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Future auditing: Machine learning's impact on audit capacity stress - young auditors' perceptions using UTAUT

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Abstract: Advancing technologies have potential to revolutionize the future of auditing. This study investigates the impact of machine learning adoption on audit capacity stress among Indonesian external auditors. A survey approach was used to collect data from 100 auditors working in public accounting firms. The Unified Theory of Acceptance and Use of Technology (UTAUT) model was employed to assess factors influencing auditors' perceptions of machine learning usage. The result that comprises of young auditors to be the most respondents show performance expectancy, effort expectancy, and social influence are insignificant towards audit capacity stress. However, facilitating conditions were found to have a significant impact on audit capacity stress, suggesting that infrastructure and resource availability are crucial for young auditors' acceptance of machine learning and its audit capacity stress-reducing effects. Thus, Indonesian auditor requires additional facilitating support to alleviate audit capacity stress. These findings contribute to the understanding of technology adoption and audit capacity stress in the evolving future audit profession.
Keywords: *Audit capacity stress, Auditor perception, Future auditing, Machine learning, UTAUT model.*

1. Introduction

Rapid global changes in technological industries have led human activities to be carried out by advanced tools. Especially in Indonesian Small and Medium-sized Enterprises (SMEs), financial technology is used as a breakthrough that it significantly effects on business performance [1]. Advanced technologies are utilised to help ease the work, especially in auditing sectors. Future of auditing model currently includes ongoing business process audits, and auditors use automation tools like risk assessment tools and decision aids to help them with their audits [2]. Advancement of technology does not only bring convenience, but also has an impact on auditors' workload which can affect audit quality. Since young people who work as accountants tend to perceive big data impact their role positively, accounting professions future is subjected to change [3].

Processing huge financial data to determine potential risks and irregurarities are part of auditing. As the advancement of technologies, machine learning can provide automation in audit tasks such as risk assessment, fraud detection, transaction testing, and real-time monitoring can increase both audit work's effectiveness and efficiency [4]. The automation can save auditors' time and allows better allocation of their focus and resources. While increasing complexity and workloads among auditors is a growing concern amid the advancing era. Auditors often work five hours above the threshold during peak seasons can lead to a decrease in audit quality and job satisfaction [5]. The overloaded work of auditors may lead to increasing audit capacity stress, especially Indonesian auditors which potentially impacts the quality of audit and career satisfaction. Therefore, mitigating the high level of perceived audit workload in Indonesia will be a challenging problem to overcome.

A study in the United Kingdom (UK) has revealed that the lacking knowledge and performance in accounting, tax and auditing software suggest a discrepancy [6]. In Indonesia, auditors' work has been perceived to be overloaded [7]. Meanwhile, Indonesian auditors are indicated to still relying on manual

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auditing procedure [8]. The perceived gap about incapability to adapt such technology due to lack of support can be the hindrance of using machine learning in Indonesia. The lack adoption of such advanced technologies becomes a concern as it links to high auditors' workload, which leads to audit stress to increase. Audit capacity stress is primarily affected by audit workload, time pressure, and resource constraints. Due to high audit workloads, both the audit quality and auditor's job satisfaction are subjected to decrease [9]. Solution to overcome the urgency of audit capacity stress is needed.

Referring to the basic agency theory, machine learning utilization in auditing could take part in the matter of minimising conflict interest between auditors and the client. Clients' demand for more reliable and accurate audit work raises the auditor's workload. While oppositely, auditors' demands for more effective and efficient way in auditing. Automation from machine learning usage enables abnormal business practices detection, which eases auditors' workload and leads to reduction of audit capacity stress [10]. Therefore, machine learning should be the solution to gap the requirements and interests of each party whilst reducing audit capacity stress. The adoption of machine learning in auditing as technological advancement can be understood through the Unified Theory of Acceptance and Use of Technology (UTAUT) model, which comprises of its four core constructs [11].

Integrating machine learning optimises audit workload efficiency [12], which alleviates audit capacity stress including higher efficiency, accuracy, and timesaving. This research is intended to determine each acceptance factors' significance of using machine learning on audit capacity stress of Indonesia external auditors. Therefore, we ask: does performance expectancy (PE) factor of using Machine Learning have a significant effect on audit capacity stress of Indonesian external auditors? Does effort expectancy (EE) factor of using Machine Learning have a significant effect on audit capacity stress of Indonesian external auditors? Does social influence (SI) factor of using Machine Learning have a significant effect on audit capacity stress of Indonesian external auditors? Lastly, does facilitating conditions (FC) factor of using Machine Learning have a significant effect on audit capacity stress of Indonesian external auditors?

In our best knowledge, there is no research concerning in adoption of machine learning in Indonesian public accounting firms, this research analyses the perception of machine learning usage on audit capacity stress of Indonesian external auditors using the UTAUT approach. In the end, the research is addressed to be the encouragement and solution for handling audit capacity stress concerns in Indonesia through machine learning usage acceptance factors. There is an expectation that the findings of this study would help improve audit quality by providing information about how the perception of machine learning utilization, by the catalysator of auditing future, can impact audit capacity stress.

2. Literature Review and Hypothesis Development

2.1. Audit Capacity Stress

Audit capacity stress is defined as the strain on auditor resources, followed by the influx of new clients and employees. Quality of an audit is likely to be affected by resource shortage in the wake of sudden increase from audit demands [13]. A finding stated that the trigger factors of audit team stress are time budget pressure, high turnover, and heavy workload, which give consequences to audit quality [14]. Further analysis suggests that alliance among noted auditors and audit quality may be reinforced by two independent and industry expertise of individual auditors.

Indonesian auditors Java Island have been found to have workload accumulation that leads to stress. Stress itself triggers dysfunction in audit work and decreases professionality at work [15]. This occurrence of audit capacity stress needs to be overcome to improve audit quality. Auditor capacity stress can be measured using the prevailing audit workload as the proxy for an auditing office in conducting audit work [13]. Workload refers to audit capacity stress, which arises from interaction of work environment demands as a workplace, skills, and work perceptions [16].

Conversely, research carried out on audit workload drivers using internal and external drivers found that time constraint and staffing shortage become the most prevalent internal drivers [5]. The variables being used as internal drivers are deadline or time constraints, staffing shortage, and budget constraint. While Publich Company Accounting Oversight Board (PCAOB) pressure, other regulatory pressure, client unprepared, client deadline pressure, and client fee pressure are used as the external drivers of audit workload. With that, this implies that the main drivers of audit capacity stress are mainly due to strains such as resource shortage and tight deadlines or time budget pressure, which accumulates high workloads into audit capacity stress.

2.2. The Unified Theory of Acceptance and Use of Technology Model (UTAUT)

The theoretical model underlies the technology acceptance testing is presented by the UTAUT model framework. The UTAUT model was constructed into factors of Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions with moderating variables of age, gender, experience, and voluntariness [17]. Performance Expectancy is defined as the extent of individual perceives that the system will improve career performance. During Effort Expectancy alludes to the simplicity level of using the system. Social Influence is the degree to which individuals perceive the expectations of others regarding their use of the system and lastly, Facilitating Conditions as the extent of individual beliefs that technical infrastructure existence supports system usage.

As the usage of machine learning in the Indonesian auditing sector has not been evenly implemented, the UTAUT model can be used to understand the acceptance of machine learning usage. UTAUT has been demonstrating its versatility widely in understanding technology acceptance applied in various sectors including education, banking, health, and e-government services, then it can also be used to forecast the adoption of technology [18]. The four main constructions of UTAUT in correlation with audit capacity stress are categorised as Structural Equation Models (SEM) due to its reflective and formative models. Structural Equation Model (SEM) is a path model in which the variables may be affecting others while it can also be the causes for variables that are hypothesised in causal sequence [19].

2.3. Machine Learning Usage in Addressing Audit Capacity Stress

The underlying agency theory, a contractual arrangement that involves the principal hiring an agent to carry out a service on behalf of them [20], can be connected to machine learning usage to gap the needs and interests of each party. Machine learning is an advanced computational methodology that uncovers intricate patterns within extensive and complex datasets, forming a crucial subset of artificial intelligence [21]. Research conducted in Indonesia found that since pandemic through COVID–19, the adoption of technology in auditing sector has accelerated [22]. However, due to perceived expertise gap among Indonesian auditors about insufficient competency to adapt such technology then such advanced technologies are not evenly adopted among them, especially machine learning. Nevertheless, still the perceptions of auditors in Indonesia toward continuous auditing technology are favourable [23]. Several studies have explored the potential of machine learning to address audit capacity stress.

Machine learning algorithms are used to automate data extraction and anomaly detection, freeing up auditors' time for higher-level analysis [24]. Meanwhile, machine learning has been shown to significantly improve audit efficiency, reduce audit risk, and change the work mode, ultimately enhancing the audit quality [25]. Similarly, machine learning has potential for continuous auditing and real-time financial data monitoring, which reduce the extensive year-end procedures need [26]. The use of machine learning for population auditing has been proposed as a method to alleviate the reliance on auditors' personal expertise and diminish audit risks inherent in conventional audit sampling techniques [10]. Therefore, this suggests that machine learning can significantly improve audit efficiency, thereby mitigating audit capacity stress.

2.4. Research Model

Adopting the basic UTAUT model from [17], the research model in Figure 1 focuses on correlating the core variables of performance expectancy, effort expectancy, social influence, and facilitating conditions on audit capacity stress as the dependent variable. This model of research in figure 1 portrays how UTAUT constructs are anticipated to influence auditors' audit capacity stress in the perception of machine learning usage.

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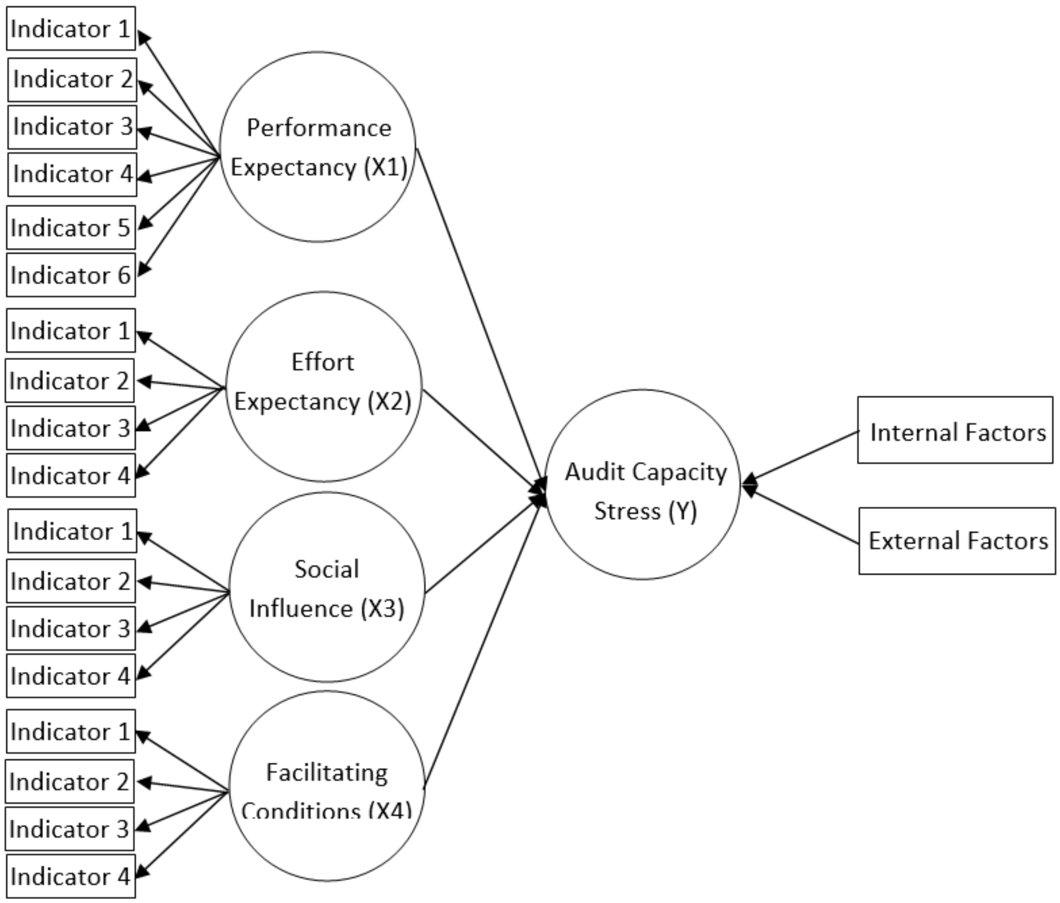

Figure 1.
Research model.

2.5. Hypotheses Development

2.5.1. Impact of performance Expectancy Factor of Machine Learning Usage on Audit Capacity Stress of Indonesian External Auditors

Agency theory posits that individuals' beliefs about how an action will impact their performance can significantly influence their acceptance of and behaviour towards technology [27]. Research within the audit domain found that auditors' confidence in the capabilities of new technology directly affects their perception of audit effectiveness [28]. This study provides empirical evidence supporting the notion that auditors' performance expectations regarding technological advancements are crucial in shaping their attitudes and behaviours towards technological adoption. Considering the insights from agency theory and the empirical evidence provided [29], it is reasonable to hypothesise that auditors' performance expectations regarding the use of Machine Learning will impact their level of audit capacity stress. Therefore, the first hypothesis formulated as follows:

H_{01}: The performance expectancy factor of using Machine Learning does not have a significant effect on the audit capacity stress of Indonesian external auditors.

H_{a1}: The performance expectancy factor using Machine Learning has a significant effect on the audit capacity stress of Indonesian external auditors.

2.5.2. Impact of Effort Expectancy Factor of Machine Learning Usage on Audit Capacity Stress of Indonesian External Auditors

According to agency theory, a person's adoption and use of technology are greatly influenced by their sense of how easy or difficult it is to use (effort expectancy) [27]. In the auditing context where professionals frequently work with complicated tasks, how simple a technology like machine learning is perceived to be can have a profound effect on auditors' inclination to use it and, in turn, how stressed out they get when doing audits. It has been the ease of founded current technology has a significant impact on auditors' acceptance of audit technology [30]. The study supports the notion that auditors' perceptions for the used updated technology influence their attitudes and behaviours towards its adoption. Therefore, it is reasonable to hypothesise that the effort expectancy factor of using machine learning will have a significant effect on audit capacity stress among Indonesian external auditors. The second hypothesis formulated as follows:

H_{02}: Effort expectancy factor of using Machine Learning does not have a significant effect on audit capacity stress of Indonesian external auditors.

H_{a2}: Effort expectancy factor of using Machine Learning has a significant effect on audit capacity stress of Indonesian external auditors.

2.5.3. Impact of Social Inlfuence Factor of Machine Learning Usage on Audit Capacity Stress of Indonesian External Auditors

Agency theory suggests that social influence from superiors and coworkers could add a substantial effect of an individual's behaviour within an organization [31]. Regarding the technology adopted by people, they frequently impacted since beliefs and actions of those in their immediate environment, which can influence how they accept and utilise technology [32]. Support from colleagues and superiors has been found can influence auditors' acceptance of new technology [33]. This research supports that social influence factors play a significant role in shaping auditors' attitudes and behaviours towards technological adoption. Therefore, it is reasonable to hypothesise that social influence factors related to machine learning usage will have a significant effect on audit capacity stress among Indonesian external auditors through the third hypotheses formulated as follows:

H_{03}: Social influence factor of using Machine Learning does not have a significant effect on audit capacity stress of Indonesian external auditors.

H_{a3}: Social influence factor of using Machine Learning has a significant effect on audit capacity stress of Indonesian external auditors.

2.5.4. Impact of Facilitating Conditions Factor Of Machine Learning Usage On Audit Capacity Stress Of Indonesian External Auditors

Agency theory links how supporting facilities in utilizing machine learning may affect auditors in doing their job for clients. Technology adoption by individuals inside businesses can be greatly facilitated by the availability of organisational support and infrastructure, according to agency theory [34]. Research within the audit domain found that infrastructure support and resource accessibility have a substantial effect on auditors' acceptance of audit technology [35]. Favourable circumstances surrounding the machine learning's application will have a major influence on audit capacity stress among Indonesian external auditors, drawing on the insights of agency theory and the empirical data presented [35]. Thus, the hypothesis implies that among Indonesian external auditors, there is a substantial correlation between audit capacity stress and facilitating conditions. This hypothesis offers a strong theoretical and empirical framework for more research because it is based on agency theory and is backed by empirical research in the audit domain. Therefore, the fourth hypothesis formulated as follows:

H_{04}: Facilitating conditions factor of using Machine Learning does not have a significant effect on audit capacity stress of Indonesian external auditors.

H_{a4}: Facilitating conditions factor of using Machine Learning has a significant effect on audit capacity stress of Indonesian external auditors.

3. Methodology

3.1. Data and Sample

This research employed quantitative methodology using a survey approach that rely on the perception of external auditors employed by public accounting firms in Indonesia regarding machine learning usage. The study's target population consists of external auditors employed by public accounting firms in Indonesia and takes 100 people as the samples. Considering our sample size of 100 respondents, this research adopted Structural Equation Modelling (SEM) techniques for analysis of data [33],[36]. Research suggests that SEM can be meaningfully employed even with modest sample sizes [37], this study acknowledges the potential limitations associated with the sample size.

3.2. Measure of Audit Capacity Stress

Audit capacity stress main drivers are due to time budget pressure, high turnover, and heavy workload [14]. This research adopts the study from [13] that uses workload as the driver of audit capacity stress. To determine audit capacity stress, the measurement of workload suits the aim of this research in which to ascertain significance of machine learning usage perception with audit capacity stress of Indonesian Auditors. Therefore, several audit workload indicators are adopted from [5] approach as follows:

Table 1.
Audit capacity stress (Workload) indicators.

Variable	Indicators
Audit workload	Internal Drivers
	1. Deadline/ Time constraints
	2. Staffing shortage
	3. Budget constraints
	External Drivers
	4. Audit standard pressure
	5. Regulatory pressure
	6. Client unprepared
	7. Client deadline pressure
	8. Client fee pressure.

3.3. Measure of Machine Learning Usage Perception using UTAUT Approach

The model of UTAUT is used as the framework to understand technology acceptance with its four constructs, performance expectancy, effort expectancy, social influence, and facilitating conditions. This study would use the primary model of UTAUT as the independent variables with indicators approach embraced [17], the surroundings of this study as follows:

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Table 2.
Independent variable indicators.

Variables	Indicators
Performance expectancy of machine learning usage	Machine learning usage is useful in carrying out my duties in auditing. Machine learning allows better time work completion. Machine learning usage would increase my productivity in conducting audit field work. Using machine learning allows higher chances of getting a promotion. Using machine learning would enhance the result quality of my audit assignment. Using machine learning would make me spend less time on clerical procedures during the audit process.
Effort expectancy of machine learning usage	I find machine learning concepts and theories are clear and understandable. I don't have any significant difficulties in maintaining the skills to operate machine learning. Overall, machine learning usage is easy for me. I don't need a lot of time to learn how to operate machine learning.
Social influence of machine learning usage	People who inspire me made me think that I should learn how to use machine learning. People who are significant to me think that I should use machine learning. My superior is very supportive of machine learning usage for my job. My company, in general, has supported the usage of machine learning.
Facilitating condition of machine learning usage	My company have the necessary resources to use machine learning. I have the required knowledge to apply in using machine learning. My company provides assistance to overcome machine learning difficulties. My company have training programs to help employees increase their machine learning skills with the current development.

3.4. Data Analysis Techniques

Partial Least Square (PLS) as one of the Structural Equation Models (SEM) is utilized to assess the predictive relationships between the model constructs. PLS-SEM has an optimal implication of prediction accuracy and is suitable for 30 - 100 sample sizes [9]. The techniques to analyse data being used in this study will be facilitated by SmartPLS version 4 and SPSS Statistics 29. SmartPLS version 3 is still compatible with a sample of 100 [38]. However, the latest version of SmartPLS will be used to ensure the maximum tool usage. The research will be carried out starting from performing the descriptive statistical test, data quality test, and measurement model assessment. The last step is to conduct the hypothesis testing through statistically calculating the coefficient of determination (R-squared) and partial t test.

4. Results and Discussions

4.1. Descriptive Statistical Test

Descriptive statistics analysis on the socio demographic of the respondents have been conducted to describe the character of the individuals that represent the population of Indonesia's external auditors as below.

Table 3.
Descriptive statistics.

Statistics		**Position**	**Age**	**Gender**	**Experience**	**Voluntariness**	**CPA Firm**	**CPA Firm Area**
N	Valid	100	100	100	100	100	100	100
	Missing	0	0	0	0	0	0	0
Mean		1.47	1.49	1.53	1.44	3.33	1.84	1.07
Median		1.00	1.00	2.00	1.00	3.00	2.00	1.00
Mode		1	1	2	1	4	2	1
Std. deviation		0.870	0.745	0.502	0.891	0.739	0.368	0.256
Variance		0.757	0.555	0.252	0.794	0.547	0.136	0.066

Table 3 summarises the descriptive statistics for the research variables. As shown in the table, voluntariness has the highest mean value of 3.33. The median values for Position, Age, Work Experience, and Area of the Certified Public Accountant (CPA) Firm are all equal to 1.00. Meanwhile, Gender and CPA Firm conduct a median of 2.00, and Voluntariness has a median of 3.00. This means that the respondents are mostly women, with 0-5 years of working experience as junior auditor positions in non-Big 4 CPA firms located in Jabodetabek, those are Jakarta, Bogor, Depok, Tangerang, and Bekasi which are the region of Indonesia, with the age of <25 years, and are willing to utilise machine learning as their tool in doing audit work.

The standard deviation (SD) and variance (VAR) capture the spread of the data around the mean. Each of them represents a good dispersion as the values are below its mean value which represents data distributions are not far from the average. Eventually, all variables (Gender, Age, Position, Area of the CPA Firm, Work Experience, and CPA Firm) have 100% valid data with zero missing values. This ensures a complete dataset for further analysis.

Table 4.
Position.

Position		**Frequency**	**Percent**	**Valid percent**	**Cumulative percent**
Valid	Auditor junior	71	71.0	71.0	71.0
	Auditor senior	17	17.0	17.0	88.0
	Supervisor	7	7.0	7.0	95.0
	Manager	4	4.0	4.0	99.0
	Partner	1	1.0	1.0	100.0
	Total	100	100	100.0	

Table 4 presents the distribution of respondents according to their position within the organisation. As can be seen from the table, Junior Auditors comprise the largest group, with 71 respondents. This finding suggests that the majority of participants in this study held entry-level audit positions which in general were occupied by millennials and Gen Z, which are young auditors.

Table 5.
Age

Age					
		Frequency	**Percent**	**Valid percent**	**Cumulative percent**
Valid	< 25	65	65.0	65.0	65.0
	25-30	22	22.0	22.0	87.0
	31-35	12	12.0	12.0	99.0
	< 35	1	1.0	1.0	100.0
	Total	100	100.0	100.0	

Table 5 details the age distribution of the study participants. As shown in table 5, the largest group (65 respondents) falls within the under-25 age category. The study sample skews younger, with a significant portion of respondents being below 25 years and the least portion of respondents above 35 years.

Table 6.
Gender.

Gender					
		Frequency	**Percent**	**Valid percent**	**Cumulative percent**
Valid	Male	47	47.0	47.0	47.0
	Female	53	53.0	53.0	100.0
	Total	100	100.0	100.0	

Table 6 presents the breakdown of respondents by gender. The table reveals that there are slightly more female participants (53 respondents) compared to male participants (47 respondents)

Table 7.
Experience.

Experience					
		Frequency	**Percent**	**Valid percent**	**Cumulative percent**
Valid	0-5 years	75	75.0	75.0	75.0
	6-10 years	12	12.0	12.0	87.0
	11-15 years	9	9.0	9.0	96.0
	16-20 years	2	2.0	2.0	98.0
	> 20 years	2	2.0	2.0	100.0
	Total	100	100.0	100.0	

Table 7 details the distribution of respondents based on their work experience. As can be seen from the table, most participants (75 respondents) have between 0-5 years of experience. Therefore, it can be said that respondents with 0–5 years related to the work experience made up the majority of this study's respondents.

Table 8.
Voluntariness.

Voluntariness					
		Frequency	**Percent**	**Valid percent**	**Cumulative percent**
Valid	Strongly disagree	3	3.0	3.0	3.0
	Disagree	7	7.0	7.0	10.0
	Agree	44	44.0	44.0	54.0
	Strongly agree	46	46.0	46.0	100.0
	Total	100	100.0	100.0	

Table 8 presents the distribution of respondent attitudes towards using machine learning in auditing. The table shows a positive sentiment, with the highest number of respondents (46) indicating strong agreement with its adoption. 44 respondents also expressed agreement, while only a smaller number (7 respondents disagreed and 3 respondents strongly disagreed). This finding suggests that a significant majority of the study participants support the use of machine learning in the auditing field.

Table 9.
CPA firm.

CPA firm					
		Frequency	**Percent**	**Valid percent**	**Cumulative percent**
Valid	Big 4	16	16.0	16.0	16.0
	Non-Big 4	84	84.0	84.0	100.0
	Total	100	100.0	100.0	

Table 9 presents the breakdown of respondents by their work location. The table reveals that a greater number of respondents (84 respondents) work in Non-Big 4 firms compared to those working in Big 4 firms (16 respondents).

Table 10.
CPA firm area.

CPA firm area					
		Frequency	**Percent**	**Valid percent**	**Cumulative percent**
Valid	Jabodetabek[a]	93	93.0	93.0	93.0
	Outside Jabodetabek	7	7.0	7.0	100.0
	Total	100	100.0	100.0	

Note: [a]Jabodetabek = Jakarta, Bogor, Depok, Tangerang, and Bekasi (regions in Indonesia).

Table 10 presents the distribution of respondents based on their work location. As can be seen from the table, a significantly larger number of respondents (93) work within the Jabodetabek area compared to those working outside this area (7 respondents).

4.2 Assessingg Measurement Models

Table 11.
Convergent validity.

Variable	Indicator	Outer loading value before removal	Outer loading value after removal
Performance expectancy (X1)	PE1	0.760	0.848
	PE2	0.798	0.830
	PE3	0.695	-
	PE4	0.642	-
	PE5	0.751	0.775
	PE6	0.692	-
Effort expectancy (X2)	EE1	0.812	0.817
	EE2	0.872	0.872
	EE3	0.797	0.791
	EE4	0.793	0.792
Social influence (X3)	SI1	0.804	0.794
	SI2	0.808	0.788
	SI3	0.803	0.777
	SI4	0.791	0.831
Facilitating condition (X4)	FC1	0.858	0.852
	FC2	0.750	0.743
	FC3	0.876	0.877
	FC4	0.900	0.908
Audit capacity stress (Workload) of Indonesia's External auditors (Y)	ID1	0.719	0.782
	ID2	0.834	0.967
	ID3	0.720	0.823
	ED1	0.620	-
	ED2	0.593	-
	ED3	0.643	-
	ED4	0.535	-
	ED5	0.696	-

Assessing convergent validity includes examine the Average Extracted Variance (AVE) and outer loading values. According to established research Haryono [45], an outer loading value exceeding 0.7 is considered acceptable. Table 11 presents the results of the outer loading computations. All variables demonstrate outer loadings exceeding 0.7 excepting indicator PE3, PE4, PE6, and all External Drivers (ED). This indicates that all the ED factors including Audit Standard Pressure, Regulatory Pressure, Client Unprepared, Client Deadline Pressure and Client Fee Pressure do not relate to audit capacity stress. While the internal drivers such as Deadline/Time Constraints, Staffing Shortage and Budget Constraints are more likely related to the audit capacity stress. Indicators with value below 0.7 are considered invalid and must be omitted. Following the removal of outliers, the final results show a satisfactory validity with all indicators value above 0.7 which means the items after removal have a good relationship with another in between the construct.

Table 12.
Internal consistency reliability test.

Variable (Reflective model)	Cronbach's alpha before removal	Cronbach's alpha after removal	Composite reliability after removal	AVE after removal
Performance expectancy (X1)	0.820	0.760	0.859	0.670
Effort expectancy (X2)	0.836	0.836	0.890	0.670
Social influence (X3)	0.816	0.816	0.875	0.637
Facilitating conditions (X4)	0.869	0.869	0.910	0.718

This internal consistency reliability test is displayed in the table inserted. The acceptable reliability scale value of Cronbach's alpha is between 0.6 to 0.8 is still acceptable [39]. According to Table 12, every measurement variable included in the reflective construct satisfies the necessary reliability standards for composite reliability and Cronbach's alpha. A trustworthy range for Cronbach Alpha is between 0.61 to 1.00. Composite reliability value of 0.7 is used as the benchmark to achieve a good reliability [40] and it is shown that all the composite reliability scores are greater than 0.7. It is resolve that this research model is trustworthy and suitable for use in other experiments. The AVE values for all research variables were discovered to be higher than 0.50. This indicates that all research variables have achieved convergent validity or a good AVE test [41]. Based on the AVE values, it can be determined that all variables of this research have achieved convergent validity and is able to effectively measure the constructs of interest.

Table 13.
Discriminant validity.

	X1	**X2**	**X3**	**X4**
Performance expectancy (X1)				
Effort expectancy (X2)	0.632			
Social influence (X3)	0.692	0.765		
Facilitating condition (X4)	0.497	0.684	0.865	

Discriminant validity is assessed to determine the extent of empirical distinction between one construct with another. Based on the result showed in table 13, all Heterotrait-Monotrait Ratio (HTMT) values are under the suggested threshold of 0.9 value. The greatest HTMT value is at 0.865, while the HTMT value was the lowest where it has a score of 0.497. All the HTMT values in table 13 indicate that the items across constructs have a good correlation (good discriminant validity).

Table 14.
Multicollinearity test.

Indicators (Formative Model)	**VIF**
ID1	2.649
ID2	1.928
ID3	3.005

This research investigated multicollinearity among the indicators of formative construct, subsequent the recommendations [42]. To detect multicollinearity, we used a Variance Inflation Factor (VIF) threshold of under value of 5 [43]. As Table 14 illustrates the VIF values of Internal Drivers (ID) are 2.649 for ID1, 1.928 for ID2, and 3.005 for ID3. These results confirm that multicollinearity is not a concern in this model, in which the formative model not excessively correlated.

4.2. Hypothesis Testing

In testing the hypothesis, linear regression on independent (Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Condition) and dependent variables is executed applying the structure that has passed measurement models assessment. The Weighted Least Square (WLS) method and Partial t Test is done with the results inserted below.

Table 15.
Heteroscedasticity test.

Model summary				
Model	**R**	**Adjusted R square**	**Std. error of the estimate**	**Durbin Watson**
1	0.904	0.810	1.166	1.547

The Weighted Least Square (WLS) method is conducted to ensure Best Linear Unbiased Estimator (BLUE) obtained, which overcomes heteroscedasticity problems in a model with a precision of 98% [44]. Based on table 15 shows a value of 0.810 for Adjusted R-squared, which means that the independent variables of Performance Expectancy (X1), Effort Expectancy (X2), Social Influence (X3), and Facilitating Condition (X4) can predict Audit Capacity Stress (workload) of Indonesia's External Auditor (Y) as much as 81%. Meanwhile the R-Square 0f 81,7% is due to other factors affected by variables unexplained in this study. On the other hand, the data result also shows a Durbin-Watson value. Following the practicle principle, Durbin-Watson test statistics value with the range of 1.5 to 2.5 is moderately acceptable. Therefore, with Durbin-Watson value of 1.547 the model passes the autocorrelation test.

Table 16.
Partial test.

Coefficients								
Model		**Unstandardized B**	**Coefficients Std. Error**	**Standardized Coefficients Beta**	**t**	**Sig**	**Collinearity Tolerance**	**Statistics VIF**
1	(Constant)	-0.215	0.630		-0.341	0.734		
	X1	-0.026	0.075	-0.019	-0.345	0.731	0.667	1.498
	X2	0.026	0.053	0.030	0.496	0.621	0.531	1.882
	X3	0.034	0.069	0.037	0.489	0.620	0.355	2.814
	X4	0.712	0.055	0.866	12.939	<0.001	0.429	2.330

As shown in Table 16, the VIF values for all four variables fall below the threshold of 5. Performance Expectancy (X1) has a VIF of 1.498, Effort Expectancy (X2) is at 1.882, Social Influence (X3) scores 2.814, and Facilitating Condition (X4) has a VIF of 2.330. These values indicate no multicollinearity, ensuring the independence of the independent variables and the validity of the subsequent regression analysis.

Based on the table 16, Performance Expectancy (X1) has sig value of 0.731, Effort Expectancy has sig value of 0.621, Social Influence (X3) has sig value of 0.620 and Facilitating Conditions (X4) has sig value of <0.001. Using a significance level of 5%, the Performance Expectancy (X1), Effort Expectancy (X2), and Social Influence (X3) variable has sig value more than the alpha of 0.05 which means the three variables are insignificant This make the null hypotheses failed to be rejected, which defines that: (1) the Performance Expectation factor using Machine Learning does not have a significant effect on the audit capacity pressure of Indonesian external auditors; (2) Effort Expectancy factor of using Machine Learning does not have a significant effect on audit capacity stress of Indonesian external auditors; and (3) Social Influence factor of using Machine Learning does not have a significant effect on audit capacity stress of Indonesian external auditors.

Although the study hypothesised that performance expectancy, effort expectancy, and social influence would influence audit capacity pressure, the results did not support these relationships. This could be due to two limitations. Firstly, the study might not have captured the most impactful factors on audit capacity pressure due to the removal of several indicators that measure the audit capacity stress. Secondly, the measurement of the independent variables (performance expectancy, effort expectancy, and social influence) might not have fully reflected their true influence on auditors. It is important to consider the moderating variables: the dominant respondent group being junior auditors (under 25 years old, with 0-5 years of experience, and not from Big 4 firms). These characteristics suggest they might be less likely to anticipate the future benefits of machine learning for reducing capacity pressure.

Meanwhile, the Facilitating Conditions (X4) variable has a sig value of <0.001 less than alpha of 0.05 which indicates that H04 can be rejected. With that so, the alternative hypothesis (Ha4) is accepted that the Facilitating Conditions factor of using Machine Learning has a significant effect on audit capacity stress of Indonesian external auditors. Therefore, Facilitating Conditions factor hold an important key role in machine learning utilization towards reduced audit capacity stress. Infrastructure support and resource accessibility are found to have a significant impact on auditors' acceptance of audit technology [35]. This also proves that facilitating conditions is crucial towards technological adoption in the audit profession and thus will have a major impact on audit capacity stress among Indonesian external auditors which support this hypothesis.

5. Conclusion

As one of the jobs with high demand and time pressure, the increasing complexity and workloads among auditors has become a growing concern. Indonesian auditors have been found to have workload accumulation that leads to stress and a solution to overcome the audit capacity stress level are needed to improve audit quality. The era after pandemic has enabled the development of digital and machine tools usage in the working environment. As a technology usage advancement in auditing sector, machine learning is a potential tool to revolutionise audit procedures by addressing audit limitations and optimises audit workload efficiency.

Using UTAUT model approach, this study object to determine the significance of Perform Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions factor of using machine learning perception on audit capacity stress of Indonesian external auditors. While at the same time assessing the reported levels of audit capacity stress amongst Indonesian external auditors. The research was conducted on 100 Indonesian external auditors using google form to question their perception of machine learning usage based on the UTAUT model and the level of audit capacity stress as well. Based on the result, it was known that the respondents are significantly represented by young external auditors working in non-Big 4 CPA firms located in Jabodetabek, those are Jakarta, Bogor, Depok, Tangerang, and Bekasi which are the region of Indonesia, and are willing to utilise machine learning as their tool in doing audit work. The hypotheses testing conducted using SmartPLS version 4 and SPSS Statistics 29 confirms that:

- The Performance Expectation factor using Machine Learning does not have a significant effect on the audit capacity pressure of Indonesian external auditors, because the respondents are mostly comprising of non-Big 4 firms, whereas Big 4 firms tend to adopt a more forward-thinking approach of integrating technology in auditing processes.
- Effort Expectancy factor of using Machine Learning does not have a significant effect on audit capacity stress of Indonesian external auditors. This can be affected by the dominant respondent group being junior auditors under 25 years old which is accustomed by instant progress, thus neglecting the learning processes.
- Social Influence factor of using Machine Learning does not have a significant effect on audit capacity stress of Indonesian external auditors because of the respondents' 0-5 years of lacking experience in working as an auditor which leads to the perception of less support from audit seniors, managers, and co-workers in influencing the utilization of machine learning for audit work.
- The Facilitating Conditions factor of using Machine Learning has a significant effect on audit capacity stress of Indonesian external auditors because nowadays is the time of rapid

technological era, moreover, it is post-pandemic era where the auditors working at CPA Firm have a favourable digitalized infrastructure support and resource.

This study can conclude that facilitating conditions are the factors that significantly capable of affecting Indonesian young external auditors' audit capacity stress in the perception of using machine learning within auditing. With young auditors as the largest respondent, Facilitating Conditions factor can be the key that may encourages machine learning usage among Indonesian external auditors in resolving audit capacity stress growing concern in Indonesia. Thus, altering the future of auditing as well, bringing a revolutionized auditing by integrating machine learning. On the results that have been stated, this study also proposes several suggestions for upcoming further research:

(1) More data samples should be acquired to obtain the optimal result on machine learning usage perception. Auditors with experience up to 5 years are suggested to explore more on the variables that affect audit capacity stress.

(2) In the upcoming study, it may be helpful to include qualitative data (such as interviews) to better understand why performance expectancy, effort expectancy, and social influence factors were insignificant.

(3) It is advisable to conduct the survey or questionnaire on external auditors outside of the peak season, to obtain the optimal amount of data.

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Appendix 1.

Research questionnaire on Indonesian external auditors		
Variables	**List of questions**	**Options**
Section 1: Socio demographic and other related general questions		
	1. Name	-
	2. WhatsApp Number	-
	3. Public Accountant Firm's Location	▪ Jakarta Selatan ▪ Jakarta Barat ▪ Jakarta Pusat ▪ Jakarta Timur ▪ Jakarta Utara ▪ Bekasi ▪ Tangerang ▪ Depok ▪ Other:
	4. Public Accountant Firm's Name	-
	5. Current Position	▪ Auditor Junior ▪ Auditor Senior ▪ Supervisor ▪ Manager ▪ Partner
	6. Age	▪ < 25 ▪ 26-30 ▪ 31-35 ▪ > 35
	7. Gender	Male / Female
	8. Work Experience	▪ 0-5 years ▪ 6-10 years ▪ 11-15 years ▪ 16-20 years ▪ > 20 years
	9. Have you ever used machine learning in carrying out audit work?	Yes / No
	10. Has your company implemented machine learning? If Yes, please specify. If No, write N/A	-
	11. Do you have any sources of information regarding machine learning usage? Ex: Discussion Forum, etc:	Yes / No
Section 2: Voluntariness of Machine Learning Usage		
	1. Are you willing to use machine learning in your work as an auditor? Answer with scale 1-4.	1 = Strongly Not Approve *(Sangat Tidak Setuju)* 2 = Not

		Approve *(Tidak Setuju)* 3 = Approve *(Setuju)* 4 = Strongly Approve *(Sangat Setuju)*
Section 3: Performance Expectancy of Machine Learning Usage (X1)		
	1. Machine learning usage is useful in carrying out my duties in auditing (PE1). 2. Machine learning allows better time work completion (PE2). 3. Machine learning usage would increase my productivity in conducting audit fieldwork (PE3). 4. Using machine learning allows higher chances of getting a promotion (PE4). 5. Using machine learning would enhance the result quality of my audit assignment (PE5). 6. Using machine learning would make me spend less time on clerical procedures during the audit process (PE6).	1 = Strongly Not Approve *(Sangat Tidak Setuju)* 2 = Not Approve *(Tidak Setuju)* 3 = Approve *(Setuju)* 4 = Strongly Approve *(Sangat Setuju)*
Section 4: Effort Expectancy of Machine Learning Usage (X2)		
	1. I find machine learning's concepts and theories are clear and understandable (EE1). 2. I don't have any significant difficulties in maintaining the skills to operate machine learning (EE2). 3. Overall, machine learning usage is easy for me (EE3). 4. I don't need a lot of time to learn how to operate machine learning (EE4).	1 = Strongly Not Approve *(Sangat Tidak Setuju)* 2 = Not Approve *(Tidak Setuju)* 3 = Approve *(Setuju)* 4 = Strongly Approve *(Sangat Setuju)*
Section 5: Social Influence of Machine Learning Usage (X3)		
	1. People who inspire me made me think that I should learn how to adopt machine learning (SI1). 2. People who are significant to me think that I should use machine learning (SI2). 3. My superior is very supportive of machine learning usage for my job (SI3). 4. My company, in general, has supported the usage of machine learning. (SI4).	1 = Strongly Not Approve *(Sangat Tidak Setuju)* 2 = Not Approve *(Tidak Setuju)* 3 = Approve *(Setuju)* 4 = Strongly Approve *(Sangat Setuju)*
Section 6: Facilitating Conditions of Machine Learning Usage (X4)		

	1. My company have the necessary resources/facility to use machine learning (FC1). 2. I have the required knowledge to apply in using machine learning (FC2). 3. My company provide assistance to overcome machine learning difficulties (FC3). 4. My company have training programs to help employees increase their machine learning skills with the current development (FC4).	1 = Strongly Not Approve *(Sangat Tidak Setuju)* 2 = Not Approve *(Tidak Setuju)* 3 = Approve *(Setuju)* 4 = Strongly Approve *(Sangat Setuju)*
Section 7: Audit Capacity Stress / Workload (Y)		
	<u>Internal Drivers</u> 1. My company always fulfils the audit deadline even in peak season (ID1). 2. My company has enough staff that works for them (enough staffing) (ID2). 3. My company have budget constraints in accepting new client (ID3). <u>External Drivers</u> 4. The Audit Standard is capable enough to comply with (ED1). 5. The prevailing audit regulatory requirement has been increasing (ED2). 6. My company's clients always prepare the data needed before they are asked to (ED3). 7. Most of client deadlines can be met on time (ED4). 8. My company's clients sometimes put pressure on fees (ED5).	1 = Strongly Not Approve *(Sangat Tidak Setuju)* 2 = Not Approve *(Tidak Setuju)* 3 = Approve *(Setuju)* 4 = Strongly Approve *(Sangat Setuju)*