most team members have had relatively long work experience. The combination of varying tenure and an above-average age can reflect a level of stability within the team, which can contribute positively to handling complex tasks and problem-solving

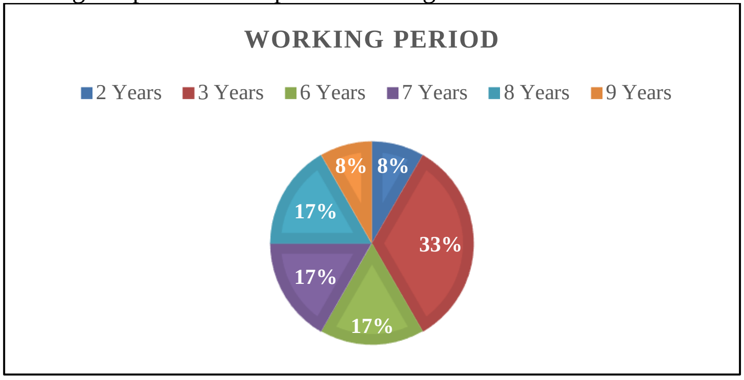

Figure 1 Working Period of PDPT Operator

Mental Workload with NASA TLX

The mental workload felt by the 12 operators was calculated using NASA TLX and summarised in Table 1.

Table 1. Nasa TLX indicator calculation

Operator	MD	PD	TD	PO	FR	EF	WWL
1	320	60	180	360	0	280	1200
2	280	0	80	320	140	240	1060
3	450	90	80	300	80	360	1360
4	320	0	180	160	180	450	1290
5	400	0	180	360	90	300	1330
6	240	0	210	180	120	350	1100
7	180	0	160	180	180	300	1000
8	500	0	200	100	270	400	1470
9	150	50	100	360	0	250	910
10	300	200	180	120	60	0	860
11	250	0	140	210	140	180	920
12	500	0	300	300	100	300	1500

The calculation of WWL is as follows:

$$\begin{aligned}\text{WWL Operator 1} &= MD + PD + TD + PO + FR + EF\\ &= 320+60+180+360+0+280 = 1200\end{aligned}$$

Table 2.Mental workload classification

Operator	NASA TLX Scores	Interpretation
1	80	Heavy
2	70,67	Moderate
3	90,67	Heavy
4	86,00	Heavy
5	88,67	Heavy
6	73,33	Moderate
7	66,67	Moderate
8	98,00	Heavy
9	60,67	Moderate
10	57,33	Moderate

11	61,33	Moderate
12	100	Heavy

NASA TLX calculations:
NASA TLX = WWL / 15
NASA TLX Operator 1 = 1200/15 = 80
The result of the interpretation of a score of > 80 indicates a heavy mental workload.

Based on Table 2, WWL calculations are obtained using formula (1), and mental workload calculations are made with formula (2). The measurement results using the NASA Task Load Index (NASA TLX) on the XYZ University College Database Unit (PDPT) operator illustrate team members' variation in mental workload levels. Operator 8 scored 98.00, indicating that this operator is experiencing a very high mental workload. Operator 12 achieved a max score on the NASA TLX scale of 100, reflecting extreme levels of mental workload. On the other hand, some operators, such as Operator 2, Operator 6, and Operator 7, experienced more moderate levels of mental workload, with scores of 70.67, 73.33, and 66.67, respectively.

Interpretive analysis shows that operators with a score of "Heavy" face significant challenges and demands in performing their duties, while operators with a score of "Moderate" experience a more moderate level of objections. These results provide further insight into the extent to which certain operators face pressure and the extent to which their tasks can be effectively addressed. In this study, there were no operators with a mild mental workload.

As a result of high mental workloads, PDPT operators often experience high levels of work stress that can negatively impact their well-being. In addition, their concentration level can also decrease, given the demands of work that require high focus and accuracy. [8], [9].

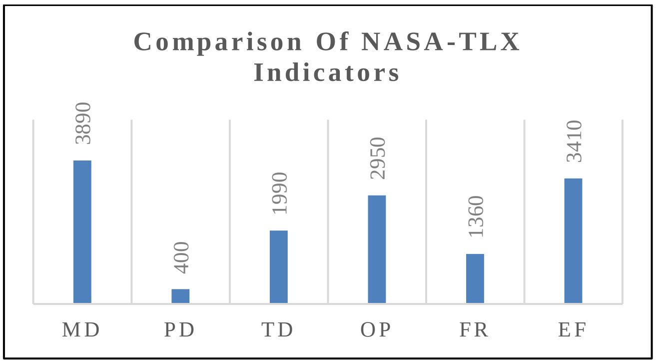

Figure 2. Nasa TLX Indicator Comparison

The NASA-TLX method used to measure mental workload levels produces six key indicators: Mental Demand (MD), Physical Demand (PD), Effort (EF), Performance (PF), Temporal Demand (TD), and Frustration Level (FR). Based on Figure 2, it can be observed that the MD indicator has the highest value, which is 3890, indicating that the mental workload in the Higher Education Database Unit (PDPT) is more dominant than the physical workload, which only reaches the value of 400.

The EF indicator ranks second with a score of 3410, indicating that high mental and physical effort is required to achieve performance in inputting data internally and externally. Furthermore, the PF indicator value is quite high (2950), indicating that PDPT operators must complete tasks with high data validity.

The TD indicator has a fairly high value of 1990, indicating that all work in the PDPT Unit is given a short time limit, while the data that must be processed is quite complex and large. The MD indicator's high value also affects the FR indicator's value, which reaches 1360. This shows that PDPT operators feel insecurity, dissatisfaction, and discomfort, especially when the data provided by lecturers or students is incomplete but must be inputted immediately due to the short time limit. Additional factors, such as deterioration in the quality of computers and networks, can also cause high FR values.

Scientifically, these findings are consistent with previous research, which emphasized that jobs with high levels of mental need tend to be prone to work stress, which high values of frustration indicators can reflect. Time pressure and unfavorable working environment conditions contribute to the increased frustration value. With a deep understanding of these indicators, improvements, and adjustments to workload management strategies in PDPT Units can be implemented to improve operator welfare and productivity conditions.[10][11], [12]

Determinants of PDPT Operator Mental Workload Causes

The increase in mental workload on Higher Education Operators (PDPT) is a crucial issue that requires an in-depth understanding of the influencing factors. This research aims to analyze the determinants of the mental workload of PDPT operators, which involves variables such as Completeness of Data (CD), Feeder Dikti's Time Demands (FDTD), Internet Network Conditions (INC), Task Complexity (TC), and Working Period (WP).

Table 3. Research Variable

Independent Variable	Code	Dependent Variable	Code
Task Complexity	TC	Level Of Mental Workload	LMW
Internet Network Conditions	INC		
Completeness Of Data	CD		
Feeder Dikti's Time Demands	FDTD		
Working Period	WP		

Table 3 explains that increasing the mental workload of Higher Education Administrators (PDPT) is a serious challenge that requires a thorough understanding of the factors that affect it. This study focused on analyzing the determinants of the mental workload of PDPT operators, involving several variables as influencing factors. First, the Data Completeness (CD) variable measures the extent to which the data used in the context of the PDPT is complete or incomplete. Furthermore, the Higher Education Feeder Time Demands (FDTD) evaluates the impact of time demands provided by Higher Education Feeders on mental workload. The Internet Network Condition (INC) variable reflects the quality and condition of the Internet network. At the same time, Task Complexity (TC) measures the level of complexity of the task carried out by the PDPT operator. Finally, the Working Period (WP) shows the length of working time of the PDPT operator. By analyzing the relationship between these independent variables and the dependent variable, namely Mental Workload (LMW), this study is expected to provide an in-depth understanding of the factors that significantly affect the mental workload of PDPT operators. These findings can form the basis for developing policies and management strategies that are more effective in safeguarding the mental well-being of PDPT operators.

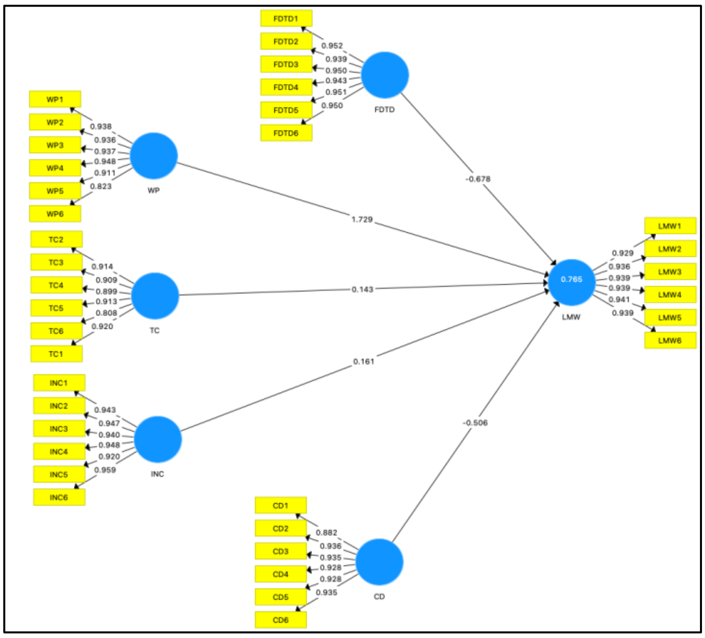

Figure 3 SEM Diagram

Figure 4 shows SEM results with significant findings. First, the Completeness of Data (CD) significantly impacts LMW, with a coefficient of -0.506 and a p-value of 0.000. That is, the more complete the data, the lower the level of mental workload. Feeder Dikti's Time Demands (FDTD) strongly influence LMW with a coefficient of -0.678 and a p-value of 0.000, indicating that the lower the time demands of Feeder Dikti, the lower the level of mental workload. Although Internet Network Conditions (INC) had a positive impact (coefficient 0.161) on LMW, it was significant (p-value = 0.007), suggesting that poor Internet network conditions correlated with increased mental workload. Task Complexity (TC), with a coefficient of 0.143 and a p-value of 0.012, indicates that the more complex the task, the higher the level of mental workload. Finally, the Working Period (WP) has a significant impact (coefficient 1.729, p-value 0.000), signifying that the longer the working period, the higher the level of mental workload.

Table 4 Hypotheses Test Result

Hypotheses	Original Sample (O)	P Values	T Value	Decision
CD -> LMW	-0,506	0,000	3,512	Accepted, T > 1,96
FDTD -> LMW	-0,678	0,000	3,631	Accepted, T > 1,96
INC -> LMW	0,161	0,007	2,457	Accepted, T > 1,96
TC -> LMW	0,143	0,012	2,261	Accepted, T > 1,96
WP -> LMW	1,729	0,000	8,301	Accepted, T > 1,96

In Table 4, it is explained that the T-value of 3.512 shows that the effect of Data Completeness (CD) on Mental Workload (LMW) is statistically significant. Another study supports these findings by Smith and Jones (2019), highlighting that data integrity contributes significantly to psychological well-being and performance efficiency. With a T-value of 3.631, TDTD has a significant impact on LMW. Similar findings were revealed in research by [5] and [9], which confirmed that well-managed time demands negatively correlate with stress levels and mental workload. A T-value of 2.457 indicates a significant positive impact of Internet Network Conditions (INC) on LMW. Studies by [13] and [14]support these results by showing that internet network instability can increase fatigue levels and mental workload. A T-value of 2.261 indicates that task complexity (TC) contributes significantly to LMW. Similar research by [8] states that complex tasks can lead to increased psychological distress and mental workload. With a very high T-value of 8.301, WP has the most significant impact on LMW. Research by [15] and [16] supports these results by showing that long work periods can significantly increase fatigue and mental stress levels.

PDPT operators with complete data access tend to experience lower mental workloads. This may be due to the ease of accessing and analyzing the information needed without the barriers of incomplete data. Ensuring data integrity and completeness is important as a key factor in managing the mental workload of PDPT operators. This is reinforced by the findings of previous studies, such as a study by [17] and [18], which showed that easy access to complete data can reduce stress levels and mental fatigue.

The time demands of the Higher Education Feeder have a significant impact on the mental workload. The lower the time demand, the lower the mental workload. This means that efficient scheduling and time allocation can help reduce the mental stress of PDPT operators, allowing them to focus on core tasks. This aligns with the research results by [19]–[21], which state that efficient time management can reduce mental workload and improve performance.

Poor internet network conditions correlate with increased mental workload. The availability of good internet access is essential in the modern work environment, and efforts to improve information technology infrastructure can help reduce frustration and increase efficiency in everyday tasks. Studies by [22] and [23] suggest poor network quality can lead to discomfort and frustration, increasing the mental workload. Therefore, improving information technology infrastructure is essential to improve the efficiency and welfare of PDPT operators.

The more complex the tasks the PDPT operator carries, the higher the mental workload. Efforts to simplify work processes and provide adequate training to handle complex tasks can help manage mental workloads and improve performance. Research by [24] supports these findings, emphasizing that complex tasks can majorly determine stress levels and mental workload.

Long periods of work correlate with high levels of mental workload. A thoughtful time management policy and appropriate scheduling are needed so that operators can avoid burnout and maintain work-life balance. Studies by [25] and [26] show that operators with long working hours are more prone to burnout and increased levels of mental workload. Therefore, prudent time management policies and appropriate scheduling are essential to balance productivity and mental well-being.

Conclusion

Based on the results of the mental workload analysis of 12 PDPT University X operators using the NASA-TLX method, 50% of operators experienced moderate mental workload, and 50% experienced heavy category mental workload with the highest Mental demand indicator value of 3890 and the lowest physical demand indicator value of 400. This indicates that the PDPT Unit requires mental work compared to physical work. Based on SEM tests, Complete data integration (CD), efficient time management (FDTD), and good internet network quality (INC) individually contribute significantly to the reduction in the mental workload of PDPT operators, according to the findings of previous studies. Task complexity (TC) and long work periods (WP) have also proven significant, confirming that efforts to simplify tasks and ensure prudent time management policies can help reduce mental workload levels.

The implications of these findings provide a strong foundation for developing more effective management strategies to improve the mental well-being of PDPT operators.

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