E.L.J. van Vijfeijken (U 565817, SNR 2104821)

Exploring the relationship between Mental Workload and In-Role Performance: The Moderating Role of Employee Usage of Generative Artificial Intelligence in the Workplace

Resit

Master Thesis Human Resource Studies (760991-M-24)

06-08-2024

Supervisor: C.Y.M Fong

Abstract

The objective of this study is to investigate the curvilinear relationship between mental workload and in-role performance as there is conflicting literature. It pioneers in testing how this relationship is moderated by employee usage of generative artificial intelligence . The study uses convenience sampling to gather a total sample of 135 respondents working in different industries. Results show no significant linear or curvilinear relationship between mental workload and in-role performance and no significant moderation of this relationship by employee usage of generative artificial intelligence. It did observe a significant relationship between education and in-role performance. Limitations of this research include performance being self-rated and thus potentially bringing bias, not taking into account different coping strategies for mental workload as well as other contextual factors. The study adds to existing literature on the relationship between mental workload and in-role performance, as it found no linear or curvilinear significant effect between mental workload and in-role performance. Something which has not been observed before in earlier published studies with the same hypothesis. It also pioneers in the effect of employee usage of generative artificial intelligence on the relationship between mental workload and in-role performance. Furthermore, it assesses the reliability and validity of the experimental questionnaire used for measuring employee usage of generative artificial intelligence. Potential practical implications of the findings are discussed.

Exploring the relationship between Mental Workload and In-Role Performance: The Moderating Role of Employee Usage of Generative Artificial Intelligence in the Workplace.

Historically, technological advancements have had a big influence on the way businesses operate and on their employees. These technological advancements can be a blessing for businesses as they have the potential to facilitate leaps in increasing productivity, efficiency, effectiveness and ultimately profit. New technological advancements like the industrial revolution and digitalization have already at least partly taken place in the western world (The Editors of Encyclopaedia Britannica, 2023; Motivity Labs, 2023). Building off of the previous technological advancements, we now see ourselves at the beginning of a new era; the era of generative Artificial Intelligence (AI). The advancement of generative AI has been impressive to say the least. Since the release of generative AI such as ChatGPT to the public on november 20th 2022, its number of users has skyrocketed to a reported 180+ million users on november 3rd 2023 (Marr, 2023; Duarte, 2023). Organizations can potentially benefit from the usage of generative AI (Soni, 2023). Its unique capability lies in the diverse dataset with which it has been trained (Dilmegani, 2024). This allows it to have a wide range of application such as creating text and photos, coding, composing music, drafting emails, summarize articles, solve math problems, simplify complex topics and improving business operations (Hetler, 2023; Kelly, 2023; Ooi et al., 2023). Generative AI is being implemented in the rapidly evolving landscape of contemporary workplaces, as businesses strive to maximize productivity and efficiency. This new technology is already being used in customer service, healthcare and advertising to name a few (Xu et al., 2020; Yang et al., 2021; Shah et al., 2020).

Technology may displace, alter or generate new jobs (Zuboff, 1988). Since the usage of generative AI is a relatively new development, the impact of employee usage of generative AI (EUGAI) is not yet fully understood. Within the field of HRM, generative AI may be used to automate recruitment, improve learning outcomes of training and development, employee engagement, minimize employee turnover and increase employee motivation (Ooi et al., 2023; Yılmaz & Yılmaz, 2023). However, there are also potential drawbacks of using generative AI. There are risks related to well-being, bias, inaccurate or inappropriate responses, lack of transparency in what the generated answers are based on and lack of data security (Budhwar et al., 2023; Ooi et al., 2023). As previously mentioned, generative AI has the ability to take over certain tasks . Individual employees may use generative AI for this purpose. Understanding the potential benefit to strategically implementing generative AI usage in the workplace could reduce the workload which individual employees have to deal with on a daily basis. As of writing this research, there is no such study published which studies this possible effect. Researching this is relevant as workload has an effect on employee performance according to some studies. The research on workload gives different answers to whether workload positively or negatively affects employee performance. Brüggen (2015) indicates that there is an inverted U-shape relationship between workload and employee performance. However, research by Rolos et al. (2018) suggests a negative linear relationship between workload and employee performance. Another study by Omolayo en Omole (2013) indicate no relationship between workload and employee performance. No significant empirical evidence was found in the existing literature indicating a positive relationship between workload and employee performance. The conflicting evidence on the effect of workload on employee performance, combined with the lack of research on the potential moderation effect of EUGAI on the aforementioned relationship, constitute the knowledge gap that this study aims to close. The goal of this study is to answer the following research question: What is the relationship between workload and employee performance and how is this relationship moderated by the employee usage of generative AI? The objective with answering this research question is to provide clarity on the relationship between workload and employee performance, thus clarifying the conflicting literature. Moreover, this study aims to pioneer in providing empirical evidence for a moderating effect of EUGAI on this aforementioned relationship. Organizations could use the outcome of this study to try to increase employee performance through the stimulation of EUGAI or at least decrease the potential negative effects of workload by stimulating EUGAI. This is desirable for organizations as employee performance is positively related to organizational performance (Tarmidi & Arsjah, 2019). How this could be achieved is discussed in the practical implication.

Theoretical Framework

There are multiple definitions for employee performance. Viswesvaran and Ones (2000, p. 216) define employee performance as "scalable actions, behavior and outcomes that employees engage in or bring about that are linked with and contribute to organizational goals." By some, in-role performance (IRP) is used to describe employee performance (Austin and Villanova, 1992; Campbell, 1990; Pawar, 2013). IRP is defined as "behavior directed toward formal tasks, duties, and responsibilities such as those included in a job description" (Williams & Anderson 1991, p. 607). As this research incorporates a behavioral moderator, the latter definition by Williams and Anderson (1991) is used as this aligns better with this research. Extensive research has shown that IRP is affected by multiple factors such as organizational citizenship behavior, individual learning, team learning and workload (Atatsi et al., 2019; Brüggen, 2015). Workload has been studied for decades (Hicks & Wierwille, 1979). Presently, studies involving workload focuses more on mental workload (MWL) (Wierwille et al., 1985). Even though the topic of MWL has been researched for decades, there is not one universal definition (Miller, 2001). One definition by Verwey (2000, p. 188) is "mental workload is related to the amount of attention required for making decisions." Another definition by Eggemeier et al., (1991, p. 210) is "mental workload refers to the portion of operator information processing capacity or resources that is actually required to meet system demands." In this research the definition by Eggemeier et al., (1991) will be used as this definition is not limited to decision making but covers information processing as a whole, thus being more complete and more fitting to this study.

Brüggen's (2015) research found that IRP increases with the value of MWL also increasing up to a certain point after which IRP decreases while MWL increases to a maximum, forming an inverted U-shape. However, research by Rolos et al. (2018) suggests a negative linear relationship between MWL and IRP. More recent research by Zhao et al. (2023) supports the evidence provided by Brüggen (2015). Zhao et al. (2023) also found an inverted U-shape relationship between MWL and IRP. Thus, the inverted U-shape relationship is supported more in the literature. For this reason, this research assumes a curvilinear relationship between MWL and IRP. Zhao et al. (2023) call the middle part of the inverted U-shape as mentioned by Brüggen (2015) the 'Capacity Zone'. In the Capacity zone the MWL value is medium high, resulting in peak IRP. Outside of the medium MWL zone is on the left the 'Laid-back zone' with a low MWL value and on the right the 'Fatigue zone' with a high MWL value. In the low MWL zone the work efficiency increases when the value of MWL increases. Here, the human beings are able to complete the assignment in the accorded amount of time. However, they could have done more work in that given time. In this zone, potential productivity and thus IRP is lost. In the high MWL zone, the IRP is decreasing as the value of MWL rises to the maximum. The high MWL zone causes fatigue and overwhelms individuals due to increased stress. In this zone the assignment is not completed on time, causing a loss in IRP. It is in the interest of organizations to have their employees operate within the medium MWL zone for consistent high work efficiency and ultimately high IRP, as IRP is positively related to organizational performance (Tarmidi & Arsjah, 2019). The different zones as described by Zhao et al. (2023) mean that MWL can have different effects on IRP depending on the value of the MWL. The low MWL zone and the high MWL zone as presented by Zhao et al. (2023) could be described as a mismatch between job demands and job resources. This logic is supported by the Job Demand-Resource (JD-R) model (Bakker et al., 2023). The JD-R model proposes that the working environment can be divided into two general categories: job demands and job resources, each having distinct relationships with specific results. Job demands refer to "physical, social, or organizational aspects of the job that require sustained physical or mental effort and are therefore associated with certain physiological and psychological costs" (Bakker et al., 2005, p 170). Job resources refer to "physical, psychological, social, or organizational aspects of the job that (a) are functional in achieving work goals, (b) reduce job demands and the associated physiological and psychological costs, or (c) stimulate personal growth and development" (Bakker et al., 2005, p 170). Following the definition of job demands, MWL fits into the job demands category. In the low MWL zone, holding constant the job resources and other job demands, there are not enough job demands to motivate the employee to do more work, causing a loss in IRP. In the high MWL zone, holding the job resources and job demands constant compared to the low MWL zone, there are too many job demands compared to job resources. If there are no additional job resources to use and higher stress levels, such as in the high MWL zone, the negative effect of MWL could come into force, decreasing IRP. The reverse is true for the low MWL zone . When there are little to no demands, there is little to no IRP. This means that a balance between the job demands and job resources should lead to peak IRP. Hence, the first hypothesis is formed.

Hypothesis 1: There will be an inverted U-shaped relationship between mental workload and in-role performance.

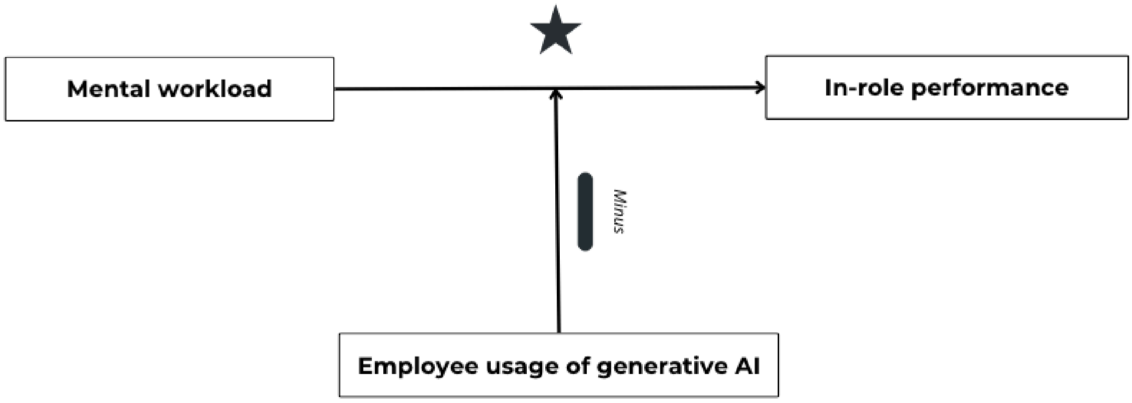
According to one assertion of the JD-R model, people are more inclined to use their job resources when facing higher stress levels, such as those caused by demanding job conditions, in this case MWL. Since MWL is a job demand and higher MWL entails a higher job demand, job resources ought to rise with the same weight. Zhao et al. (2023) mention that the interventions from either computers or human instructors are crucial to support the Capacity zone. Following the definition of job resources, these interventions can be described as job resources. EUGAI may be such a job resource to support the Capacity zone. Generative AI can be defined as "an umbrella term that refers to systems that exhibit intelligent behavior, such as learning reasoning and problem-solving" (Brynjolfsson et al., 2023, p. 1). Moreover, job resources have previously been found to be useful in coping with high demands such as MWL and maintaining IRP through increased engagement. (Hakanen et al., 2005, J, 2014).

Generative AI models use vast amounts of publicly accessible data to read and generate text that closely resembles that of human language. The models demonstrate creativity by proficiently producing written content ranging creating text and photos, coding, composing music, drafting emails, summarize articles, solve math problems, simplify complex topics and improving business operations (Aydın & Karaarslan, 2023; Hetler, 2023; Kelly, 2023; Ooi et al., 2023). Following the logic of the JD-R model, generative AI could act as a job resource as employees may use it to craft their jobs. Job crafting can be defined as "The physical and cognitive changes individuals make in the task or relational boundaries of their work" (Wrzesniewski & Dutton, 2001, p. 179).

In the low MWL zone, employees could engage in job crafting through the use of generative AI to enhance their roles by automating routine tasks, freeing up time for more meaningful and engaging activities, and developing new skills, leading to higher IRP with the same low MWL values (Almasradi et al., 2023). In the high MWL zone, job crafting through the use of generative AI can help to reduce the job demand of the psychological cost of the job in the high MWL zone. This could cause less fatigue and not overwhelming the individual employees leading to lower MWL and higher IRP levels compared to when EUGAI is not present. Following this logic, EUGAI could potentially moderate the inverted-U shape relationship between MWL and IRP through job crafting behaviors. As of writing this research, no study has been conducted to research this despite the theoretical grounds for a relationship between EUGAI, MWL and IRP. Thus, the second hypothesis is formed.

Hypothesis 2: Employee usage of generative AI moderates the inverted U-shape relationship between mental workload and in-role performance such that this relationship is more pronounced among employees lower in usage of generative AI, compared to employees higher in usage of generative AI.

Figure 1. Conceptual model



* The star in the conceptual model indicates the expected curvilinear relationship between MWL and IRP.

Methods

Research design and procedures

The research aims to develop a quantitative description of the relationship between MWL and IRP and the moderating role of EUGAI on this same relationship.

Sample

The data for this study was collected through employees of all sectors who have experience in using generative AI. Convenience sampling was used to facilitate the easiest access to respondents. The sample data gathered for analysis was collected through a collaborative effort encompassing both the researcher and fellow students. The data collection process was a collective undertaking, with each collaborator conforming to a standardized protocol to ensure reliability and validity. This approach allowed for a more diverse and thorough dataset, increasing the robustness of the findings presented in this research.

Instruments

To ensure reliability, the independent variable and dependent variable were measured using scales which have already been tested as recommended by Sürücü en Maşlakçı (2020). The full scales can be found in the appendix. Exploratory Factor Analysis (EFA) was used to discover the factor structures of the measurements and its reliability. The cutoff point for all three scales on the KMO value was set at > .7 and Bartletts test at $p < .05$. Firstly, to measure MWL, the questionnaire and combined scale by Van Veldhoven and Meijman (1994) consisting of 11 items ($\alpha = .88$) and 7 items ($\alpha = .87$) was used. The questionnaire was modified to use a 5 point Likert scale ranging from 1 (always), to 5 (never) as opposed to the 4 point scale in the original version. This was done so that a neutral answer could be given when a respondent felt neutral about a question. This avoided the risk of forcing participants into giving an answer which they did not agree with and influencing the results. A 4 factor model proposing amount of work, pace of work, meticulousness required for work and cognitive load of work dimensions was evaluated. This is different to the hypothesized one dimensional construct. However, it can be explained by the scale that was used. The scale that was used according to the authors included pace of work, amount of work and cognitive load. The factor analysis showed one more factor being meticulousness required for work which can be explained by the wording of the originally cognitive load scale using words like precision and carefulness. These two words are different to paying attention constantly and having to be constantly reminded for example. As shown in Table 1, the eigenvalue for the first four factors were 6,39, 2,29, 1,55 and 1,15 making up 63,2% of the variance in the items. Maximum likelihood factor analysis with an oblique rotation was conducted with the original 18 items. Using a cutoff value of .30, all of the 18 items loaded on the appropriate factor. Factor 1 and 2 correlated the highest at .57. Additionally, though it is not shown in table 1, there was 1 additional eigenvalue greater than 1.0 (1,006) associated with an additional 5,6% of variance. However, based on the drop in the eigenvalues with factors 2 through 4, the 4 factor model of MWL was retained. Therefore, the items mentioned above that exceeded the .3 value were put together to form a 18 item MWL scale ($\alpha = .84$, KMO = .83, $p < .001$). Due to the presence of example items in the scale like ‘Are you working under time pressure?’, the scale aligned with the definition of MWL used in this study.

Secondly, IRP was measured using a 5 point Likert scale ranging from 1 (disagree) to 5 (very strongly agree) with 7 items ($\alpha = .91$) (Williams & Anderson, 1991). Once more EFA was used to discover the factor structure of the measurement and its reliability. A 2 factor model composed of meeting jobstandards and neglect on the job dimensions was evaluated. This is different to the hypothesized one dimensional construct of IRP. However, this can be explained by the fact that both items that loaded onto factor 2 were reverse coded. This brings with it the possibility that respondents answering behavior changes, introducing variance even though they seem to measure the same construct. As shown in Table 2, the eigenvalue for the first two factors were 2,76 and 1,45 making up 60,2% of the variance in the items. Maximum likelihood factor analysis with an oblique rotation was conducted with the original 7 items. A 2 factor model was evaluated with the factor correlation being .03. Using a cutoff value of .30, only one of the 7 items failed to load on either of the two factors. All of the remaining 6 items loaded on the appropriate factors. Therefore, the 6 items mentioned above that exceeded the .30 value were put together to form an IRP scale. Deleting the one item also improved reliability slightly from $\alpha = .62$ to $\alpha = .63$. Removing one additional item would have increased the reliability to $\alpha = .67$. However, this items loaded heavily on factor 2 at .91. Because of this high factor loading, it was decided to leave the item in the scale, in spite of deleting it resulting in a higher reliability. The KMO of the scale was .72 with $p < .001$. The questionnaire included topics like formal performance requirements and failing to perform duties (reverse coded) and included items such as 'I fulfill the responsibilities specified in my job description.' These topics and this example item align with the definition of IRP used in this study.

Lastly, EUGAI was measured using an experimental questionnaire developed by Fong, C.Y.M. (2024). The questionnaire consisted of two sub questionnaires: one for automating job demands, consisting of 7 items ($\alpha = .86$), and one for augmenting job demands, consisting of 9 items ($\alpha = .92$). The questionnaire made use of a 5 point Liker scale ranging from 1 (never) to 5 (always). Once again EFA was used to discover the factor structure of the measurement and its reliability. A 2 factor model composed of automating work tasks and augmentation work tasks dimensions was evaluated. Once again, this differs from the hypothesized one dimensional construct. However, this can be explained by the fact that the questionnaire consisted of two sub questionnaires. One for automating job demands and one for augmenting job demands. Some items had overlap in their wording when it came to automating or augmenting job demands, making it possible for them to load onto both factors. As shown in Table 3, the eigenvalue for the first two factors were 8,48 and 1,16 making up 60,3% of the variance in the items. Maximum likelihood factor analysis with an oblique rotation was conducted with the original 16 items. A 2 factor model was evaluated with the factor correlation being .77. Using a cutoff value of .30, 12 items loaded on one of the two factors uniquely. 4 items loaded into both factors. Since these items touch both dimensions, it was decided to keep them in. Therefore, the 16 items mentioned above that exceeded the .30 value were put together to form an EUGAI scale ($\alpha = .94$, KMO = .92, $p < .001$). The questionnaire contained items concerning job demands and job resources. Hence, it is aligned with this research. No example items can be shared in this research due to the author of the scale explicitly requesting the items to not be shared.

Control variables

To refine the accuracy of the analysis it included the amount of hours an individual works per week, education level, industry and tenure as control variables as these variables are all possible predictors of IRP as shown by Chandrasekar (2011), DeVaro (2022), Ng and Feldman (2009) and Ng and Feldman (2010). Age and gender are included only for demographic statistics purposes and are not part of the predictive models, as no empirical evidence of these variables influencing IRP was found. By incorporating the control variables, the objective was to separate and evaluate the distinct effect of MWL on IRP and the moderation effect of EUGAI on this relationship and thus increasing the accuracy of this research.

Analysis

The data was analyzed in IBM SPSS 27. Before the analysis, the dataset was prepared by checking for missing values, which were coded as 999 and subsequently deleted. The significance level for this research was set at $p < 0.05$. After deleting missing values, outliers were identified by making a boxplot. The assumption of homoscedasticity was checked using a scatter plot. With the same scatterplot, a first indication of the relationship between the two variables could be realized. Since this study predicts a curvilinear relationship between MWL and IRP, a curvilinear analysis was performed and checked for a significant effect. After this, the moderation effect is checked for significance. To provide meaningful information for the discussion and practical information, the difference in the relationship between MWL and IRP with and without the moderation effect of EUGAI was needed through a visual representation.

Results

Sample and data collection

The initial sample size for this study consisted of 207 participants from various organizations and occupations who consented to taking part in this research. After deleting 72 missing values, the final data set for analysis was a sample size of 135. The sample included 71 male (52,6%), 62 female (45,9%) and 2 preferred not to say (1,5%). The average age was 33,6 years old with a SD of 12,9 years. The average of hours worked per week was 33,4 hours with a SD of 12,2 hours. The average tenure was 6 years with a SD of 7,3 years. The average level of education was university bachelor with a SD of .993. Of the 135 respondents, the four most common industries were technology (12,6%), finance (8,1%), education (8,1%) and retail (7,4%). 46.7% of respondents worked in sectors other than the ones provided as options. The survey did not record what these sectors were. On average, respondents reported a MWL of 3.15 with a SD of .60 and an average of 4.35 with a .41 SD for their IRP. The average score of EUGAI was 2.47 with a SD of .84. All descriptive statistics and correlations are described in Table 4. The frequency statistics for gender and industry are described in Table 5 and 6.

Table 4

Descriptive Statistics and Correlations for Study Variables

Variable	*N*	*Minimum*	*Maximum*	*M*	*SD*	1	2	3	4	5	6	7	8	9
1. In-role performance	135	3.00	5.00	4.35	0.41	-								
2. Mental workload	135	1.72	4.44	3.15	0.60	-.14	-							
3. Employee usage of generative AI	135	1.00	4.20	2.47	0.84	-.09	.01	-						
4. Education	135	2.00	6.00	5.12	0.99	.16	.17*	-.12	-					
5. Industry	135	1.00	11.00	8.31	3.04	.11	-.01	-.15	.01	-				
6. Tenure	135	0.00	33.00	5.98	7.29	.04	.20*	-.30**	.22**	.11	-			
7. Hours per week worked	135	1.00	60.00	33.39	12.22	-.01	.34**	-.12	.22**	0	.24**	-		
8. Age	135	20.00	62.00	33,56	12,94	-	-	-	-	-	-	-	-	
9. Gender	135	0.00	2.00	0.49	0.53	-	-	-	-	-	-	-	-	-

Notes

* Correlation is significant at the 0.05 level (2-tailed)

** Correlation is significant at the 0.01 level (2-tailed)

4. With higher scores indicating a higher level of education

9. With 0 = male, 1 = female and 2 = prefer not to say

8. & 9. are only included for demographic statistics purposes

Table 5.

Frequencies statistics Gender

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Male	71	52.6	52.6	52.6
	Female	62	45.9	45.9	98.5
	Prefer not to say	2	1.5	1.5	100.0
	Total	135	100.0	100.0	

Table 6.

Frequency statistics Industry

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Healthcare	2	1.5	1.5	1.5
	Energy	7	5.2	5.2	6.7
	Hospitality	3	2.2	2.2	8.9
	Manufacturing	2	1.5	1.5	10.4
	Technology	17	12.6	12.6	23.0
	Finance	11	8.1	8.1	31.1
	Retail	10	7.4	7.4	38.5
	Logistics	7	5.2	5.2	43.7
	Education	11	8.1	8.1	51.9
	Pharmaceutical	2	1.5	1.5	53.3
	Other	63	46.7	46.7	100.0
	Total	135	100.0	100.0	

Using Pearson's correlation as an index of association, the correlations between the variables in this research are presented in table 4. For age and gender, no correlations are shown as these variables were only included for sample describing purposes. None of the variables correlated significantly with IRP; MWL (r -.14, $p = .10$), EUGAI (r -.09, $p = .29$), education (r .16, $p = .07$), industry (r .11, $p = .21$), tenure (r .04, $p = 67$) and hours per week worked (r -.01,$p = .91$). EUGAI was not significantly correlated with MWL (r .01, $p = .95$) and significantly negatively correlated with tenure (r-.30, p = < .001). MWL on the other hand was significantly positively correlated to tenure (r .20, p = .02). Tenure was significantly positively correlated to education (r .22, p = .01). Furthermore MWL was significantly positively correlated to education level (r .17, p > .05) as well as hours per week worked (r .34, p = < .001). Hours per week worked was significantly correlated with educational level (r. 22, p = .01) and tenure (r .24, p = .01).

Models

The hypotheses were tested with two models. The first model tests the relationship between MWL (X) and IRP (Y), with IRP as its dependent variable. Since this research expects a curvilinear relationship, the square of MWL is added to the model as an additional predictor (X^2). Thus, using EUGAI (W), education (U1), hours per week worked (U2), industry (U3) and tenure (U4) as covariates, the model estimated is

$$\textit{In-role performance} = iY + b1X + b2X^2 + b3W + b4U1 + b5U2 + b6U3 + b7U4 + eY. \quad \text{(Model 1)}$$

To test if there is a moderation effect of EUGAI (W) on the expected curvilinear relationship between MWL (X) and IRP (Y), the model estimated is

$$\hat{Y} = iY + b1X + \theta X^2 \rightarrow Y^{X^2} + b3W + b4XW + b6U1 + b7U2 + b8U3 + b9U4 \quad \text{(Model 2)}$$

Hypothesis testing

The results of model 1 are provided in Table 7. The relationship of model 1 is shown in figure 2. For testing H1, the squared value of MWL was added in the model. Before testing for the curvilinear effect, the linear effect of MWL on IRP was tested. The linear regression analysis resulted in MWL not significantly affecting IRP whilst controlling for education level, hour per week worked, industry, and tenure, b = -.12, t(130) = -1.95, p = .05. The curvilinear regression analysis also resulted in MWL not significantly affecting IRP whilst controlling for education level, hour per week worked, industry, and tenure, b = -.04, t(129) = -0.47, p = .64. Education did significantly affect IRP b = .08, t (129) = 2.06, p = .04. Therefore, MWL does not significantly affect IRP linearly or curvilinearly. Adding MWL in order to test for a curvilinear effect did not add significant predicting power to the model. This contradicts H1. Thus, based on this research H1 can be rejected.

Table 7

Hypothesis 1

Output regression analysis

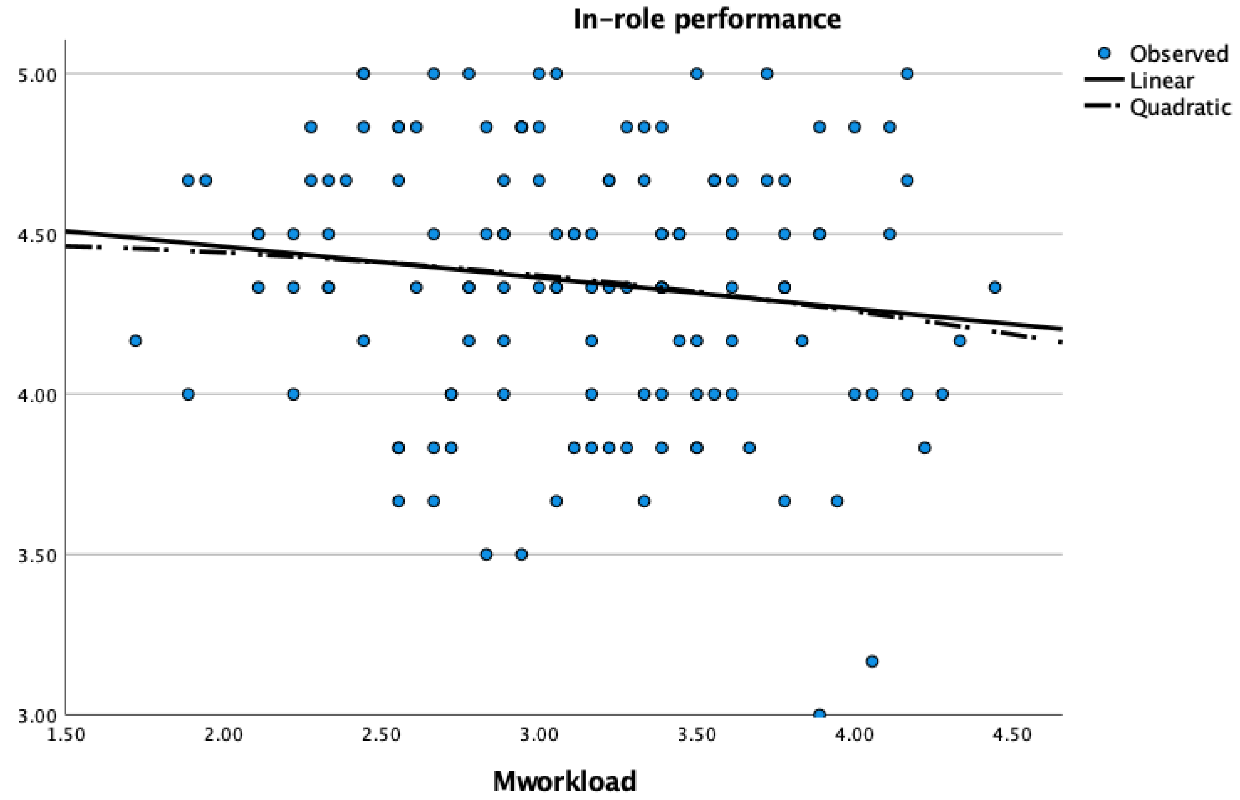
Model 1 (Outcome In-role performance)				
Variables	*b*	*Se*	*t*	*p*
(Constant)	4.66	0.19	24.63	<.001
Mental workload	-.08	0.06	-1.95	.10
R^2 change	.02			
F-change	2.70			

Model 2 (Outcome In-role performance)				
Variables	*b*	*Se*	*t*	*p*
(Constant)	4.22	0.26	15.960	<.001
Mental workload	-.12	0.06	-1.950	.05
Education	0.08*	0.04	2.050	.04
Hours per week worked	0	0.00	0.054	.96
Industry	.01	0.01	1.218	.23
Tenure	0	0.01	0.216	.83
R^2 change	.05			
F-change	1.60			

Model 3 (Outcome In-role performance)				
Variables	*b*	*Se*	*t*	*p*
(Constant)	3.84	0.96	4.485	<.001
Mental workload	.12	0.53	0.232	.82
Education	.08*	0.04	2.06	.04
Hours per week worked	0	0.00	0.34	.97
Industry	.02	0.01	1.265	.21
Tenure	0	0.01	0.207	.84
Mental workload^2	-.04	0.85	-0.465	.64
R^2 change	0			
F-change	0.22			

n = 135 * p < .05 ** p < .01

Figure 2



For testing H2, PROCESS by Hayes (2022) as recommended by professor Guy Moors was used as PROCESS can calculate the moderation of curvilinear effects. It does this through calculating how the steepness of the hypothesized bend changes depending on the value of the moderator and gives an output of the unique R^2 change contributed by the moderator, EUGAI. It also uses the pick-a-point method to determine whether or not the moderation effect is significant at all values of the moderator or only at certain levels. The results are presented in Table 8. As shown, EUGAI did not significantly moderate the relationship between MWL and IRP b = .02, F(125) = .04, p = .52, R^2 change of .00. Furthermore, using the pick-a-point method by PROCESS, no significant effect was found at the probed values of EUGAI. This contradicts H2. Thus, based on this research H2 can be rejected.

Table 8
Hypothesis 2
Output PROCESS analysis

	Model 1 (Moderator Employee usage of generative AI)			
Variables	*b*	*Se*	*t*	*p*
constant	2.90	2.39	1.21	.23
Mental workload^2	-.09	0.25	-0.38	.71
Employee usage of generative AI	.38	0.98	0.39	.70
Mentalworkload^2 X Employee usage of generative AI	.02	0.10	0.19	.85
Industry	.01	0.01	1.24	.22
Education	0.08*	0.04	2.03	.04
Tenure	0	0.01	-0.07	.94
Hours per week worked	0	0.00	-0.07	.94
Mental workload	.63	1.55	0.40	.69
Mental workload X Employee usage of generative AI	-.19	0.64	-0.30	.76
R^2 change full model	.08			
F-change full model	1.19			.31
R^2 Change moderator only	0			
F-change moderator only	0.04			.52
n = 135	* p < .05	** p < .01		

Discussion

This paper examined the relationship between MWL on IRP and how this relationship is moderated by EUGAI. The key findings are presented below. The results for the absence of correlation between MWL and IRP and the results for H1 contradict previous research by Brüggen, (2015), Rolos et al., (2018) and Zhao et al (2023) but do align with the results of Omolayo & Omole (2013). However, Omolayo and Omole (2013) did not have a concrete answer based on academic insights on the result they found. An explanation for this result is that there is a relatively high mean score for IRP at 4.35 out of 5 with a .41 SD, a minimum of 3.00 and a maximum of 5.00. A consequence of this is that there is little room for variance in the scores. This is most likely due to the respondent having to rate their own IRP, opening the door for positive bias as theorized in self-enhancement theory (Alicke & Sedikides, 2009; Taylor & Brown, 1988). Positive bias is the tendency for people to report positive views of reality (Hoorens, 2014). Meta analysis by Harris and Schaubroek (1988) also showed an average of over .50 of a standard deviation higher self ratings compared to supervisor ratings. This effect was found to be moderated by job type, meaning more positive bias in ambiguous contexts such as managerial and professional jobs compared to more well defined jobs (i.e., blue-collar/service). Since the average education of the sample in this research is university bachelor level, it is plausible that the vast majority of respondents in this sample have managerial and/or professional jobs, meaning an even bigger positive bias towards IRP ratings. Results also showed a significant effect between education and IRP. Research by Weidman et al. (1972) indicated a relationship between level of education and self rating of performance. All the possible biases as mentioned above could have had the effect that respondents rated themselves more positively on IRP, creating more bias in the results and possibly explaining the observed significant relationship between education and IRP. In reality, the respondents IRP may be lower and a different result may have been observed. However, this is only speculation and cannot be substantiated in this research. Alongside the methodological possible explanation for the result of H1, there is also a possible theoretical explanation, namely The two-level compensatory control model by Hockey (1997). The lower level is a default amount of effort for a given task, based on the anticipated resources needed such as level of skill. Increases in demand below this level are not felt as effortful and control of IRP appears automatic. The upper set point indicates the maximum level of effort that can be expended, with the gap between the upper and lower set points serving as a reserve effort budget to address extra demands, unexpected changes in the demands-resources balance, or the added strain of stressful environments. The model states that IRP levels may be protected under higher reported MWL values by recruiting further resources, but only at the expense of increased effort and behavioral and physiological costs as described as level two. Alternatively, the model states that recruiting additional resources may not be needed by reducing IRP goals. As reducing IRP is often not an option in working environments due to the risk of employees losing their job, the second level of the compensatory control model is most likely to occur in workplace scenarios which is what this study focuses on. In this research, the second level - and thus increased effort - is observed in the positive correlation between MWL and hours per week worked. The increase in hours per week worked as MWL increases could mask the effect of MWL on IRP as it diminishes the potential negative effect of MWL on IRP. This could have resulted in the non significant relationship between MWL and IRP.

The results also indicate that EUGAI does not significantly moderate the curvilinear relationship between MWL and IRP. This defies the expected result (H2) based on the JD-R model, but is also expected given the non significant curvilinear relationship between MWL and IRP. The JD-R model is based on the premise that there are job demands and job resources. In this research the job demands are MWL and the job resources are EUGAI. Based on the JD-R model, the moderation effect of EUGAI is expected to come into effect between the end of the medium high MWL zone and through the high MWL zone as described by Zhao et al. (2023). Yet, in this research no such medium high and high MWL zones were observed to be affecting IRP possibly because if the high average IRP rating leaving little room for variance. This study recognizes the possibility of a significant effect of EUGAI on the relationship between MWL and IRP even though there is not a significant direct effect. However, this possibility can be ruled out because the pick-a-point method of PROCESS was used to try the different values for EUGAI for significance and no significant effect was found. Based on the results, it is tempting to conclude that respondents did not use AI as a solution for high MWL. However, there are multiple possible explanations for this. One explanation is based on Task-Technology Fit (TTF) theory. TTF theory states that technology adoption is predicted by the perceived fit between tasks and technology (Goodhue & Thompson, 1995). If there is a mismatch between the tasks of the respondent and the perceived fit of the technology by the respondents, there may not be an effect of EUGAI on - in this study's case - the relationship between MWL and IRP. If this perceived fit is not present, it might not encourage employees to craft their job. Desirable technology characteristics such as perceived fit determine the room employees have to execute job crafting behaviors (M. Xu et al., 2022). Absence of this fit could result in less EUGAI. This reasoning is supported by the Technology Acceptance Model (TAM), which states that the perceived ease of use and usefulness determine the acceptance and use of technology (Davis, 1989). This means that generative AI might lead to minimal impact on the relationship between MWL and IRP if respondents find it difficult to use or not useful. Since both perceived fit of technology and perceived ease of use and usefulness were not measured in this research, it can not be definitively concluded that the reasons as proposed by TTF and TAM are the reasons for the result of H2. Moreover, it is possible that respondents used other job resources than EUGAI to buffer the relationship between MWL and IRP. The definition of job resources is so broad that it is practically impossible to capture all of them in one research and be able to control for all of them. This makes it difficult to isolate the true effect of EUGAI on the relationship between MWL and IRP. Following the rejection of both H1 and H2, it can be concluded that in this study no relationship was found between MWL and IRP and that no moderation effect by EUGAI was observed on this relationship. Finally, the absence of significant correlation between IRP, MWL and EUGAI is to be expected given the non significant results for H1 and H2.

Limitations

This research has a few limitations which need to be addressed in order to place the results in its full context. First, there are limitations concerning the sample size and the diversity of the sample. Since convenience sampling was used, the sample size was relatively small. This had the consequence of not a lot of variance in education level for example. Convenience sampling also had the consequence of having a relatively high average education level. Because of this, the result of education being a predictor of IRP may be influenced. Second, respondents had to self-rate their performance. As mentioned in the discussion, this very well could have added great biases to the IRP scores. In turn this could have tainted the scores on this variable, resulting in potentially unreliable results for H1. Third, the research does not take into account the different preferred strategies for coping with MWL. Some respondents prefer to complete as much workload as possible in the early part of the projects or tasks, while others may prefer to do most of the workload closer to the deadline of said projects and tasks. This could influence the way respondents perceive their mental workload differently depending on their coping strategy. Fourth, no other job resources other than the hypothesized EUGAI were taken into account in this study. This makes it very hard - if not impossible - to argue for evidence of there not being a moderating effect of EUGAI on the relationship between MWL and IRP. Ffith, contextual factors such as organizational culture, work environment, job complexity, and individual differences were not taken into account in this study. These factors could influence the relationship between MWL and IRP and may affect EUGAI. Finally, since both perceived fit of technology and perceived ease of use and usefulness were not measured in this research, it can not be definitively concluded that the reasons as proposed by TTF and TAM are the reasons for the result of H2.

Future Research Directions

For future research, it may be recommended to have a bigger and more diversified sample and to avoid self-rated performance scales as they could bring bias to the results. Future studies should consider selecting a sample with a set maximum hours per week worked, to avoid the possibility of hours per week working masking the potential effect of MWL on IRP through compensational behavior. As EUGAI is still in its infancy, it will progress (probably rapidly) in the coming years in areas like accuracy in responses, complexity of tasks it can take over and diversity of implementation options. It is recommended to study the effects of EUGAI as a job resource in the future when its abilities and its acceptance to usefulness in the workplace increases. This could have a significant effect on not just the relationship between MWL and IRP but on other relationships between job demand and outcome variables. Moreover, including different preferred strategies of coping with MWL could add to models with more predictive power on the relationship with IRP as well as contextual differences. Additionally, perceived fit of technology and perceived ease of use and usefulness should be investigated to verify whether or not the results of H2 are caused for reasons proposed by TTF and TAM. Lastly, longitudinal studies may be needed to understand how EUGAI may develop over time as employees learn to effectively use the resource and how this development may influence the relationship between MWL and IRP.

Contributions

This study adds to the existing literature on the relationship between MWL and IRP and has added a new angle to the previously studied linear and curvilinear relationship between them. The observed non significant effect between mental workload and in-role performance is something that has been observed before (Omolayo & Omole, 2013), however this study used more advanced statistical analysis and then the study by Omolayo and Omole (2013) with a curvilinear hypothesis and still found no significant effect. Furthermore, it has pioneered in the moderating effect of EUGAI on this relationship. In doing so, it has assessed the reliability and validity of the experimental questionnaire by Fong, C.Y.M. (2024). This study shows that the scale can measure the automation and augmentation of job demands reliably and is fit to use in future research aiming to study this. It has also raised points of improvement regarding research design and methodology. The study adds to existing literature on the relationship between mental workload and in-role performance, as it found no significant effect between mental workload and in-role performance. Something which has not been observed before in earlier published studies.

Practical implications

The practical implications of this study should be interpreted with a big question mark behind them. The finding that there is no relationship between MWL and IRP suggests that organizations can keep mounting MWL on their employees without their IRP taking a hit. However, this seems very unlikely in the real world, as other studies have previously shown (Brüggen, 2015; Rolos et al. 2018, Zhao et al. 2023). Moreover, this study does not take into account the possible negative health effects of continued high MWL on individuals and organizations such as decreased wellbeing, burnout and increased turnover intention (Gaillard, 1993, Werdani, 2017, Yanchus et al., 2016).

Another practical implication of this study is that organizations should not invest into strategically implementing EUGAI to buffer the - in previous studies - found negative effects of MWL, as this study shows no buffering effect. Rather, organizations could invest in electroencephalogram-based systems to detect high MWL in real time and use this information to mitigate the MWL (Sejnowski et al., 2007). This would however be complicated to achieve effectively on a large scale in the real world due to ethical and privacy. Companies could also choose to invest on the individual level in educating employees to not be distracted from their essential tasks, prioritizing said tasks and mental exercises (Ghaderi et al., 2022). On the organizational level companies could install policies to prevent mental workload like having a hard limit on how many hours an employee is allowed to work or the minimum number of employees in a team with a calculated amount of workload.

Reference list

Alicke, M. D., & Sedikides, C. (2009). Self-enhancement and self-protection: What they are and what they do. *European Review Of Social Psychology*, *20*(1), 1–48. https://doi.org/10.1080/10463280802613866

Almasradi, N. R. B., Anjum, T., Shams, N. F., & Iqbal, N. E. H. (2023). Effect of Job Crafting on Faculty's Job Satisfaction and Performance; The Moderating Role of Perceived Organizational Support. *Journal Of Research in Psychology*, *4*(2), 94–107. https://doi.org/10.31580/jrp.v4i2.2709

Atatsi, E. A., Stoffers, J., & Kil, A. J. (2019). Factors Affecting Employee Performance: A Systematic Literature review. Journal of Advances in Management Research, 16(3), 329–351. https://doi.org/10.1108/jamr-06-2018-0052

Austin, J. T., & Villanova, P. (1992). The Criterion problem: 1917–1992. Journal of Applied Psychology, 77(6), 836–874. https://doi.org/10.1037/0021-9010.77.6.836

Aydın, Ö., & Karaarslan, E. (2023). Is ChatGPT leading generative AI? What is beyond expectations? Academic Platform Journal of Engineering and Smart Systems, 11(3), 118–134. https://doi.org/10.21541/apjess.1293702

Azaria, A. (2022). ChatGPT Usage and Limitations. HAL Open sciences. https://doi.org/10.31219/osf.io/5ue7n

Bakker, A. B., Demerouti, E., & Euwema, M. C. (2005). Job Resources Buffer the Impact of Job Demands on Burnout. Journal Of Occupational Health Psychology, 10(2), 170–180. https://doi.org/10.1037/1076-8998.10.2.170

Bakker, A. B., Demerouti, E., & Sanz‐Vergel, A. I. (2023). Job Demands–Resources Theory: Ten years later. *Annual Review Of Organizational Psychology And Organizational Behavior*, *10*(1), 25–53. https://doi.org/10.1146/annurev-orgpsych-120920-053933

Brüggen, A. (2015). An empirical investigation of the relationship between workload and performance. Management Decision, 53(10), 2377–2389. https://doi.org/10.1108/md-02-2015-0063

Brynjolfsson, E., Li, D., & Raymond, L. (2023). Generative AI at Work. National bureau of economic research. https://doi.org/10.3386/w31161

Budhwar, P., Chowdhury, S., Wood, G., Aguinis, H., Bamber, G. J., Beltran, J. R., Boselie, P., Cooke, F. L., Decker, S., DeNisi, A. S., Dey, P. K., Guest, D., Knoblich, A. J., Malik, A., Paauwe, J., Papagiannidis, S., Patel, C., Pereira, V., Ren, S., . . . Varma, A. (2023). Human Resource Management in the age of Generative Artificial Intelligence: Perspectives and research Directions on ChatGPT. *Human Resource Management Journal*, *33*(3), 606–659. https://doi.org/10.1111/1748-8583.12524

Campbell, J. P. (1990). Modeling the performance prediction problem in industrial and organizational psychology. Handbook of Industrial and Organizational Psychology, 1(2), 687–731. https://psycnet.apa.org/record/1993-97198-012

Chandrasekar, K. (2011). Workplace environment and its impact on organisational performance in public sector organisations. *International Journal Of Enterprise Computing And Business Systems*, *1*(1). http://www.ijecbs.com/January2011/N4Jan2011.pdf

Davis, F. D. (1989). Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. *Management Information Systems Quarterly*, *13*(3), 319. https://doi.org/10.2307/249008

DeVaro, J. (2022). Performance pay, working hours, and health‐related absenteeism. *Industrial Relations*, *61*(4), 327–352. https://doi.org/10.1111/irel.12308

Dilmegani, C. (2024, 1 january). *Chatbot vs ChatGPT: Understanding the differences & features*. AIMultiple.

https://research.aimultiple.com/chatbot-vs-chatgpt/#:~:text=ChatGPT%3A%20Trained%20on%20more%20diverse,biggest%20current%20appeal%20to%20users.

Duarte, F. (2023, 3 november). Number of ChatGPT users (Nov 2023). Exploding Topics. https://explodingtopics.com/blog/chatgpt-users

Eggemeier, F. T., Wilson, G. F., Kramer, A. F., & Damos, D. L. (1991). Workload assessment in multi-task environments. In CRC Press eBooks (pp. 207–216). https://doi.org/10.1201/9781003069447-12

Fong, C.Y.M. (2024). Generative AI Scale. [Unpublished paper]. Tilburg University.

Gaillard, A. W. K. (1993). Comparing the concepts of mental load and stress. *Ergonomics*, *36*(9), 991–1005. https://doi.org/10.1080/00140139308967972

Ghaderi, M., Abdessalem, H. B., & Frasson, C. (2022). An Analysis of Mental Workload Involved in Piloting Tasks. In *Lecture notes in networks and systems* (pp. 211–220). https://doi.org/10.1007/978-3-031-17601-2_21

Goodhue, D. L., & Thompson, R. L. (1995). Task-Technology Fit and Individual Performance. *Management Information Systems Quarterly*, *19*(2), 213. https://doi.org/10.2307/249689

Gozalo-Brizuela, R., & Garrido-Merchán, E. C. (2023). ChatGPT is not all you need. a state of the art review of large generative AI models. arXiv (Cornell University). https://doi.org/10.48550/arxiv.2301.04655

Hakanen, J. J., Bakker, A. B., & Demerouti, E. (2005). How dentists cope with their job demands and stay engaged: the moderating role of job resources. *European Journal Of Oral Sciences*, *113*(6), 479–487. https://doi.org/10.1111/j.1600-0722.2005.00250.x

Harris, M. M., & Schaubroeck, J. (1988). A meta-analysis of self-supervisor, self-peer, and peer-supervisor ratings. *Personnel Psychology*, *41*(1), 43–62. https://doi.org/10.1111/j.1744-6570.1988.tb00631.x

Hayes, A. F. (2022). Hacking PROCESS for estimation and probing of linear moderation of quadratic effects and quadratic moderation of linear effects. *CCRAM Technical Report*, *22*(2).

Hetler, A. (2023, 17 november). ChatGPT. WhatIs.com. https://www.techtarget.com/whatis/definition/ChatGPT#:~:text=ChatGPT%20is%20an%20artificial%20intelligence,%2C%20essays%2C%20code%20and%20emails.

Hicks, T. G., & Wierwille, W. W. (1979). Comparison of five MWL assessment procedures in a Moving-Base driving simulator. Human Factors, 21(2), 129–143. https://doi.org/10.1177/001872087902100201

Hockey, G. R. J. (1997). Compensatory control in the regulation of human performance under stress and high workload: A cognitive-energetical framework. *Biological Psychology*, *45*(1–3), 73–93. https://doi.org/10.1016/s0301-0511(96)05223-4

Hoorens, V. (2014). Positivity bias. In *Springer eBooks* (pp. 4938–4941). https://doi.org/10.1007/978-94-007-0753-5_2219

J, A. (2014). Determinants of employee engagement and their impact on employee performance. *International Journal Of Productivity And Performance Management*, *63*(3), 308–323. https://doi.org/10.1108/ijppm-01-2013-0008

Karasek, R. (1979). Job demands, job decision latitude, and mental strain: Implications for job redesign. Administrative Science Quarterly, 24(2), 285. https://doi.org/10.2307/2392498

Kelly, S. M. (2023, 16 maart). 5 jaw-dropping things GPT-4 can do that ChatGPT couldn't. CNN.com. Geraadpleegd op 26 november 2023, van https://edition.cnn.com/2023/03/16/tech/gpt-4-use-cases/index.html

Marr, B. (2023, 19 mei). A short history of ChatGPT: How we got to where we are today. Forbes. https://www.forbes.com/sites/bernardmarr/2023/05/19/a-short-history-of-chatgpt-how-we-got-to-where-we-are-today/?sh=2414a776674f

Miller, S. (2001). Workload measures. National Advanced Driving Simulator.

Motivity Labs. (2023, 5 mei). Reasons why digitization is a must for any business. https://motivitylabs.com/reasons-why-digitalization-is-a-must-for-any-business/#:~:text=Digitalization%20business%20model%20greatly%20improves,in%20the%20digitalization%20business%20model.

Ng, T. W. H., & Feldman, D. C. (2009). How broadly does education contribute to job performance? *Personnel Psychology*, *62*(1), 89–134. https://doi.org/10.1111/j.1744-6570.2008.01130.x

Ng, T. W. H., & Feldman, D. C. (2010). Organizational Tenure and Job Performance. *Journal Of Management*, *36*(5), 1220–1250. https://doi.org/10.1177/0149206309359809

Omolayo, O., & Omole, C. (2013). Influence of Mental Workload on Job Performance. *International Journal Of Humanities And Social Science*, *3*(15). https://www.ijhssnet.com/journals/Vol_3_No_15_August_2013/27.pdf

Ooi, K., Tan, G. W., Al-Emran, M., Al-Sharafi, M. A., Căpățînă, A., Chakraborty, A., Dwivedi, Y. K., Huang, T., Kar, A. K., Lee, V., Loh, X., Micu, A., Mikalef, P., Mogaji, E., Pandey, N., Raman, R., Rana, N. P., Sarker, P., Sharma, A., . . . Wong, L. (2023). The potential of generative artificial intelligence across disciplines: perspectives and future directions. *Journal Of Computer Information Systems*, 1–32. https://doi.org/10.1080/08874417.2023.2261010

Pawar, B. S. (2012). A proposed model of organizational behavior aspects for employee performance and well-being. Applied Research in Quality of Life, 8(3), 339–359. https://doi.org/10.1007/s11482-012-9193-7

Rolos, J. K. R., Sambul, S. A. P., & Rumawas, W. (2018). The effect of work pressure on employee performance at PT. Jiwasraya Insurance, Manado City Office. Journal of Business Administration, 6(4), ISSN : 2338-9605. https://ejournal.unsrat.ac.id/v3/index.php/jab/article/view/21074/20785

Sejnowski, T., Kubier, A., Müller, K., Seilers, E., Krusienski, D., Mcfarland, D., Wolpaw, J., Hinterberger, T., Nijboer, F., Matuz, T., Furdea, A., Mochty, U., Jordan, M., Lal, T., Hill, N., Mellinger, J., Bensch, M., Tangermann, M., Widman, G., . . . Parra, L. (2007). Toward Brain-Computer interfacing. In *The MIT Press eBooks*. https://doi.org/10.7551/mitpress/7493.001.0001

Shah, N., Bhagat, N., Chauhan, H., & Shah, M. (2020). Research trends on the usage of machine learning and artificial intelligence in advertising. Augmented Human Research, 5(1). https://doi.org/10.1007/s41133-020-00038-8

Siegrist, J. (1996). Adverse health effects of high-effort/low-reward conditions. Journal of Occupational Health Psychology, 1(1), 27–41. https://doi.org/10.1037/1076-8998.1.1.27

Soni, V. (2023). Impact of Generative AI on Small and Medium Enterprises' Revenue Growth: The Moderating Role of Human, Technological, and Market Factors. *RCBA*, *6*(1). https://researchberg.com/index.php/rcba/article/view/169

Sürücü, L., & Maşlakçı, A. (2020).Validity and reliability in quantitative research. *Business And Management Studies: An International Journal*, *8*(3), 2694–2726. https://doi.org/10.15295/bmij.v8i3.1540

Tarmidi, D., & Arsjah, R. (2019). Employee and organizational performance: impact of employee internal and external factors, moderated by online application. Journal of Resources Development and Management. https://doi.org/10.7176/jrdm/57-04

Taylor, S. E., & Brown, J. D. (1988). Illusion and well-being: A social psychological perspective on mental health. *Psychological Bulletin*, *103*(2), 193–210. https://doi.org/10.1037/0033-2909.103.2.193

The Editors of Encyclopaedia Britannica. (2023, 15 november). Industrial Revolution | Definition, History, Dates, Summary, & Facts. Encyclopedia Britannica. https://www.britannica.com/money/topic/Industrial-Revolution

Van Veldhoven, M., & Meijman, T. (1994). Het meten van psychosociale arbeidsbelasting met een vragenlijst : de Vragenlijst Beleving en Beoordeling van de Arbeid (VBBA). https://publications.tno.nl/publication/34623067/5YjvNW/veldhoven-1994-meten.pdf

Verwey, W. B. (2000). On-line driver workload estimation. Effects of road situation and age on secondary task measures. Ergonomics, 43(2), 187–209. https://doi.org/10.1080/001401300184558

Viswesvaran, C., & Ones, D. S. (2000). Perspectives on models of job performance. International Journal Of Selection And Assessment, 8(4), 216–226. https://doi.org/10.1111/1468-2389.00151

Weidman, J. C., Phelan, W. T., & Sullivan, M. A. (1972). The Influence of Educational Attainment on Self-Evaluations of Competence. *Sociology Of Education*, *45*(3), 303. https://doi.org/10.2307/2112150

Werdani, Y. D. W. (2017). The Effect of Mental Workload To The Nurse's Burnout Level In The Private Hospitals. *Atlantis Press*. https://doi.org/10.2991/inc-17.2017.9

Wierwille, W. W., Rahimi, M., & Casali, J. G. (1985). Evaluation of 16 measures of MWL using a simulated flight task emphasizing mediational activity. Human Factors, 27(5), 489–502. https://doi.org/10.1177/001872088502700501

Williams, L. J., & Anderson, S. E. (1991). Job Satisfaction and Organizational Commitment as Predictors of Organizational Citizenship and In-Role Behaviors. *Journal Of Management*, *17*(3), 601–617.

Wright, T. A., & Bonett, D. G. (1997). The contribution of burnout to work performance. Journal of Organizational Behavior, 18(5), 491–499. https://doi.org/10.1002/(sici)1099-1379(199709)18:5

Wrzesniewski, A., & Dutton, E. (2001). Crafting a Job: Revisioning Employees as Active Crafters of Their Work. *The Academy Of Management Review*, *26*(2), 179. https://www.jstor.org/stable/259118

Xu, M., Wang, W., Ou, C. X., & Song, B. (2022). Does IT matter for work meaningfulness?: Exploring the mediating role of job crafting. *Information Technology & People*, *36*(1), 313–331. https://doi.org/10.1108/itp-08-2020-0563

Xu, Y., Shieh, C., Van Esch, P., & Ling, I. (2020). AI customer service: task complexity, Problem-Solving ability, and usage intention. Australasian Marketing Journal, 28(4), 189–199. https://doi.org/10.1016/j.ausmj.2020.03.005

Yanchus, N. J., Periard, D., & Osatuke, K. (2016). Further examination of predictors of turnover intention among mental health professionals. *Journal Of Psychiatric And Mental Health Nursing*, *24*(1), 41–56. https://doi.org/10.1111/jpm.12354

Yang, Y. C., Islam, S. U., Noor, A., Khan, S., Afsar, W., & Nazir, S. (2021). Influential usage of big data and artificial intelligence in healthcare. Computational and Mathematical Methods in Medicine, 2021, 1–13. https://doi.org/10.1155/2021/5812499

Yılmaz, F. G. K., & Yılmaz, R. (2023). The effect of generative artificial intelligence (AI)-based tool use on students' computational thinking skills, programming self-efficacy and motivation. *Computers & Education: Artificial Intelligence*, *4*, 100147. https://doi.org/10.1016/j.caeai.2023.100147

Zhao, M., Qiu, D., & Zeng, Y. (2023). How much workload is a 'good' workload for human beings to meet the deadline: human capacity zone and workload equilibrium. Journal of Engineering Design, 34(8), 644–673. https://doi.org/10.1080/09544828.2023.2249216

Zuboff, S. (1988). *Dilemmas of the transformation in the age of the machine*. New York : Basic Books.

Appendix

Table 1

Results of Exploratory Factor Analysis of Mental Workload items - Oblique Rotation (n = 135)

Scale items		Factors			
To what extent do the following questions apply to you?		I	II	III	IV
1. Do you have problems with work pressure?			.87		
2. Would you like to slow down in your work?			.61		
3. Do you need to work very fast?		.81			
4. Do you gave a lot of work to do?		.83			
5. Do you have to work extra hard to get something done?		.55			
6. Are you working under time pressure?		.65			
7. Do you have to rush?		.71			
8. Can you do your work at ease? (R)		.32			
9. Are you experiencing a backlog of work?			.51		
10. Do you have too little work? (R)		.56			
11. Do you have problems with the pace of the work?			.78		
12. Does your work require a lot of concentration?		.50			
13. Do you have to work very precisely?				.62	
14. Are you required to pay attention to a lot of different things at your job?					.39
15. Does your job require you to constantly think?					.83
16. Does your job require your constant attention?					.68
17. Do you need to be reminded of a lot of things on your job?			.52		
18. Does your job require a great amout of carefulness?				1.04	
Eigenvalue		6.39	2.29	1.55	1.15
Percent variance explained		35.5%	12.7%	8.6%	6.4%
Cumulative percent variance explained		35.5%	48.2%	56.8%	63.2%
Factor correlation		I	II	III	IV
	I	-			
	II	.57	-		
	III	.35	.19	-	
	IV	.46	.26	.43	-

Table 2

Results of Exploratory Factor Analysis of In-Role Performance items - Oblique Rotation (n = 135)

Scale items		Factors	
To what extent does each statement apply to you?		I	II
1. I adequately complete my assigned duties		.73	
2. I fulfill the responsibilities specified in my job description		.65	
3. I perform tasks that are expected of me		.77	
4. I meet formal performance requirement for the job		.81	
5. I engage in activities that will directly affect my performance evaluation			
6. I neglect aspects of the job I am obligated to perform (R)			.91
7. I fail to perform essential duties (R)			.49
Eigenvalue		2.76	1.45
Percent variance explained		39.4%	20.7%
Cumulative percent variance explained		39.4%	60.2%
Factor correlation		I	II
	I	-	
	II	.03	-

Table 3

Results of Exploratory Factor Analysis of Employee Usage of Generative AI items - Oblique Rotation (n = 135)

Scale items		Factors	
At work I proactively...		I	II
1		.81	
2		.82	
3		.61	
4		.55	
5		.49	
6		.56	
7		.60	
8		.46	.33
9		.45	.34
10		.35	.46
11		.42	.34
12		.40	
13			.57
14			.86
15			.87
16			.93
Eigenvalue		8.48	1.16
Percent variance explained		53.0%	7.3%
Cumulative percent variance explained		53.0%	60.3%
Factor correlation		I	II
	I	-	
	II	.77	-

*The items are redacted in the table, following a direct request from the author of the scale C.Y.M. Fong due to the scale not being pusblished as of writing this research. The items can be specifically requested for review by emailing Y.M.Fong@tilburguniversity.edu.